

A Base Camp for Scaling AI

C.J.C. BURGESS, T. HART, Z. YANG,*
S. CUCERZAN, R.W. WHITE, A. PASTUSIAK, J. LEWIS

Microsoft Research

December 21st, 2016

Abstract

Modern statistical machine learning (SML) methods share a major limitation with the early approaches to AI: there is no scalable way to adapt them to new domains. Human learning solves this in part by leveraging a rich, shared, updateable world model. Such scalability requires modularity: updating part of the world model should not impact unrelated parts. We have argued that such modularity will require both “correctability” (so that errors can be corrected without introducing new errors) and “interpretability” (so that we can understand what components need correcting).

To achieve this, one could attempt to adapt state of the art SML systems to be interpretable and correctable; or one could see how far the simplest possible interpretable, correctable learning methods can take us, and try to control the limitations of SML methods by applying them only where needed. Here we focus on the latter approach and we investigate two main ideas: “Teacher Assisted Learning”, which leverages crowd sourcing to learn language; and “Factored Dialog Learning”, which factors the process of application development into roles where the language competencies needed are isolated, enabling non-experts to quickly create new applications.

We test these ideas in an “Automated Personal Assistant” (APA) setting, with two scenarios: that of detecting user intent from a user-APA dialog; and that of creating a class of event reminder applications, where a non-expert “teacher” can then create specific apps. For the intent detection task, we use a dataset of a thousand labeled utterances from user dialogs with Cortana, and we show that our approach matches state of the art SML methods, but in addition provides full transparency: the whole (editable) model can be summarized on one human-readable page. For the reminder app task, we ran small user studies to verify the efficacy of the approach.

*Currently at Carnegie Mellon University. This work was done while Yang was an intern at MSR.

CONTENTS

1	Introduction and Related Work	4
1.1	Teacher Assisted Learning	6
1.2	Factored Dialog Learning	7
1.3	Predicates, Templates, and TAL and FDL compared	8
2	Teacher Assisted Learning	10
2.1	Design	10
2.1.1	Templates	11
2.1.2	Predicates	12
2.1.3	Text Preprocessing	14
2.1.4	The Parsed Components List	14
2.1.5	The Template Matching Process	16
2.1.6	The TAL Training Process	16
2.1.7	Editing the TAL Model	18
2.1.8	Testing TAL	18
2.2	Experiments: Learning Curves	18
2.2.1	Data	18
2.2.2	TAL and LUIS: Learning Curve Experiments	19
2.3	Experiments: Full Training	22
2.3.1	LUIS Baseline Results	22
2.3.2	TAL Results	22
2.3.3	Comparison	22
2.3.4	The Complete TAL Intent Detection Classifier	23
3	Factored Dialog Learning	25
3.1	The Ask-How-To-Say Dialog Structure	25
3.2	The Train-Predicate Dialog Structure	27
3.3	Overview of the Module Specification Language	28
3.3.1	Script Blocks	28
3.3.2	The “Turn” in detail	29
3.3.3	Other Turn Types in the MSL	29
3.4	Case Study: Adapting the Event Reminder Module	30
3.4.1	Teacher Task Description	30
3.4.2	Teacher Task Results	31
3.4.3	Teacher Task Summary	32

3.4.4	User Task Description	32
3.4.5	User Task Results	33
3.4.6	User Task Summary	33
4	Discussion	33
5	Some Ideas for Future Work	34
5.1	Wake Phase Error Correction	34
5.2	Dream Phase Error Correction	34
5.2.1	Template Error Correction Using Unlabeled Data	34
5.2.2	Template Unification	35
5.3	Extensibility	36
5.3.1	Multiple Languages	36
5.3.2	TAL's World Model	36
5.3.3	Extending to Large Numbers of Templates and Predicates	37
5.3.4	Extending the MSL	37
5.4	Other Benefits of Model Transparency	37
5.5	The Machine Comprehension of Language	37
6	Acknowledgements	38
7	Appendix 1: Specification of the Module Specification Language	39
7.1	YAML Basics	39
7.2	Script blocks	40
7.3	Script Parameters	41
7.3.1	Parameter Names and References	41
7.3.2	Special Parameter Names	42
7.3.3	Parameter Types	43
7.3.4	Conditional Operations on Parameters	45
7.3.5	Arithmetic Operations on Parameters	45
7.4	Script Handlers	46
7.5	Turn Types	46
7.5.1	Prompt	46
7.5.2	ParamValueTurn	47
7.5.3	TrainPredicateTurn	49
7.5.4	TestPredicateTurn	49
7.5.5	NIterations	53
7.5.6	SetParamValues	54

7.5.7	RemoveParamValues	54
7.5.8	ScriptConditionalActions	55
7.5.9	UserConditionalActions	55
7.5.10	ParamValueOrConstantTurn	56
7.5.11	SetConstantValues	58
7.5.12	EndIterationAction	58
7.5.13	EndScriptAction	59
7.5.14	NoAction	59
7.6	Finding the App the User Wants	59
8	Appendix 2: TAL's American Slang and Abbreviations Map	61

1. INTRODUCTION AND RELATED WORK

AI has had a long and difficult childhood [4], with nine “AI Winters” of varying degrees commonly identified [31]. A key technical roadblock seems to be the problem of scale, both in terms of tasks (it is much easier to build a system that solves one domain-specific task well, than to build one whose domain can be easily extended to new tasks) and complexity (it is easy to build small systems, but as they grow, systems can rapidly become unmanageable). This has led to our reliance on statistical methods, in particular on statistical machine learning (SML), where tasks are essentially defined by labels on large datasets and by models that are carefully constructed to solve those tasks. SML has had recent impressive successes [6], and in fact major inroads have been made into the first three “AI Winters” listed (“the failure of machine translation”, “the abandonment of connectionism” and “speech understanding research”) [31]. But all statistical machine learning methods to date share some critical limitations when it comes to scalability: there is no procedure to make one machine-learned model maximally leverage what another has learned, on a different task. How can different models that solve different problems be built in such a way that one can take advantage of the other’s world model, for shared basic concepts like space, time and number? And how can one system take advantage of the natural language learning that another has performed - how can we achieve the desideratum: *Every teacher benefits from what any teacher teaches*? In the world of SML, “Transfer learning” and its variants have been proposed to attack this problem. Transfer learning takes the form of models sharing features, parameters, or data (for a review, see [17]), but the set up is very close to the SML backbone; the problem is viewed as a mismatch of the data distributions that one’s model sees, rather than the lack of a shared, fundamental, growable world model.

The key to a scalable world model is modularity. We have argued that modularity in turn requires *correctability* [3]. A system is correctable if its errors can be corrected in such a way that its generalization performance is improved while no (or, controllably few) new errors are introduced. We have also argued that *interpretability*, by which we mean the ability of the designer to easily understand why the system makes the assertions it does, is a desirable stepping stone towards correctability, although perhaps not a necessary one.

The vast majority of current statistical models have complex, unseen, and essentially uncontrollable decision surfaces that make full correctability and interpretability beyond our reach. (Statistical models unencumbered by such problems tend to be very small.) In these circumstances the

simplest option available for error correction is to add labeled training data and then either continue training starting from the current model, or re-train. But this is a clumsy tool for a delicate task: previously correct predictions can become errors, training data is expensive to gather, and we have little control over whether the new model actually solves the errors in question. One can certainly take a more nuanced approach to balance robustness with improved generalization: see for example (Wang et al., 2012) [30] for an interesting application of such ideas to ranking. But currently, the tide is flowing in the opposite direction. Large neural network models are powerful but are becoming increasingly complex. Furthermore, it is worrying that deep nets for vision tasks generate their highest confidence outputs when presented with inputs that to a human looks like noise [16]; and that almost imperceptible changes can be added to an input image that was previously classified correctly by a deep neural net, causing that net to make an error (and that the same changes, found using a sensitivity analysis for one net, can be applied to another, trained on a subset of the same data, with the same result) [25]. These are striking departures from how we understand the human visual system to work and would seem to be another barrier to both interpretability and correctability.

The machine comprehension of text (MCT) presents particularly stark challenges for statistical methods. An effective automated open domain dialog system will likely require a rich world model and the ability to perform commonsense reasoning over it [14]. It is possible that purely statistical methods will be all that is needed (see for example [10] for work on extending LSTM dialog models to model individual speakers, and [9] for using CNNs and RNNs for dialog topic tracking). But the performance of machines currently lags far behind that of humans in comprehending even language familiar to a typical first or second grader. Such a dataset, in multiple choice format, was presented by [21] and the state of the art results on that data is approximately 70% accuracy [29, 27], compared to the 100% that humans can easily achieve. A much larger question answering dataset provided by (Rajpurkar et al., 2016) [20] for MCT paints a similar picture, with F1 scores achieved by a strong machine learning baseline of 51%, compared to 87% for humans.

The vast majority of the approaches proposed not just for MCT, but for the general algorithmic modeling of various aspects of human intelligence, are statistical in nature (for recent work, see, for example, [11], [26], [18] and [8]). This is a very appealing research strategy for several well-known reasons. But when it comes to building interpretable and correctable methods, a natural question arises: how far can we get with methods for which interpretability and correctability are built in from the ground up, before resorting to statistical machine learning methods? Specifically, can the problems associated with SML be controlled by carefully compartmentalizing its role in such a system?

The work in this paper investigates this question. We adopt a machine teaching approach, and ask specifically: how much progress can be made with an interpretable, correctable, rule-based system that can be taught using crowd-sourcing? While the end goal is to answer whether such a system could help address the core scalability issues facing AI today, in this work we are simply searching for the hard limitations that the simplest possible methods will run into; in particular, the points at which SML methods become clearly required, if such points exist. We view this exercise as constructing a base camp for the expedition, and as we will see, the initial results are surprising: we find that a crowd-sourced rule-based system, with generalization built in using a taxonomy, can perform as well as a state of the art machine learning system, but correctly and interpretably, on an MCT task.

Such a bottom-up approach is reminiscent of the early work in AI, perhaps the closest being the work of (Schank, 1977), where particular scenarios are encapsulated by scripts [23]. The more

recent work of (Hixon et al., 2015), in which a knowledge graph is learned from conversational dialogs, is similar in spirit to ours: there, human knowledge is leveraged more deeply than by just extracting labels, and an editable ontology is used to aid in representing world knowledge. However, their focus is very different [7]: they investigate the construction of a knowledge base to support question answering, given a set of background true/false statements about the world (in their case, 4th grade science), and they gather user input through dialogs structured around multiple choice questions. In contrast, our focus is on methods to achieve scalability in general, on modeling language directly to support this, and on the general development of apps for APAs, rather than question answering.

Our base camp is built on two foundations: *Teacher Assisted Learning (TAL)* and *Factored Dialog Learning (FDL)*, which we now describe. Since FDL uses TAL but not vice versa, we describe TAL first¹.

1.1. Teacher Assisted Learning

Traditionally, developing machine learning models has required expertise in machine learning and programming. However, some recent research has focused on how to help someone who is a domain expert, but who knows little about machine learning, to quickly build machine learned models [24, 35]. LUIS [34] provides user-friendly interfaces, available through a web portal, that allow the user to perform necessary machine learning steps, such as defining labels, adding examples, and training and evaluating models, in an interactive fashion. LUIS also provides visualizations that show the prediction performance, and it integrates an active learning component (“Suggest”) to allow the users to label the “most uncertain” utterances.

However, a non-expert’s knowledge and intuition about the problem domain is a highly valuable resource that is not fully leveraged by traditional machine learning techniques, beyond asking for labels. For example, when predicting speaker intent for dialog utterances [28], a non-expert can not only easily interpret the meaning of each utterance, but can also explain why they believe their interpretation, why some utterances are ambiguous, when some utterances don’t make sense, and so forth. Current SML approaches, including the above machine teaching methods, ignore this extra rich information.

We hypothesize that a learning task can benefit from teachers who are experts in their domain, but not in machine learning, in the two most important steps of learning: representation learning and model generalization. The core idea in TAL is to use language-based templates and predicates which the teacher can tune to solve the problem at hand, using examples from the training set and other resources for guidance. TAL is by construction interpretable and correctable. In this setting, we have to address the following fundamental questions:

- TAL shares its objective with traditional machine learning, namely, maximizing generalization performance. How can we make maximal use of the Teacher’s language skills and domain expertise to achieve this?
- How can we build interpretability and correctability into the model from the ground up?
- As we assume the teachers are usually not technical experts, how do we design simple natural-language-based dialogs between TAL and the teacher during the teaching process, which will work for *any language modeling task*, thus taking a step towards addressing the scale problem described above?

¹We also use “TAL” to denote the overall dialog system itself, when the meaning is clear from context.

- Could this approach address the core scaling problem facing AI - that is, how can we ensure that all teachers (or systems) benefit from what any teacher teaches?

Because the representation is interpretable, highly modular, and language-based, the Teacher can adjust it as desired, giving them much more control over how the system detects meaning compared to SML approaches. Teaching is an iterative process where, once the teacher has taught a pattern, TAL can then run it over labeled data, looking for false positives and negatives, which then guide the teacher to further tune their pattern. This approach thus leverages the deeper language skills mentioned above, because at any point the teacher can reason why their pattern fails and take steps to correct it.

The work presented here focuses on the first three items above. The fourth is a very interesting open problem; some discussion is offered in Section 5.

We present more details on TAL below. In a case study in MCT, where the task is to detect when the user has the intent to make a purchase, we demonstrate how an English speaker, using a TAL instance that integrates the WordNet semantic taxonomy [5], can train an intent prediction model for dialog utterances, correctly and interpretably, and attain results comparable with LUIS [34].

1.2. Factored Dialog Learning

Automated Personal Assistants (APAs) have a long history in AI (see for example [12, 15]) and modern APAs, such as Siri or Cortana, can perform various useful tasks through conversational dialogs with users: for example, they can detect when the user wants to make a phone call, or find an address, or add an item to their calendar, and can then take an appropriate action. However, scaling APAs to large numbers of different kinds of tasks, and eventually, to having them anticipate the user's needs through natural, engaging dialog, is still beyond us. The traditional software development process [2] is not well suited to this problem. Typically, to support a new task, designers and developers must first write and review the new design and its requirements, they must make necessary changes to the implementation (if not start again from scratch), and finally, the new system must undergo a suite of unit and system wide tests, which may require beta testing with users. For dialog apps, these changes include redesigning the turn-taking structure of the dialog and implementing any extra needed underlying logic. Moreover, the language skills (for both speaking and understanding) of an APA are crucial for a good user experience, from intent detection to task completion. This process thus usually requires the developers to “teach” the languages the agent needs for each application, in some form, and to continue training to understand what the user says even if the domain is fixed.

Here we investigate addressing this scalability issue by leveraging two key ideas: first, by factoring the development in such a way that the entire language learning part of the problem can be performed by non-experts; and second, by developing a shared world model that can be re-used by widely different classes of applications. The goal is to achieve scalability by opening up the possibility of using crowd sourcing for application development (in addition to using crowd source for language learning, as above). We call this approach *Factored Dialog Learning* (FDL).

FDL uses TAL as a language learning component, but it also introduces two additional roles to those found in the traditional development process: the *Teacher* and the *Designer*, each of which deals with a different aspect of the scalability issue. We define the Teacher as the person who teaches the APA the language skills required to engage in a user dialog, for a particular application. We define the Designer as the person who identifies a *class* of tasks that they want the APA to

handle, and who then designs the abstract dialog flow for every application domain within that class (including user-system dialog shared across all applications in the class).

As opposed to the complex skillset required of the developer in the traditional development process, here, the Teacher need only be familiar with the application that they want to build, in addition to being fluent in their native language. The FDL framework requires more of the Designer (but still far less expertise than that required of a developer): the Designer must learn a simple, high level scripting language which we call the Module Specification Language (MSL). The Designer uses the MSL to specify how the Teacher will create an app from the Designer’s class of applications. Although MSL is a simple scripting language, it does support basic programming concepts such as loops and conditionals. We will describe the MSL in detail below.

In this paper, in order to contrast the different roles played by FDL and TAL, we choose a development example where FDL’s dependence on TAL is very light: we implement FDL for a class of *Event Reminder* applications, and we demonstrate its use to create reminder scheduling apps for tracking the consumption of medications, visits to the gym, birthdays, and some other reminder tasks.

FDL factors the language development out of the overall development process and thus can assign all language development tasks to the Designer and Teacher. However, of course the Developer still plays a crucial role in the overall process. For example, for the Event Reminder class, there are seven quantities that the APA must extract from the user, given that the user wants to create a reminder: two strings (a name for the reminder itself, and any notes to add to the reminder) and five numbers (the event duration, frequency, group frequency, start time, and end time). These will be explained more below, but the point here is that the developer must write the code to have the APA do the appropriate thing once the user is running the app and this data is received (in this case, the APA would simply add the notated events to the calendar). However, notice that the APA’s actions triggered by these seven quantities are independent of the particular reminder app being run. Thus it is the Developer’s (and Designer’s) role to identify *classes* of applications such that the APA actions taken for any app in a given class need only be coded once.

Figure 1 summarizes the development process flow diagram of the FDL framework.

1.3. Predicates, Templates, and TAL and FDL compared

The key concept underlying both TAL and FDL is that of a *predicate*. A predicate can be thought of as a Boolean function over text where the function has ‘state’. The state is modeled with a data structure that contains slots and handler functions. When the predicate fires (i.e. takes the value ‘true’), its slots are populated, and its handler functions tell the APA what to do.

Thus for example, a predicate for the concept *is collocated with* might contain a slot for the set of entities that are deemed to be collocated, whenever the predicate returns true. No constraints are imposed on the text: in particular, we do not require the presence of a verb².

TAL distinguishes two kinds of predicates: *Parsed Predicates* and *Learned Predicates*. Parsed predicates currently form TAL’s world model; they encapsulate notions such as time, space, and number, and they are currently hardwired. Parsed predicates are thus easily shared across classes of applications. For example, in building the event reminder class of applications described in this paper, the developer had to create parsed predicates for time, frequency, period, and duration

²Our earlier work did, and predicates are associated with verbs in theories of syntax and grammar [32]. However, queries submitted to intelligent agents often lack verbs but nonetheless convey intent (for example, self-reminders like *Sophie’s piano lesson*).

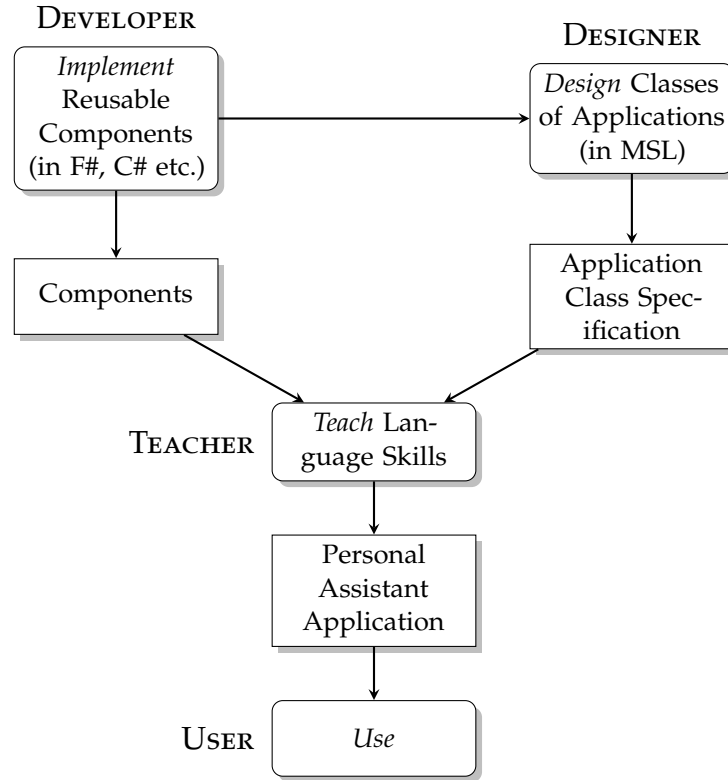


Figure 1: The Factored Dialog Learning (FDL) framework.

- which could then all be used by any other designer in their creation of a different class of applications. It seems reasonable to allow that the world model, at least at the level of physics and mathematics, warrants its own special development effort, since physics and mathematics themselves form such a succinct yet powerful world model³.

Learned predicates, on the other hand, are used to model all other forms of meaning in language. We thus expect that learned predicates will greatly outnumber parsed predicates as TAL grows. Learned predicates are not hard-coded but instead are learned entirely using human teachers. For learned predicates, we divide the problem, and introduce *templates*, which are used to detect patterns in language. A learned predicate is declared to be true if and only if its containing template “fires” (matches a text fragment). Templates are also entirely taught (rather than coded): they are language-based and they leverage a semantic taxonomy, as well as teacher input, to achieve generalization. In this study we use WordNet for our semantic taxonomy [5], but teachers can also both add and remove items from the taxonomy as needed.

Thus, any given template has an associated set of learned predicates, and whenever that template matches a piece of text, its predicates are declared true for that text. For example, the text “*Jesse ate a sandwich*” might fire a “Collocated” predicate, and also a “Consumes” predicate. In addition, a given predicate can be fired by several different templates: for example, “*Jesse ate a sandwich*” and “*The sponge absorbed the liquid*” might both fire a “One entity consumes another” predicate,

³The only alternative that comes to mind is to try to learn the laws that govern the physical world from labeled examples. But at its core, SML is for modeling functions that we don’t know how to describe in closed mathematical form, which is not the case here.

even though the templates that fire that predicate are different.

Since learned predicates and their containing templates are all learned from teachers, TAL attacks the scalability problem by leveraging the expertise of crowd-sourced teachers who need only be experts in their own native language. By factoring the problem in this way, the pool of available teachers becomes very large.

In contrast to TAL, FDL’s main task is to factor the language needed for the application development process in such a way that one designer can create a script that could be used by hundreds of teachers, who then in turn create apps to support millions of users. Thus FDL attacks the scalability problem by further factoring the language modeling problem in such a way that the available expertise matches each subtask well.

In our Event Reminder class of apps described below, the TAL system relies almost entirely on parsed predicates, and it had to learn only one extra learned predicate (to allow it to detect when the user wants to call up the app). (When TAL searches for predicates matching a piece of text, it always tests both parsed and learned predicates.) However in our study of learning user intent, TAL relies entirely on learned predicates. We chose to use these two examples with as little overlap of the predicate types they need as possible, to more clearly test, and contrast, the ideas in each approach.

2. TEACHER ASSISTED LEARNING

In the following, for succinctness, we replace the phrase “correctable and interpretable”, as defined above, with “transparent”.

The main design goal for Teacher Assisted Learning (TAL) is that the resulting models be fully transparent: TAL’s behaviour should always be fully and explicitly attributable to the underlying data and rules (the WordNet taxonomy, our gazetteers, the hardwired lists of tokens (e.g. personal pronouns)), or to the data and rules input by a Teacher. In earlier versions of the system we used dependency and constituency tree parsing, semantic role labeling, and other NLP constructs, using the SPLAT NLP tool from MSR [19] and the Stanford NLP package [13]. These tools are the culmination of decades of development effort and it seemed wise to use them rather than try to reinvent the wheel. But using them revealed four significant drawbacks: they are brittle, they are slow, they are not transparent, and they solve a harder problem than we need to solve. The brittleness and lack of transparency are unavoidable consequences of the statistical models underlying the tools; one could investigate building “shims” around the tools to correct errors, and then retrain the underlying models when enough data was gathered, but the overhead would be high, and retraining does not guarantee that the errors are resolved. The speed issues are harder to address and would likely have proven a show stopper to shipping TAL (imagine having to compute the parse trees and SRL for the inputs from millions of users, simultaneously). At the time, we only had a hunch that these systems also solve a harder problem than we really needed to solve, but this indeed turned out to be the case. In this section, we describe in detail the current processing that TAL uses.

2.1. Design

Here we extend the high level overview given in the Introduction to give a detailed description of templates and predicates, and of the process used to train TAL.

2.1.1 Templates

The template data structure consists of an ordered list of items used for pattern matching, together with a pointer to a set of predicates. Each item can be roughly thought of as either a string, a synset, or a set of synsets (details are given below). For efficiency, templates are indexed by the first synset occurring in their list (every template must have at least one synset); thus, rather than scanning all templates over a piece of text to detect patterns, only those templates indexed by the possible synsets corresponding to the current token in the text are tested for possible matches with that and subsequent tokens. A template is said to “match” or “fire” if and only if a sequence of tokens in the text is found that matches that template’s list, in order. During the matching process, only tokens that could be nouns, verbs, adjectives, adverbs, pronouns, or negation terms, are considered. If a template fires, then TAL asserts that all of the predicates associated with that template are true, for that piece of text. As mentioned above, the template/predicate map is many-to-many: a given predicate can also be pointed at by more than one template.

Each template’s list is of fixed length but different templates can have different length lists. There is no limit to the possible length of a template’s list, but typically the list has between two and four elements: see Table 1 for the histogram of the lengths of list for the TAL classifier trained for this paper (see Section 2.3.4 for details).

List Length	Number of Lists
2	1
3	8
4	14
5	1

Table 1: Histogram of template list lengths for the TAL classifier trained for this paper.

Concretely, each item in a template’s list can be one of three types: a string; a set of noun synsets; or a pair, consisting of a single verb synset, together with a simplified form of that verb’s tense. Currently TAL supports the simple tense types *Past*, *Present* or *Future*, or the catchall *PastOrPresentOrFuture*. An element in the template matches a token in the text if one of the following three conditions holds:

1. The element is a string, and the token is the same string.
2. The element is a single verb synset S with simple tense T , and the token appears as a possible verb in the taxonomy, such that one of the possible synsets of that verb is a hyponym of S , and such that that token could also have simple tense T^4 .
3. The element is a set of noun synsets S , and the token appears as a possible noun in the taxonomy, such that one of the possible synsets of that noun is a hyponym of one or more of the synsets appearing in S .

We reserve the use of string matching for parts of speech that have a small number of possible instantiations: currently, TAL only allows question adverbs, as listed in Table 2. Note that if needed, other specialized parts of speech (e.g. prepositions) could also be used (for example,

⁴Note that a single token can have several possible simple tenses: for example “cut” is the infinitive/present, past tense, and past participle of the verb “to cut”.

“Let’s get Taco Bell” and “Let’s get to Taco Bell” connote different user intents). We decided to make question adverbs the first such direct match type, to give TAL rudimentary question detection abilities.

who	whoever	when	whenever	what	whatever
how	however	why	whyever	where	wherever

Table 2: Question adverb strings used by TAL for direct matching.

During processing, template matching is not done over the raw text, but over a list of *parsed components*. The construction of these is described below. Here we just note that while our templates currently model nouns, verbs and question adverbs, our parsed components in addition model adjectives, general adverbs, prepositions, pronouns, and negation. Some of these take part in the current matching process (see below), while the others were included to facilitate the extension of the template data structure if desired.

2.1.2 Predicates

As mentioned in the Introduction, TAL distinguished two kinds of predicates: *learned predicates*, which a Teacher constructs by interacting with TAL via natural language only, and *parsed predicates*, which form the backbone of TAL’s world model and which are currently hardwired.

Learned Predicates: The learned predicate data structure consists of the predicate’s name (a string), the names of its components (a list of strings), a slot for optional notes (also a string), and a set of handlers for specifying the scripts and actions to be launched when this predicate fires (which occurs when and only when any template that points to it fires). For example, a predicate modeling “Entity ingests something” might have component names “Ingester” and “Ingested”. It is important to note that mapping the text to these component names is straightforward, since TAL can just ask the Teacher for the mapping once the template has been trained. Thus “*It was eaten by him*” would fire a different template than that fired by “*He ate it*” (recall that templates take word order into account) and the slots, at run time, would be filled automatically, based on the mapping specified by the Teacher at train time. This is an important advantage of using Teachers: we do not have to solve the Semantic Role Labeling problem to compute this mapping. Table 3 shows the properties of the **LearnedPredicate**. The last item - LearnedSynsetMap - was added purely to lower the cognitive load on the Teacher: the chances are good that a synset found for a word used to train a previous templates for a given predicate, is also the correct synset for that word, for a different template being trained for that same predicate. (The Teacher always has the option of choosing a different synset.)

Name	Description
PredicateName	The name of this predicate.
ComponentNames	The mapping between the matching template and the relevant item of the predicate, such as a value that would be retrieved by an application that receives notice the predicate has fired.
Notes	Additional information about the predicate.
Handlers	A set of action names that map to the script that is to be executed to implement that action when the predicate has fired. See section 7.4 (Script Handlers) for a detailed description.
LearnedSynsetMap	A mapping from a word to the last synset that was selected for that word for this predicate. Used to eliminate duplicate questions to the Teacher during predicate training, and presents a confirmation to use this previous selection, which the Teacher may override.

Table 3: *LearnedPredicate properties.*

Parsed Predicates: So far we have written built-in parsed predicates to support notions of time (for the Event Reminder module described below). A parsed predicate has a name and may have properties. Table 4 gives a brief description of the built-in **ParsedPredicates** currently implemented by FDL; see table 24 in section 7.5.4 (TestPredicateTurn) for a detailed description for script usage.

Name	Description
Frequency	This has properties for the period of time (e.g. “day”), the number of events per period (which can either be single integer, or a range of integers, as in “three to four times per day”), and the starting time of the first occurrence in each period.
SequenceDuration	The duration of the sequence of reminders (how long the reminders are to remain on the user’s calendar; e.g. the number of recurring events to place in the user’s calendar).
EventDuration	The duration of a single event (e.g. a medication reminder might specify 5 minutes, while an exercise reminder might use two hours).
StartDate	The date the sequence of reminders is to start (e.g. a specific date or “tomorrow”).

Table 4: *TAL’s current built-in Parsed Predicates.*

Parsed predicates do not use templates; they are fired by (currently built-in) pattern detectors. We chose to hard-wire several pattern detectors since these patterns are likely to be shared across many different applications, and since the quantities they represent can be modeled extremely succinctly by mathematical notions such as time, and the number line. We wrote patterns to model date, time, duration and frequency. As an example, Table 5 shows the pattern detectors used to detect frequencies from English text. Each pattern detector is written as an F# *active pattern*; we found the F# language to be particularly well-suited for this kind of modeling. Each active pattern’s name encapsulates one of the possible patterns it captures, to facilitate code readability: thus for example, the *OncePerSecond* active pattern models text snippets such as “Once a second”, “Twice per day” or “Three times every week”. The order of the scans (from top to bottom, in Table 5)

matters: more complex patterns can contain simpler ones (e.g. the “Hourly” detector should be scanned over the text only if the “OnceHourly” detector failed to fire).

OncePerSecond
OnceHourly
NtoMTimesHourly
NtoMTimesASecond
OnceEveryNtoMSeconds
NtoMTimesEveryNtoMSeconds
EveryNtoMSeconds
EverySecond
Hourly
NtoMHertz

Table 5: *The scan used to detect frequencies in text. Pattern detectors are run in order, from first to last, above.*

2.1.3 Text Preprocessing

Since we use no more sophisticated standard NLP processing than lemmatization and basic part of speech tagging, we can describe the process in full here.

First, the user’s input is broken into sentences. Then, terminators (characters in the set {“.”, “!”, “?”}) are removed from the end of each sentence, and any leading or trailing space is then removed⁵. The text is lower-cased, and then any tokens that appear in the Slang Map (see Appendix 8) are replaced (for example, “wanna” is replaced by “want to”). Apostrophes (“’s” and “’”) are then removed. Then two mappings corresponding to TAL’s internal model of time intervals are performed: first, strings matching the pattern $\# \#$, where $\#$ represent an integer (i.e. dashed intervals), are mapped to $\# \text{ to } \#$. Then, strings matching the pattern $\#x/T$, where “ $\#$ ” is an integer and T is one of the hardwired time intervals (e.g. *day*) (i.e. slashed intervals) are expanded to the form $\# \text{ times per } T$. We expect these mappings to be shared across all applications that use TAL’s world model and so they are hardwired. Finally, tokens are mapped to lemmas as follows: we use two files, one that lists verbs and their declinations, and one that lists nouns and their plurals. If a token appears as a declination of a verb, and that declination does not appear in the noun list, then that token is declared to have type verb. Otherwise, we gather all possible parts of speech for the token. In all cases, tokens are replaced by their lemmas, and for verbs, their declination is mapped to one of *Past*, *PresentOrFuture*, *PastPresentOrFuture*. Throughout processing, both the original tokens and their lemmas are kept.

2.1.4 The Parsed Components List

We then construct a *parsed components list* for the sentence. This amounts to mapping each token, or compound phrase, to a set of its possible parts of speech (POS); keeping track of negations; and handling modal verbs. The parts of speech we track are shown in Table 6. We reserve the ‘Unkown’ flag to model tokens whose POS does not map to one of those listed. Note that the code that implements the processing described in this section is language-specific and currently would have to be rewritten to map TAL to handle new languages, although the amount of code is small.

⁵Currently TAL only handles single sentence input; if it detects more than one sentence at this point it issues a warning

Noun
Verb
Adverb
Adjective
Preposition
Personal Pronoun
Non-personal Pronoun
Unknown

Table 6: *Tracked parts of speech.*

Compound Phrases: In Teach phase, known compound phrases (phrases consisting of two or more tokens that appear in our extended WordNet taxonomy, for example *look for* or *White House*) are shown to the Teacher for confirmation, and the Teacher can then either confirm, or declare a found compound phrase as non-compound (for example, *get to* has three synsets in WordNet, but none of them have the meaning as in *I need to get to the store*). Then the Teacher is given the option of adding any compound phrases that TAL missed (for example, the name of a new video game). New compound phrases thus formed are then added to the taxonomy. In Test phase, currently, TAL assumes that any compound phrases it finds are correct (but see Section 5).

Negation: We simply track negation, as the negation of the tracked part of speech immediately following the negator. It turns out that every part of speech we track can be negated; Table 7 gives an example for each.

Noun: "No deal!"
Verb: "I did not walk."
Adverb: "I walked, but not quickly."
Adjective: "The paint is not wet."
Preposition: "This is not for me."
PersonalPronoun: "It was not me."
NonPersonalPronoun: "That is not it."

Table 7: *Negation examples.*

Modal Verbs: We distinguish *semi-modal* verbs from *pure modal* ones. A modal is “semi” if it can be a standalone verb, or a modal verb, such as “have” or “did”. A modal is “pure” if it cannot occur as a standalone verb. Our list of pure modals is *can; could; may; might; must; shall; should; will; would*. We include modals like *can* and *must* since although they can occur in their own sentence (e.g. *I can.*), they always refer to an action. We also cast modals as past tense, or ‘present or future’ tense, and update the verb’s tense based on its modal, if it has one. Finally we also distinguish modals with possible noun meanings (*can; may; will; might; must*).

Processing of modals occurs as follows. As mentioned, negation is detected and attached to the following POS, and verb tense is detected attached to a following verb. A pure modal that can also be a noun is declared a noun if it is preceded by a determiner or a possessive pronoun (e.g. *The can is heavy.*). Otherwise, pure modals themselves are not kept for further processing. For semi modals, if they modify a verb, that verb’s tense is kept, and the modal is skipped; if not, they are

and takes only the first.

kept as 'stand alone' verbs (e.g. *I have one.*).

Finally, all parsed components that could not *possibly* be a noun, verb, pronoun, or directly matchable token (which in the current system are restricted to question adverbs) are dropped; the remaining noun and verb meanings are mapped to sets of possible synsets (in Teach phase, the Teacher is first asked to identify whether the token is a noun, verb or neither, if it's ambiguous); and certain pronouns are mapped to special purpose synsets (for example, the pronoun *I* is mapped to a synset which derives from the first noun meaning of *narrator*); and personal pronouns other than *I*, *you* or *we* are mapped to the synset *person.n.01*). This was done mainly to make patterns containing these pronouns more clearly readable.

2.1.5 The Template Matching Process

Template matching to a phrase is straightforward. First, the phrase is mapped to its parsed component list as above. The template matching is done by an ordered comparison between the template's list, and the phrase's parsed component list. To greatly reduce computational overhead, templates are stored in a dictionary, where the key is also the first synset occurring in the template's list. In order to search for a match at a given position in the text, only those templates whose key is a hypernym of, or equal to, the synset at the current position in the parsed component list (allowing for skipping of fixed token patterns such as "where") are examined. This is done by constructing all hypernyms for the current token (if it is a possible verb or noun) and using each as a key.

All positions in the template list must match, for a match to be declared. If the text's parsed component list is longer than the template's list, all subsequence matches are attempted (only one has to succeed for a match to be declared). If the template item is a fixed token (e.g. "where"), that token must match exactly. If the template item is a verb synset *VS*, together with its tense, the set of synsets for the corresponding position in the text must contain at least one synset which is a hyponym of *VS*, and the tenses must match. Finally, if the template item is a set of noun synsets *SNS*, then for a match to occur, at least one member of that set must be a hypernym of (or equal to) one of the synsets in the set of synsets for the corresponding position in the text. Allowance is also made for skippable items: parsed components whose POS set contains one or more of [*adjective*, *adverb*, *unknown*]. For example, if a token's parsed component POS set contains *adjective* and *noun*, then that token can be skipped in the search for a match (if it itself does not take part in the match), and the next noun set examined for a match. In "*He likes blue cheese*", the token *blue*, taken alone, could be a noun or an adjective, so the matching process will both attempt to make it part of the match, or will skip it if that match fails.

2.1.6 The TAL Training Process

In Train phase, the POS (noun or verb or neither) is confirmed with the Teacher, and the Teacher is then asked to identify the single best matching synset for each noun or verb thus identified. As described above, to lighten the cognitive load on the Teacher, TAL "guesses" the correct synset to use to confirm with the Teacher, based on previous Teacher inputs. Also as mentioned, the Teacher confirms any compound phrases found by TAL (if the Teacher declines the confirmation, the phrase is left in non-compound form), and is asked to identify any compound phrases TAL missed; any such phrases are then added to the taxonomy, with the Teacher's guidance.

Training can be done either in batch mode (which requires a set of positive and negative labeled examples), or in free form mode (where the Teacher simply enters example phrases instantiating

the predicate they wish to teach). We summarize below the iterative steps involved in training a TAL model, in batch training mode:

1. A small number of labeled positive and negative phrases are first input for training.
2. TAL's first task is to elicit from the Teacher the predicate they wish to train. First, all predicates that match one or more of the positive training examples are listed, and the Teacher is asked to select one or "Train another predicate". If the latter is chosen, TAL lists all the predicates it knows about, along with an option to train a new predicate. If no existing predicates are found, the Teacher must train a new predicate.
3. TAL presents the next positive example to the Teacher, lets them know if the text already matches the predicate (i.e. matches a template containing the predicate), and asks them if they wish to train on this example. If there are no more positive examples, training is complete.
4. If Yes, TAL asks them to enter a phrase inspired by the input text, that captures the predicate being trained. This allows the Teacher to zero in on just that part of the text that should fire the predicate, and to enter related text that should also fire the predicate, if desired.
5. TAL then shows any compound nouns and verbs it found, and asks for confirmation. Any that are confirmed as incorrect are dissolved back into single token form.
6. TAL asks if it missed any compound nouns, and adds them as indicated by the Teacher. For the rest of the discussion, we will refer to both individual tokens and compound phrases as "tokens".
7. TAL asks the Teacher for the meaning of any tokens it doesn't know, and adds the new definitions to its WordNet ontology. Thus the ontology is grown as needed, and these additions are shared between Teachers.
8. TAL assigns a set of possible parts of speech (POSS) to each token. It only keeps tokens that are a question adverb, or that could possibly be a noun or verb.
9. If the POS set is ambiguous (still contains more than one POS), TAL asks the Teacher if the token is a noun, verb, or neither.
10. TAL lists the synsets for each noun or verb and asks the Teacher to pick one. It then lists the possible generalizations (hypernyms) of that synset and asks the Teacher to generalize by picking one, if appropriate.
11. Once a unique set of synsets or strings has been identified, TAL constructs the corresponding template from them, and adds the predicate to that template.
12. TAL shows the template to the Teacher and asks them if it looks correct. If they say no, TAL returns to step [4].
13. TAL then runs the new template over the negatively labeled training samples. If this results in any false positives, TAL shows them to the Teacher and asks if they still want to keep the template. If so, the loop continues from [3] above; else, it continues from [4], but also gives the Teacher the opportunity to move to the next training sample (i.e. go to step [3]).
14. After the iterative training process is complete, the Teacher can read and modify the learned templates file (a text file in YAML format).

We found the last step - editing the templates file - to be a simple and very useful exercise: note that this can only be done with such a transparent (correctable and interpretable) system. We also allowed the Teacher to edit the templates on the fly, as described in the next Section.

Thus the teaching process can result in new synsets (or nodes) being added to, or deleted from, the taxonomy. Examples of both of these are given in Section 2.3 below.

2.1.7 Editing the TAL Model

After training, TAL's transparency allows us to manually edit the model. This process can be very efficient, especially when the number of templates is small, compared to adding labeled data and retraining an SML model. We followed the following procedure:

1. We extended each template's sets of noun synsets, based on noun synsets occurring in the other templates. Thus, for example, if one template allowed "get.v.01" followed by "currency.n.01", and another allowed the same verb synset but was missing a following "currency.n.01", we added it⁶.
2. We removed any resulting duplicate templates.
3. Over-generalization is checked. For example, for the intent model trained below, we noticed during the teaching process that TAL suggested "get.v.01" as a more general version of "buy.v.01". We found that replacing the latter by the former did indeed improve performance on the training set, for some templates, but for others, many false positives were generated.
4. We manually checked, using the online version of WordNet [5], that the synsets chosen previously made sense, again removing any resulting duplicates.

2.1.8 Testing TAL

Test phase for TAL is simpler and involves no Teacher interaction. The text is normalized, compound phrases are identified using the (possibly extended) WordNet, and all the templates are matched against the text, using the template matching logic described in section 2.1.1. If a template fires, TAL asserts that all of its associated predicates are true. In the experiments described below, we had only one predicate; a test example was declared positive if the predicate was true for that example.

2.2. Experiments: Learning Curves

2.2.1 Data

We generated training and test data from Cortana logs as follows: we searched for user inputs containing one of more of the strings shown in Table 8.

Note the lack of a space after tokens "purchas" and "acquir", resulting in matches for user inputs containing these strings as stems. In addition, we added filters to restrict the user inputs to either speech or SMS texts; to inputs issued on Windows devices, and to inputs issued to Cortana

⁶This could all be done during the initial training process, but the instantiation used did allow parallel templates to develop (templates containing the same verb but different following or preceding noun synsets).

“ buy “	“ buying “	“ bought “	
“ get “	“ got “	“ purchas”	“ acquire”

Table 8: Strings used to filter user inputs from the Cortana logs.

(as opposed to other Windows services). Running these queries over 18 days of logs from May, 2016 resulted in 15,310 records. Uniquing this data resulted in 12,690 records. We also took the most recent 200 (distinct) queries in the logs as unbiased background data. We shuffled the 12,690 records and then took the first 800. We then labeled the resulting combined 1000 sentences as indicating the user’s intent to buy, or not. The remaining 11,890 records were kept for use with the LUIS active learning experiments. Because some of the sample sets were very small (e.g. the process only resulted in 14 queries containing “ acquire”), we split each individual dataset in two (e.g. the “ acquire” positives, and “ acquire” negatives, were each split in two) to create train and test sets. This resulted in the totals shown in Table 9⁷.

	Sample Sizes	
	Train	Test
Positives	78	82
Negatives	417	422

Table 9: Train and Test Sample Sizes

2.2.2 TAL and LUIS: Learning Curve Experiments

As mentioned above, we used the LUIS system [34] as a state of the art machine learning baseline. LUIS uses a logistic regression model with bag of words features (inverse document frequencies) and the number of tokens as inputs. LUIS also gives the ability to use domain-specific dictionaries; we experimented with this but did not find improved performance on this task. Internally, LUIS performs 10 fold cross validation to choose the optimal model parameters, and then trains on all the training data, using the found parameter values.

Since constructing the learning curves required training 490 models for LUIS, in order to make the comparisons both feasible and as fair as possible, for these experiments we used both systems in maximally automated mode. For LUIS this simply meant that no active learning was used, while for TAL, we used a simplified version of the full system: the user was not allowed to delete items from the ontology; they were not given the option of editing the learned templates; and the templates used were a simplified version where each synset set was constrained to be a singleton. For TAL, full training (on 495 training samples; see section 2.3 below) resulted in a total of 99 templates (compare this with 24 templates, for the full system below trained on the same data, when sets of noun synsets were allowed; and 21 templates if verbs are further combined into sets where possible).

Figure 2 shows the training curves for accuracy, precision and recall on the 504 sample test set as a function of training set size. For the LUIS experiments, training set sizes were increased by 10

⁷The sizes in Table 9 add up to 999 because one non-English query had slipped though the filters, which we later decided to drop since the language of the problem domain is English.

samples from one experiment to the next, starting at 10 samples. For TAL, the data was split into sets of size 20, 40, 60 and 78 positives.

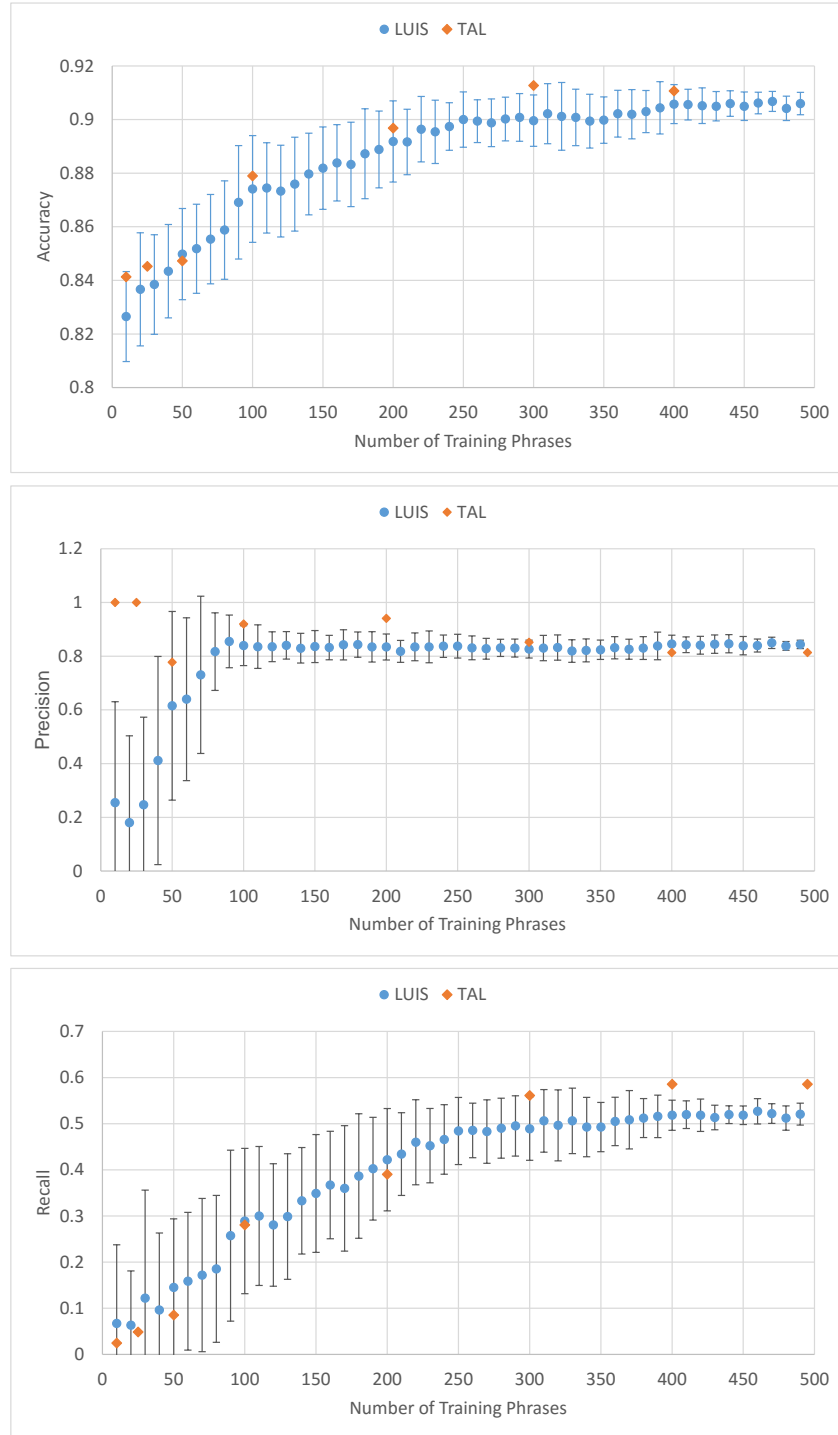


Figure 2: Accuracy, Precision and Recall Training Curves for LUIS and TAL.

2.3. Experiments: Full Training

We used the same training data as above.

2.3.1 LUIS Baseline Results

LUIS supports Active Learning (AL) via its ‘Suggest’ option. The user can upload a set of unlabeled samples and then enter Suggest mode. LUIS will present up to 10 of the unlabeled samples that it decides will most benefit the model to verify, along with its current prediction for them. The user changes the prediction if necessary, or accepts the current label. After the set of samples is labeled, LUIS retrains its model, then presents the next set of up to 10 unlabeled samples.

After training LUIS initially from the full 495-sample test set, we ran it on the full test set, then performed active learning using the 11,890 unlabeled samples. We did three runs of active learning, creating 25 newly labeled samples, and ran it on the test set again. Table 10 shows these results along with TAL’s scores on the test set.

Note that the LUIS team made significant improvements to its intent prediction classifier after we had performed the learning-curve experiments above. This resulted in a pre-AL baseline with significantly higher recall and somewhat less precision than before. Adding active learning to LUIS increased its precision with no change in recall.

2.3.2 TAL Results

After training on the first 20 sentences, the manual editing process described above resulted in reducing the number of templates from ten to seven. This template collapse pattern repeated, until after training on all the data, we arrived at 24 templates. All the templates found for the fully trained TAL user intent model are shown below, in Table 13. In addition, since the model is fully transparent, we could also check the other user-entered data, as shown in 11.

We also noticed that the 24 templates could easily be further reduced to 21 if verb synsets are combined into sets where possible. See Section 2.3.4 and Table 13 for details.

2.3.3 Comparison

Compared to LUIS with active learning, TAL is significantly higher in precision and lower in recall, for a marginal increase in overall accuracy. A natural next step would be to tune LUIS for the same precision and then measure its recall, and compare again. However, these results alone demonstrate that comparable performance can be achieved with a fully transparent, succinct, and editable model. Because of these advantages, we believe that TAL could take advantage of more training data to increase accuracy arbitrarily (up to the level of label noise).

Experiment	Precision	Recall	Accuracy
LUIS (no AL)	0.800	0.683	0.919
LUIS (with AL)	0.824	0.683	0.925
TAL	0.911	0.622	0.929

Table 10: Comparison of TAL’s precision and recall to LUIS with and without active learning.

2.3.4 The Complete TAL Intent Detection Classifier

We present here the entire classifier that TAL learned to detect *intent to buy*. First, the Teacher removed a single synset from the WordNet taxonomy. TAL uses a YAML file to track such removals, and in this case the file contains the single mapping *get: get.v.22*, meaning that the 22nd verb synset listed for the token *get* is to be removed from the graph. This was done to remove a loop in WordNet that causes TAL to generalize incorrectly⁸.

Table 11 shows the Teacher-taught extensions to WordNet, with tokens on the left and their mappings on the right. The table distinguishes *concepts* and *instances*: all mappings not denoted by the string *InstanceOf* are concepts. Table 12 shows a noun set referred to by many of the templates, referred to as *SNS* (for *shared noun set*). Finally Table 13 shows the 24 templates used. There, for example, *cost.v.01* denotes the first verb synset listed in WordNet for the token *cost*; *PPF* is shorthand for past, present or future tense, and *PF* for present or future tense. Recall that the pronoun “I” is mapped to the special synset *tal_narrator_i.n.01*, and “you” is mapped to the special synset *tal_audience_you.n.01* (see Section 2.1.1). Finally sets of noun synsets are denoted by the curly braces. All templates fire the same “intent to buy” predicate, which is therefore not shown.

It is a striking fact that the entire classifier can be written with complete transparency (with consequent full interpretability and correctability) in one page.

app	application.n.04
at&t	company.n.01
at&t hotspot	(InstanceOf) wireless local area network.n.01
best buy	shop.n.01
black ops 3	(InstanceOf) computer game.n.01
blu ray	videodisk.n.01
cheeseburgers	food.n.01
ge portable water dispenser	dispenser.n.01
hoverboard	plaything.n.01
killer instinct	(InstanceOf) computer game.n.01
opal automobile	car.n.01
sd cards	circuit board.n.01
taco bell	restaurant.n.01

Table 11: The Teacher-taught extensions to WordNet.

⁸get.v.22 (purchase) is a hyponym of buy.v.1 (purchase, acquire) which is a hyponym of get.v.1 (acquire); the occurrence of “get” being a hyponym of “get” prevented the Teacher from using “buy” as a special meaning of “get”.

artifact.n.01
commercial document.n.01
currency.n.01
dish.n.02
domestic animal.n.01
food.n.01
food.n.02
game.n.03
license.n.01
music.n.01
plant.n.02
precious metal.n.01
software.n.01
vehicle.n.01
wireless local area network.n.01

Table 12: The set of nouns shared by multiple templates, denoted by SNS in Table 13.

cost.v.01 (PPF)	buy.v.01 (PF)	{SNS}	
get.v.01 (PF)	{dish.n.02}		
“how”	buy.v.01 (PF)	{SNS}	
“how”	{tal_audience_you.n.01}	buy.v.01 (PF)	{SNS}
{tal_narrator_i.n.01}	achieve.v.01 (PF)	get.v.01 (PF)	{SNS}
{tal_narrator_i.n.01}	buy.v.01 (PF)	{SNS}	
{tal_narrator_i.n.01}	desire.v.01 (PF)	buy.v.01 (PF)	
{tal_narrator_i.n.01}	desire.v.01 (PF)	get.v.01 (PF)	{SNS}
{tal_narrator_i.n.01}	expect.v.01 (PF)	get.v.01 (PF)	{SNS}
{tal_narrator_i.n.01}	want.v.01 (PF)	get.v.01 (PF)	{SNS}
{tal_narrator_i.n.01}	refer.v.02 (PF)	get.v.01 (PF)	{SNS}
{place.n.02}	{district.n.01}	buy.v.01 (PF)	{SNS}
{place.n.02}	{district.n.01}	{district.n.01}	buy.v.01 (PF) {SNS}
{place.n.02}	get.v.01 (PF)	{SNS}	
remind.v.01 (PF)	{person.n.01}	get.v.01 (PF)	{SNS}
{tal_audience_you.n.01}	commend.v.04 (PF)	buy.v.01 (PF)	{SNS}
“what”	{SNS}	get.v.01 (PF)	
“what”	{SNS}	{tal_narrator_i.n.01}	get.v.01 (PF)
“what”	{prerequisite.n.01}	buy.v.01 (PF)	{SNS}
“where”	buy.v.01 (PF)	{game.n.01}	{artifact.n.01}
“where”	get.v.01 (PF)	{SNS}	
“where”	get.v.01 (PF)	cook.v.03 (PF)	{food.n.02}
“where”	{tal_narrator_i.n.01}	buy.v.01 (PF)	
“where”	{tal_narrator_i.n.01}, {tal_audience_you.n.01}	get.v.01 (PF)	{SNS}

Table 13: The templates used by the classifier. Each row, left to right, forms a single template. Note that most are quite general; some are specific to the training data (e.g. the template with two {district.n.01}’s arose from the sentence Cheapest place in Saint Louis Missouri to buy X); and some lie in between (e.g. the template with the {game.n.01}, {artifact.n.01} synsets arose from Where to buy golf shoes? but would also apply to e.g. Where to buy a tennis racquet?

3. FACTORED DIALOG LEARNING

The language skills required of an APA can be broadly classified as the generation and comprehension of language⁹. To model this, we designed two corresponding dialog structures which we call *Ask-How-To-Say* and *Train-Predicate*.

3.1. The Ask-How-To-Say Dialog Structure

In the FDL framework, the language teaching stage occurs after the Designer has completed their design for the class of applications and created the corresponding module specification (this will be covered in the next section). In the language teaching stage the Teacher teaches the system the language it will need to converse with the User (beyond any language that can be shared across all apps in the class; that too is specified by the Designer). Throughout the rest of this section we will use *Event Reminders* as an example class of applications.

Ask-How-To-Say is a dialog between the system and the Teacher that is intended to develop the system's language generation skills. The system asks the Teacher explicitly how to say something pertaining to a given, general scenario, and it then uses the Teacher's response later, when interacting with the User. However, the system is not limited to simply parroting the Teacher's phrases. For example, for the Event Reminders class, the system extracts a verb phrase from the Teacher that it can use throughout its dialog with the User, as in:

S¹⁰: *I need to know how to refer to the type of reminders created by your app. If I tell the user, "I understand that you'd like me to help remind you when to X", what would be a good phrase for X? Please be sure that:*

1. *X starts with a verb (because it is an action, and will be inserted as a verb phrase into many sentences to request input and confirmation from the user).*
2. *X refers to the type of reminder rather than a specific instance of the reminder; for example, "feed the fish", but not "feed the fish once a day".*

Thus when the Teacher is creating an Events Reminder app for tracking medications, for example, they might type:

T: *take your medications*

This verb phrase would then be used by the system in multiple different interactions with the User.

Another way that the Designer can reduce the cognitive load on the Teacher is by making judicious use of defaults. Continuing with the meds tracking example, it might go like this:

S: *I will ask the user to provide some optional notes for their reminder by saying "What would you like to name this particular reminder?". Does that sound good?*

T: *Yes.*

⁹By "the APA comprehends X" we simply mean that the phrase X triggered the desired actions by the APA, and did not trigger any undesired actions.

¹⁰We use **S**, **T**, **U** to represent the utterances of system, Teacher, and User respectively.

Then later, when in dialog with the User,

S: *What would you like to name this particular reminder?*

U: *Take aspirin.*

This dialog would then trigger the APA to add an event to the User’s calendar labeled “Take aspirin”.

The Module Specification Language is described below, but we just make the connection to the MSL here by pointing out that in the MSL YAML file, the above actually appears as follows:

```
ParamValueTurn:
  Confirm: I will ask the user to provide a name for their new reminder by saying
    "<ask_event_name>". <DoesThatSoundGood>
  Loopback: <OKEnterSentence>
  Param: <ask_event_name>
  Type: STRING
  Default: What would you like to name this particular reminder?
```

Figure 3: Example *ParamValueTurn* that suggests to the Teacher default language to use to ask the User for a name for their reminder app, and accepts and stores an alternative form if the Teacher so desires.

where the system asks the Teacher whether the default language is acceptable, and if it is not, then asks them for the sentence that they would like to use instead. This sentence is then stored by the system in the variable `<ask_event_name>`. Note that the system can also use its own variables (like `<DoesThatSoundGood>`, which in this case translates to the string “*Does that sound good?*”). The MSL has several such constructs that are intended to make the Designer’s task easier, and they are described below.

In User mode, the system gathers the data it needs for the running application by asking the User questions, using application-specific language. To keep the load on the User as light as possible, the system at first prompts the User to simply enter the data in free form, and then confirms its understanding with the User, and queries the User for any missing data. Thus, for example, for the Prescriptions Reminder app, the User can just directly enter their prescription, and as long as all the required data is there, TAL can then just confirm, and then populate the User’s calendar.

In order to be able to do this, TAL needs to be able to parse, and to model, fundamental concepts such as space, time, and number. To this end we use *Parsed Predicates*, as opposed to *Learned Predicates* (see above). Parsed predicates are patterns that are coded by the developer to parse text and extract key quantities. To make this concrete, we briefly describe the F# structures we use for the built-in parsed predicates. For example, TAL’s code contains a *Frequency* module that collects several active patterns; one is called *OncePerSecond* and models frequencies written in the form “Once per second”, “Twice per day”, “4 times an hour”, etc. (We adopt the convention that the active pattern’s name be like one of the patterns it matches, to make the code easier to read). We call these collections of active patterns, each designed to detect a particular pattern in language, *microgrammars*. At run time, all microgrammars are scanned across the text, in a particular order: it is thus important to keep the active patterns independent or, if one contains another, to call the more specific version first. For example, in our current code the active pattern *Hourly*, which matches “hourly”, “daily”, “annually” etc., is called after the active pattern *OnceHourly*, which

detects “once hourly”, “twice daily”, etc. However, such dependencies are rare: active patterns can be similar yet still independent. For example, the active pattern for *EverySecond*, which matches “Every day”, “In the morning”, etc., is similar to the more specific pattern *EveryNtoMSeconds*, which matches “every 3-4 seconds”, “every 6 to 9 minutes”, etc., but these patterns are independent (i.e. they will never both be triggered by the same text) and so can be used in the scan in either order.

The parsed predicates scan the microgrammar active patterns over the text to fill their slots. For example, our built-in parsed predicate for *Frequency* has two slots, *Period* (to model the base frequency, like “weekly”) and *NumberOfEventsPerPeriod* (to model the “twice” in “twice daily”).

Thus TAL’s built-in parsed predicates form a rudimentary world model. The hard-wiring raises the concern that this would limit scalability. However, the concepts modeled are fundamental, and can be shared across all apps: we argue that it makes sense to allow limited hardwiring, to take advantage of the extreme succinctness of basic physical models (imagine learning to count, from positive and negative examples only, with no underlying model of the number line). We touch on this issue again in Section 5.3.

3.2. The Train-Predicate Dialog Structure

While Factored Dialog Learning is centered around factoring the language out of the problem using built-in parsed predicates, we still need Teacher Assisted Learning to learn any predicates the app needs that are not covered by the built-ins. In our running example of the Events Reminders, the only place learned predicates are used is to detect which app the User wants to run. In general, apps will need more learned predicates: we minimized the dependence on learned predicates here to simplify our exploration (and exposition) of FDL. So here, we just use TAL to learn when the User wants to run their app. This will be important in practice, for two reasons: the primary interface is expected to be speech only; and the number of apps is likely to become large¹¹, so listing them all is not practical (especially with a speech-only interface).

For example, in the module specification for the event reminder class of apps, the Designer can introduce a “Train Predicate” dialog:

S: *When the user wants to run an app, they will type a phrase that describes what they want to do, and I will find apps that match that intent. So, you need to teach me how to recognize when the user wants to run your app, by entering example phrases that the user might type to do this; for example, “feed the fish” to create a fish-feeding reminder.*

*I will try to generalize your examples, so that you don’t have to type in too many.
I will use what you tell me to build a “predicate”, which describes the meaning I will look for in the user’s text.*

For each sentence, I will retrieve and display all existing templates that match for your sentence at one or more Verb positions. This will allow you to merge synsets from your new template into an existing template, remove synsets from existing templates, or remove existing templates.

Then, the Teacher can type in phrases like

T1: *track meds*

¹¹ AppBrain estimates that the number of Android apps is currently at the 2.5 million mark[1].

T2: *take my medications*

Note that it is advantageous for the Teacher to zero in on key phrases, since they can be detected in longer sentences which may also contain irrelevant details. The process is as described above in section 2 (Teacher Assisted Learning): the Teacher will specify the meaning of each noun and verb according to the ontology, and, for example, the system will generalize “medication” to “drug”, if the Teacher chooses to. The system then will recognize User input such as

U: *tell me when to take my pills*

since there exists a synset for “pill” which is a hyponym of “medication”, and since possessive pronouns are ignored by the template matching process.

3.3. Overview of the Module Specification Language

The MSL (Module Specification Language) is specified in detail in Appendix 1: Specification of the Module Specification Language. Here, we give an overview of the main ideas behind the MSL. In order to extend the APA to support a new application domain, the Designer must create a module specification script that supports the new class of applications¹².

3.3.1 Script Blocks

A module specification script consists of four sections, or blocks, listed below. We will describe the notion of a *turn* in more detail below, but at a high level, it is a series of system-User interactions that together aim to acquire a single piece of information from the User, or to deliver a single piece of information to the User.

Name: A string that defines the name of the module (for example, *Event Reminders*).

Initialize block: A set of app-independent constants used to streamline the interactions with the Teacher (and, less commonly, the User).

Teach block: Both the Teach and Use blocks consist of a series of two kinds of turn: predicate detecting turns, and parameter value turns. At a high level, the Teach block is a turn-taking structure, where the Designer designs a series of questions intended to leverage the Teacher’s language skills to teach the application the language comprehension and generation skills that are to be used in User mode.

Use block: This is a turn-taking structure that obtains and parses free User input in order to create the actual entity. In the Events Reminder example, a predicate detecting turn is used to parse free User input describing their reminders, and a series of parameter value turns confirms the values found or to ask the User to fill in missing values (such as the length of time the reminders should run for).

¹²We use the term “module” here to denote the class of applications being considered.

3.3.2 The “Turn” in detail

The *Turn* is the key atomic building block in a module specification. Depending on what type of information is to be gathered or delivered, one of four core turn types are used: `Prompt`, `ParamValueTurn`, `TrainPredicateTurn`, and `TestPredicateTurn`.

Prompt: A message that the system will show the Teacher/User.

ParamValueTurn: The system can ask the Teacher/User a question and obtain the answer and/or confirm with the Teacher/User that some value is correct. Any parameter value thus obtained can be referenced in the subsequent turns (or in the current turn if it is used after the value is assigned). Figure 4 shows an example that asks for and confirms the start date for a reminder app.

TrainPredicateTurn: Used to train the templates needed to form a learned predicate detector, where the Teacher supplies example phrases to train the desired `Predicate`. The Teacher types an example phrase that should fire the predicate, and the system engages in dialog with the Teacher to select the correct parse, synsets, and their generalizations for the identified terms or compound terms. The system uses this information to create a template which it associates with the predicate.

TestPredicateTurn: The system displays a `Question` to prompt the User to provide needed information: for example, for a medications tracker app in the Event Reminder class, the User might be prompted to input their prescription. The system then parses the User’s input to detect matches with both parsed and learned predicates. The components of any matching predicates (such as frequency, time, and duration) are mapped to the parameters defined in the `PredicateParamMappings` field, which can then be referenced in subsequent turns. Values that are present are used to populate a confirmation question (“*You would like your reminder at 7:00 a.m. Is that correct (Y/N)?*”); missing values require the user to enter that value (“*Please tell me what time you would like your reminder*”) before confirming it.

```
ParamValueTurn:
  Question: <ask_start_date_language>
  Confirm: You would like to start on <start_date>. Is that correct?
  MistypeFollowup: What date is that? You could enter “today”, “tomorrow”, or a specific
date such as “July 19, 2016”.
  Param: start_date
  Type: DATE
```

Figure 4: Example *ParamValueTurn* that asks for and confirms the start date of a reminder app.

3.3.3 Other Turn Types in the MSL

In addition to the above four core **Turn** types, the MSL provides composite **Turn** types that define iteration and conditional execution, auxiliary **Turn** types that support these, and **Turn** types that explicitly control parameter values. We briefly describe these here; see Appendix 1: Specification of the Module Specification Language for complete details.

SetParamValues: Allows the Designer to set parameter values directly in the script.

RemoveParamValues: For deleting previously assigned parameter values.

ScriptConditionalActions: Equivalent to an if-else-then dialog flow, based on the boolean value of a condition written in a simple conditional grammar that allows testing whether a script parameter is set or has an infinite value, comparing numeric values ($=$, $>$, $>=$, etc.), and parentheses for precedence.

UserConditionalActions: Like **ScriptConditionalActions**, but the condition is the boolean result of a question presented to the User. For example, in the Reminder application, if all necessary slots are filled, the User will be presented with a single sentence to confirm; if *No* is returned, then the script presents the series of **ParamValueTurns**.

ParamValueOrConstantTurn: Like **ParamValueTurn**, but allows the Teacher to enter a constant value if so doing is more appropriate for the app they are creating. For example, a Teacher creating a birthday reminder app would not want to have the app ask the User how often their reminder should fire.

SetConstantValues: Sets script variables to constant values (such as those set by **ParamValueOrConstantTurn**) if they were not already set (such as by a **TestPredicateTurn**).

NIterations: Equivalent to a for-loop.

EndIterationAction: For **NIterations**; the equivalent of a break in a for-loop, with a parameter to specify ending either the innermost or all nested loops (if any).

EndScriptAction: Ends the script, with a parameter indicating success or failure.

NoAction: A no-operation; functions as an empty branch of an “if”.

3.4. Case Study: Adapting the Event Reminder Module

To evaluate the generalizability of the FDL framework, we performed a small (3 participants) user study to determine whether ordinary English speakers can easily and effectively function as Teachers, creating reminder applications based in the Event Reminder application class (module). One Teacher participant and one new participant then operated as Users, testing whether these applications could be used to easily and intuitively create reminders for their domains.

3.4.1 Teacher Task Description

Using the Event Reminder Module, we assigned the participants to create two reminder applications: a yearly reminder (such as a birthday) and a regular reminder (such as going to the gym). We provided an informational document that described both their role as a Teacher (creating an application that a User will use to create actual reminders) and the general form of the prompts they would receive and the answers they should supply. Other information was contained in the prompts themselves, many of which showed examples taken from a prototype Medication Tracker application.

Subject A had some linguistic background, and created a birthday reminder application with an early version of the FDL system; feedback from this session was incorporated into a new version. With this second version, Subject A re-did the birthday reminder application and then created a

gym reminder application. Subject B, who had no linguistic background, did the gym reminder application first, then the birthday reminder application. Neither subject had any programming or application-development experience.

Subject C is a software developer with no significant linguistic background, and used a third version of FDL that had been modified based upon the feedback from Subjects A and B, creating first a regular “Call your Friend” reminder application, and then a Wedding Anniversary reminder application. Additionally, for Subject C, the “medication tracker” examples in the prompts were largely replaced with a “feed the fish” imaginary application, and some additional features were added to the FDL system (these are discussed below in the relevant subsections).

We observed the teachers as they performed the tasks and asked them to provide feedback when complete. In particular, we asked whether they felt the system was expressive enough to create the desired application, whether the task was harder or easier than expected, and whether any parts of the task were particularly difficult, confusing, or easy.

3.4.2 Teacher Task Results

The distinction between the Teacher creating an application vs. a User who will use that application to create the actual instances (in this case, reminders) is a key focus of FDL. Subject A’s initial use of the system incorrectly started from the User perspective, for example by using an actual reminder description (“my father’s birthday”) instead of a reminder creation action (e.g. “remember a birthday”) for the application activity (“you would like me to help you remember to ...”). The documentation and prompts were modified to clarify this distinction and this was not an issue for Subject A’s subsequent pass. Subject B still exhibited some confusion in this, although much less than Subject A did initially. Subject C had only minor confusion about this. A detailed tutorial combined with experience using the app will be sufficient to clarify this important distinction.

Subject A provided additional valuable feedback to streamline and clarify the system between the first two iterations, in particular in generalizing from the medication reminder examples to a different reminder topic, clarifying how multiple reminders (delimited by “then”) are detected, clarifying when a response should be “yes/no” vs. a sentence or phrase, improving the flow of specific and generalized synset selection (including eliminating duplicate selection requests), and merging or omitting some steps. After this iteration of user feedback and system revisions, the first-use experience for Subjects B was much more straightforward. Building upon feedback from Subjects A and B, additional features (discussed below) were added to address specific pain-points, which led to an improved first-use experience for Subject C.

Subjects A and B found the gym reminder much easier to understand and create, for the following reasons:

- The gym reminder shares its schedule structure with the example medication reminder; both are geared towards daily, while the birthday reminder is annual.
- The gym reminder, like the medication reminder, refers to a specific, concrete event; the birthday reminder is more ambiguous, as it may be for sending an email or card, buying a gift, planning or attending a party, taking a trip to visit, or simply an indefinite reminder to “remember the birthday.”
- Some questions have only one applicable value in the reminder domain, such as “*how often do you want the reminder sent?*” for the birthday reminder. Both subjects suggested that these should allow the Teacher to set a constant value such as “annually” and not present the question to the User.

The FDL system allows the Teacher to provide multiple example sentences for the same Learned Predicate. For Subjects A and B, FDL required that the Teacher explicitly create a new predicate for the application, and create a different one when the meaning changed. Neither subject understood this clearly from the prompts. Subject B, lacking a linguistic background, found the concept of predicates confusing until more explanation was provided, and also did not initially realize that the example sentences were to be supplied as the User would enter them. Additionally, Subject B felt some of the instructions (such as requiring that the phrase referring to the application start with a verb) were unnecessarily restrictive.

This feedback led us to make the following changes before Subject C's session:

- The ability to specify constant values was added. Subject C happily used this to specify that reminders for the Wedding Anniversary would occur once annually, forever.
- Because each application should define a single function or a small set of closely related functions, the creation and selection of Learned Predicates was removed in favor of a single predicate per application, reducing complexity for the Teacher.
- Additional explanation was added in the prompts. For example, to address Subject B's feeling that requiring a Verb to start the phrase referring to the application was too restrictive, additional text was added to explain that this is due to how it will be used in subsequent prompts.

These changes resulted in much less confusion and a more streamlined experience for Subject C. However, subject C was still puzzled in a couple of areas, such as not knowing the definition of a compound, and in seeing the name of a script variable. These were subsequently modified for clarity. Subject C also mentioned that some of the prompts were long enough to be difficult to read. Moving much of the material from the prompts to a tutorial that includes both a detailed walk-through of Teaching an application and a parallel demonstration of that application in action during the Use phase would improve both the first-use and, by reducing clutter, subsequent uses by the Teacher.

Both subjects felt that the turn-by-turn dialog was helpful in building up the app, and were much more comfortable with the process at the conclusion of their tasks. However, for the Teacher, a GUI rather than the command-line interface would reduce clutter (such as when selecting synsets and generalizations, which can take multiple screens) and could add support for Undo functionality, which would reduce the need for multiple confirmations.

3.4.3 Teacher Task Summary

While there were some initial mistakes by all subjects, the FDL system's evolution led to a much better experience as testing proceeded. All subjects became more comfortable as they developed experience using the system. With a better tutorial providing a more detailed walk-through of both Teacher and Use phases and a GUI that reduces screen clutter and supports Undo, we believe that Teachers who have solid English skills and no programming or application-development experience will be able to quickly learn how to use the FDL system to create applications, especially if they have some linguistic background.

3.4.4 User Task Description

Subject A and a new Subject D (who has linguistic and machine-learning experience) used the Medication Reminder script to create actual reminders to take medication.

3.4.5 User Task Results

Subject A again went first, and created reminders for each of 10 prescriptions. Having operated twice previously as a Teacher, Subject A was by now familiar with the goals of the process. There was some confusion when being asked to specify a single value for a range (for example, “every 4 to 6 hours” must be converted to a single “every N hours” within that range). Here the dialog was not clear as to the context, and there was no clear error message when it retried on out-of-range values. There were also some missing recognitions of abbreviations for intervals. Once these were encountered and understood, the process proceeded quickly, and the last few reminders were completed easily.

Subject D used the system after Subject A’s feedback was incorporated. Subject D entered only a single prescription and found the process quite straightforward; the only negative feedback was that the number of confirmations slowed the process down.

3.4.6 User Task Summary

Both subjects felt the turn-taking process made it easy to provide the necessary information to create the reminder. Both subjects felt that the confirmations could be streamlined to make the process flow more smoothly.

4. DISCUSSION

In this section, we look back, and assess how things went; in the next, we look ahead, and map out some possible routes upward, from our newly established base camp, for developing fully transparent and scalable approaches to AI.

Our main result is that, with the tools we’ve developed, it’s straightforward to build a user-intent detector that is fully transparent, editable, and succinct, and that performs as well as a state of the art machine learning approach. Furthermore, the tools themselves do not rely on sophisticated NLP methods such as semantic role labeling or constituency or dependency parsing; they do not employ statistical methods at all - yet. Thus not only are the results transparent, so are the tools used to achieve them. Finally the ideas should apply equally well to detecting other meanings in text.

However we found that our initial hope, that the Teacher would only need a clear understanding of the app they wish to build, and of their own native language, was only partially fulfilled; while it’s certainly possible to so restrict the teacher’s role, we found that allowing them to edit the text files that contain the templates, and the extensions and deletions in the taxonomy, was very useful. This requires an extra level of training for the Teachers. But if the hope of just a few designers, feeding hundreds of teachers, who can then support millions of users, comes to pass, perhaps it’s not too much to ask a little more of the Teacher role.

A more serious issue is that we made little headway towards our “Every teacher benefits from what any teacher teaches” North Star. The built-in parsed predicates are shared, and certainly, teachers can reuse predicate detectors that others have built. But true reusability will likely have to employ hierarchical structures of predicates. We will discuss some ideas for this in the next section.

An earlier version of TAL used gazetteers to identify US cities and retailers. We found that we did

not need these gazeteers, at least for the “intent to buy” detection task. Later versions may need them. However, compound phrase handling does need to be improved. We found that allowing both paths (i.e. searching for a match by treating a possibly compound phrase as compound, and also as non-compound) introduced training errors, as did treating possibly compound phrases as definitely compound. It seems that to solve this robustly we will need to use context; if the phrase itself could be a compound noun, check that a noun phrase is a possible part of speech, given the surrounding tokens; similarly for verbs; and only employ the ‘try both paths’ trick if the compoundness is truly ambiguous. Note that this still does not require a full NLP parse of the text.

Finally the ideas outlined in this paper need to be further checked against more tasks and on other datasets. Our hope is that the benefits resulting from a fully transparent approach will warrant such explorations.

5. SOME IDEAS FOR FUTURE WORK

For the discussion in this section it is helpful to name two phases of learning that TAL can do: “wake” phase, in which TAL learns directly from a human, and “dream” phase, in which no human is involved. In dream phase, for example, TAL could learn either by leveraging large, unlabeled datasets, or by directly making more sense of what it has already learned.

5.1. Wake Phase Error Correction

We will describe ideas for error correction using large unlabeled datasets below, but we can also ask the teacher for confirmation of consequences of their choices that they may not have anticipated. If the teacher has arrived at a template using labeled data, TAL could run it in real time over a large unlabeled dataset, show the resulting matches to the teacher, and then allow them to modify the template accordingly. False positives are thus easy to control. False negatives pose a harder challenge. For these, perhaps the simplest approach would be to run the unlabeled data through both TAL and a statistical system such as LUIS, then have the teacher manually inspect any samples on which the two systems disagree and update the templates as needed.

5.2. Dream Phase Error Correction

5.2.1 Template Error Correction Using Unlabeled Data

Suppose that a teacher has taught TAL an overly general template intended to fire the predicate “person ingests food”. Suppose that their template is (schematically) as illustrated in Table 14, where the synsets of the template are in the first column and the corresponding roles defined by the teacher (i.e. the corresponding predicate’s components) are in the right column. This template overgeneralizes because, for example, it will fire for the phrase “building eats person”.

One way to leverage a large, offline, unlabeled dataset to check that a template does not overgeneralize is as follows. First, run the template over the dataset, making a record of all matches. For each match, increment a counter in the node in the WordNet-based taxonomy, where the counter is labeled by its component name in the corresponding predicate (e.g. “ingerter”). (Note that a given token will correspond to multiple nodes since at test time, we don’t know its correct synset.) The taxonomy hypernym tree (for each component of the predicate) can thus be represented as a heat

Synset	Role
entity.n.01	ingerter
eat.v.01	act of ingesting
entity.n.01	ingested

Table 14: *Synsets and Roles*

map. If the template is too general, then the heat map will contain cold spots at, or close to, the leaves. (The token “building” will rarely occur as an “ingerter” in the dataset). This computation gives us a distribution over the nodes of a subtree of the taxonomy for each predicate component, where the root of the subtree is that component’s synset. We can extend this reasoning to handle templates with sets of synsets, but for clarity here we consider components that correspond to a single synset in the template being tested.

For concreteness consider just the first component, and call its tree T . If some subtree $S \subset T$ has nodes that are sufficiently “cold”, one could try to find a subtree $S' \subset T$ that maximizes the number of “hot” nodes and minimizes the number of “cold” nodes. If necessary, one could split the original template into two or more, such that each has only “hot” nodes, and all “hot” nodes in T are covered (this fits naturally into our template model that uses sets of noun synsets). This process is necessarily statistical, since rare phrases do occur (buildings can eat people, in fiction or metaphors).

An interesting line for future work is to take the brakes off this process and simply ask: given a large, unlabeled text dataset, how can one choose N templates for which the amount of matching text is maximized, but such that amount of text for which pairs of templates match is minimized? If $N = 1$, presumably a template could be chosen that will cover most, or all, of the data. For $N \geq 2$, templates compete to explain the data. In this way, one might approach the fully offline learning of templates. How far can one get by using only the taxonomy and large unlabeled datasets, in this way? Could some predicates arise naturally from the resulting templates? Could such a set of templates help inform us on how to build a suitable hierarchy of predicates?

5.2.2 Template Unification

Similarly a large unlabeled dataset can be used to identify templates that are essentially the same, even if their sets of synsets differ, by the similarity of their heat maps. First, two templates that are candidates for unification could be found by automatically comparing pairs of heat maps. Those templates might then be unified if a template could be found that maximally agrees with the combined heat maps of the individual templates. A process like this will likely be needed to identify similar templates proposed by different teachers, if the automated checking process used during training (“your input phrase fired this template: combine or add?”) fails. Similar ideas can be applied to identify when the predicate being trained is likely the same as one already learned. Note that these ideas are already instantiated, to some extent, in TAL: any phrase input by a Teacher is tested against all existing predicates, and the Teacher is alerted if there is a match; similarly, TAL currently allows the unification of parts of templates, if those templates share a verb synset.

5.3. Extensibility

5.3.1 Multiple Languages

TAL's language dependence currently resides in the WordNet taxonomy; a "microgrammars" file that instantiates the built-in parsed predicates; an "English POS" file that lists parts of speech that only occur via small numbers of tokens (e.g. pronouns, and question adverbs); the function that maps text to lemmas and tense, using the Slang Map; the function that maps annotated lemmas to the 'parsed components list'; and two supporting files, of verb declinations and nouns with their plurals. Clearly the adherence to transparency comes with a development cost when it comes to adding new languages. WordNet is supported for languages other than English [33], and one can certainly envision using other, similar taxonomies. Extending templates and predicates from one language to another requires more than just having a mapping of synsets available, since different languages can express the same concept in very different ways. Even so, it may be possible to use machine translation systems to accomplish this automatically. If one has a large database of paired phrases for the two languages, then the templates in the new language could be learned automatically, and its predicates' component names could be translated similarly. This idea, combined with a given mapping of synsets from one language to the other, could also be used to learn the mapping of the predicate components to their corresponding template components in the new language.

5.3.2 TAL's World Model

We think of the built-in parsed predicates - e.g. detecting properties of time, space, and number - as forming the basis of TAL's world model. Currently the structure containing the predicates is flat, but it's clear that a hierarchy will be needed: velocity needs the concepts of space and time, acceleration needs velocity and time, etc. It seems likely that a hierarchy would also be required to make learned predicates scalable. If one entity is about to eat the other, then the two entities must be colocated. If two people are married then they must know each other, must have made a joint commitment, etc.

One way to encode logical relationships is to have a directed graph whose nodes are negatable predicates (by a negatable predicate, we just mean a predicate with an added negation flag: thus *he is not eating fish* would fire the *Ingests(person, food)* predicate with its **Not** flag set). If a node is true only if its children are all true, then we have the logical connectives **And** and **Not**, which form a functionally complete set (a set from which any truth table can be constructed). It may however be more convenient to explicitly model the **Or** connective by instead having a directed bigraph in which nodes are either predicates or connectives, and for which every node has an attached Boolean variable. For example, if several predicate nodes are connected to an **Or** node, the latter is true only if one or more of those predicates is true. Such a graph is one way of implementing logical inference, and such a hierarchy would also help with the interpretability of the overall model. One can apply similar ideas to those above, to detect logical relations between predicates automatically. Thus if a set of templates and predicates is run over a very large dataset, and predicate *A* is always found to be true whenever predicate *B* holds, then the relation $B \Rightarrow A$ could be added to the graph. It is more likely, however, that a probabilistic way of modeling logic, such as Markov logic networks [22], would be required.

For scalability, if a new parsed predicate must be added, and it can be defined in terms of existing parsed predicates (for example, speed or velocity in terms of position and time), ideally one would

define the new predicate in terms of the others in a script file, without having to write new code.

5.3.3 Extending to Large Numbers of Templates and Predicates

TAL already uses a simple mechanism to limit its search: roughly speaking, only those templates that are indexed by the token currently being examined are tested for a match for the following tokens. The search can be further limited by partitioning templates using context. For example, when TAL is awaiting user input to determine which app to run, it knows it's in a particular state, and so it can safely use templates that would overgeneralize in other situations: so for example a template containing the single verb "exercise" can be used to select a "go to the gym" reminder app, and not used elsewhere. More generally, TAL can represent its inner state using a finite state automaton, and have only subsets of templates (and their predicates) available for each state. This could be extended to its interactions with the user: TAL could model the user's state using a Markov chain, where each state again links to a limited set of templates, and only those templates corresponding to states whose probability exceeds a threshold would be tested for matches.

5.3.4 Extending the MSL

We currently define a number of Turn types in MSL (see Appendix 1: Specification of the Module Specification Language). These are intended to be generic and flexible enough to accommodate all the necessary question-answering and control-flow operations needed by a Designer. Supporting domain-specific Turn types would require a plug-in model for FDL to understand which actions to take for which questions.

We may consider supporting module reuse through some form of *module inheritance*, allowing a module to extend a *base module*. The *base module* might include all the required metadata-collecting operations such as those in the `Initialize` block, so the *derived modules* do not need to repeat them. This is similar to the superclass constructor execution when constructing subclass instances in object-oriented programming. Similarly, we might extend the script blocks to allow a base module to define a set of Turns that could be "called" by a derived module.

5.4. Other Benefits of Model Transparency

Suppose you have several statistical models that were trained (possibly using different data) for the same task. How best to combine them? Model averaging often works well. But that's a hack and it requires running all the models. With a fully transparent model such as TAL, the models (i.e. their templates) can be directly combined, resulting in a model with the benefits of all the trained models but that is both more compact and efficient than using all of the models independently. This is another way that transparency can contribute to scalability. Multiple Teachers can do their thing on their own data, training the same predicate (task), and the results can be combined. Being able to handle the inputs of many teachers is a key requirement for scalability.

5.5. The Machine Comprehension of Language

In [3]), the following practical definition of the machine comprehension of text was proposed:

A machine comprehends a passage of text if, for any question regarding that text that can be answered correctly by a majority of native speakers, that machine can provide

a string which those speakers would agree both answers that question, and does not contain information irrelevant to that question.

We can recast this in terms of predicates as follows:

A machine comprehends a passage of text if, for every (possibly implicit) assertion made by the text, as identified by a majority of native speakers, that machine asserts the corresponding predicate to be true, and it does not assert any other predicates to be true.¹³

Note that some ‘false negatives’ are easy to detect automatically: if no predicate fires for a passage, and if we know that the passage has some meaning that should have been detected (as would be the case, for example, in parsing a passage for general question answering), then the machine necessarily does not comprehend that text.

The above definition gives us a way to measure how well a system comprehends a dataset of text samples. We could first crowd source the labeling, asking workers to write down all assertions (predicates) made by each sample text, and then determine the overlap between the human generated predicates, and those predicates declared to be true by the system when run over the text. Errors introduced during labeling could be controlled by using multiple workers for each sample, and by asking a further set of workers to verify any outlier claims. We might further test the system’s world model by distinguishing those predicates that follow directly from the text, and those that are implied indirectly by it.

This measurement strategy would of course work for any system that makes assertions via predicates, giant black-box neural nets included. However, as we have argued above, we believe that the fully transparent, interpretable, correctable, predicate-based approach presented in this paper at least provides us with a good starting point - a base camp - for further investigations into scaling AI.

6. ACKNOWLEDGEMENTS

We thank Jason Williams, Paul Bennett and Richard Hughes for many valuable discussions and for their support of this work. We also thank Vishal Thakkar, the Stargate Support team, and Hisami Suzuki for their help and guidance in our generating the Cortana dataset.

This work is the culmination of several years of explorations. We thank Erin Renshaw for her steadfast help with the earlier work. We thank John Platt for his vision in supporting big-bet, long-term research at MSR, which freed us to (repeatedly) fail. We additionally thank Eric Horvitz, Jeannette Wing and Harry Shum for their leadership and vision in supporting long term research in general and this work in particular.

¹³Note that this definition also covers negations.

7. APPENDIX 1: SPECIFICATION OF THE MODULE SPECIFICATION LANGUAGE

This section provides the detailed specification of the Module Specification Language (MSL) used by the Designer to create module scripts for FDL. A brief overview was given above in section 3.3 (Overview of the Module Specification Language).

7.1. YAML Basics

YAML¹⁴ is a serialized data representation format that can be edited easily by humans and parsed by a program. Our module specification language uses Yaml as a representation medium. In this section, we discuss the elements of YAML that are used in the example Medication Reminder Module script.

Scalar is the basic data type, which can represent a single value, e.g. a number or a string. Type inference is automatically done most of the time in Yaml; Table 15 contains some examples.

Value	Type
25'	integer
"25"	string
25.0'	float
Yes	boolean

Table 15: Examples of YAML type inference.

Mapping and *sequence* are two basic ways to composite scalars. *Mapping* is similar to the *map* or *dictionary* data structures in most programming languages; values are referenced by unique keys, and the key/value pairs are unordered. The key and the value are separated by *a colon and a space*, for example

```
name: Tom
age: 15
married: Yes
```

is a mapping. In Yaml, the indentation really matters; all entries in a mapping must have the same indentation.

Sequence is similar to the *list* data structure in most programming languages, which means the values are ordered and referenced by the index (position in the list). Each entry begins with *a hyphen and a space*. For example

```
- Tom
- Jerry
- Jack
```

is a list of three entries. Again, indentation matters; the hyphens must have the name indentation. An empty sequence or map is indicated by:

¹⁴<http://yaml.org>

```
MyList: []  
MyMap: {}
```

Complex objects can be represented by a combination of mappings and sequences. For example, a sequence of instances of a data structure containing the fields “name”, “age”, and “married” would be:

```
- name: Tom  
  age: 15  
  married: Yes  
- name: Jerry  
  age: 14  
  married: No  
- name: Jack  
  age: 12  
  married: No
```

Again, note that the hyphens are indented at the same level, and each hyphen is the start of an instance of the structure.

By default, YAML concatenates all lines together in a single value. You can use a special sequence starting with ‘|’ to preserve linebreaks and whitespace; ‘|-’ suppresses the final one linebreak.

```
Question: This becomes  
          one line, with one space between "becomes one".  
Question: |-  
          This remains three lines with  
          1. Item One  
          2. Item Two
```

The comment indicator in Yaml is ‘#’; anything from this to the end of the line is ignored.

7.2. Script blocks

A module specification script partitions the specification into four sections, or blocks, listed below. We will describe the notion of a *turn* in more detail below, but at a high level, it is a series of system-User interactions that together aim to acquire a single piece of information from the User, or to deliver a single piece of information to the User.

Name: A string that defines the name of the module (for example, *Event Reminders*).

Initialize block: A set of app-independent constants used to streamline the interactions with the Teacher (and in principle with the User, although most variables used in User mode are set in the Teach block). For example, our Event Reminders module defines the <OKEnterSentence> string constant to have the value “OK, then please enter the sentence you would like me to use here.” and it’s used six times in the Teach block. The Initialize block can also be used to ask the teacher any questions needed to acquire metadata about the application; this data is then saved using reserved keys.

Teach block: Both the Teach and Use blocks consist of a series of two kinds of turn: predicate detecting turns, and parameter value turns. At a high level, the Teach block is a turn-taking

structure, where the Designer designs a series of questions intended to leverage the Teacher's language skills to teach the application the language comprehension and generation skills that are to be used in User mode. Both turn types can also be embedded in conditional blocks. In the Events Reminder example, a predicate turn is used to elicit from the Teacher sentences that exemplify the language that the User is likely to input in order to identify this application from the pool of apps available to the User; this lets the APA know which app the User wants to run. In the parameter value turns, the Teacher specifies, for example, the language used to elicit a name for the series of reminders that the User is creating. The Designer can also elicit from the Teacher any language that is likely to be repeated (as in the example above); for example, the Designer might want to extract a general verb phrase from the Teacher, to refer to the type of reminders created by the app (for example, "take your medications" for a meds reminder app); this verb phrase is then referred to throughout the remainder of the script (in both Teach and Use blocks).

Use block: This contains a set of sub-blocks named for the action being performed on the instance. In the Event Reminder module, the only action defined is `create`, when creating the reminder. This could be extended with, for example, `edit`, which reads an existing reminder and allows the user to edit it. Each Use sub-block is a turn-taking structure that obtains that parses free user input in order to execute the action on the entity; for the `create` action, this is to create the entity. In the Events Reminder example, a **TestPredicateTurn** parses free User input describing their reminders and obtains parsed predicates, and a series of parameter value turns confirms the values found or asks the User to fill in missing values (such as the length of time the reminders should run for). Thus, for an individual reminder, ideally a single predicate detecting turn receives a sentence from the User that contains all the information needed to create the reminder, and the system then confirms the information in a single turn. If the user chooses to change some of this information, or if some necessary information is missing, further parameter value turns are run to gather the needed data.

Note that the natural sequential nature of an MLS script means that one can create variables early in the script that can be used throughout the rest of the script, in all blocks.

7.3. Script Parameters

Values are obtained from the Teacher or User and stored in parameters; parameters also contain the values to be presented to the user.

7.3.1 Parameter Names and References

The parameter should be named using only A-Z, a-z, 0-9, underscore ("_"), or period ("."), and is case sensitive. There are some special name formats with the underscore that should be reserved for a specific purpose; see section 7.3.2 (Special Parameter Names).

In the following discussion and subsections, we occasionally use as an example a parameter named `par`.

A parameter value can be referenced in the subsequent turns (or in the current turn if it is used after the value is assigned) using the syntax `${par}`. The process of converting from this name representation to its value is referred to as expansion. Depending on the context of the parameter

reference, the parameter value may be converted to the various types (e.g. to string if used in screen printing).

Parameter names can be built up from other parameters into a composite name. For example, `${frequency.${i}.period}` first obtains the value for `${i}`, for example 0, and then forms the name `${frequency.0.period}`, which can then be looked up directly. The bracketing `${}` is required if expansion is to be done, and otherwise should not be present. In particular, when a parameter's name is to be used rather than its value, expansion should not be done for the entire name, but it may have to be done for embedded names if the parameter is a composite. This is discussed in more detail below.

7.3.2 Special Parameter Names

We suggest reserving names that begin with an underscore for parameters with special meaning. In particular, names using all uppercase letters with two underscores at both the beginning and end should indicate “external” values, such as the state of the script, parameters that have a special meaning to FDL, or a value that an application will look for. For example, section section 7.6 (Finding the App the User Wants) describes how some special parameters are used to find the application the user wants to run.

Table 16 shows the current set of special names in FDL.

Name	Meaning
<code>__NAME__</code>	The name of the application. Another application may look for this.
<code>__IS_EDITING__</code>	Indicates that the script is being edited rather than being a newly created script. This means that some parameter values may already be present, which will let the script designer present a more relevant dialog.
<code>__ACTION_DESCRIPTION__</code> . <i>action_name</i>	<code>__ACTION_DESCRIPTION__</code> is the base name for a collection of parameters of type <code>STRING</code> , one for each action in the <code>Use</code> block, that is used by FDL to give the user a friendly description of what this action does. For example, <code>__ACTION_DESCRIPTION__.create</code> provides a description of the <code>create</code> action of the <code>Use</code> block, such as “create a reminder to go to the gym”.
<code>__ACTION_CONFIRMATION__</code> . <i>action_name</i>	<code>__ACTION_CONFIRMATION__</code> is the base name for a collection of parameters of type <code>STRING</code> , one for each action in the <code>Use</code> block, that is used by FDL to ask the user a question to confirm that this script and action is really what the user intends to do. For example, <code>__ACTION_CONFIRMATION__.create</code> provides a confirmation question for the <code>create</code> action of the <code>Use</code> block, such as “do you want to create a reminder to go to the gym?”.
<code>_anything</code>	Indicates a parameter intended to hold a value for “internal” use by a SetParam-Values Turn , such as reducing duplicate strings, rather than being obtained from the user.

Table 16: *Special Parameter Names in FDL.*

7.3.3 Parameter Types

Table 17 lists the parameter types currently supported by FDL.

Name	Type	Description
STRING	StringValue	The user's answer is saved as it is without further language understanding or information extraction.
NUMBER	NumberValue	Extracts a number expression from the user's input and saves it as a float value. It supports digit expressions in English format (e.g. "3.14") or English cardinals (e.g. "thirty five") for integers only. If the user's input starts with "i don't know" or is "forever", the infinity value is assigned. NUMBERS can be compared to other NUMBERS or to INFINITY; see section 7.3.4 (Conditional Operations on Parameters).
none	NumberValueRange	A NUMBER range such as "2-3". This is created by a User entering a string during a TestPredicateTurn; script turns require a single value.
DATE	DateValue	Extracts a Date from the user's input. This supports a) .NET DateTime.Parse compatible strings (e.g. "July 21, 2016"), b) special days (e.g. "today", "tomorrow", "now"), c) days of the week (e.g. "Tuesday"), d) the day of the next week as in "next Tuesday".
TIME	TimeValue	Extracts a Time from the user's input. This supports a) .NET DateTime.Parse compatible strings (e.g. "8AM"), b) time expressed using English words (e.g. "three thirty five"), c) offset by 12 hours if "pm", "p.m.", "evening", or "afternoon" is present.
INTERVAL	IntervalValue	Extracts a time interval from the user's input. The supported units include "second", "minute", "hour", "day", "week", "month" and "year", and the value can be either digits (e.g. "3 years") or English words (e.g. "three years"). We also support "half" (e.g. "one year and a half"). All interval expressions are stored as a .NET TimeSpan object. The number of "months" and "years" is converted to "days" depending on the current month and year, i.e. "one month" can be converted to "28 days" to "31 days". It also supports an "i don't know" or "forever" answer from the user, in which case TimeSpan.MaxValue is used. INTERVALs can be compared to INFINITY; see section 7.3.4 (Conditional Operations on Parameters).
none	IntervalValueRange	An INTERVAL range such as "2-3 hours". This is created by a User entering a string during a TestPredicateTurn; script turns require a single value.
YESNO	YesNoValue	If you expect the user to answer with either "yes" or "no", then you could use this parameter type.
NOMINAL	StringValue	If you have a list of all valid answer strings, you could specify the parameter type 'NOMINAL' and list the valid strings of the answer.

Table 17: *Parameter types.*

Here is an example of defining a parameter's name and type, for example in a **SetParamValues** or **ParamValueTurn**:

```
Param: person_name
Type: STRING
```

To define a parameter of **NOMINAL** type, specify the values as a mapping, which should start on a new line with extra indentation, e.g.:

```
Param: fruit_category
Type:
  NOMINAL: [apple, orange, pear]
```

7.3.4 Conditional Operations on Parameters

FDL supports conditional comparisons to provide if-then-else logic for selecting which **Turns** to execute. Table 18 lists the conditional operations currently supported by FDL; these are the ones that were useful in developing the Medication Reminder module, and more may be added in the future. These comparisons are done in a **ScriptConditionalActions Turn**.

Operation	Supported On	Description
=, <, >, <=, >=, <=	NUMBER	Boolean result of the comparison.
IS [NOT] INFINITY	NUMBER, INTERVAL	Boolean result indicating whether the named parameter's value is or is not infinity. If the parameter is not set, an exception is thrown; check with IS SET first.
IS [NOT] SET	all	Boolean result indicating whether the named parameter has or has not been assigned a value. If the parameter has been removed by a RemoveParameterValues Turn , it IS NOT SET.
IS [NOT] NUMBER	all	Boolean result indicating whether the named parameter is or is not a NUMBER.
IS [NOT] INTERVAL	all	Boolean result indicating whether the named parameter is or is not an INTERVAL.

Table 18: Conditional operations supported on parameters.

Comparisons may be combined with AND and OR (which short-circuit), and parentheses may be used for precedence.

7.3.5 Arithmetic Operations on Parameters

FDL supports a limited set of binary operations on parameter values; the syntax is similar to parameter references except that two parameter names (or a parameter name and a value) are

present in the expression and are separated by an operator. Currently, we support the binary operators "+" and "-" between a 'DATE' and an 'INTERVAL' parameter, and between a 'NUMBER' parameter and a float value. This is illustrated in Table 19.

Type 1	Type 2	Operator	Example
DATE	INTERVAL	+, -	Assuming a DATE parameter <code>date</code> with value July 21, 2016 and an INTERVAL parameter <code>interval</code> with value 3 days, then <code>\${date+interval}</code> results in the DATE value July 24, 2016.
NUMBER	float	+, -	Assuming a NUMBER parameter <code>i</code> with value 1, then <code>\${i-1}</code> results in the float value 0.

Table 19: Arithmetic operations supported on parameters.

7.4. Script Handlers

A **Handler** combines a script name with an action name and is the means by which the FDL system determines which scripts apply to a user's intended action. For a discussion and example of how Handlers are used, see section 7.6 (Finding the App the User Wants). Table 20 describes the Handler properties.

Property	Type	Required	Description
ActionName	string	yes	The action to be performed when this predicate fires.
ScriptName	string	yes	The name of the script to execute <code>ActionName</code> in when this predicate fires.

Table 20: Handler properties.

7.5. Turn Types

A **Turn** in our context is a series of interactions that together aim to acquire a single piece of information from the user or deliver a single piece of information to the user. This is the atomic building block of an interactive application.

7.5.1 Prompt

This defines a message that the system will show the Teacher or User. It has no properties; the value of the Turn itself is the message to be displayed.

Example:

Prompt: Let's edit your application.

7.5.2 ParamValueTurn

Presents a question to the Teacher or User and obtains the result value. There are numerous possible interaction flows, depending upon the presence or absence of the referenced parameter and properties.

Property	Type	Required	Description
Description	string	no	Provides a description that is shown only once per execution of the step
Param	string	yes	The name of the parameter being asked for or confirmed.
Type	ParamType	yes	The type of the parameter, from section 7.3.3 (Parameter Types).
Default	string	no	A default value to assign to the parameter if it is not set.
Question	string	no	A question to ask the Teacher or User to request the parameter value.
Confirm	string	no	A confirmation message to use when the parameter is set.
Loopback	string	no	If the user does not confirm when asked, then this is the prompt that is used to repeat the request for the parameter value. If it is not present, then the Question property is used.
MistypeFollowup	string	no	If the value entered by the user cannot be parsed into a value of Type, then this is a custom message to display; if it is not present, a general message is shown.

Table 21: *ParamValueTurn properties.*

The FDL system will append “(Y/N)?” to the the Confirm question when it displays it to the Teacher or User.

Examples:

The simplest **ParamValueTurn** consists of only Param, Type, and Question properties, where the system asks the user a question defined in the Question property, converts the answer to the type specified in the Type property, and assigns the result to the parameter named in the Param property.

Example:

```
ParamValueTurn:
  Question: Please name the script (e.g. "AMI Medication Tracker").
  Param: __NAME__
  Type: STRING
```

If there is a viable default value for the parameter, the script can confirm this value with the

Teacher or User without asking him or her the initial question. In this case, the **ParamValueTurn** would have the Default, Confirm, and Loopback properties. The system *first* assigns the value in the Default property to the parameter named in the Param property, and then confirms with the user using the question in the Confirm property. If the user says "no" to the Confirm question, then the Loopback question will be asked and the user will be asked to Confirm again. Usually the Param should be referenced in the Confirm.

Example:

```
ParamValueTurn:
  Default: 3 days
  Loopback: Please tell me over what duration you'd like your reminders set?
  Confirm: You would like to take medication for ${duration}. Is that correct?
  Param: duration
  Type: INTERVAL
```

A single ParamValueTurn can contain both a Question and a Confirm. In this case, the system first asks the user the Question and saves the value in the Param before Confirming with the user. If the user denies the confirmation, then user will be asked the the Loopback question if it exists; otherwise the same Question will be asked again. Either way, the Confirm is asked again and the process continues.

If you specify a particular type, but the system couldn't recognize an instance of that type in the user's input, then you could also define the MistypeFollowup property to give the user more hints on what we expect the user to input.

Example:

```
ParamValueTurn:
  Question: When are you going to start taking the medication?
  Confirm: You would like to start on ${start_date}. Is that correct?
  MistypeFollowup: What date is that? You could enter "today", "tomorrow", or a specific date s
  Param: start_date
  Type: DATE
```

Another important feature of ParamValueTurn is that if Param has been initialized in the previous turns, then the current turn will be skipped, *unless the existing value type doesn't match the required param type*, in which case the system forces the type mapping with the user's help. For example, if we define a parameter duration with the type INTERVAL, then the expected value type should be IntervalValue; if we find the value of this parameter has the value type IntervalValueRange (see section 7.3.3 (Parameter Types)), then the system asks the user to select an IntervalValue from the IntervalValueRange and assigns the updated value to the parameter duration. A similar dialog occurs if a NUMBER parameter has a value that is a NumberValueRange.

To summarize, the value is assigned to a parameter in the following order:

- 1 . Existing value assigned in the past, if any;
- 2 . The expanded Default property of the **ParamValueTurn**;
- 3 . The User's input as response to the Question.

7.5.3 TrainPredicateTurn

The **TrainPredicateTurn** leverages the Teacher's language skills to train the templates needed to form a **LearnedPredicate** detector. When the system enters a **TrainPredicateTurn** it asks the teacher to type an example phrase that should fire the **LearnedPredicate** associated with the application being created. The system then engages in dialog with the Teacher to select the correct parse, synsets, and their generalizations for the identified terms or compound terms, creates a template, and associates the predicate with that template. The process of supplying example sentences continues until the Teacher has no further phrases they wish to use; for example, when every new phrase the Teacher enters is matched by an existing template.

The **TrainPredicateTurn** has the following properties:

Property	Type	Required	Description
PredicateName	string	yes	Names the LearnedPredicate associated with the application. The PredicateName property is usually named for the application, as there is currently only support for one LearnedPredicate in FDL.
Notes	string	no	Any additional free-form information associated with the LearnedPredicate .
Handler	struct	yes	A structure containing the mapping between action names and the names of scripts that implement those actions. See section 7.4 (Script Handlers)
ActionName	string	yes	The action to be performed when this predicate fires.
ScriptName	string	yes	The name of the script to execute ActionName in when this predicate fires.

Table 22: *TrainPredicateTurn* properties.

Example:

```
- TrainPredicateTurn:
  PredicateName: ${event_phrase} # The phrase used to refer to the event
  Notes: ""
  Handler:
    ActionName: "create"
    ScriptName: ${__NAME__} # The name of the current script
```

7.5.4 TestPredicateTurn

The **TestPredicateTurn** is used in User mode to determine which predicates match input from the user. The system displays the **Question** to prompt the User to provide needed information: for example, for a medications tracker app in the Event Reminder class, the User might be prompted to input their prescription. The system then parses the User's input to detect matches with both parsed and learned predicates. The components of any matching predicates are mapped to the parameters defined in the **PredicateParamMappings** field. For example, our built-in parsed predicates currently identify the frequency, time, event duration, start date, and the duration of

the reminder sequence (how long the reminder should remain on the calendar). If these predicates fire due to the user’s input, their slots are then assigned to the corresponding script parameters, which can then be referenced in subsequent turns; the script can populate a confirmation question (“You would like your reminder at 7:00 a.m. Is that correct (Y/N)?”) without requiring the user to first enter that value (“Please tell me what time you would like your reminder”), which must be done if the slot is not filled.

The **TestPredicateTurn** has the following properties:

Property	Type	Required	Description
Question	string	yes	Prompts the user to enter a sentence describing the event.
Param	string	yes	The name of the parameter that will store the answer to the Question.
CountParam	string	yes	The name of the parameter that will store the number of phrases entered by the user (separated by "then"; see the discussion in the example).
PredicateParamMappings	struct	yes	A structure containing the names of the parsed predicates that are applicable to this application, and for each, the name of the parameter that will store the value of that parsed predicate. See examples below.
PredicateCountParam	NUMBER	yes	The name of the parameter that will receive the number of parsed predicates found.

Table 23: *TestPredicateTurn* properties.

Example:

TestPredicateTurn:

Question: Please read me the instructions on your prescription.

Param: description_string

CountParam: count

PredicateParamMappings:

Pred_Freq: frequency

Pred_SequenceDuration: sequence_duration

Pred_EventDuration: event_duration

Pred_StartDate: start_date

PredicateCountParam: description_predicate_count

In this example, the user will input a sentence in response to the Question. First, the system splits the sentence into phrases by splitting on the "then" keyword; this can be extended to other keywords or syntactic structures. The number of clauses found is stored in the parameter named by the CountParam property. The system then parses each clause to extract parsed predicates from it.

The system creates a set of parameters for each clause, regardless of whether the phrase contained a parsed predicate or not. For each clause, numbered from 0 to the value in the `CountParam` parameter, the system creates a parameter for each parsed predicate, with the ordinal of that clause appended to the parameter name specified in the **TestPredicateTurn**. In the above example, if the user's sentence contained 3 clauses, the system would create the following parameters `frequency.0`, `frequency.1`, `frequency.2`, and similar parameters for the other parsed predicates found in the clause. These parameters are used by a subsequent `NIterations` turn to engage in a dialog with the User for each clause.

FDL currently supports the built-in parsed predicate types in table 24.

Name	PropertyName	Description
Pred_Freq "frequency"		A frequency such as "every day", "daily", "twice a day", "2-3 times a day", etc. If there is a single value ("twice a day") then an IntervalValue is created; otherwise ("2-3 times a day") an IntervalValueRange is created, and the User will be prompted to select a single value in that range. Pred_Freq has the following three properties.
	period	The period of the frequency, e.g. daily.
	number_of_events_per_period	E.g., for "twice daily" this would be two.
	start_time	The starting time for each period; for "daily" this might be "7 am".
Pred_SequenceDuration "sequence_duration"		The duration of the entire sequence; for the Event Reminder, this is how long the reminder should remain on the calendar.
Pred_EventDuration "event_duration"		The duration of a single event; for the Event Reminder, this might be how long a single appointment would take.
Pred_StartDate "start_date"		E.g. for the Event Reminder, this is the date of the first reminder.

Table 24: Built-In Parsed Predicates; the *Name* column shows, in quotes, the name of the parameter to be given the predicate value in the Medication Reminder example, and the *PropertyName* column shows the names the FDL system assigns to these properties.

Once the TestPredicateTurn is complete, a subsequent series of Turns, usually within an NIterations Turn, presents confirmation of each parsed predicate that was detected in the clause, as well as asking for any that were not (and any other values needed). If the User's sentence fully specifies all the necessary information (including all required parsed predicates), then a single confirmation sentence can be presented; in this case it would be necessary to confirm each individual value only if the User rejects this initial confirmation.

7.5.5 NIterations

An NIterations composite turn is similar to a for-loop in most programming languages. It has the following properties:

The **NIterations Turn** has the following properties:

Property	Type	Required	Description
IterVar	string	yes	The name of the parameter holding iteration variable (the "i" in the usual for loop, zero-based).
N	string	yes	The name of the parameter holding the maximum number of iterations.
Turns	Turn list	yes	The Turns to be executed on each iteration (the body of the for-loop).

Table 25: *NIterations properties.*

Example:

```
NIterations:
  N: '10'
  IterVar: i
  Turns:
    - Prompt: Now ${i}!
```

is similar to

```
for (int i = 0; i <= 10; i++) {
  printf "Now %d!" i
}
```

To present the iteration number in a more user-friendly way, the system provides a special parameter `${ordinal}` that maps the `IterVar` value (which is zero-based) to the corresponding ordinal word (which is one-based). For example, in iteration 0 (i.e. "i = 0"), then `${ordinal}` has a value of "first".

NIterations loops can be nested; the Turns list may contain an inner NIterations turn. In this case, the `${ordinal}` special parameter is scoped to the inner iteration's `IterVar`.

It is often possible to set the parameter reference `N` to a previously assigned `NumberValue`. For example, in the previous example, we define a parameter `count` as the number of clauses in the sentence; to iterate over these clauses, the `N` parameter would be set to `${count}`.

Example:

```
NIterations:
  N: ${count}
  IterVar: i
  Turns:
    - Prompt: Let's confirm the ${ordinal} reminder.
    - ParamValueTurn:
      Question: Please tell me over what duration you'd like your reminders set.
      Param: duration.${i}
      Type: INTERVAL
```

The **NIterations** step allows date-sequencing logic. For the first iteration, the frequency `start_date` is as set by the user. In subsequent iterations, the `start_date` is the end date of the previous iteration, and this can be tracked in a script parameter using the **SetParamValues** turn.

Example:

```
SetParamValues:
  Param: next_start_date
  Type: DATE
  Value: ${start_date.${i}} + sequence_duration.${i}}
```

7.5.6 SetParamValues

An **SetParamValues** turn allows the Designer to set parameter values directly in the script.

The **SetParamValues Turn** has a list of structures that specify the parameters to be set; each has the following properties:

Property	Type	Required	Description
Param	string	yes	The name of the parameter that will receive the value.
Type	ParamType	yes	The type of the parameter, from section 7.3.3 (Parameter Types).
Value	string	yes	The value to be set, converted to Type.

Table 26: *SetParamValues properties.*

Example:

```
SetParamValues:
  Param: i
  Type: NUMBER
  Value: 0
```

7.5.7 RemoveParamValues

An **RemoveParamValues** turn allows the Designer to remove parameter values directly from the script.

The **RemoveParamValues Turn** has a list of the following property:

Property	Type	Required	Description
Param	string	yes	The name of the parameter that will be removed.

Table 27: *RemoveParamValues properties.*

Example:

```

RemoveParamValues:
  Param: frequency.${i}.period
  Param: i

```

7.5.8 ScriptConditionalActions

A **ScriptConditionalActions** is equivalent to an if-else-then dialog flow, based on the boolean value of a condition written in a simple conditional grammar that allows testing whether a script parameter is set or has an infinite value, comparing numeric values ($=$, $>$, $>=$, etc.), and parentheses for precedence.

The **ScriptConditionalActions Turn** has a list of the following property:

Property	Type	Required	Description
Condition	string	yes	The condition to evaluate; see section 7.3.4 (Conditional Operations on Parameters).
IfYesTurns	Turn list	yes	The turns to execute if Condition is true; may be a NoAction turn.
IfNoTurns	Turn list	yes	The turns to execute if Condition is false; may be a NoAction turn.

Table 28: *ScriptConditionalActions properties.*

Example:

```

ScriptConditionalActions:
  Condition: ${i} > 0 AND start_date.${i} IS NOT SET AND next_start_date IS SET
  IfYesTurns:
    - SetParamValues:
      - Param: start_date.${i}
        Type: DATE
        Value: ${next_start_date}
  IfNoTurns:
    - NoAction

```

See also **EndIterationAction** and **EndScriptAction**.

7.5.9 UserConditionalActions

An **UserConditionalActions** turn allows the Designer to remove parameter values directly from the script.

The **UserConditionalActions Turn** is similar to **ScriptConditionalActions**, but the condition is the boolean result of a question presented to the user. For example, in the Reminder application, if all necessary slots are filled, the user will be presented with a single sentence to confirm; if No is returned, then the script presents the series of **ParamValueTurns**.

Property	Type	Required	Description
Question	string	yes	The question to ask the user; the user will be allowed to enter only a yes or no answer.
IfYesTurns	Turn list	yes	The turns to execute if the user answers "Yes"; may be a NoAction turn.
IfNoTurns	Turn list	yes	The turns to execute if the user answers "No"; may be a NoAction turn.

Table 29: *UserConditionalActions properties.*

The FDL system will append "(Y/N)?" to the the Question when it displays it to the Teacher or User.

Example:

```
UserConditionalActions:
  Condition: ${i} > 0 AND start_date.${i} IS NOT SET AND next_start_date IS SET
  IfYesTurns:
    - SetParamValues:
      - Param: start_date.${i}
        Type: DATE
        Value: ${next_start_date}
  IfNoTurns:
    - NoAction
```

See also EndIterationAction and EndScriptAction.

7.5.10 ParamValueOrConstantTurn

The ParamValueOrConstantTurn is similar to the ParamValueTurn, but also allows the Teacher to enter a constant value if so doing is more appropriate for the app they are creating. For example, a Teacher creating a birthday reminder app would not want to have the app ask the user how often the reminder should fire.

The system will ask the Teacher to select one of three options:

1. *Ask the user a question:* This will display the question that the user will be asked. If this option is selected, no confirmation is requested.
2. *Ask the user a different question:* This will enter into a dialog with the Teacher to specify the question to be asked.
3. *Specify a constant value:* This will enter into a dialog with the Teacher to specify the constant value to be used instead of asking the user a question.

The properties of the ParamValueOrConstantTurn are:

Property	Type	Required	Description
Description	string	no	Provides a description that is shown only once per execution of the step
AskQuestionConfirm	string	yes	The text that will be shown for the first option above; it presents the question that the User would be asked.
AskDifferentQuestion	string	yes	The text that will be shown for the second option above, allowing the Teacher to specify a different question.
AskSpecifyConstant	string	yes	The text that will be shown for the third option above, allowing the Teacher to specify a constant value.
QuestionLoopback	string	yes	The sentence the system will use to ask the Teacher to enter the new question to ask the User.
QuestionConfirm	string	yes	The sentence the system will use to ask the Teacher to confirm the new question to ask the User.
QuestionParam	string	yes	The name of the parameter that will store the question to ask the User.
QuestionDefault	string	yes	The default question to ask the User.
ConstantLoopback	string	yes	The sentence the system will use to ask the Teacher to enter the constant value.
ConstantConfirm	string	yes	The sentence the system will use to ask the Teacher to confirm the constant value.
ConstantParam	string	yes	The name of the parameter that will store the constant value.
ParamType	ParamType	yes	The type of the parameter, from section 7.3.3 (Parameter Types).

Table 30: *UserConditionalActions* properties.

The FDL system will append “(Y/N)?” to the the QuestionConfirm and ConstantConfirm when it displays them to the Teacher.

Example:

```

- ParamValueOrConstantTurn:
  Description: I will ask the user how long to keep the reminder in their calendar.
  AskQuestionConfirm: I will ask the user: "${ask_sequence_duration_language}".
  AskDifferentQuestion: Ask the user a different question.
  AskSpecifyConstant: Do not ask the User; instead, specify a constant value.
  QuestionLoopback: Please enter the new question to ask the user.
  QuestionConfirm: You want me to ask the user "${ask_sequence_duration_language}".
  ${_IsThatCorrect}
  QuestionParam: ask_sequence_duration_language
  QuestionDefault: Please tell me how long to keep the reminder in your calendar.
  ConstantLoopback: Please enter the constant value you would like to use here.
  ConstantConfirm: You would like to stop the reminders after a constant period of
  ${constant_sequence_duration}. ${_IsThatCorrect}
  ConstantParam: constant_sequence_duration
  ParamType: INTERVAL

```

7.5.11 SetConstantValues

The **SetConstantValues Turn** sets script variables to constant values (such as those set by **ParamValueOrConstantTurn**) if they were not already set (such as by a **TestPredicateTurn**).

The **SetConstantValues Turn** has a list of structures that specify the parameters to be set; each has the following properties:

Property	Type	Required	Description
ConstantParam	string	yes	The name of the parameter that contains the constant value.
Param	string	yes	The name of the parameter to receive the constant value.

Table 31: *SetConstantValues properties.*

Example:

```

- SetConstantValues:
  - ConstantParam: constant_sequence_duration
    Param: sequence_duration.${i}
  - ConstantParam: constant_period
    Param: frequency.${i}.period

```

7.5.12 EndIterationAction

The **EndIterationAction Turn** exits an **NIterations** loop. It contains the following property:

Property	Type	Required	Description
CurrentIterationOnly	bool	yes	If true, exits only the innermost iteration; otherwise, exits all loops.

Table 32: *EndIterationsAction* properties.

Example:

```
- EndIterationAction:
    CurrentIterationOnly: true
```

7.5.13 EndScriptAction

The **EndScriptAction** **Turn** exits the script. It contains the following property:

Property	Type	Required	Description
IsSuccess	bool	yes	If true, exits successfully; otherwise exits with an error.

Table 33: *EndScriptAction* properties.

Example:

```
- EndScriptAction:
    IsSuccess: true
```

7.5.14 NoAction

The **NoAction** **Turn** is a no-op; it is an empty branch in the conditional actions turns and has no parameters.

7.6. Finding the App the User Wants

When the user wants to use an app to perform an action, the FDL system will ask for a sentence that describes the action, and will then parse this action and find any matching `LearnedPredicates` that have a `Handler` (see `Script Handlers`) for that action. Following are the steps taken by the FDL system when the user wants to use an app to perform a `create` action; for example, using the `Medication Reminder` app to create a reminder to take medication.

1. The FDL system asks the user to enter a sentence describing the activity to create a reminder for. It parses this sentence, determines which templates match it, and forms a set of all the `LearnedPredicates` that are fired by those templates and have an entry in their `Handlers` set for the `ActionName` `create`.
 - (a) If there is only one such `LearnedPredicate` and it has only one `Handler` for the `create` `ActionName`, then that app is selected automatically.

- (b) If there is no matching `LearnedPredicate`, the FDL system presents a list of all available apps for which one or more `LearnedPredicates` have a `Handler` with the `create ActionName`. These apps are identified by their scripts' `__ACTION_DESCRIPTION__`s. The user is asked to select an app.
- (c) If there is more than one matching `LearnedPredicate` or one or more matching `LearnedPredicates` have more than one `Handler` with the `create ActionName`, the FDL system presents a list of all matching apps, again identified by their scripts' `__ACTION_DESCRIPTION__`s. The user is asked to select an app.

When the user selects an app (or if an app is selected automatically because it is the only matching app), then the FDL system asks the user to confirm the action by presenting the app's `__ACTION_CONFIRMATION__` question. If the user says "Yes", then the FDL system loads the script for that app (as identified by the selected `Handler`'s `ScriptName`) and begins the app's dialog with the user.

8. APPENDIX 2: TAL’S AMERICAN SLANG AND ABBREVIATIONS MAP

During preprocessing, tokens found in the left column in user input data are mapped to the right (see Section 2.1.3). Teachers can edit this file if they wish: note that here, a teacher added the mapping “meds” to “medications” for their app (this was not necessary, as otherwise TAL would ask the teacher what “meds” means the first time the teacher used it, and add it as a new definition to its taxonomy).

wanna	want to	gonna	going to	shoulda	should have
coulda	could have	woulda	would have	sorta	somewhat
kinda	somewhat	tonite	tonight	pls	please
thx	thanks	meds	medications	wont	will not
cant	can not	aren’t	are not	can’t	can not
didn’t	did not	don’t	do not	doesn’t	does not
hadn’t	had not	hasn’t	has not	haven’t	have not
he’d	he would	he’ll	he will	he’s	he is
i’d	i would	i’ll	i will	i’m	i am
isn’t	is not	it’d	it would	it’s	it is
it’ll	it will	i’ve	i have	let’s	let us
mustn’t	must not	needn’t	need not	she’d	she would
she’ll	she will	she’s	she is	shouldn’t	should not
that’d	that would	that’ll	that will	that’s	that is
there’ll	there will	there’s	there is	there’ve	there have
they’d	they would	they’ll	they will	they’re	they are
they’ve	they have	wasn’t	was not	we’ll	we will
we’d	we would	we’re	we are	we’ve	we have
weren’t	were not	won’t	will not	wouldn’t	would not
you’d	you would	you’ll	you will	you’re	you are
you’ve	you have				

Table 34: TAL’s slang and abbreviations map.

REFERENCES

- [1] AppBrain. Number of available apps, 2016. <http://www.appbrain.com/stats/number-of-android-apps>.
- [2] B.W. Boehm. A spiral model of software development and enhancement. *Computer*, 21(5):61–72, 1988.
- [3] C.J.C. Burges. Towards the machine comprehension of text: An essay. Technical Report MSR-TR-2013-125, Microsoft Research, 2013.
- [4] D. Crevier. *AI: The tumultuous history of the search for artificial intelligence*. Basic Books, Inc., 1993.
- [5] C. Fellbaum. *WordNet*. Wiley Online Library, 1998.

- [6] I. Goodfellow, Y. Bengio, and A. Courville. Deep learning. Book in preparation for MIT Press: <http://www.deeplearningbook.org>, 2016.
- [7] B. Hixon, P. Clark, and H. Hajishirzi. Learning knowledge graphs for question answering through conversational dialog. In *Proceedings of the the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado, USA*, 2015.
- [8] Z. Hu, X. Ma, Z. Liu, E. Hovy, and E. Xing. Harnessing deep neural networks with logic rules. In *54th Annual Meeting of the Association for Computational Linguistics*, 2016.
- [9] S. Kim, R.E. Banchs, and H Li. Exploring convolutional and recurrent neural networks in sequential labelling for dialogue topic tracking. In *54th Annual Meeting of the Association for Computational Linguistics*, 2016.
- [10] J. Li, M. Galley, C. Brockett, J. Gao, and B. Dolan. A persona-based neural conversation model. In *54th Annual Meeting of the Association for Computational Linguistics*, 2016.
- [11] P. Liang. Learning executable semantic parsers for natural language understanding. *Communications of the ACM*, 59, 2016.
- [12] Pattie Maes. Agents that reduce work and information overload. *Communications of the ACM*, 37(7):30–40, 1994.
- [13] C.D. Manning, M. Surdeanu, J. Bauer, J. Finkel, S.J. Bethard, and D. McClosky. The Stanford CoreNLP natural language processing toolkit. In *Association for Computational Linguistics (ACL) System Demonstrations*, pages 55–60, 2014.
- [14] Erik T Mueller. *Commonsense Reasoning*. Morgan Kaufmann, 2014.
- [15] Karen Myers, Pauline Berry, Jim Blythe, Ken Conley, Melinda Gervasio, Deborah L McGuinness, David Morley, Avi Pfeffer, Martha Pollack, and Milind Tambe. An intelligent personal assistant for task and time management. *AI Magazine*, 28(2):47, 2007.
- [16] A. Nguyen, J. Yosinski, and J. Clune. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 427–436. IEEE, 2015.
- [17] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2010.
- [18] K. Pichotta and R.J. Mooney. Statistical script learning with recurrent neural networks. In *Proceedings of the Workshop on Uphill Battles in Language Processing (UBLP) at EMNLP 2016*, 2016.
- [19] C. Quirk, P. Choudhury, J. Gao, H. Suzuki, K. Toutanova, M. Gamon, W. Yih, L. Vanderwende, and C. Cherry. Msr splat, a language analysis toolkit. In *Proceedings of the NAACL-HLT 2012: Demonstration Session*, pages 21–24, 2012.
- [20] P. Rajpurkar, J. Zhang, K. Lopyrev, and P. Liang. Squad: 100,000+ questions for machine comprehension of text. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2016.
- [21] M. Richardson, C.J.C. Burges, and E. Renshaw. Mctest: A challenge dataset for the open-domain machine comprehension of text. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2013.

- [22] M. Richardson and P. Domingos. Markov logic networks. *Machine learning*, 62(1-2):107–136, 2006.
- [23] Roger C Schank and Robert P Abelson. *Scripts, plans, goals, and understanding: An inquiry into human knowledge structures*. Psychology Press, 1977.
- [24] P. Simard, D. Chickering, A. Lakshmiratan, D. Charles, L. Bottou, C. Suarez, D. Grangier, S. Amershi, J. Verwey, and J. Suh. Ice: enabling non-experts to build models interactively for large-scale lopsided problems. *arXiv preprint arXiv:1409.4814*, 2014.
- [25] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*, 2013.
- [26] D.G.R. Tervo, J.B. Tenenbaum, and S.J. Gershman. Toward the neural implementation of structure learning. *Current Opinion in Neurobiology*, 37, 2016.
- [27] A. Trischler, Z. Ye, X. Yuan, J. He, P. Bachman, and K. Suleman. A parallel-hierarchical model for machine comprehension on sparse data. *arXiv preprint arXiv:1603.08884*, 2016.
- [28] G. Tur and R. De Mori. *Spoken language understanding: Systems for extracting semantic information from speech*. John Wiley & Sons, 2011.
- [29] H. Wang, M. Bansal, K. Gimpel, and D. McAllester. Machine comprehension with syntax, frames, and semantics. *Volume 2: Short Papers*, page 700, 2015.
- [30] L. Wang, P.N. Bennett, and K. Collins-Thompson. Robust ranking models via risk-sensitive optimization. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, pages 761–770. ACM, 2012.
- [31] Wikipedia. AI Winter, 2016. https://en.wikipedia.org/wiki/AI_winter.
- [32] Wikipedia. Predicate (grammar), 2016. [https://en.wikipedia.org/wiki/Predicate_\(grammar\)](https://en.wikipedia.org/wiki/Predicate_(grammar)).
- [33] Wikipedia. Wordnet for other languages, 2016. https://en.wikipedia.org/wiki/WordNet#Other_languages.
- [34] J.D. Williams, E. Kamal, H.A. Mokhtar Ashour, J. Miller, and G. Zweig. Fast and easy language understanding for dialog systems with microsoft language understanding intelligent service (luis). In *16th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, page 159, 2015.
- [35] J.D. Williams, N.B. Niraula, P. Dasigi, A. Lakshmiratan, C. Suarez, M. Reddy, and G. Zweig. Rapidly scaling dialog systems with interactive learning. In *Natural Language Dialog Systems and Intelligent Assistants*, pages 1–13. Springer, 2015.