Probabilistic grammar induction in an incremental semantic framework

Arash Eshghi[1], Matthew Purver[1], Julian Hough[1], and Yo Sato[2]

[1] Interaction Media and Communication
School of Electronic Engineering and Computer Science
Queen Mary University of London
{arash,mpurver,jhough}@eecs.qmul.ac.uk
[2] Adaptive Systems Research Group
Science and Technology Research Institute
University of Hertfordshire
y.sato@herts.ac.uk

Abstract. We describe a method for learning an incremental semantic grammar from a corpus in which sentences are paired with logical forms as predicate-argument structure trees. Working in the framework of Dynamic Syntax, and assuming a set of generally available compositional mechanisms, we show how lexical entries can be learned as probabilistic procedures for the incremental projection of semantic structure, providing a grammar suitable for use in an incremental probabilistic parser. By inducing these from a corpus generated using an existing grammar, we demonstrate that this results in both good coverage and compatibility with the original entries, without requiring annotation at the word level. We show that this semantic approach to grammar induction has the novel ability to learn the syntactic and semantic constraints on pronouns.

1 Introduction

Human language processing has long been thought to function incrementally, both in parsing and production [1, 2]. This incrementality gives rise to many characteristic phenomena in conversational dialogue, including unfinished utterances, interruptions and compound contributions constructed by more than one participant, which pose problems for standard grammar formalisms [3]. In particular, examples such as (1) suggest that a suitable formalism would be one which defines grammaticality not in terms of licensing strings, but in terms of constraints on the semantic construction process, and which ensures this process is common between parsing and generation.

(1) A: I burnt the toast.
B: But did you burn ...
A: Myself? Fortunately not.

One such formalism is Dynamic Syntax (DS) [4]. DS is an inherently incremental semantic grammar formalism [4, 5] in which semantic representations are projected on a word-by-word basis. It recognises no intermediate layer of syntax (see below), and generation and parsing are interchangeable. Given these properties, it seems well suited

for dialogue processing, and can in principle model common dialogue phenomena such as unfinished or co-constructed utterances, mid-utterance interruption and clarification etc. [6]. However, its definition in terms of semantics (rather than the more familiar syntactic phrase structure) makes it hard to define or extend broad-coverage grammars: expert linguists are required. On the other hand, as language resources are now available which pair sentences with semantic logical forms (LFs), the ability to automatically induce DS grammars could lead to a novel and useful resource for dialogue systems.

From a language acquisition perspective, this problem can be seen as one of constraint solving for a child: given (1) the constraints imposed through time by her understanding of the meaning of linguistic expressions (from evidence gathered from e.g. her local, immediate cognitive environment, or interaction with an adult), and (2) innate cognitive constraints on how meaning representations can be manipulated, how does she go about separating out the contribution of each individual word to the overall meaning of a linguistic expression? And how does she choose among the many guesses she would have, the one that best satisfies these constraints?

This paper presents a method for automatically inducing DS grammars, by learning lexical entries from sentences paired with complete, compositionally structured, propositional LFs. By assuming only the availability of a small set of general compositional semantic operations, reflecting the properties of the lambda calculus and semantic conjunction, we ensure that the lexical entries learnt include the grammatical constraints and corresponding compositional semantic structure of the language; by additionally assuming a general semantic copying operation, we can also learn the syntactic and semantic properties of pronouns.

2 Previous work on grammar induction

Existing grammar induction methods can be divided into two major categories: supervised and unsupervised. Fully supervised methods, which use a parsed corpus as the training data and generalise over the the phracslpse structure rules to apply to a new set of data, has achieved significant success, particularly when coupled with statistical estimation of the probabilities for production rules that share the same LHS category (e.g. PCFGs [7]). However, such methods at best only capture part of the grammar learning problem, since they presuppose prior linguistic information and are not adequate as human grammar learning models. Unsupervised methods, on the other hand, which proceed with unannotated raw data and hence are closer to the human language acquisition setting, have seen less success. In its pure form —positive data only, without bias— unsupervised learning has been demonstrated to be computationally too complex ('unlearnable') in the worst case [8]. Successful cases have involved some prior learning or bias, e.g. a fixed set of known lexical categories, a probability distribution bias [9] or a hybrid, semi-supervised method with shallower (e.g. POS-tagging) annotation [10].

More recently another interesting line of work has emerged: supervised learning guided by *semantic* rather than syntactic annotation – more justifiably arguable to be 'available' to a human learner with some idea of what a string in an unknown language could mean. This has been successfully applied in Combinatorial Categorial Grammar [11], as it tightly couples compositional semantics with syntax [12, 13] and [14] also

demonstrates a limited success of a similar approach with partially semantically annotated data that comes from a controlled experiment. Since these approaches adopt a lexicalist framework, the grammar learning involves inducing a lexicon assigning to each word its syntactic and semantic contribution.

Such approaches are only lightly supervised, using sentence-level propositional logical form rather than detailed word-level annotation. Also, grammar is learnt ground-up in an 'incremental' fashion, in the sense that the learner collects data and does the learning in parallel, sentence by sentence. Here we follow this spirit, inducing grammar from a propositional meaning representation and building a lexicon which specifies what each word contributes to the target semantics. However, taking advantage of the DS formalism, a distinctive feature of which is *word-by-word* processing of semantic interpretation, we bring an added dimension of incrementality: not only is learning sentence-by-sentence incremental, but the grammar learned is word-by-word incremental, commensurate with psycholinguistic results showing incrementality to be a fundamental feature of human parsing and production [15, 16]. Incremental parsing algorithms have correspondingly been proposed [17–19], however, to the best of our knowledge, a learning system for an explicitly incremental grammar is yet to be presented – this work is a step towards such a system.

3 Dynamic Syntax

Dynamic Syntax is a parsing-directed grammar formalism, which models the word-by-word incremental processing of linguistic input. Unlike many other formalisms, DS models the incremental building up of *interpretations* without presupposing or indeed recognising an independent level of syntactic processing. Thus, the output for any given string of words is a purely *semantic* tree representing its predicate-argument structure; tree nodes correspond to terms in the lambda calculus, decorated with labels expressing their semantic type (e.g. $Ty(e)$) and formula, with beta-reduction determining the type and formula at a mother node from those at its daughters (Figure 1).
These trees can be *partial*, containing unsatisfied requirements for node labels (e.g. $?Ty(e)$ is a requirement for future development to $Ty(e)$), and contain a *pointer* $\Diamond$ labelling the node currently under development. Grammaticality is defined as parsability: the successful incremental construction of a tree with no outstanding requirements (a *complete* tree) using all information given by the words in a sentence (see Figure 1 for a word by word parse of "John upset Mary"). The input to our induction task here is therefore sentences paired with such complete, *semantic* trees, and what we try to learn are constrained lexical procedures for the incremental construction of such trees.

3.1 Actions in DS

The central tree-growth process is defined in terms of conditional *actions*: procedural specifications for monotonic tree growth. These take the form both of general structure-building principles (*computational actions*), putatively independent of any particular natural language, and of language-specific actions corresponding to particular lexical items (*lexical actions*). Like CCGs, DS is a highly lexicalised framework and thus grammar induction amounts to inducing the lexicon, i.e. the set of *lexical actions*, from data.

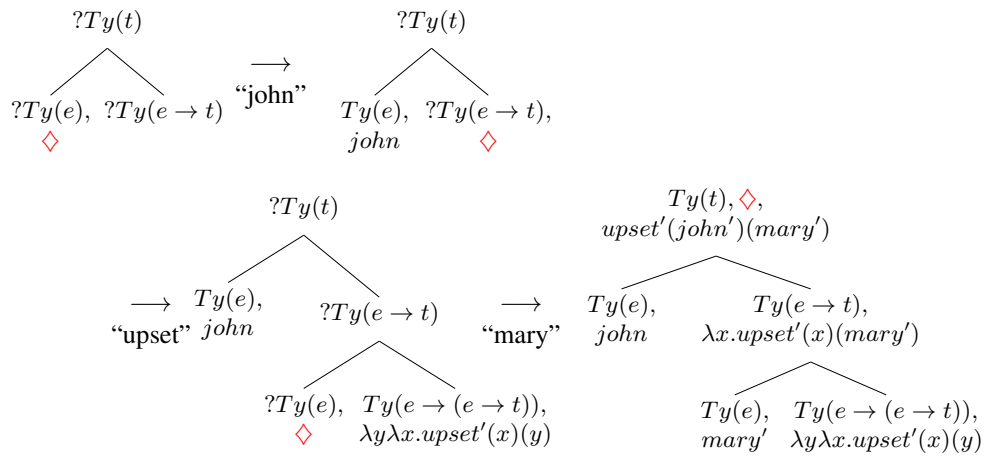


Fig. 1. Incremental parsing in DS producing semantic trees: *"John upset Mary"*

Computational actions These form a small, fixed set. Some merely encode the properties of the lambda calculus itself and the logical tree formalism (LoFT, [20]) – these we term *inferential* actions. Examples include THINNING (removal of satisfied requirements) and ELIMINATION (beta-reduction of daughter nodes at the mother). These actions are entirely language-general, cause no ambiguity, and add no new information to the tree; as such, they apply non-optionally whenever their preconditions are met.

Other computational actions reflect DS's predictivity and the dynamics of the framework. For example, COMPLETION moves the pointer up to the mother node if the current (pointed) node is type-complete; this is to allow subsequent beta-reduction; replacing feature-passing concepts, e.g. for long-distance dependency, *ADJUNCTION introduces a single unfixed node with underspecified tree position, to be merged later on in the parse with an appropriately typed node once it becomes available; LINK-ADJUNCTION builds a paired ("linked") tree corresponding to semantic conjunction and licensing relative clauses, apposition and more.

These actions represent possible parsing strategies and can apply optionally at any stage of a parse if their preconditions are met. While largely language-independent, some are specific to language type (e.g. INTRODUCTION-PREDICTION in the form used here applies only to SVO languages).

Lexical actions The lexicon associates words with lexical actions, which like computational actions, are each a sequence of tree-update actions in an IF..THEN..ELSE format, and composed of explicitly procedural *atomic actions* like `make`, `go`, `put` (and others). `make` creates a new daughter node. `go` moves the pointer to a daughter node, and `put` decorates the pointed node with a label. Fig. 2 shows a simple lexical action for *John*. The action says that if the pointed node (marked as ◇) has a requirement for type e, then decorate it with type e (thus satisfying the requirement); decorate it with formula $John'$ and finally decorate it with the bottom restriction $\langle\downarrow\rangle\bot$ (meaning that the node cannot have any daughters). In case the IF condition $?Ty(e)$ is not satisfied, the action aborts, meaning that the word 'John' cannot be parsed in the context of the current tree.

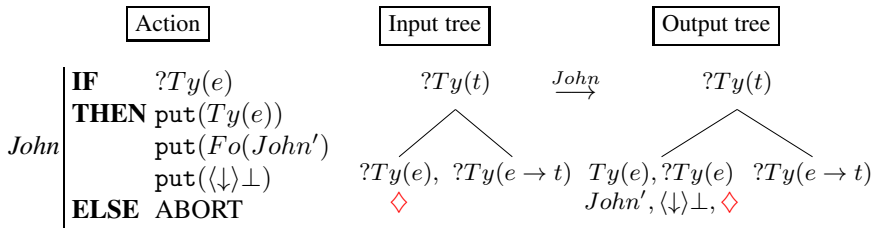


Fig. 2. Lexical action for the word 'John'

A more complex lexical action for a transitive verb *dislike* takes the following form, first making a new predicate node of type $e \rightarrow (e \rightarrow t)$, and then an argument node with a requirement for type e (to be satisfied after parsing the object):

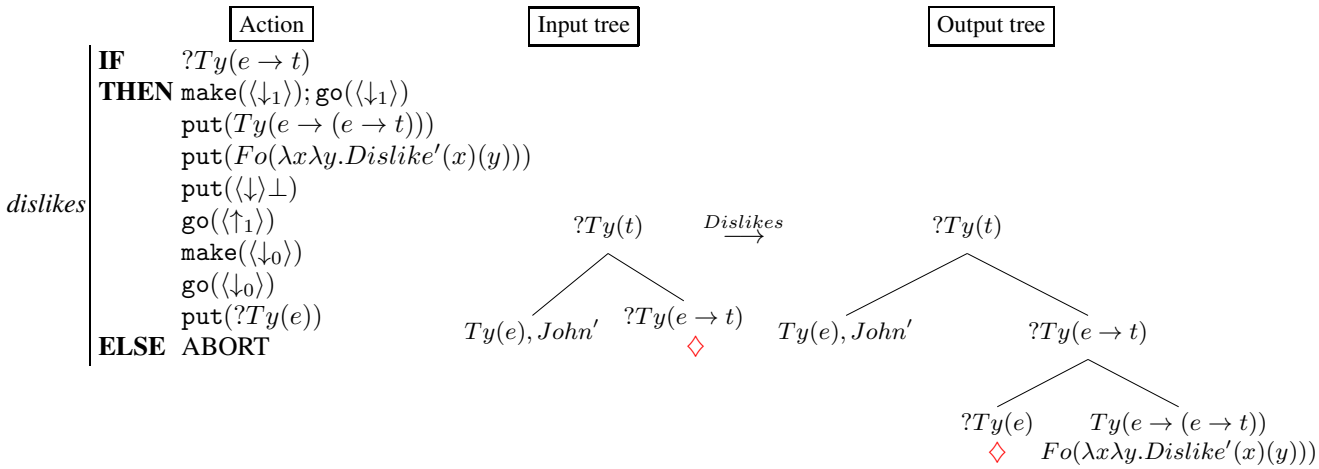


Fig. 3. Lexical action for the word 'dislikes'

3.2 Graph Representation of DS Parsing

Given a sequence of words $(w_1, w_2, ..., w_n)$, the parser starts from the *axiom* tree T_0 (a requirement $?Ty(t)$ to construct a complete tree of propositional type), and applies the corresponding lexical actions $(a_1, a_2, \ldots, a_n)$, optionally interspersing computational actions – see Figure 4.

This parsing process can be modelled as a directed acyclic graph (DAG) rooted at T_0, with partial trees as nodes, and computational and lexical actions as edges (i.e. transitions between trees) [21]. Figure 4 shows an example: here, *intro*, *pred* and *-*adj* correspond to the computational actions INTRODUCTION, PREDICTION and *-ADJUNCTION

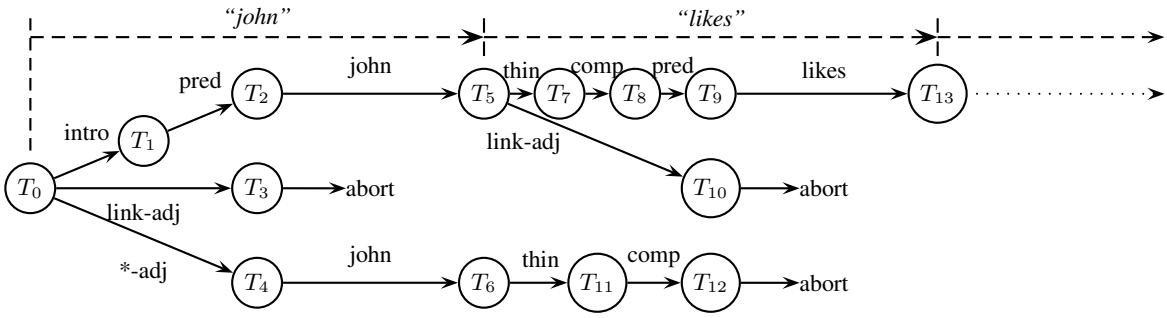


Fig. 4. DS parsing as a graph: actions (edges) are transitions between partial trees (nodes).

respectively; and 'john' is a lexical action. Different DAG paths represent different parsing strategies, which may succeed or fail depending on how the utterance is continued. Here, the path $T_0 - T_3$ will succeed if *'John'* is the subject of an upcoming verb ("John upset Mary"); $T_0 - T_4$ will succeed if *'John'* turns out to be a left-dislocated object ("John, Mary upset").

This incrementally constructed DAG makes up the entire *parse state* at any point. The rightmost nodes (i.e. partial trees) make up the current maximal semantic information; these nodes with their paths back to the root (tree-transition actions) make up the *linguistic context* for ellipsis and pronominal construal [22]. Given a conditional probability distribution $P(a|w, T)$ over possible actions a given a word w and (some set of features of) the current partial tree T, we can parse probabilistically, constructing the DAG in a best-first, breadth-first or beam parsing manner.

Generation uses exactly the same actions and structures, and can be modelled on the same DAG with the addition only of a *goal* tree; partial trees are checked for subsumption of the goal at each stage. The framework therefore inherently provides both parsing and generation that are word-by-word incremental and interchangeable, commensurate with psycholinguistic results [15, 16] and suitable for modelling dialogue [3]. While standard grammar formalisms can of course also be used with incremental parsing or generation algorithms [17–19], their string-based grammaticality and lack of inherent parsing-generation interrelation means examples such as (1) remain problematic.

4 Learning lexical actions

4.1 Problem Statement

Our task here is data-driven, probabilistic learning of lexical actions for all the words occurring in the corpus. Throughout, we will assume that the (language-independent) *computational actions* are known. We also assume that the supervision information is structured: i.e. our dataset pairs sentences with complete DS trees encoding their predicate-argument structures, rather than just a flat logical form (LF) as in e.g. [12]. DS trees provide more information than LFs in that they disambiguate between different possible predicate-argument decompositions of the corresponding LF; note however that this provides *no* extra information on the mapping from words to meaning. The input to the induction procedure is now as follows:

– the set of computational actions in Dynamic Syntax, G.
– a set of training examples of the form $\langle S_i, T_i \rangle$, where $S_i = \langle w_1 \dots w_n \rangle$ is a sentence of the language and T_i – henceforth referred to as the *target tree* – is the complete semantic tree representing the compositional structure of the meaning of S_i.

The output is a grammar specifying the possible lexical actions for each word in the corpus. Given our data-driven approach, we take a probabilistic view: we take this grammar as associating each word w with a probability distribution θ_w over lexical actions. In principle, for use in parsing, this distribution should specify the posterior probability $p(a|w, T)$ of using a particular action a to parse a word w in the context of a particular partial tree T. However, here we make the simplifying assumption that actions are conditioned solely on one feature of a tree, the semantic type Ty of the currently pointed node; and that actions apply exclusively to one such type (i.e. ambiguity of type leads to multiple actions). This effectively simplifies our problem to specifying the probability $p(a|w)$.

In traditional DS terms, this is equivalent to assuming that all lexical actions have a simple IF clause of the form IF $?Ty(X)$; this is true of most lexical actions in existing DS grammars (see examples above), but not all. This assumption will lead to some over-generation – inducing actions which can parse some ungrammatical strings – we must rely on the probabilities learned to make such parses unlikely, and evalute this in Section 5. Given this, the focus of what we learn here is effectively the THEN clause of lexical actions: a sequence of DS atomic actions such as *go*, *make*, and *put* (see Fig. 2), but now with an attendant posterior probability. We will henceforth refer to these sequences as *lexical hypotheses*. We first describe our method for constructing lexical hypotheses with a single training example (a sentence-tree pair). We then discuss how to generalise over these outputs, while updating the corresponding probability distributions incrementally as we process more training examples.

4.2 Hypothesis Construction

DS is *strictly monotonic*: actions can only *extend* the tree under construction, deleting nothing except satisfied requirements. Thus, hypothesising lexical actions consists in an incremental search through the space of all monotonic, and well-formed extensions of the current tree, T_{cur}, that subsume (i.e. can be extended to) the target tree T_t. This gives a bounded space which can be described by a DAG equivalent to the parsing DAG of section 3.2: nodes are trees, starting with T_{cur} and ending with T_t, and edges are possible extensions. These extensions may be either DS's basic computational actions (already known) or new *lexical hypotheses*.

This space is further constrained by the fact that not all possible trees and tree extensions are well-formed (meaningful) in DS, due to the properties of the lambda-calculus and those of the modal tree logic LoFT. Mother nodes must be compatible with the semantic type and formula of their daughters, as would be derived by beta-reduction; formula decorations cannot apply without type decorations; and so on. We also prevent arbitrary type-raising by restricting the types allowed, taking the standard DS assumption that noun phrases have semantic type e (rather than a higher type as in Generalized Quantifier theory) and common nouns their own type cn (see [5], chapter 3 for details).

We implement these constraints by packaging together permitted sequences of tree updates as macros (sequences of DS atomic actions such as `make`, `go`, and `put`), and hypothesising possible DAG paths based on these macros. We can divide these into two classes of lexical hypothesis macros: (1) *tree-building* hypotheses, independent of the target tree, and in charge of building appropriately typed daughters for the current node; and (2) *content decoration* hypotheses in charge of the semantic decoration of the leaves of the current tree (T_{cur}), with formulae taken from the leaves of the target tree (T_t).

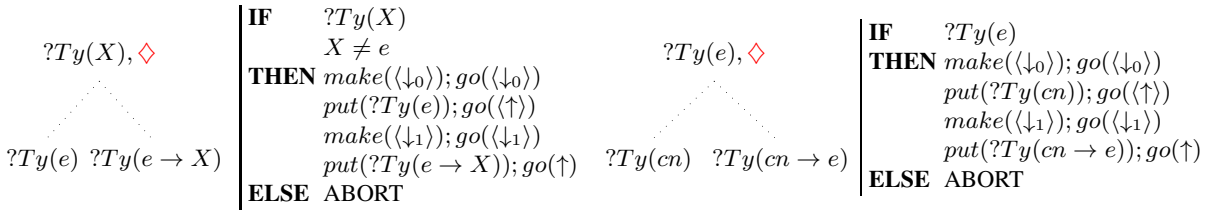


Fig. 5. Target-independent tree-building hypotheses

Figure 5 shows example *tree-building* hypotheses which extend a mother node with a type requirement to have two daughter nodes which would (once themselves developed) combine to satisfy that requirement. On the left, an general rule in which a currently pointed node of some type X can be hypothesised to be formed of types e and $e \rightarrow X$ (e.g. if $X = e \rightarrow t$, the daughters will have types e and $e \rightarrow (e \rightarrow t)$). This reflects only the fact that DS trees correspond to lambda calculus terms, with e being a possible type. The other is more specific, suitable only for a type e node, allowing it to be composed of nodes of type cn and $cn \rightarrow e$ (where $cn \rightarrow e$ turns out to be the type of determiners), but again reflects only general semantic properties which would apply in any language.

Content decoration hypotheses on the other hand depend on the target tree: they posit possible addition of semantic content, via sequences of `put` operations (e.g. `content-dec: put(Ty(e)); put(Fo(john))` which develop the pointed node on T_{cur} towards the corresponding leaf node on T_t. They are constrained to apply only to *leaf* nodes (i.e. nodes in T_{cur} whose counterparts on T_t are leaf nodes), other nodes being assumed to receive their content via beta-reduction of their daughters.

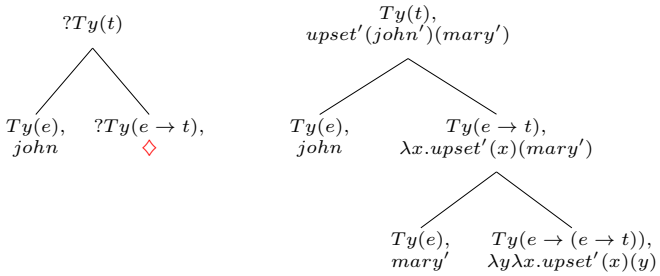


Fig. 6. The tree under development T_{cur} (left) and the target tree T_t (right)

Figure 6 shows an example. Here, T_t is the complete tree on the right, and T_{cur} the partial tree on the left. Since T_{cur}'s pointed node corresponds to a non-leaf node in T_t, we hypothesise two local action sequences: one which builds an argument daughter with appropriate type requirement ($\texttt{make}(\downarrow_0); \texttt{go}(\downarrow_0); \texttt{put}(?Ty(e))$), and another which does the same for a functor daughter ($\texttt{make}(\downarrow_1); \texttt{go}(\downarrow_1); \texttt{put}(?Ty(e \rightarrow (e \rightarrow t))$).

4.3 Hypothesis Splitting

Hypothesis construction therefore produces, for each training sentence $\langle w_1 \dots w_n \rangle$, all possible sequences of actions that lead from the axiom tree T_0 to the target tree T_t (henceforth, the *complete* sequences); where these sequences contain both lexical hypotheses and general computational actions. To form discrete lexical entries, we must split each such sequence into n sub-sequences, $\langle cs_1 \dots cs_n \rangle$, with each *candidate subsequence* cs_i, corresponding to a word w_i, by hypothesising a set of word boundaries.

This splitting process is subject to two constraints. Firstly, each candidate sequence cs_i must contain exactly one *content decoration* lexical hypothesis (see above); this ensures both that every word has some contribution to the sentence's semantic content, and that no word decorates the leaves of the tree with semantic content more than once. Secondly, candidate subsequences cs_i are *computationally maximal* on the left: cs_i may begin with (possibly multiple) computational actions, but must end with a lexical hypothesis. This reduces the splitting hypothesis space, and aids lexical generalisation (see below).

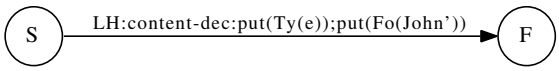
Each such possible set of boundaries corresponds to a *candidate sequence tuple* $\langle cs_1 \dots cs_n \rangle$. Importantly, this means that these cs_i are not independent, e.g. when processing "John arrives", a hypothesis for 'John' is only compatible with certain hypotheses for 'arrives'. This is reflected below in how probabilities are assigned to the word hypotheses.

4.4 Hypothesis Generalisation

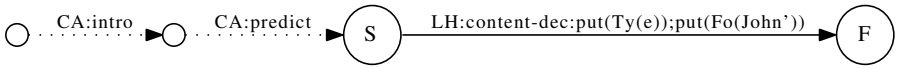
DS's general computational actions can apply at any point before the application of a lexical action, thus providing strategies for adjusting the syntactic context in which a word is parsed. Removing computational actions on the left of a candidate sequence will leave a more general albeit equivalent hypothesis: one which will apply successfully in more syntactic contexts. However, if a computational subsequence seems to occur *whenever* a word is observed, we would like to lexicalise it, including it within the lexical entry for a more efficient and constrained grammar. We therefore want to generalise over our candidate sequence tuples to partition them into portions which seem to be achieved lexically, and portions which are better achieved by computational actions alone.

We therefore group the candidate sequence tuples produced by splitting, storing them as members of equivalence classes which form our final *word hypotheses*. Two tuples belong to the same equivalence class if they can be made identical by removing *only* computational actions from the beginning of either one. We implement this via a single packed data-structure which is again a DAG, as shown in Fig. 7; this represents the full set of candidate sequences by their intersection (the solid central common

First Training Example: 'john' in fixed object position;
Sequence intersected: $\langle LH : content\text{-}dec : put(Ty(e)); put(Fo(John'))\rangle$:



Second Training Example: 'john' in subject position;
Sequence intersected: $\langle CA : intro, CA : predict, LH : content\text{-}dec : put(Ty(e)); put(Fo(John'))\rangle$



Third Training Example: 'john' on unfixed node, i.e. left-dislocated object;
Sequence intersected: $\langle CA : star\text{-}adj, LH : content\text{-}dec : put(Ty(e)); put(Fo(John'))\rangle$

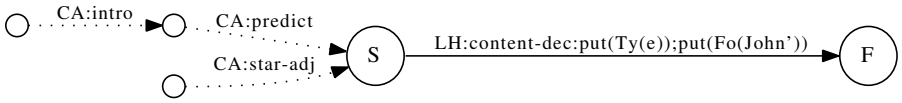


Fig. 7. Incremental intersection of candidate sequences; CA=Computational Action, LH=Lexical Hypothesis

path) and differences (the dotted diverging paths at beginning). Nodes here therefore no longer represent single trees, but sets of trees. Figure 7 shows this process over three training examples containing the unknown word 'John' in different syntactic positions. The 'S' and 'F' nodes mark the start and finish of the intersection – initially the entire sequence. As new candidate sequences arrive, the intersection – the maximal common path – is reduced as appropriate. Word hypotheses thus remain as general as possible.

In our probabilistic framework, these DAGs themselves are our lexical entries, with associated probabilities (see below). If desired, we can form traditional DS lexical actions: the DAG intersection corresponds to the THEN clause, with the IF clauses being a type requirement obtained from the pointed node on all partial trees in the initial 'S' node. As lexical hypotheses within the intersection are identical, and were constrained when formed to add type information before formula information (see Section 4.2), any type information must be common across these partial trees. In Figure 7 for 'john', this is $?Ty(e)$, i.e. a requirement for type e, common to all three training examples.

4.5 Probability Estimation

The set of possible word hypotheses induced as above can of course span a very large space: we must therefore infer a probability distribution over this space to produce a useful grammar. This can be estimated from the observed distribution of hypotheses, as these are constrained to be compatible with the target tree for each sentence; and the estimates can be incrementally updated as we process each training example. For this process of probability estimation, the input is the output of the splitting and generalisation procedure above, i.e. for the current training sentence $S = \langle w_1 \dots w_n \rangle$ a set HT of *Hypothesis Tuples* (sequences of word hypotheses), each of the form $HT_j = \langle h_1^j \dots h_n^j \rangle$, where h_i^j is the word hypothesis for w_i in HT_j. The desired output is a probability dis-

tribution θ_w over hypotheses for each word w, where $\theta_w(h)$ is the posterior probability $p(h|w)$ of a given word hypothesis h being used to parse w.

Re-estimation Given some prior estimate of θ'_w, we can use a new training example to produce an updated estimate θ''_w directly. We assign each hypothesis tuple HT_j a probability based on θ'_w; the probability of a sequence $\langle h_1^j \ldots h_n^j \rangle$ is the product of the probabilities of the h_i's within it (by the Bayes chain rule):

$$p(HT_j|S) = \prod_{i=1}^{n} p(h_i^j|w_i) = \prod_{i=1}^{n} \theta'_{w_i}(h_i^j) \tag{1}$$

Now, for any word w and possible hypothesis h, we can re-estimate the probability $p(h|w)$ as the normalised sum of the probabilities of all observed tuples HT_j which contain h, that is the set of tuples, $HT^h = \{HT_j | h \in HT_j\}$:

$$\theta''_w(h) = p(h|w) = \frac{1}{Z} \sum_{HT_j \in HT^h} p(HT_j|S) = \frac{1}{Z} \sum_{HT_j \in HT^h} \prod_{i=1}^{n} \theta'_{w_i}(h_i^j) \tag{2}$$

where Z, the normalising constant, is the sum of the probabilities of all the HT_j's:

$$Z = \sum_{HT_j \in HT} \prod_{i=1}^{n} \theta'_{w_i}(h_i^j)$$

Incremental update Our procedure is now to update our overall esimate θ_w incrementally: after the Nth example, our new estimate θ_w^N is a weighted average of the previous estimate θ_w^{N-1} and the new value from the current example θ''_w from equation (2), with weights reflecting the amount of evidence on which these estimates are based:

$$\theta_w^N(h) = \frac{N-1}{N} \theta_w^{N-1}(h) + \frac{1}{N} \theta''_w(h) \tag{3}$$

Note that for training example 1, the first term's numerator is zero, so θ_w^{N-1} is not required and the new estimates are equal to θ''_w. However, to produce θ''_w we need some prior estimate θ'_w; in the absence of any information, we simply assume uniform distributions $\theta'_w = \theta_w^0$ over the lexical hypotheses observed in the first training example.

In subsequent training examples, there will arise new hypotheses h not seen in previous examples, and for which the prior estimate θ'_w gives no information. We incorporate these hypotheses into θ'_w by discounting the probabilities assigned to known hypotheses, reserving some probability mass which we then assume to be evenly distributed over the new unseen hypotheses. For this we use the same weight as in equation (3):

$$\theta'_w(h) = \begin{cases} \frac{N-1}{N} \theta_w^{N-1}(h) & \text{if } h \text{ in } \theta_w^{N-1} \\ \frac{1}{N_u} \sum_{h \in \theta_w^{N-1}} \frac{1}{N} \theta_w^{N-1}(h) & \text{otherwise} \end{cases} \tag{4}$$

where N_u here is number of new unseen hypotheses in example N. Given (4), we can now more accurately specify the update procedure in (3) to be:

$$\theta_w^N(h) = \theta'_w(h) + \frac{1}{N}\theta''_w(h) \quad (5)$$

Non-incremental estimation Using this incremental procedure, we use the estimates from previous sentences to assign prior probabilities to each hypothesis tuple (i.e. each possible path through the hypothesised parse DAG), and then derive updated posterior estimates given the observed distributions. Such a procedure could similarly be applied non-incrementally at each point, by repeatedly re-estimating and using the new estimates to re-calculate tuple probabilities in a version of the Expectation-Maximisation algorithm [23]. However, this would require us to keep all HT sets from every training example; this would be not only computationally demanding but seems psycholinguistically implausible (requiring memory for all lexical and syntactic dependencies for each sentence). Instead, we restrict ourselves here to assuming that this detailed information is only kept in memory for one sentence; intermediate versions would be possible.

4.6 Pronouns

Standard approaches to grammar induction treat pronouns simply as entries of a particular syntactic category. Here, as we learn from semantic annotations, we can learn not only their anaphoric nature, but syntactic and semantic constraints on their resolution. To achieve this, we assume one further general strategy for lexical hypothesis formation: a copying operation from context whereby the semantic content (formula and type decorations) can be copied from any existing type-compatible and complete node on T_{cur} (possibly more than one) accessible from the current pointed node via some finite tree modality. This assumption therefore provides the general concept of anaphoricity, but nothing more: it can be used in hypothesis formation for any word, and we rely on observed probabilities of its providing a successful parse to rule it out for words other than pronouns. By requiring access via some tree modality ($\uparrow_0, \downarrow_*$ etc), we restrict it to intrasentential anaphora here, but the method could be applied to intersentential cases where suitable LFs are available.

This modal relation describes the relative position of the antecedent; by storing this as part of the hypothesis DAG, and subjecting it to a generalisation procedure similar to that used for computational actions in Section 4.4, the system learns constraints on these modal relations. The lexical entries resulting can therefore express constraints on the possible antecedents, and grammatical constraints on their presence, akin to Principles A and B of Government and Binding theory (see [5], chapter 2); in this paper, we evaluate the case of relative pronouns only (see below).

5 Evaluation

5.1 Parse coverage

This induction method has been implemented and tested over a 200-sentence artificial corpus. The corpus was generated using a manually defined DS grammar, with words randomly chosen to follow the distributions of the relevant POS types and tokens in the

CHILDES maternal speech data [24] - see Table 1. 90% of the sentences were used as training data to induce a grammar, and the remaining 10% used to test it. We evaluate the results in terms of both parse coverage and semantic accuracy, via comparison with the logical forms derived using the original, hand-crafted grammar.

Word class	Type	Token	Type%	Token%
noun	119	362	76.3%	48.7%
verb	29	263	18.6%	35.4%
determiner	3	56	1.9%	7.5%
pronoun	5	62	3.2%	8.4%
Total	156	743	100.00%	100.00%
Total of 200 sentences				
Min, Max and Mean sentence lengths : 2, 6, 3.7 words				
Mean tokens per word = 4.01				

Table 1. Training and test corpus distributions and means

The induced hypotheses for each word were ranked according to their probability; three separate grammars were formed using the top one, top two and top three hypotheses and were then used independently to parse the test set. Table 2 shows the results, discounting sentences containing words not encountered in training at all (for which no parse is possible). We give the percentage of test sentences for which a complete parse was obtained; and the percentage of those for which one of the top 3 parses resulted in a logical form identical to the correct one.

	Parsing Coverage	Same Formula
Top one	26%	77%
Top two	77%	79%
Top three	100%	80%

Table 2. Test parse results: showing percentage parsability, and percentage of parses deriving the correct semantic content for the whole sentence

As Table 2 shows, when the top three hypotheses are retained for each word, we obtain 80% formula derivation accuracy. Manual inspection of the individual actions learned revealed that the words which have incorrect lexical entries at rank one were those which were sparse in the corpus - we did not control for the exact frequency of occurrence of each word. The required frequency of occurrence varied across different categories; while transitive verbs require about four occurrences, intransitive verbs require just one. Count nouns were particularly sparse (see type/token ratios in Table 1).

As we have not yet evaluated our method on a real corpus, the results obtained are difficult to compare directly with other baselines such as that of [25] who achieve state-of-the-art results; cross-validation of this method on the CHILDES corpus is work in progress, which will allow direct comparison with [25].

Lexical Ambiguity We introduced lexically ambiguous words into the corpus to test the ability of the system to learn and distinguish between their different senses; 10%

of word types were ambiguous between 2 or 3 different senses with different syntactic category. Inspection of the induced actions for these words shows that, given appropriately balanced frequencies of occurrence of each separate word sense in the corpus, the system is able to learn and distinguish between them. 57% of the ambiguous words had lexical entries with both senses among the top three hypotheses, although in only one case were the two senses ranked one and two. This was the verb 'tramped' with transitive and intransitive readings, with 4 and 21 occurrences in the corpus respectively.

5.2 Pronouns

For pronouns, we wish to learn both their anaphoric nature (resolution from context) and appropriate syntactic constraints. Here, we tested on relative pronouns such as 'who' in "John likes Mary, who runs": the most general lexical action hypothesis learned for these is identical to hand-crafted versions of the action (see [5], chapter 3):

who	**IF**	$?Ty(e)$
		$\langle\uparrow_*\uparrow_L\rangle Fo(X)$
	THEN	$put(Ty(e))$
		$put(Fo(X))$
		$put(\langle\downarrow\rangle\bot)$
	ELSE	ABORT

This action instructs the parser to copy a semantic type and formula from a type $Ty(e)$ node at the modality $\langle\uparrow_*\uparrow_L\rangle$, relative to the pointed node. The system has therefore learnt that pronouns involve resolution from context (note that many other hypotheses are possible, as pronouns are paired with different LFs in different sentences). It also expresses a syntactic constraint on relative pronouns, that is, the relative position of their antecedents $\langle\uparrow_*\uparrow_L\rangle$ (the first node above a dominating LINK tree relation – i.e. the head of the containing NP).

Of course, relative pronouns are a special case: the modality from which their antecedents are copied is relatively fixed. Equivalent constraints could be learned for other pronouns, given generalisation over several modal relations; e.g. locality of antecedents for reflexives is specified in DS via a constraint $\langle\uparrow_0\uparrow_1^*\downarrow_0\rangle$ requiring the antecedent to be in *some* local argument position. In learning reflexives, this modal relation can come from generalisation over several different modalities obtained from different training examples; this will require larger corpora.

6 Conclusions and Future work

In this paper we have outlined a novel method for the probabilistic induction of new lexical entries in an inherently incremental and semantic grammar formalism, Dynamic Syntax, with no independent level of syntactic phrase structure. Our method learns from sentences paired with semantic trees representing the sentences' predicate-argument structures, assuming only very general compositional mechanisms. While the method still requires evaluation on real data, evaluation on an artificial but statistically representative corpus demonstrates that the method achieves good coverage. A further bonus

of using a semantic grammar is that it has the potential to learn both semantic and syntactic constraints on pronouns: our evaluation demonstrates this for relative pronouns, but this can be extended to other pronoun types.

Our research now focusses on evaluating this method on real data (the CHILDES corpus), and on reducing the level of supervision by adapting the method to learn from sentences paired not with trees but with less structured LFs, using Type Theory with Records [26] and/or the lambda calculus. Other work planned includes the integration of the actions learned into a probabilistic parser.

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References

1. Crocker, M., Pickering, M., Clifton, C., eds.: Architectures and Mechanisms in Sentence Comprehension. Cambridge University Press (2000)
2. Ferreira, V.: Is it better to give than to donate? Syntactic flexibility in language production. Journal of Memory and Language **35** (1996) 724–755
3. Howes, C., Purver, M., McCabe, R., Healey, P.G.T., Lavelle, M.: Predicting adherence to treatment for schizophrenia from dialogue transcripts. In: Proceedings of the 13th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL 2012 Conference). (2012) 79–83
4. Kempson, R., Meyer-Viol, W., Gabbay, D.: Dynamic Syntax: The Flow of Language Understanding. Blackwell (2001)
5. Cann, R., Kempson, R., Marten, L.: The Dynamics of Language. Elsevier, Oxford (2005)
6. Gargett, A., Gregoromichelaki, E., Kempson, R., Purver, M., Sato, Y.: Grammar resources for modelling dialogue dynamically. Cognitive Neurodynamics **3**(4) (2009) 347–363
7. Charniak, E.: Statistical Language Learning. MIT Press (1996)
8. Gold, E.M.: Language identification in the limit. Information and Control **10**(5) (1967) 447–474
9. Klein, D., Manning, C.D.: Natural language grammar induction with a generative constituent-context mode. Pattern Recognition **38**(9) (2005) 1407–1419
10. Pereira, F., Schabes, Y.: Inside-outside reestimation from partially bracketed corpora. In: Proceedings of the 30th Annual Meeting of the Association for Computational Linguistics. (1992) 128–135
11. Steedman, M.: The Syntactic Process. MIT Press, Cambridge, MA (2000)
12. Zettlemoyer, L., Collins, M.: Online learning of relaxed CCG grammars for parsing to logical form. In: Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL). (2007)
13. Kwiatkowski, T., Zettlemoyer, L., Goldwater, S., Steedman, M.: Inducing probabilistic CCG grammars from logical form with higher-order unification. In: Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing. (2010) 1223–1233
14. Sato, Y., Tam, W.: Underspecified types and semantic bootstrapping of common nouns and adjectives. In: Proceedings of Language Engineering and Natural Language Semantics. (2012)

15. Lombardo, V., Sturt, P.: Incremental processing and infinite local ambiguity. In: Proceedings of the 1997 Cognitive Science Conference. (1997)
16. Ferreira, F., Swets, B.: How incremental is language production? evidence from the production of utterances requiring the computation of arithmetic sums. Journal of Memory and Language **46** (2002) 57–84
17. Hale, J.: A probabilistic Earley parser as a psycholinguistic model. In: Proceedings of the 2nd Conference of the North American Chapter of the Association for Computational Linguistics. (2001)
18. Collins, M., Roark, B.: Incremental parsing with the perceptron algorithm. In: Proceedings of the 42nd Meeting of the ACL. (2004) 111–118
19. Clark, S., Curran, J.: Wide-coverage efficient statistical parsing with CCG and log-linear models. Computational Linguistics **33**(4) (2007) 493–552
20. Blackburn, P., Meyer-Viol, W.: Linguistics, logic and finite trees. Logic Journal of the Interest Group of Pure and Applied Logics **2**(1) (1994) 3–29
21. Sato, Y.: Local ambiguity, search strategies and parsing in Dynamic Syntax. In: The Dynamics of Lexical Interfaces. CSLI Publications (2011)
22. Purver, M., Eshghi, A., Hough, J.: Incremental semantic construction in a dialogue system. In: Proceedings of the 9th International Conference on Computational Semantics. (2011) 365–369
23. Dempster, A., Laird, N., Rubin, D.B.: Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society. Series B (Methodological) **39**(1) (1977) 1–38
24. MacWhinney, B.: The CHILDES Project: Tools for Analyzing Talk. Third edn. Lawrence Erlbaum Associates, Mahwah, New Jersey (2000)
25. Kwiatkowski, T., Goldwater, S., Zettlemoyer, L., Steedman, M.: A probabilistic model of syntactic and semantic acquisition from child-directed utterances and their meanings. In: Proceedings of the Conference of the European Chapter of the Association for Computational Linguistics (EACL). (2012)
26. Cooper, R.: Records and record types in semantic theory. Journal of Logic and Computation **15**(2) (2005) 99–112