Probabilistic Learning of Labeled Grammars

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Overview

Organization of this Talk:
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1. What does it mean to learn a language?
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   Do we learn possible rules or probabilistically weighted rules?
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1. What does it mean to learn a language? Do we learn possible rules or probabilistically weighted rules?
2. Problems with learning possible rules.
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1. What does it mean to learn a language?
   Do we learn possible rules or probabilistically weighted rules?
2. Problems with learning possible rules.
3. A successful experiment in probabilistic learning.
Grammar as rules to accept/reject sentences

Can formalize knowledge about sentence structure as ‘context-free’ rules:

Sentence $\rightarrow$ Noun Phrase (you), Verb Phrase (have a cookie)

Verb Phrase $\rightarrow$ Verb (have), Noun Phrase (a cookie)

Noun Phrase $\rightarrow$ you

Noun Phrase $\rightarrow$ Determiner (a), Noun (cookie)

Strings that obey the rules have a derivation or ‘parse:’

Sentence $\rightarrow$ Verb Phrase $\rightarrow$ Noun Phrase $\rightarrow$ Noun (cookie) $\rightarrow$ Determiner (a) $\rightarrow$ Verb (have) $\rightarrow$ Noun Phrase (you)

Strings that don’t obey (have a cookie you) are considered ‘ungrammatical.’
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```
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Strings that obey the rules have a derivation or ‘parse:’

Strings that don’t obey (have a cookie you) are considered ‘ungrammatical.’
Claims about acquisition: ‘poverty of stimulus’

Formulated in this way, grammars are very hard to learn.

Caregivers don't and can't give negative examples of all unused rules. (And even if they did, children don't seem to pay attention to this.)

This ‘poverty of stimulus’ argument used to justify ‘universal grammar’ (UG): (Chomsky, 1965)

▶ In UG, structural rules are innate, learners just set true/false parameters (e.g.: allow pronominal subject to be dropped = true/false).
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- In UG, structural rules are innate, learners just set true/false parameters (e.g.: allow pronominal subject to be dropped = true/false).
Grammar as preferences over speech decisions

But we could also formulate grammar as \textit{probabilistically weighted} rules:
Grammar as preferences over speech decisions

But we could also formulate grammar as probabilistically weighted rules:

Sentence → Noun Phrase (you), Verb Phrase (have a cookie) = 0.999

The grammar is now a probabilistic process for generating a string. Strings with high probability sound more fluent: you have a cookie. Strings with low probability sound less fluent: have a cookie you. Defined this way, grammars can be learned probabilistically with no UG. They are not learned exactly, but to some probabilistic distance (ranked by the probability the grammar assigns to training sentences). Incentive to assign high weights to common rules, low weights to rare rules.
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But we could also formulate grammar as \textit{probabilistically weighted} rules:

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Noun Phrase $\rightarrow$ *you* $= 0.5$

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Probabilistically learning grammars from sentences

How can grammars be learned probabilistically?

Consider a space of possible probabilistic grammars with 15 labels:

▶ Generate (sample) many possible distributions of rule probabilities.
  (Distributions are generated randomly from a Dirichlet prior model, which is a model of distributions consistent with observed counts; e.g. given 2 heads, 10 tails, coin is more likely biased than fair.)

▶ Generate (sample) many possible sets of trees given these weights.
  (Generate random number and select outcome from rule distribution.)

▶ Remove all trees whose terminals (words) are not in the sentences.
  (Can’t just write in words; must sample proportionally to grammar!)

Trees that remain incorporate constraints of observations (common co-occurrences are chunked together).

This is called rejection sampling.

It is very inefficient: odds of generating actual corpus sentence are very low.
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Alternate model:
Probabilistically learning grammars from sentences

Alternate model:

Consider space of possible CFGs with 15 labels

Start with random set of values for rule distributions and trees.

Iterate through rule distributions and tree decisions:

- Resample distributions/decision given surrounding context (posterior).

The model gradually comes to accommodate observations. This is called Gibbs sampling.

It is way more efficient. We do this.
Probabilistically learning grammars from sentences

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Acquisition experiments

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E.g. *You have another cookie right on the table.*
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Experiments run for a week on 10 GPUs in Ohio Supercomputer Center.
Evaluation Parameters

We evaluate several configurations of the learner:

▶ Manipulate number of categories: $K \in \{15, 30, 45\}$.
▶ Manipulate maximum center-embedding depth: $D \in \{1, 2\}$.

We also compare against other recent learners & right-branching baseline:
▶ UPPARSE (Ponvert et al., 2011)
▶ CCL (Seginer, 2007)
▶ BMMM+DMV (Christodoulopoulos et al., 2012)
▶ UHHMM (Shain et al., 2016)
▶ right-branching baseline: left children are always terminals (words).

Evaluate vs. unlabeled versions of human-annotated ‘gold standard’ trees:
▶ recall: % of actual constituents that model predicts.
▶ precision: % of model’s predictions that are actual constituents.
▶ F1 score: product of recall & precision / average of recall & precision.
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Evaluate vs. unlabeled versions of human-annotated ‘gold standard’ trees:

- Recall: % of actual constituents that model predicts.
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Results

Results on constituent trees with punctuation removed after training:

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>(rival) CCL</td>
<td>60.1</td>
<td>48.7</td>
<td>53.8</td>
</tr>
<tr>
<td>(rival) UPPARSE</td>
<td>60.5</td>
<td>51.9</td>
<td>55.9</td>
</tr>
<tr>
<td>(rival) UHHMM</td>
<td>55.5</td>
<td>69.3</td>
<td>61.7</td>
</tr>
<tr>
<td>(rival) BMMM+DMV</td>
<td>63.5</td>
<td>63.3</td>
<td>63.4</td>
</tr>
<tr>
<td>(rival) UHHMM(flattened)</td>
<td>62.9</td>
<td>68.4</td>
<td>65.6</td>
</tr>
<tr>
<td>This model w. D=1,K=15</td>
<td>55.5</td>
<td>69.3</td>
<td>61.6</td>
</tr>
<tr>
<td>This model w. D=1,K=30</td>
<td>61.6</td>
<td>76.7</td>
<td>68.4</td>
</tr>
<tr>
<td>This model w. D=1,K=45</td>
<td>53.9</td>
<td>66.9</td>
<td>59.5</td>
</tr>
<tr>
<td>This model w. D=2,K=15</td>
<td>50.6</td>
<td>63.2</td>
<td>56.2</td>
</tr>
<tr>
<td>(baseline) Right-branching</td>
<td>68.7</td>
<td>85.8</td>
<td>76.3</td>
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This model is competitive with rivals, but not better than right-branching.
Evaluation Parameters

Model also learns category labels — do these correspond to NP, PP, etc?
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Problem: different theories make different predictions about category labels.
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- NP recall: % of actual NPs hypothesized with any label,
Evaluation Parameters

Model also learns category labels — do these correspond to NP, PP, etc?

Problem: different theories make different predictions about category labels.

Solution: most theories make same predictions about NPs; just test these.

- NP recall: % of actual NPs hypothesized with any label,
- NP identification: % of actual NPs hypothesized w. label mapped to NP.
Model also learns category labels — do these correspond to NP, PP, etc?

Problem: different theories make different predictions about category labels.

Solution: most theories make same predictions about NPs; just test these.

- NP recall: % of actual NPs hypothesized with any label,
- NP identification: % of actual NPs hypothesized w. label mapped to NP.
  (Mapping function trained on separate data w. human NP annotation.)
### Results

Results for noun phrase recall and noun phrase identification:

<table>
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<tr>
<th>System</th>
<th>NP recall</th>
<th>NP ident</th>
</tr>
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<td>32.4</td>
<td>-</td>
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<td>81.9</td>
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<td>80.1</td>
<td><strong>63.1</strong></td>
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<td>60.8</td>
</tr>
<tr>
<td>This model w. D=2,K=15</td>
<td><strong>86.3</strong></td>
<td><strong>63.1</strong></td>
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<td>64.2</td>
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Category labels appear to be quite coherent!
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Category labels appear to be quite coherent!

(Similar results obtain for PP and, to a lesser extent, VP.)
Structures hypothesized during training

Iteration 5 (first iteration after re-initialization trials) — not much familiar:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 6:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 7:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 8:

you have another cookie right on the table.
you have another cookie right on the table.
Structures hypothesized during training

Iteration 10 — the model discovers *on* and *the* co-occur a lot, clumps them:

```
you have another cookie right on the table.
```
Structures hypothesized during training

Iteration 25 (now showing every 25th iteration):

you have another cookie right on the table.
Structures hypothesized during training

Iteration 50:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 75:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 100:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 125:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 150:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 200 (now showing every 50th iteration):

1
  4
    13
    12
      3
  6
    10
      8
        4
          13
          3
      13
    1
      10
        4
          13
          3
Structures hypothesized during training

Iteration 250 – determiners (*the/another*), nouns (*table/cookie*) clumped:

```
you have another cookie right on the table.
```

```
1
  9
  9
  9
  15
  7
  13
  13

1
  1
  4
  13
  10
```

```
1
  1
  6
  3
  12
  10
```

```
1
  1
  9
  3
  4
```
Structures hypothesized during training

Iteration 250 – learner can re-use Det+Noun rule more than Prep+Det:
Structures hypothesized during training

Iteration 250 – also, verb *have* clumped with noun phrase *another cookie*:

```
you have another cookie right on the table.
```
Structures hypothesized during training

Iteration 300:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 350 – preposition on and noun phrase the table now clumped:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 400:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 450:

you have another cookie right on the table.
Structures hypothesized during training

Iteration 500 — category labels for Prep/Det/Noun/NP/PP mostly stable:

```
you have another cookie right on the table.
```
you have another cookie right on the table.
Structures hypothesized during training

Iteration 600 — adverb *right* clumped with prepositional phrase *on the table*:

```
1
  /     /
  9     1
 /     /
15     11
   /     /
  7     12
     /     /
 13     10


4
  /     /
 9     3
   /     /
 2     12
     /     /
13     10
```

you have another cookie right on the table.
Structures hypothesized during training

Iteration 650 — adverb *right* now clumped with sentence *you...cookie*:
Structures hypothesized during training

Iteration 700 — re-type noun phrase you and verb phrase have ... cookie:

Not much structural change anymore.
Structures hypothesized during training

Iteration 750 – change back noun phrase and verb phrase:

you have another cookie right on the table.
Structures hypothesized during training

Final constituent types consistent with linguistic theory:

1. You have another cookie right on the table.

Diagram:

```
1 ≈ S
  
4 ≈ S
  
6 ≈ PU
  
9 ≈ S
  9 ≈ S
  
3 ≈ ADVP
  3 ≈ ADVP
  
12 ≈ NP
  2 ≈ P
  12 ≈ NP
  13 ≈ D
  10 ≈ N

you  have  another  cookie  right  on  the  table .
```
Conclusion

In this talk:

1. Learning possible rules from just words is hard: anything's possible!
2. But defined probabilistically, grammar learning is feasible.
3. This makes justification of Universal Grammar more tenuous.

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