Learning maximum-entropy models of salience via EM

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The White Queen looked timidly at Alice, who felt she ought to say something kind, but really couldn’t think of anything at the moment.

- Pronouns are potentially ambiguous.
- Does she mean Alice, or the White Queen?
- Technically could be either, but strong intuitions.
Starting point: machine translation

IBM model 2

Generate German from English:

- *Align*: pick a random English word to translate.
- *Translate*: pick an appropriate German word.

English: He can sing well

German: Er kann gut singen
Our generative setting

- “Translate” the context into a pronoun...
  - Via a hidden alignment.

Source text: The White Queen looked at Alice who felt

Target text: she
The “translation” model  (Charniak+Elsner ‘09)

Pronouns uniquely identified by:

- Person (I/you/it)
- Number (it/they)
- Gender of singular pronouns (he/she/it)
  - English plural pronouns (“they”) unmarked for gender.

\[ P(pro|ante) \text{ modeled as:} \]

\[
P(pers(pro)|pers(ante)) \times \\
P(num(pro)|num(ante)) \times \\
\sum_{\text{possible gen(pro)}} P(gen(pro)|gen(ante))
\]
Modeling alignment: issues

The White Queen and Alice: both feminine singular, so translation model doesn’t help us. Need alignment function based on the syntax.
Features

- syntactic role: subject
- position: beginning of sentence
- proximity: same sentence
- within-sentence proximity: 6 words away
- phrase type: proper noun phrase
- determiner: “the”
- head word: “Queen”
The alignment function

Each pronoun $i$ has set of possible antecedents $A_i$. A noun phrase $a$ has some features $S(a, i)$.

Alignment function:

$$P(ante(i) = a \in A_i \mid S(a, i), \{S(A_i, i)\})$$
The ugly method (Charniak+Elsner ‘09)

\[ P(ante(i) = a \mid S(a, i), \{S(A_i)\}) = \]
\[ P(ante(i) = a \mid S(a, i)) \sim \]
\[ \text{Bernoulli}(\bullet; \theta_{S(a,i)}) \]  

For every possible antecedent, flip a coin to decide if it’s the true antecedent. Just assume one, and only one, coin will come up heads.
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- Not probabilistically legitimate
- One parameter \( \theta \) for each possible feature vector \( S(a, i) \): can’t be too sparse
Using log-linear models

A more standard approach:

\[
P(ante(i) = a \mid S(a, i), \{S(A_i)\}) = \frac{\exp(w \cdot S(a, i))}{Z}
\]

\[
Z = \sum_{x \in A_i} \exp(w \cdot S(x, i))
\]

Like softmax multilabel classification, but the set of ‘labels’ is different for every datapoint.
Using EM

Log-linear form specifies a *conditional* distribution...
Part of overall *generative* model.

**Simple EM algorithm**

- **E-step**: compute probabilities $P(ante(i) = a)$

and sum to compute $E [S(ante(i), i), \{S(A_i, i)\}]$

...the expected number of times we pick an antecedent with features $S$ from a set of available phrases with features $\{S\}$

- **M-step**: estimate $w$ by gradient descent on the likelihood
Problem: there are a lot of sufficient statistics:

\[ E[S(ante(i), i), \{S(A_i, i)\}] \]

...and feature vector \( S \) is probably sparse.

Possibility: online perceptron-style updates: 

*Stepwise EM* ((Sato+Ishii ‘00) and (Liang+Klein ‘09)):

- Compute expectations for a batch of examples
- Estimate the gradient \( w' \) and update \( w = \eta w + (1 - \eta)w' \)

Getting the batch size and learning rate right is tricky...
Preliminary results

Initialized the max-ent alignment to the distribution learned by the previous system.

<table>
<thead>
<tr>
<th>system</th>
<th>performance</th>
<th># of alignment params</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Charniak+Elsner ‘09)</td>
<td>67.2</td>
<td>2592</td>
</tr>
<tr>
<td>my reimplemention</td>
<td>65.4</td>
<td>2592</td>
</tr>
<tr>
<td>max-ent</td>
<td>65.7</td>
<td>61</td>
</tr>
</tbody>
</table>

- There is a compact representation of the alignment function
- It occurs near a local max of the (legitimate) likelihood
Why no improvement?

- Max-ent alignment could be similar to the “ugly” distribution...
  - if partition function $Z$ for each example approximately equal

Would imply:
Most syntactic environments have approximately same amount of important noun phrases.

Haven’t tested this!
Same-head coreference

Most NPs with the same *head word* are coreferent:

*Alice* thought to herself... *Alice* said...

But some are not:

the White *Queen* ... the Red *Queen*...

one *day* at a time ... the *day* before...

it sighed and the *consequence* was...

it wouldn’t come out and the *consequence* was...
Modeling idea

Generate the NPs from left to right...

Alignment

- Max-ent produces coreferent NPs
- Uniform distribution produces others

\[
P(ante(i) = a \mid S(a, i), \{S(A_i)\}) \propto \lambda \ast \exp(w \bullet S(a, i)) + (1 - \lambda) \ast \frac{1}{|S|}
\]

Translation model

Input: antecedent NP
Output: similar NP with different modifiers
Really, really preliminary results

Pronoun model plus model for NPs with same heads:

<table>
<thead>
<tr>
<th></th>
<th>link all</th>
<th>our model</th>
</tr>
</thead>
<tbody>
<tr>
<td>cluster overlap</td>
<td>69</td>
<td>74</td>
</tr>
<tr>
<td>link precision</td>
<td>54</td>
<td>65</td>
</tr>
<tr>
<td>link recall</td>
<td>50</td>
<td>35</td>
</tr>
<tr>
<td>f-score</td>
<td>52</td>
<td>45</td>
</tr>
</tbody>
</table>

Better cluster overlap, but trades recall for precision.
Future directions

Current goals:
► Better tuning for perceptron-style updates
► Analysis of different roles of translation/alignment
► Link NPs with different heads

Thanks for listening!
Please ask questions, or contact me:

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