A Study of Imitation Learning Methods for Semantic Role Labeling
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Problem
Task: Semantic Role Labeling (SRL): label the “who”, “what”, “when”, “where”, “why” w.r.t. a predicate
Frame Semantic Parsing: predicate disambig. + SRL
Goal: Train models which work well with greedy inference and global features

Local and Global Features
Local features from Hermann et al. (2014)

<table>
<thead>
<tr>
<th>Global</th>
<th>Definition</th>
<th>Example</th>
<th>Intuition</th>
</tr>
</thead>
<tbody>
<tr>
<td>numArgs</td>
<td>how many (realized) arguments so far?</td>
<td>2</td>
<td>valence, dynamic intercept</td>
</tr>
<tr>
<td>argLoc</td>
<td>does current span overlap, border, nest, w/ other arguments</td>
<td>E-R-A-R (FOIL)</td>
<td>overlap, bordering, nesting*</td>
</tr>
<tr>
<td>roleCooc</td>
<td>pair of current role with previous roles</td>
<td>+Instrument, -Ingestibles</td>
<td>Cont., excludes, requires roles; misc. correlations</td>
</tr>
</tbody>
</table>

Refine these features with frame, role, or frame+role of current action (tune granularity on dev).

Transition System/Action Ordering
Label a frame, choose a role, choose a span, repeat. Greedy search means inference order matters.
Freq: most likely roles first
easyfirst-static: sort roles by model accuracy
easyfirst-dynamic: sort roles by model score
rand-static: random order chosen once
rand-dynamic: random order chosen once per pass

Inconsistency:
When not separable, similar to training with oracle roll-in.

Experiment:
Make problem easier, see if inconsistency problems go away

Local Objective:
Add (unstructured) perceptron update, don’t skip examples at the end of trajectory.

Violation Fixing Perceptron
Early update (Collins and Roark 2004)
Max-violation and Latest update (Huang et al. 2012)
Assumes prefix separability, else suffix training data may be skipped.

Locally Optimal Learning to Search
Chang et al. (2015)
Reduction to cost-sensitive classification over actions. Action costs determined by roll-outs, O(1) in this case due to optimal oracle (this work).
Update is a sum over states along predicted trajectory.

Hybrid Roll-in:
Mistakes in frame stage cause oracle to avoid role false pos. by predicting NIL.
Learned model over-predicts NIL.
One solution: split policy by stage, pipeline train

Cost function:
Found hinge (multiclass) to work better than hamming reduction.

Results
PB: 73.6, FN: 55.6, well behind neural SOTA
Zhou and Xu (2015) and FitzGerald et al. (2015)
LOLS+hinge+hybrid: Global models outperform local

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