Lecture 12 – Discriminative Parsing

- 1. Grammars
 - a. Dependency Grammars
- 2. Discriminative Parsers
 - a. Graph based parsing
 - i. Parameterization
 - ii. Inference
 - iii.
 - iv. Learning
- 3. Two extensions
 - a. Neural representation (Kipperwasser and Goldberg)
 - b. Randomized greedy parsing

Regular Languages

- Σ
 - 1. Ø
 - 2. $a \in \Sigma$
 - 3. A and B are regular $\rightarrow A \cup B$, AB, A^* is regular
- Not all languages are regular

Context Free Languages

- $S \rightarrow \alpha S \beta$ (recursive construction/center embedding), cannot be represented by regular languages
 - o i.e. The dog that snores sleeps.
- It was though that context free was sufficient...
 - o But it was found that it was not; in fact we need context sensitive

Dependency Grammars

- Only one type of relationship between words
 - o Parent child or governs or depends...
- Easier to train
- Problems
 - No constituents
 - o Can be hard to annotate

Tree Adjoining Grammar

- More powerful than PCFG (can be context sensitive)

Generative vs Discriminative

- Discriminative p(y|x)
 - Slower to get good performance
 - Easily add more features

- Generative p(x, y)
 - o This distribution can be sampled
 - o Can very quickly get good performance
 - o Difficult to add more features
 - o NLP is mostly generative models

Dependency Parsing

- Words represented as x
- Arcs represented as y (pairs (i, j))
- y(x) = all the direct rooted trees over x (universe of possibilities)
- Scoring $score(x, y, \theta)$
 - Arc-factored scoring
 - Sum of arc scores $s = \sum_{i,j} score(a(i,j), \theta) = \sum f(x,i,j)\theta$
 - Can have many features f(x, i, j)...is this a problem?
 - No, can rely on other features...unlike language model where its possible no features exist.
- Inference argmax $score(x, y, \theta)$
 - o Find the maximum weight spanning tree for a directed graph
- Estimation of θ
 - \circ For each x
 - Compute $\hat{y} = \max_{y} f(x, y)\theta$
- If $y \neq \hat{y}$ $\theta = \theta + f(x, y) f(x, \hat{y})$