Dependency parsing and logistic regression

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(based on slides by Sharon Goldwater)

21 October 2019

Last class

Dependency parsing:

- a fully lexicalized formalism; tree edges connect words in the sentence based on head-dependent relationships.
- a better fit than constituency grammar for languages with free word order; but has weaknesses (e.g., conjunction).
- Gaining popularity because of move towards multilingual NLP.

Today's lecture

- How do we evaluate dependency parsers?
- Discriminative versus generative models
- How do we build a probabilistic model for dependency parsing?

Example

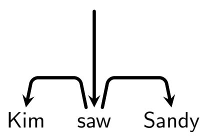
Parsing Kim saw Sandy:

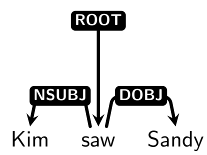
Step	←bot. Stacktop→	Word List	Action	Relations
0	[root]	[Kim,saw,Sandy]	Shift	
1	[root,Kim]	[saw,Sandy]	Shift	
2	[root,Kim,saw]	[Sandy]	LeftArc	Kim←saw
3	[root,saw]	[Sandy]	Shift	
4	[root,saw,Sandy]	[]	RightArc	saw→Sandy
5	[root,saw]	[]	RightArc	root→saw
6	[root]	[]	(done)	

- Here, top two words on stack are also always adjacent in sentence. Not true in general! (See longer example in JM3.)

Labelled dependency parsing

- These parsing actions produce **unlabelled** dependencies (left).
- For **labelled** dependencies (right), just use more actions: LeftArc(NSUBJ), RightArc(NSUBJ), LeftArc(DOBJ), ...





Differences to constituency parsing

- Shift-reduce parser for CFG: not all sequences of actions lead to valid parses. Choose incorrect action $\rightarrow$ may need to backtrack.
- Here, all valid action sequences lead to valid parses.
  - Invalid actions: can't apply LeftArc with root as dependent; can't apply RightArc with root as head unless input is empty.
  - Other actions may lead to **incorrect** parses, but still **valid**.
- So, parser doesn't backtrack. Instead, tries to greedily predict the correct action at each step.
  - Therefore, dependency parsers can be very fast (linear time).
  - But need a good way to predict correct actions (coming up).

Notions of validity

- In constituency parsing, valid parse = grammatical parse.
  - That is, we first define a grammar, then use it for parsing.
- In dependency parsing, we don't normally define a grammar. Valid parses are those with the properties mentioned earlier:
  - A single distinguished root word.
  - All other words have exactly one incoming edge.
  - A unique path from the root to each other word.

Summary: Transition-based Parsing

- **arc-standard** approach is based on simple shift-reduce idea.
- Can do labelled or unlabelled parsing, but need to train a **classifier** to predict next action, as we'll see.
- Greedy algorithm means time complexity is linear in sentence length.
- Only finds **projective** trees (without special extensions)
- Pioneering system: Nivre's MaltParser.

Alternative: Graph-based Parsing

- Global algorithm: From the fully connected directed graph of all possible edges, choose the best ones that form a tree.
- **Edge-factored** models: Classifier assigns a nonnegative score to each possible edge; **maximum spanning tree** algorithm finds the spanning tree with highest total score in $O(n^2)$ time.
- Pioneering work: McDonald's MSTParser
- Can be formulated as constraint-satisfaction with **integer linear programming** (Martins's TurboParser)
- Details in JM3, Ch 14.5 (optional).

Graph-based vs. Transition-based vs. Conversion-based

- TB: Features in scoring function can look at any part of the stack; no optimality guarantees for search; linear-time; (classically) projective only
- GB: Features in scoring function limited by factorization; optimal search within that model; quadratic-time; no projectivity constraint
- CB: In terms of accuracy, sometimes best to first constituency-parse, then convert to dependencies (e.g., Stanford Parser). Slower than direct methods.

Choosing a Parser: Criteria

- Target representation: constituency or dependency?
- Efficiency? In practice, both runtime and memory use.
- Incrementality: parse the whole sentence at once, or obtain partial left-to-right analyses/expectations?
- Accuracy?

Probabilistic transition-based dep'y parsing

At each step in parsing we have:

- Current configuration: consisting of the stack state, input buffer, and dependency relations found so far.
- Possible actions: e.g., Shift, LeftArc, RightArc.

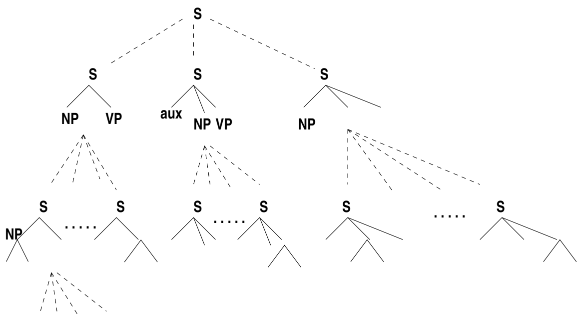
Probabilistic parser assumes we also have a model that tells us $P(\text{action}|\text{configuration})$. Then,

- Choosing the most probable action at each step (**greedy** parsing) produces a parse in linear time.
- But it might not be the best one: choices made early could lead to a worse overall parse.

Recap: parsing as search

Parser is searching through a very large space of possible parses.

- Greedy parsing is a depth-first strategy.
- **Beam search** is a limited breadth-first strategy.



Beam search: basic idea

- Instead of choosing only the **best** action at each step, choose a few of the best.
- Extend previous partial parses using these options.
- At each time step, keep a fixed number of best options, discard anything else.

Advantages:

- May find a better overall parse than greedy search,
- While using less time/memory than exhaustive search.

The agenda

An ordered list of configurations (parser state + parse so far).

- Items are ordered by score: how good a configuration is it?
- Implemented using a **priority queue** data structure, which efficiently inserts items into the ordered list.
- In beam search, we use an agenda with a fixed size (**beam width**). If new high-scoring items are inserted, discard items at the bottom below beam width.

Won't discuss scoring function here; but beam search idea is used across NLP (e.g., in best-first constituency parsing, NNet models.)

Evaluating dependency parsers

- How do we know if beam search is helping?
- As usual, we can evaluate against a gold standard data set. But what evaluation measure to use?

Evaluating dependency parsers

- By construction, the number of dependencies is the same as the number of words in the sentence.
- So we do not need to worry about precision and recall, just plain old accuracy.
- **Labelled Attachment Score** (LAS): Proportion of words where we predicted the correct head and label.
- **Unlabelled Attachment Score** (UAS): Proportion of words where we predicted the correct head, regardless of label.

Building a classifier for next actions

We said:

- Probabilistic parser assumes we also have a model that tells us $P(\text{action}|\text{configuration})$.

Where does that come from?

Classification for action prediction

We've seen **text classification**:

- Given (features from) text document, predict the class it belongs to.

Generalized classification task:

- Given features from observed data, predict one of a set of classes (labels).

Here, **actions** are the labels to predict:

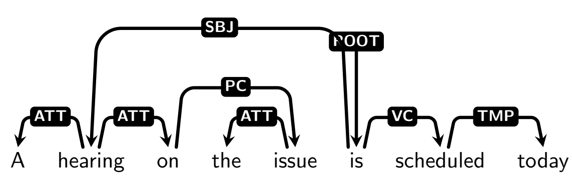
- Given (features from) the current configuration, predict the next action.

Training data

Our goal is:

- Given (features from) the current configuration, predict the next action.

Our corpus contains annotated sentences such as:



Is this sufficient to train a classifier to achieve our goal?

Creating the right training data

Well, not quite. What we need is a sequence of the correct (configuration, action) pairs.

- Problem: some sentences may have **more than one** possible sequence that yields the correct parse. (see tutorial exercise)
- Solution: JM3 describes rules to convert each annotated sentence to a **unique** sequence of (configuration, action) pairs.[1]

OK, finally! So what kind of model will we train?

[1]This algorithm is called the *training oracle*. An *oracle* is a fortune-teller, and in NLP it refers to an algorithm that always provides the correct answer. Oracles can also be useful for evaluating certain aspects of NLP systems, and we may say a bit more about them later.

Logistic regression

- Actually, we could use any kind of classifier (Naive Bayes, SVM, neural net...)
- Logistic regression is a standard approach that illustrates a different type of model: a **discriminative** probabilistic model.
  - So far, all our models have been **generative**.
- Even if you have seen it before, the formulation often used in NLP is slightly different from what you might be used to.

Generative probabilistic models

- Model the joint probability $P(\vec{x}, \vec{y})$
  - $\vec{x}$: the observed variables (what we'll see at test time).
  - $\vec{y}$: the latent variables (not seen at test time; must predict).

Model	$\vec{x}$	$\vec{y}$
Naive Bayes	features	classes
HMM	words	tags
PCFG	words	tree

Generative models have a "generative story"

- a probabilistic process that describes how the data were created
  - Multiplying probabilities of each step gives us $P(\vec{x}, \vec{y})$.
- Naive Bayes: For each item i to be classified, (e.g., document)
  - Generate its class c_i (e.g., SPORT)
  - Generate its features $f_{i1} \dots f_{in}$ conditioned on c_i (e.g., ball, goal, Tuesday)

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Result:
$$P(\vec{c}, \vec{f}) = \prod_i \left[P(c_i) \prod_j P(f_{ij}|c_i) \right]$$

Other generative stories

- HMM: For each position i in sentence,
  - Generate its tag t_i conditioned on previous tag t_{i-1}
  - Generate its word w_i conditioned on t_i
- PCFG:
  - Starting from S node, recursively generate children for each phrasal category c_i conditioned on c_i, until all unexpanded nodes are pre-terminals (tags).
  - For each pre-terminal t_i, generate a word w_i conditioned on t_i.

Inference in generative models

- At test time, given only $\vec{x}$, infer $\vec{y}$ using Bayes' rule:

$$P(\vec{y}|\vec{x}) = \frac{P(\vec{x}|\vec{y})P(\vec{y})}{P(\vec{x})}$$

- So, notice we actually model $P(\vec{x}, \vec{y})$ as $P(\vec{x}|\vec{y})P(\vec{y})$.
  - You can confirm this for each of the previous models.

Discriminative probabilistic models

- Model $P(\vec{y}|\vec{x})$ directly
  - No model of $P(\vec{x}, \vec{y})$
  - No generative story
  - No Bayes' rule
- One big advantage: we can use arbitrary features and don't have to make strong independence assumptions.
- But: unlike generative models, we can't get $P(\vec{x}) = \sum_{\vec{y}} P(\vec{x}, \vec{y})$.

Discriminative models more broadly

- Trained to **discriminate** right v. wrong value of $\vec{y}$, given input $\vec{x}$.
- Need not be probabilistic.
- Examples: support vector machines, (some) neural networks, decision trees, nearest neighbor methods.
- Here, we consider only multinomial logistic regression models, which *are* probabilistic.
  - *multinomial* means more than two possible classes
  - otherwise (or if lazy) just *logistic regression*
  - In NLP, also known as **Maximum Entropy** (or **MaxEnt**) models.

Example task: word sense disambiguation

Remember, logistic regression can be used for any classification task.
The following slides use an example from lexical semantics:

- Given a word with different meanings (**senses**), can we classify which sense is intended?

  I visited the Ford **plant** yesterday.
  The farmers **plant** soybeans in spring.
  This **plant** produced three kilos of berries.

WSD as example classification task

- Disambiguate three senses of the target word plant
  - $\vec{x}$ are the words and POS tags in the document the target word occurs in
  - y is the latent sense. Assume three possibilities:

$y =$	sense
1	Noun: a member of the plant kingdom
2	Verb: to place in the ground
3	Noun: a factory

- We want to build a model of $P(y|\vec{x})$.

Defining a MaxEnt model: intuition

- Start by defining a set of **features** that we think are likely to help discriminate the classes. E.g.,
  - the POS of the target word
  - the words immediately preceding and following it
  - other words that occur in the document
- During training, the model will learn how much each feature contributes to the final decision.

Defining a MaxEnt model

- Features $f_i(\vec{x}, y)$ depend on both observed and latent variables. E.g., if `tgt` is the target word:
  - f_1 : `POS(tgt) = NN` & $y = 1$
  - f_2 : `POS(tgt) = NN` & $y = 2$
  - f_3 : `preceding_word(tgt) = 'chemical'` & $y = 3$
  - f_4 : `doc_contains('animal')` & $y = 1$

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- Each feature f_i has a real-valued weight w_i (learned in training).
- $P(y|\vec{x})$ is a monotonic function of $\vec{w} \cdot \vec{f}$ (that is, $\sum_i w_i f_i(\vec{x}, y)$).

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- $P(y|\vec{x})$ is a monotonic function of $\vec{w} \cdot \vec{f}$ (that is, $\sum_i w_i f_i(\vec{x}, y)$).
  - To make $P(y|\vec{x})$ large, we need weights that make $\vec{w} \cdot \vec{f}$ large.

Example of features and weights

- Let's look at just two features from the **plant** disambiguation example:

  f_1 : `POS(tgt) = NN` & $y = 1$

  f_2 : `POS(tgt) = NN` & $y = 2$
- Our classes are:
  {1: member of plant kingdom; 2: put in ground; 3: factory}
- Our example doc ($\vec{x}$):
  `[... animal/NN ... chemical/JJ plant/NN ...]`

Two cases to consider

- Computing $P(y = 1|\vec{x})$:
  - Here, $f_1 = 1$ and $f_2 = 0$.
  - We would expect the probability to be relatively high.
  - Can be achieved by having a **positive** value for w_1.
  - Since $f_2 = 0$, its weight has no effect on the final probability.
- Computing $P(y = 2|\vec{x})$:

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- Computing $P(y = 2|\vec{x})$:
  - Here, $f_1 = 0$ and $f_2 = 1$.
  - We would expect the probability to be close to zero, because sense 2 is a verb sense, and here we have a noun.
  - Can be achieved by having a large **negative** value for w_2.
  - By doing so, f_2 says: "If I am active, do **not** choose sense 2!".

Classification with MaxEnt

- Choose the class that has highest probability according to

$$P(y|\vec{x}) = \frac{1}{Z} \exp\left(\sum_i w_i f_i(\vec{x}, y)\right)$$

where
  - $\exp(x) = e^x$ (the monotonic function)
  - $\sum_i w_i f_i$ is the *dot product* of $\vec{w}$ and $\vec{f}$, also written $\vec{w} \cdot \vec{f}$.
  - The normalization constant $Z = \sum_{y'} \exp(\sum_i w_i f_i(\vec{x}, y'))$

Which features are active?

- Example doc:
  `[... animal/NN ... chemical/JJ plant/NN ...]`

$P(y = 1|\vec{x})$	will have	$f_1, f_4 = 1$	and	$f_2, f_3 = 0$
$P(y = 2|\vec{x})$		$f_2 = 1$		$f_1, f_3, f_4 = 0$
$P(y = 3|\vec{x})$		$f_3 = 1$		$f_1, f_2, f_4 = 0$

- Notice that zero-valued features have no effect on the final probability
- Other features will be multiplied by their weights, summed, then exp.

Feature templates

- In practice, features are usually defined using **templates**

  `POS(tgt)=`t & y
  `preceding_word(tgt)=`w & y
  `doc_contains(`w`)` & y

  - instantiate with all possible POSs t or words w and classes y
  - usually filter out features occurring very few times
  - templates can also define real-valued or integer-valued features
- NLP tasks often have a few templates, but 1000s or 10000s of features

Features for dependency parsing

- We want the model to tell us $P(\text{action}|\text{configuration})$.
- So y is the action, and $\vec{x}$ is the configuration.
- Features are various combinations of words/tags from stack/input:

Source	Feature templates		
One word	$s_1.w$	$s_1.t$	$s_1.wt$
	$s_2.w$	$s_2.t$	$s_2.wt$
	$b_1.w$	$b_1.w$	$b_0.wt$
Two word	$s_1.w \circ s_2.w$	$s_1.t \circ s_2.t$	$s_1.t \circ b_1.w$
	$s_1.t \circ s_2.wt$	$s_1.w \circ s_2.w \circ s_2.t$	$s_1.w \circ s_1.t \circ s_2.t$
	$s_1.w \circ s_1.t \circ s_2.t$	$s_1.w \circ s_1.t$	

Figure 14.9 Standard feature templates for training transition-based dependency parsers. In the template specifications s_n refers to a location on the stack, b_n refers to a location in the word buffer, w refers to the wordform of the input, and t refers to the part of speech of the input.

Summary

We've discussed

- Beam search.
- Evaluation for probabilistic dependency parsing.
- The logistic regression classifier.