CS395T: Structured Models for NLP
Lecture 10: Trees 4

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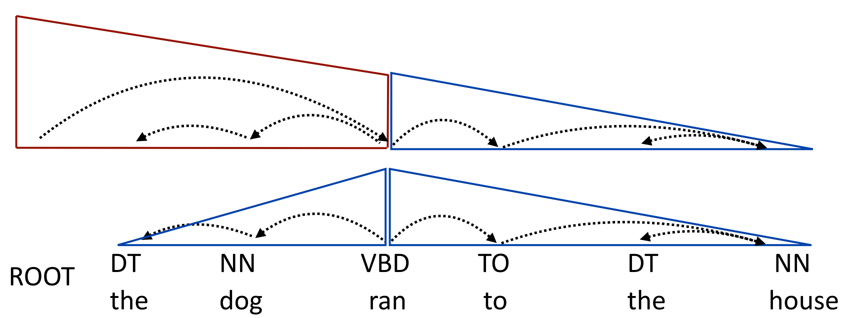
Administrivia

- Project 1 graded by late week / this weekend

Recall: Eisner's Algorithm

- Left and right children are built independently, heads are edges of spans
- Complete item: all children are attached, head is at the "tall end"
- Incomplete item: arc from "tall end" to "short end", may still expect children



Recall: MST Algorithm

- Eisner: search over the space of projective trees, $O(n^3)$
- MST: find maximum directed spanning tree — finds nonprojective trees as well as projective trees $O(n^2)$
- MST restricted to features on single dependencies, Eisner can be generalized to incorporate higher-order features (grandparents, siblings, etc.) at a time complexity cost, or with beaming

Recall: Transition-Based Parsing

- Start: stack contains [ROOT], buffer contains [I ate some spaghetti bolognese]
- Arc-standard system: three operations
  - Shift: top of buffer -> top of stack
  - Left-Arc: $\boxed{\sigma|w_{-2}, w_{-1}} \rightarrow \boxed{\sigma|w_{-1}}$, w_{-2} is now a child of w_{-1}
  - Right-Arc $\boxed{\sigma|w_{-2}, w_{-1}} \rightarrow \boxed{\sigma|w_{-2}}$, w_{-1} is now a child of w_{-2}
- End: stack contains [ROOT], buffer is empty []
- Must take 2*n* steps for *n* words (*n* shifts, *n* LA/RA)

Recall: Transition-Based Parsing

ROOT

I ate some spaghetti bolognese

S	top of buffer -> top of stack
LA	pop two, left arc between them
RA	pop two, right arc between them

[ROOT ate] [some spaghetti bolognese]

↓ I

S

S

[ROOT ate some spaghetti] [bolognese]

↓ I

L

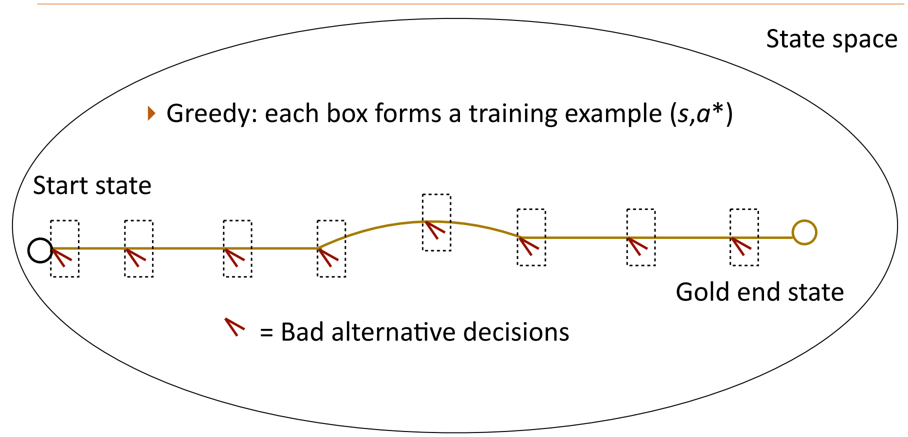
[ROOT ate spaghetti] [bolognese]

↓ I ↓ some

This Lecture

- Global Decoding
- Early updating
- Connections to reinforcement learning, dynamic oracles
- State-of-the-art dependency parsers, related tasks

Greedy Training: Static States



Global Decoding

- Greedy parser: trained to make the right decision (S, LA, RA) from any gold state we might come to
- What we optimizing when we decode each sentence?
  - Nothing…we're executing:

$$a_{\text{best}} \leftarrow \text{argmax}_a w^\top f(s,a)$$
$$s \leftarrow a_{\text{best}}(s)$$

- Why might this be bad?

Global Decoding

ROOT
I gave him dinner

[ROOT gave him]   [dinner]
I

- Correct: Right-arc, Shift, Right-arc, Right-arc

[ROOT gave]   [dinner]
I him

[ROOT gave dinner]   []
I him

[ROOT gave]   []
I him dinner

Global Decoding: A Cartoon

ROOT
I gave him dinner

[ROOT gave him]   [dinner]
I

[ROOT gave him dinner]   []
I

LA

RA

- Both wrong! Also both probably low scoring!

S

LA

RA

[ROOT gave]   [dinner]
I him

S

- Correct, high scoring option

Global Decoding: A Cartoon

ROOT
I gave him dinner

[ROOT gave him]   [dinner]
I

- Lookahead can help us avoid getting stuck in bad spots
- Global model: maximize sum of scores over all decisions
- Similar to how Viterbi works: we maintain uncertainty over the current state so that if another one looks more optimal going forward, we can use that one

Global Shift-Reduce Parsing

- Greedy: repeatedly execute

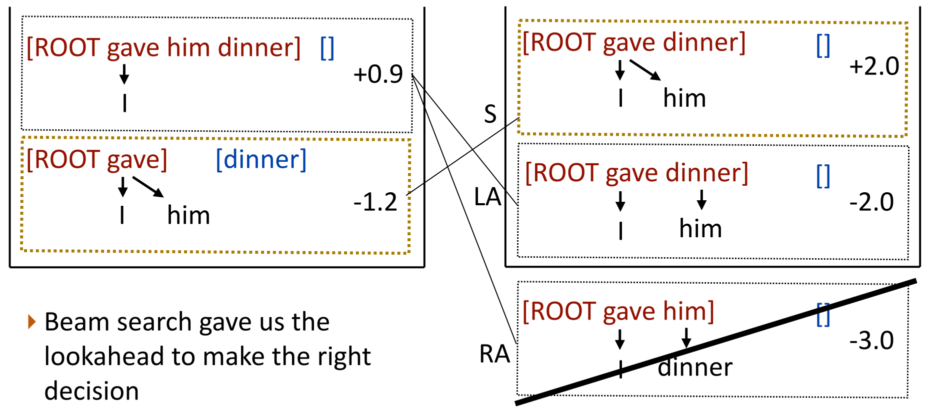
$$a_{\text{best}} \leftarrow \text{argmax}_a w^\top f(s,a)$$
$$s \leftarrow a_{\text{best}}(s)$$

- Global:

$$\text{argmax}_{\mathbf{s},\mathbf{a}} f(\mathbf{s},\mathbf{a}) = \sum_{i=1}^{2n} w^\top f(s_i,a_i)$$
$$s_{i+1} = a_i(s_i)$$

- Can we do search exactly?
  - How many states *s* are there?
- No! Use beam search

Global Shift-Reduce Parsing



- Beam search gave us the lookahead to make the right decision

Training Global Parsers

- Can compute approximate maxes with beam search

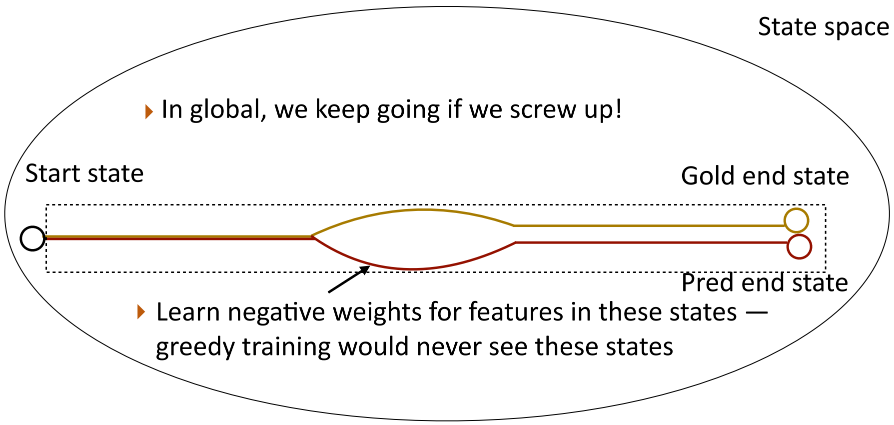
$$\text{argmax}_{\mathbf{s},\mathbf{a}} f(\mathbf{s},\mathbf{a}) = \sum_{i=1}^{2n} w^\top f(s_i,a_i)$$

- Structured SVM: do loss-augmented decode, gradient = gold feats - guess feats
- Structured perceptron: normal decode, gradient = gold feats - guess feats
- What happens if we set beam size = 1?

Global Training

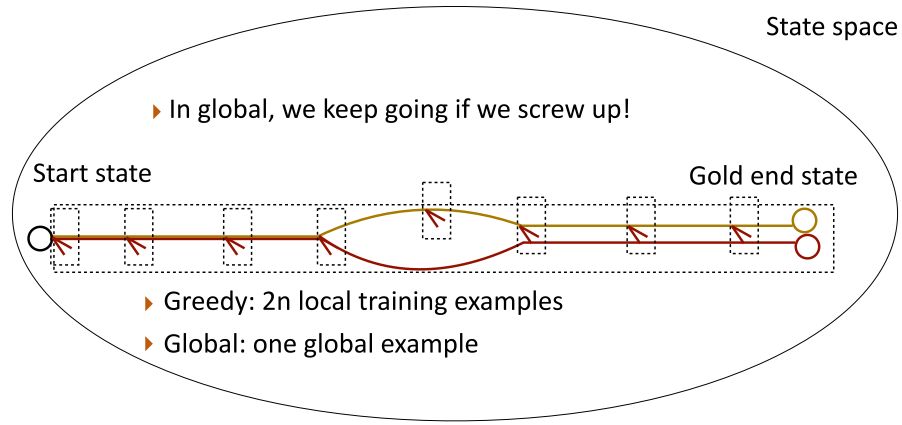
```
For each epoch
  For each sentence
    For i=1…2*len(sentence)      # 2n transitions in arc-standard
      beam[i] = compute_successors(beam[i-1])
    prediction = beam[2*len(sentence),0]    # argmax = top of last beam
    # Feats are cumulative over the whole sentence
    apply_gradient_update(feats(gold) - feats(prediction))
```

Global Training



- In global, we keep going if we screw up!
- Learn negative weights for features in these states — greedy training would never see these states

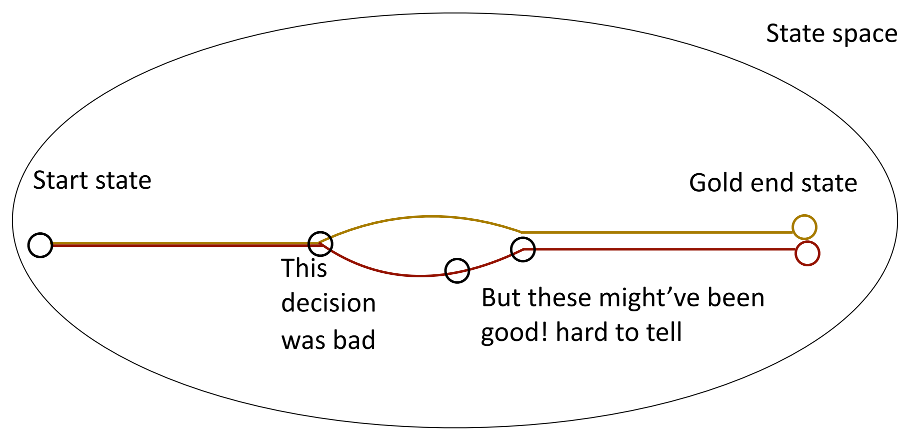
Global vs. Greedy



- In global, we keep going if we screw up!
- Greedy: 2n local training examples
- Global: one global example

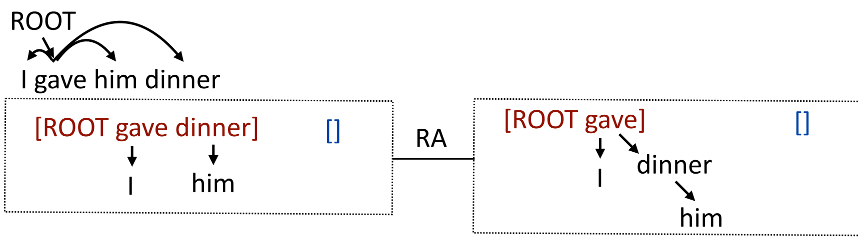
Early Updating

Early Updating



Collins and Roark (2004)

Early Updating



- Wrong state — we already messed up!
- Made the best of a bad situation by putting a good arc in (gave->dinner)
- Ideally we don't want to penalize this decision (update away from it) — instead just penalize the decision that was *obviously* wrong

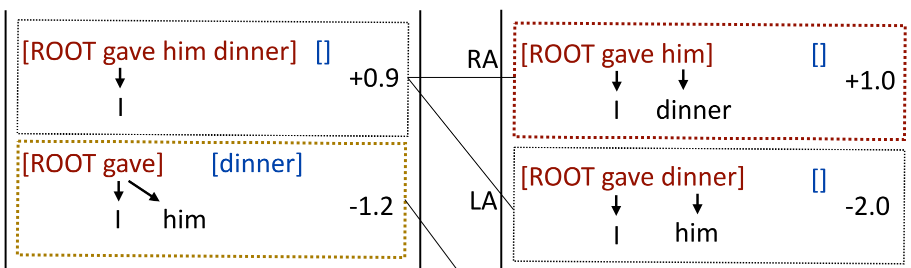
Collins and Roark (2004)

Early Updating

- Solution: make an update as soon as the gold parse falls off the beam

- gold feats - guess feats *computed up to this point*

Early Updating



- Gold has fallen off beam!
- Update: gold feats - pred feats

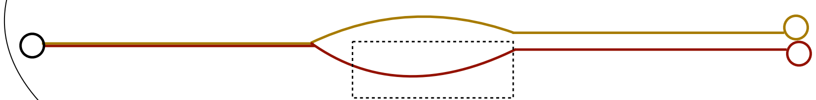
Training with Early Updating

```
For each epoch
  For each sentence
    For i=1…2*len(sentence)     # 2n transitions in arc-standard
      beam[i] = compute_successors(beam[i-1])
      If beam[i] does not contain gold:
        # Feats are cumulative up until this point
        apply_gradient_update(feats(gold[0:i]) - feats(beam[i,0]))
        break
    # Gold survived to the end but may still not be one-best
    apply_gradient_update(feats(gold) - feats(beam[2*len(sentence),0]))
```

Connections to Reinforcement Learning

Motivation

- Part of the benefit is we see states we wouldn't have seen during greedy decoding
- (Still true even with early updating due to beam search)



Better Greedy Algorithm

For each epoch:

  For each sentence:

    Parse the sentence with the current weights

    For each state *s* in the parse:

      Determine what the right action *a** was

      Train on this example (update towards $f(s, a^*)$, away from $f(s, a_{\text{pred}})$)

- How do we determine this?

Dynamic Oracles

- When you make some bad decisions, how do you dig yourself out?
- best_possible_tree(s): computes the optimal decision sequence from state *s* to the end resulting the lowest overall loss
- Implemented by a bunch of logic that looks at the tree: "if we put a right-arc from a->b, we can't give b any more children, so lose a point for every unbound child, also lose a point if a isn't b's head..."
- Score of decision *a* in state *s* leading to *s'*:
  loss(a) = loss(best_possible_tree(*s'*)) - loss(best_possible_tree(*s*))
- $a^* = \text{argmin}_a \text{ loss}(a)$

Goldberg and Nivre (2012)

Connections to Reinforcement Learning

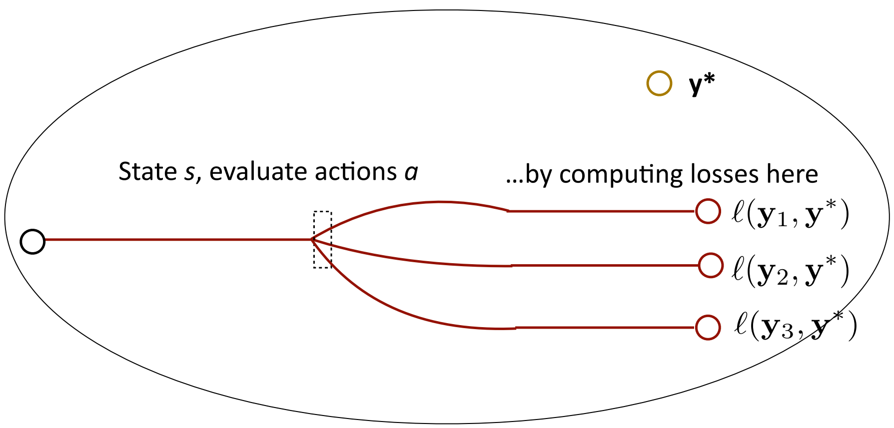
- Markov Decision Process: states *s*, actions *a*, transitions *T*, rewards *r*, discount factor γ
- *T* is deterministic for us, γ = 1 (no discount)
- Maximize sum of rewards over the parse
- One reward system: *r* = 1 if action is what dynamic oracle says, 0 otherwise
- Using the "better greedy algorithm" corresponds to on-policy learning here
- But dynamic oracles are hard to build :(

Searn

- What if we just had a loss function *l*(y,y*) that scored whole predictions? I.e., all reward comes at the end
- Searn: framework for turning structured problems into classification problems
- Take the current policy (= weights), generate states *s* by running that policy on a given example
- Evalute action *a* in state *s* by taking *a*, then following your current policy to completion and computing the loss (= best_possible_loss is approximated by current policy)
- DAGGER algorithm from RL literature

Daume et al. (2009)

Motivation



Global Models vs. RL

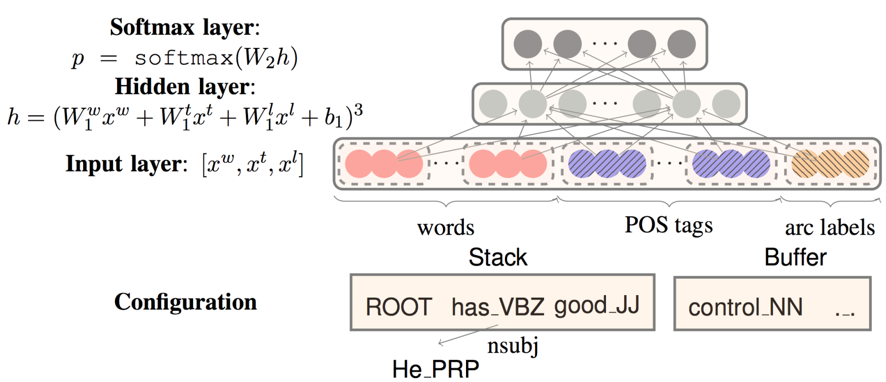
- Structured prediction problems aren't really "RL" in that the environment dynamics are understood
- RL techniques are usually not the right thing to do unless you loss function and state space are *really* complicated
- Otherwise, best to use dynamic oracles or global models
- These issues arise far beyond parsing! Coreference, machine translation, dialogue systems, ...

State-of-the-art Parsers

State-of-the-art Parsers

- 2005: MSTParser got solid performance (~91 UAS)
- 2010: Koo's 3rd-order parser was SOTA for graph-based (~93 UAS)
- 2012: Maltparser was SOTA was for transition-based (~90 UAS), similar to what you'll build
- 2014: Chen and Manning got 92 UAS with transition-based neural model

State-of-the-art Parsers



Chen and Manning (2014)

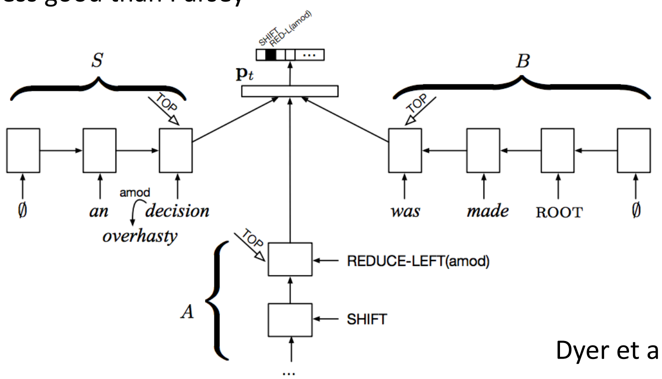
Parsey McParseFace

- Current state-of-the-art, released by Google publicly
- 94.61 UAS on the Penn Treebank using a global transition-based system with early updating
  - Additional data harvested via "tri-training"
- Feedforward neural nets looking at words and POS associated with
  - Words at the top of the stack
  - Those words' children
  - Words in the buffer
- Feature set pioneered by Chen and Manning (2014), Google fine-tuned it

Andor et al. (2016)

Stack LSTMs

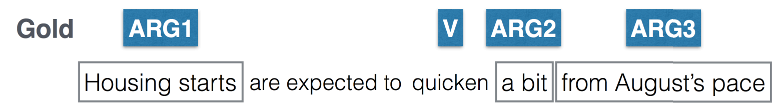
- Use LSTMs over stack, buffer, past action sequence. Trained greedily
- Slightly less good than Parsey



Dyer et al. (2015)

Semantic Role Labeling

- Another kind of tree-structured annotation, like a subset of dependency
- Verb roles from Propbank (Palmer et al., 2005), nominal predicates too



quicken:

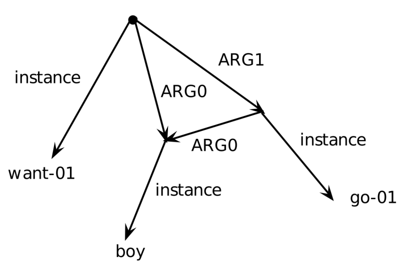
Arg0-PAG: *causer of speed-up*
Arg1-PPT: *thing becoming faster* (vnrole: 45.4-patient)
Arg2-EXT: *EXT*
Arg3-DIR: *old speed*
Arg4-PRD: *new speed*

Figure from He et al. (2017)

Abstract Meaning Representation

Banarescu et al. (2014)

- Graph-structured annotation
- Superset of SRL: full sentence analyses, contains coreference and multi-word expressions as well
- F1 scores in the 60s: hard!
- So comprehensive that it's hard to predict, but still doesn't handle tense or some other things...



The boy wants to go

Takeaways

- Global training is an alternative to greedy training
- Use beam search for inference combined with early updating for best results
- Dynamic oracles + following the predicted path in the state space looks like reinforcement learning

Survey

- Pace of last lecture + this lecture: [too slow] [just right] [too fast]
- Pace of class overall: [too slow] [just right] [too fast]
- Write one thing you like about the class
- Write one thing you don’t like about the class