POS tagging (3)

LING 570

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Outline

- POS tagging with rich features
- Sequence labeling problem
- Beam search

N-gram POS tagger

$$argmax_{t_1^n} P(t_1^n|w_1^n)$$

$$\approx argmax_{t_1^n} \prod_i P(w_i|t_i)P(t_i|t_{i-N+1}^{i-1})$$

Bigram model: $$\prod_i P(w_i|t_i)P(t_i|t_{i-1})$$

Trigram model: $$\prod_i P(w_i|t_i)P(t_i|t_{i-2},t_{i-1})$$

Unknown word handling

- HMM was good at using ***POS-tag context*** to pick POS for unknown words

- Bad at using information about the word itself

- Let's treat this as a classification problem:
  - Predict some target class
  - Use a bunch of ***features*** to make that prediction
  - ***Feature templates*** generate each feature

POS Tagging with a classifier

- POS tagging as classification
  - What are the inputs?
    - What units are classified?
  - What are the classes?
  - What information should we use?

Cues for unknown words

- Affixes: unforgettable: un-, -able ➔ JJ
- Capitalization: Hyderabad ➔ NNP
- Word shapes: 123,456 ➔ CD
- The previous word: prevWord=San ➔ NNP

How can we take advantage of these cues?

➔ Treat them as features

An example

- I am going to San Diego next week
- San NNP IsCap 1 PrevW=to 1 ContainNum 0
- Diego NNP IsCap 1 PrevW=San 1 ContainNum 0

Feature templates for all the words

- Previous word: w_{-1}
- Current word: w_0
- Next word: w_{+1}
- Previous two words: $w_{-2}\ w_{-1}$
- Surrounding words: $w_{-1}\ w_{+1}$

- Previous tag: t_{-1}
- Previous two tags: $t_{-2}\ t_{-1}$

- How many feature templates?
- How many features? $3|V|+2|V|^2+|T|+|T|^2$

An example

Mary will come tomorrow

	W_{-1}	W_0	$W_{-1}\ W_0$	W_{+1}	t_{-1}	**y**
x1 (Mary)	<s>	Mary	<s> Mary	will	BOS	PN
x2 (will)	Mary	will	Mary will	come	PN	V
x3 (come)	will	come	will come	tomorrow	V	V

This can be seen as a shorthand of a much bigger table.

	W_{-1}	W_0	$W_{-1}\ W_0$	W_{+1}	t_{-1}	y
x1 (Mary)	<s>	Mary	<s> Mary	will	BOS	PN
x2 (will)	Mary	will	Mary will	come	PN	V
x3 (come)	will	come	will come	tomorrow	V	V

Mary PN prevW=<s> 1 curW=Mary 1 prevW-curW=<s>-Mary 1
nextW=will 1 prevTag=BOS 1

will V prevW=Mary 1 curW=will 1 prevW-curW=Mary-will 1
nextW=come 1 prevTag=PN 1

come V prevW=will 1 curW=come 1 prevW-curW=will-come 1
nextW=tomorrow 1 prevTag=V 1

Ratnaparkhi's feature templates

Condition	Feature templates	
w_i is not rare	$w_i = X$	$\& \ t_i = T$
w_i is rare	w_i has prefix X, $\lvert X \rvert \leq 4$	$\& \ t_i = T$
	w_i has suffix X, $\lvert X \rvert \leq 4$	$\& \ t_i = T$
	w_i contains number	$\& \ t_i = T$
	w_i contains uppercase character	$\& \ t_i = T$
	w_i contains hyphen	$\& \ t_i = T$
For all w_i	$t_{i-1} = X$	$\& \ t_i = T$
	$t_{i-2}, t_{i-1} = X, Y$	$\& \ t_i = T$
	$w_{i-1} = X$	$\& \ t_i = T$
	$w_{i-2} = X$	$\& \ t_i = T$
	$w_{i+1} = X$	$\& \ t_i = T$
	$w_{i+2} = X$	$\& \ t_i = T$

Word:	the	stories	about	well-heeled	communities	and	developers
Tag:	DT	NNS	IN	JJ	NNS	CC	NNS
Position:	1	2	3	4	5	6	7

Assume “well-heeled” is a rare word

well-heeled JJ pref=w 1 pref=we 1 pref=wel 1 pref=well 1
suf=d 1 suf=ed 1 suf=led 1 suf=eled 1
containsNum 0 containsUppercase 0 containshyphen 1
prevTag=IN 1 prev2Tags=NNS-IN 1 prefW=about 1
pref2W=stories 1 nextW=communities 1 next2W=and 1

Rare words: words that occur less than N_r times in the training data

Feature selection: remove features that appear less than N_f times in the training data

Building a tagger

- training data: w1/t1 w2/t2 … wn/tn
- test data: w1/t1 w2/t2   … wn/tn

- Steps:
  1. Create train.vectors.txt from training data
  2. Create test.vectors.txt from test data
  3. Run “mallet import-file” to convert training vectors to binary format
  4. Train a model using train.vectors:

     mallet train-classifier --input train.vectors --trainer MaxEnt --output-classifier me_model --report train:accuracy > me.stdout 2>me.stderr

  5. Run the model on test.vectors:

     mallet classify-file --input test.vectors.txt --classifier me_model --output resultFile --report test:accuracy > me_dec.stdout 2>me_dec.stderr

- Any problem?

	W_{-1}	W_0	$W_{-1}\ W_0$	W_{+1}	t_{-1}	y
x1 (Mary)	<s>	Mary	<s> Mary	will	BOS	PN
x2 (will)	Mary	will	Mary will	come	PN	V
x3 (come)	will	come	will come	tomorrow	V	V

Mary PN prevW=<s> 1 curW=Mary 1 prevW-curW=<s>-Mary 1
nextW=will 1 prevTag=BOS 1

will V prevW=Mary 1 curW=will 1 prevW-curW=Mary-will 1
nextW=come 1 prevTag=PN 1

come V prevW=will 1 curW=come 1 prevW-curW=will-come 1
nextW=tomorrow 1 prevTag=V 1

Sequence labeling problem

Sequence Labeling

- Classifier
  - Predict ***single output***, given potentially complex input

- Sequence classification
  - Predict ***sequence of output labels***, given sequence of potentially complex inputs

Examples

- POS tagging
- NP chunking
- NE tagging
- Word segmentation
- Table detection
- …

Using a classifier

- Training data: $\{(x_i, y_i)\}$
- What is x_i? What is y_i?
- What are the features?
- How to convert x_i to a feature vector for training data? How to do that for test data?

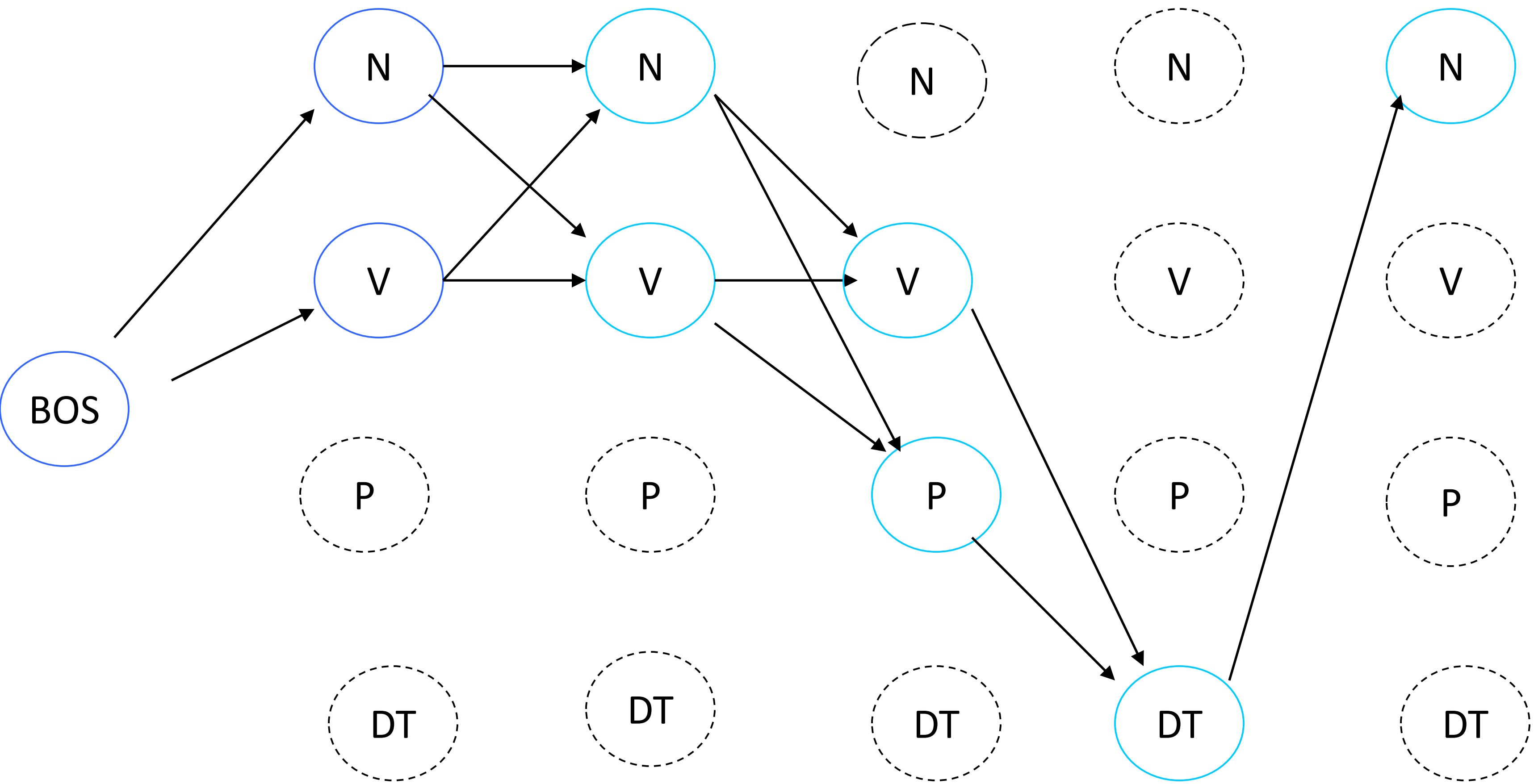
How to solve a sequence labeling problem?

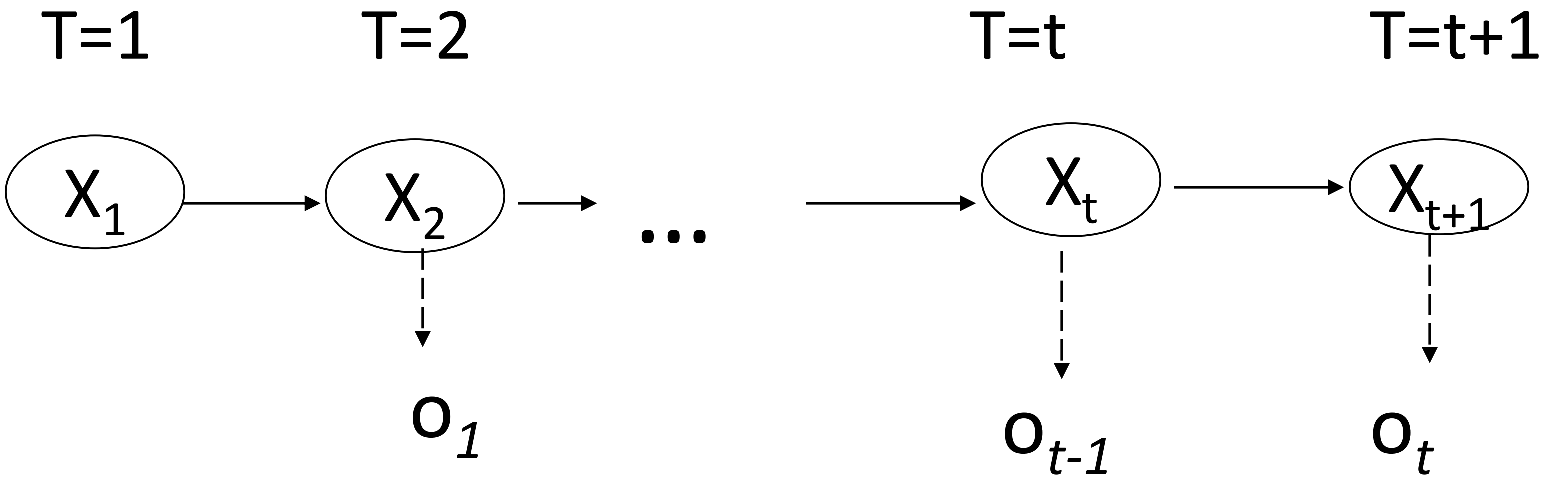
- Using a sequence labeling algorithm: e.g., HMM

- Using a classification algorithm:
  - Don’t use features that refer to class labels
  - Use those features and get their values by running other processes
  - Use those features and find a good (global) solution.

Viterbi for HMM

time flies like an arrow





$$\delta_j(t) \overset{def}{=} \max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = j)$$

$$\delta_j(1) = \pi_j$$

$$\delta_j(t+1) = \max_i \delta_i(t) a_{ij} b_{jo_t}$$

Time complexity: O(N^2 T)

Can we use Viterbi for a classifier that uses tags of previous words?

Beam search

Why do we need beam search?

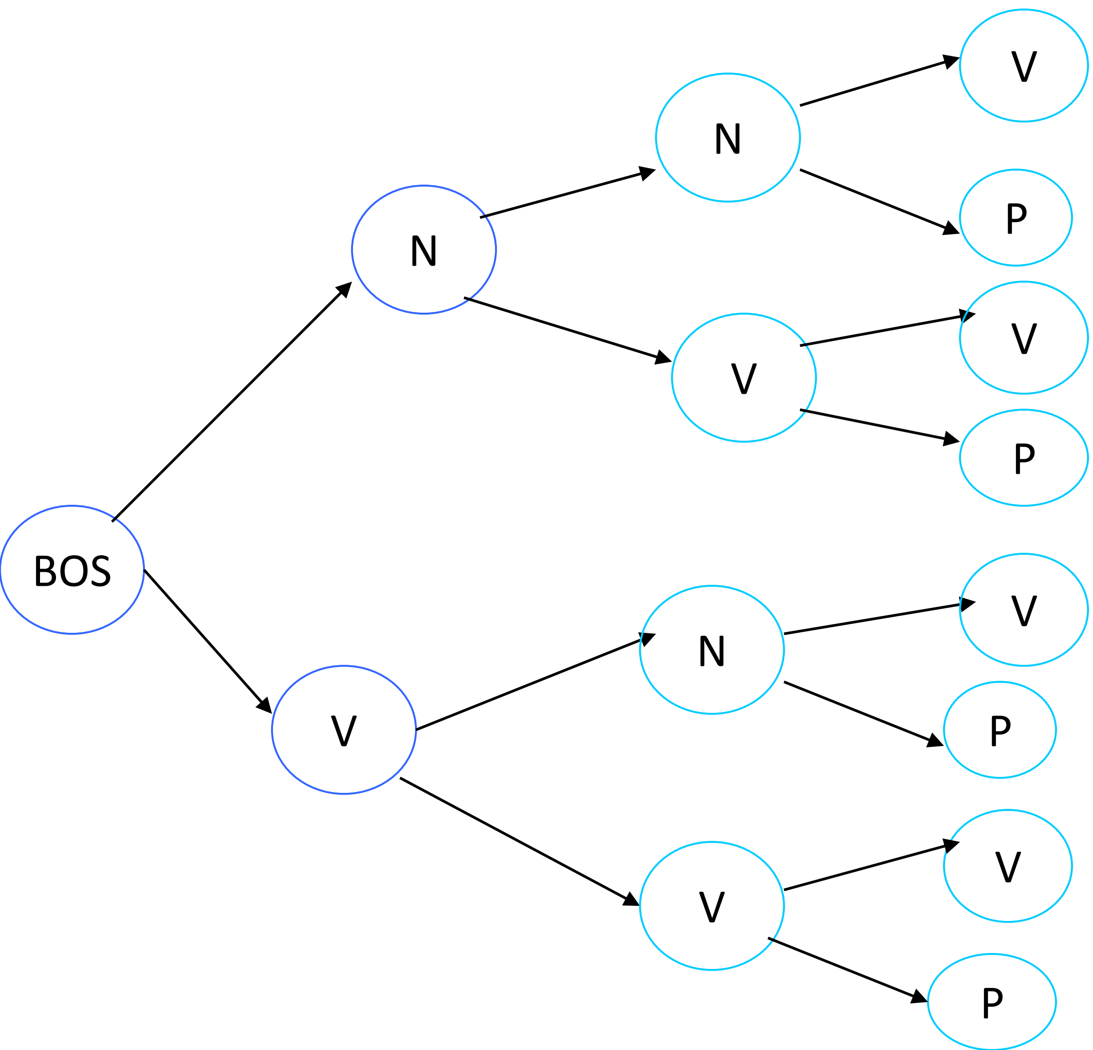
- Features refer to tags of previous words, which are not available for the TEST data.

- Knowing only the best tag of the previous word is not good enough.

- So let's keep multiple tag sequences available during the decoding.

Beam search

time flies like an arrow



Beam search

- Generate m tags for w_1, set s_{1j} accordingly
- For i=2 to n (n is the sentence length)
  - Expanding: For each surviving sequence $s_{(i-1),j}$
    - Generate m tags for w_i, given $s_{(i-1)j}$ as previous tag context
    - Append each tag to $s_{(i-1)j}$ to make a new sequence.
  - Pruning: keep only the top k sequences
- Return highest prob sequence s_{n1}.

Beam search (basic)

- Beam inference:
  - At each position keep the top k complete sequences.
  - Extend each sequence in each local way.
  - The extensions compete for the k slots at the next position.
- Advantages:
  - Fast; and beam sizes of 3–5 are as good or almost as good as exact inference in many cases.
  - Easy to implement (no dynamic programming required).
- Disadvantage:
  - Inexact: the globally best sequence can fall off the beam.

Viterbi search

- Viterbi inference:
  - Dynamic programming or memoization.
  - Requires small window of state influence (e.g., past two states are relevant).
- Advantage:
  - Exact: the global best sequence is returned.
- Disadvantage:
  - Harder to implement long-distance state-state interactions (but beam inference tends not to allow long-distance resurrection of sequences anyway).

Viterbi vs. Beam search

- DP vs. heuristic search
- Global optimal vs. inexact
- Small window vs. big window for features

Summary

- POS tagging with a classifier: use a classifier to determine the class of the word

- Sequence labeling problem: the feature of the current word depends on the tags of previous words

- Beam search: brute-force search with pruning