Structured prediction: practical

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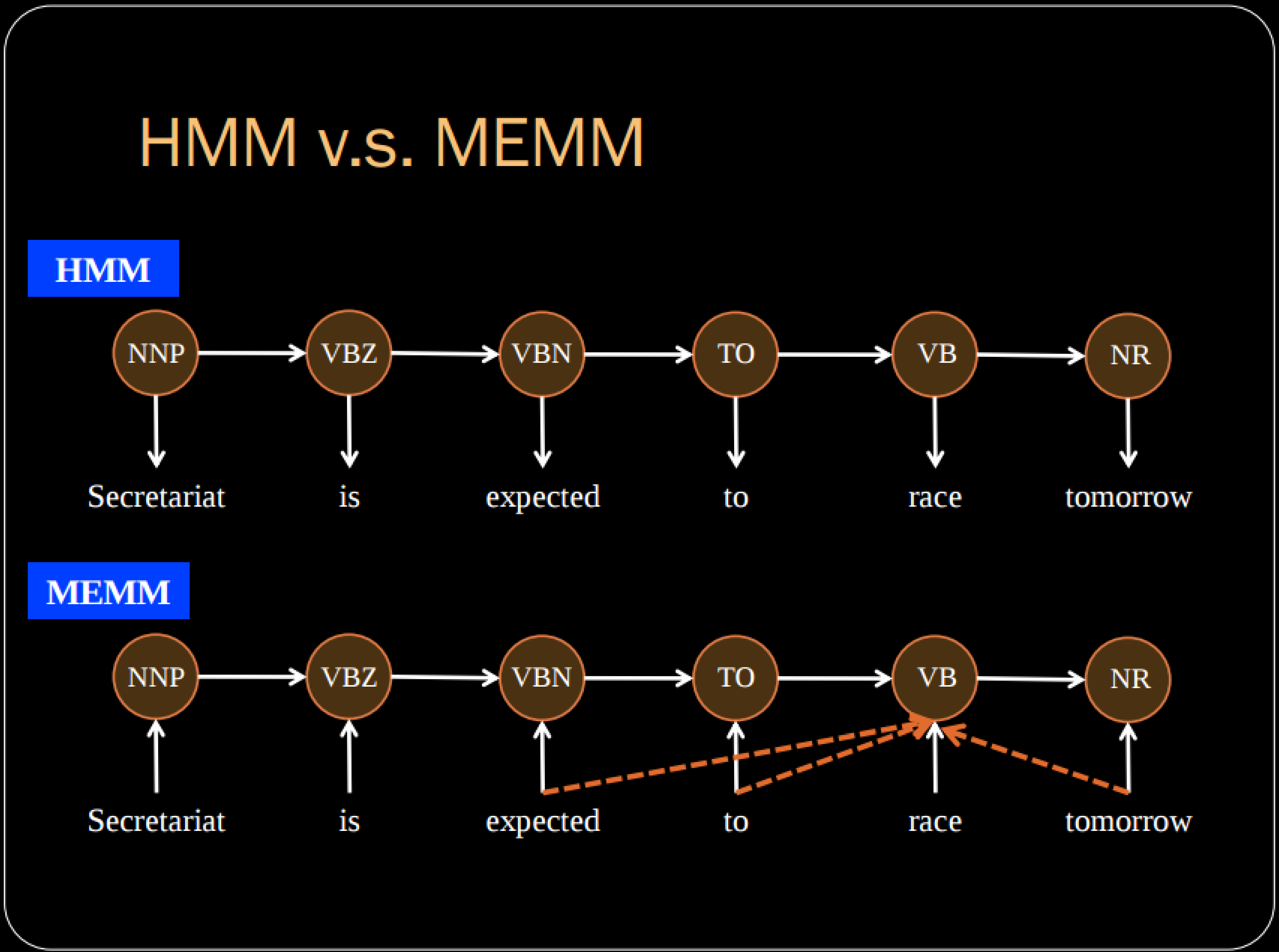
Beyond HMMs

- HMM: generative
  - States emit words
  - Joint probability: p(words, tags)
  - No long-distance features

- MEMM: discriminative
  - Words emit states
  - Conditional probability: p(tags | words)
  - Long distance features are a go

Beyond HMMs


HMM v.s. MEMM
HMM
NNP
VBZ
VBN
TO
VB
NR
Secretariat
is
expected
to
race
tomorrow
MEMM
NNP
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HMM, MEMM, CRF

- MEMM is a discriminative HMM
  - It chooses labels
- HMM and MEMM are similar
- Super-class of these: CRF
  - Conditional Random Fields
  - Plenty of software for these
  - Flexible!
- Kind of problems..?
- Bias..?

CRFsuite

- Let's do some PoS tagging!
- First step: get the tools
  - Data from website
  - CRFsuite
    - OSX:
      - Install Homebrew
      - brew tap homebrew/science
      - brew install crfsuite
    - Linux, Windows: binaries at http://www.chokkan.org/software/crfsuite/
- Second step: feature extraction
- Remaining steps: getting a good score

Feature extraction

- Data format is "CoNLL":
  - One example per line
  - Tab-separated
  - Reference label in the first position
  - Other columns are features

```
VB Have  prefix_Ha  suffix_ve  lower_have
DT a     prefix_a   suffix_a   lower_a
JJ Good  prefix_Go  suffix_od  lower_good
NN day   prefix_da  suffix_ay  lower_day
UH :)    prefix_:)  suffix_:)  lower_:)
```

- Sequences separated by a blank line

Write a feature extractor

- Read in examples, and convert to features
- Input is a label/data pair
- Write a feature extraction function
  - Prefix, suffix (what lengths?)
  - Lower case version
  - All numbers / uppercase / lowercase?
  - Is it a capital?
  - Is it a monetary amount?
- Output the data with features to a file

Learn and view a classifier

- crfsuite learn -h
- crfsuite learn -m my.model train.input
- crfsuite dump my.model | less

- You will see:
  - Transition probabilities
  - State probabilities

Test a classifier

- crfsuite tag -h
- Convert the evaluation data to features, too
- crfsuite tag -q -m my.model -t test.input

- How well did it do?
- Which tags are hardest?

Tuning the model

- With NER, we had three states; i.e. $\Lambda = \{$

  O (outside)

  B (begin)

  I (inside) $\}$

- $|\Lambda|^2 = 9$ transitions
- With PoS data, $|\Lambda|$ is often 11 – 60
- We won't see all the transitions!
  - crfsuite learn -m extra-transitions.model -p feature.possible_transitions=1 train.input
- Does this make a difference?

Too many features

- Many things will occur only once in the data
- The more features, the more likely this is to happen
- Low-frequency features can be distracting
  - Why?
- Trim them out!

Graphical models

1d: 1st-order Markov CRF wit

The 1st-order Markov CRF
combinations of attributes

feature.minfreq=VALUE
Cut-off threshold for
occurrences in the tr

Exercise

- Play with feature extraction, CRFsuite
- Keep a note of what you try and what works
- Write it up, and submit your feature extraction code and model
  - Describe what you tried and, if applicable, why

- Opportunities:
  - Google's Universal PoS tag set
  - Data for many languages
  - Suggests features

Reading

- http://universaldependencies.org/u/pos/
- Petrov, Das, McDonald; “A Universal Part-of-Speech Tagset” - Proc. LREC, 2012