

Maximum entropy sequence models

Maximum entropy Markov models (MEMMs) or Conditional Markov models



Sequence problems

- Many problems in NLP have data which is a sequence of characters, words, phrases, lines, or sentences ...
- We can think of our task as one of labeling each item

VBG	NN	IN	DT	NN	IN	NN
Chasing	opportunity	in	an	age	of	upheaval

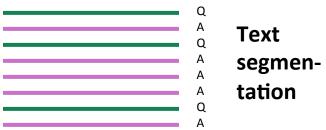
POS tagging

PERS	0	0	0	ORG	ORG
Murdoch	discusses	future	of	News	Corp.

Named entity recognition



Word segmentation





DT

The

NNP

Dow

MEMM inference in systems

- For a Conditional Markov Model (CMM) a.k.a. a Maximum Entropy
 Markov Model (MEMM), the classifier makes a single decision at a time,
 conditioned on evidence from observations and previous decisions
- A larger space of sequences is usually explored via search

???

%

Local Context Decision Point -3 -2 -1 0 +1

???

22.6

(Ratnaparkhi 1996; Toutanova et al. 2003, etc.)

VBD

fell

Features

W_0	22.6
W ₊₁	%
W ₋₁	fell
T ₋₁	VBD
T ₋₁ -T ₋₂	NNP-VBD
hasDigit?	true



Example: POS Tagging

- Scoring individual labeling decisions is no more complex than standard classification decisions
 - We have some assumed labels to use for prior positions
 - We use features of those and the observed data (which can include current, previous, and next words) to predict the current label

Decision Point

Local Context

-3	-2	-1	0	#1
DT	NNP	VBD	????	???
The	Dow	fell	22.6	%

(Ratnaparkhi 1996; Toutanova et al. 2003, etc.)

Features

W _o	22.6
W_{+1}	%
W ₋₁	fell
T ₋₁	VBD
T ₋₁ -T ₋₂	NNP-VBD
hasDigit?	true



Example: POS Tagging

- POS tagging Features can include:
 - Current, previous, next words in isolation or together.
 - Previous one, two, three tags.
 - Word-internal features: word types, suffixes, dashes, etc.

Decision Point

Local Context

-3	-2	-1	0	+1
DT	NNP	VBD	????	???
The	Dow	fell	22.6	%

(Ratnaparkhi 1996; Toutanova et al. 2003, etc.)

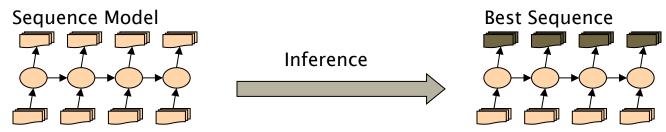
Features

W_0	22.6
W ₊₁	%
W ₋₁	fell
T ₋₁	VBD
T ₋₁ -T ₋₂	NNP-VBD
hasDigit?	true

Christopher Manning Inference in Systems Sequence Model Sequence Level Inference Sequence Data Local Level Classifier Type Label Label Feature Optimization Local Extraction Data **Smoothing Features** Features Maximum Entropy Conjugate Quadratic Models Gradient **Penalties**



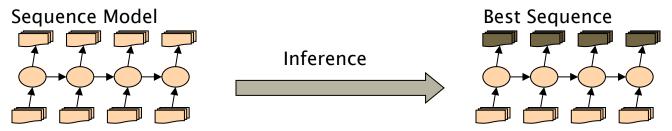
Greedy Inference



- Greedy inference:
 - We just start at the left, and use our classifier at each position to assign a label
 - The classifier can depend on previous labeling decisions as well as observed data
- Advantages:
 - Fast, no extra memory requirements
 - Very easy to implement
 - With rich features including observations to the right, it may perform quite well
- Disadvantage:
 - Greedy. We make commit errors we cannot recover from



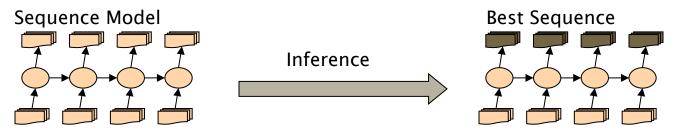
Beam Inference



- 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; beam sizes of 3-5 are 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 Inference



- 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).



CRFS [Lafferty, Pereira, and McCallum 2001]

- Another sequence model: Conditional Random Fields (CRFs)
- A whole-sequence conditional model rather than a chaining of local models.

$$P(c \mid d, \lambda) = \frac{\exp \sum_{i} \lambda_{i} f_{i}(c, d)}{\sum_{c'} \exp \sum_{i} \lambda_{i} f_{i}(c', d)}$$

- The space of c' s is now the space of sequences
 - But if the features f_i remain local, the conditional sequence likelihood can be calculated exactly using dynamic programming
- Training is slower, but CRFs avoid causal-competition biases
- These (or a variant using a max margin criterion) are seen as the state-of-theart these days ... but in practice usually work much the same as MEMMs.



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