Statistical Learning Models for Text and Graph Data Sequence Labeling and Structured Output Learning: HMM and Conditional Models and Local Classifiers

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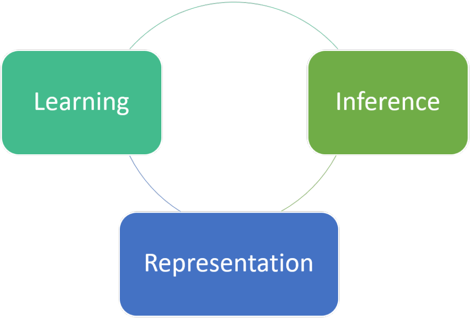
$*$Contents are based on materials created by Vivek Srikumar, Dan Roth, Xiaojin (Jerry) Zhu, Chris Manning

Reference Content

- Vivek Srikumar. CS 6355 Structured Prediction. https://svivek.com/teaching/structured-prediction/spring2018/
- Dan Roth. CS546: Machine Learning and Natural Language . http://l2r.cs.uiuc.edu/~danr/Teaching/CS546-16/
- Xiaojin (Jerry) Zhu. CS 769: Advanced Natural Language Processing. http://pages.cs.wisc.edu/~jerryzhu/cs769.html
- Chris Manning. CS 224N/Ling 237. Natural Language Processing. https://web.stanford.edu/class/cs224n/

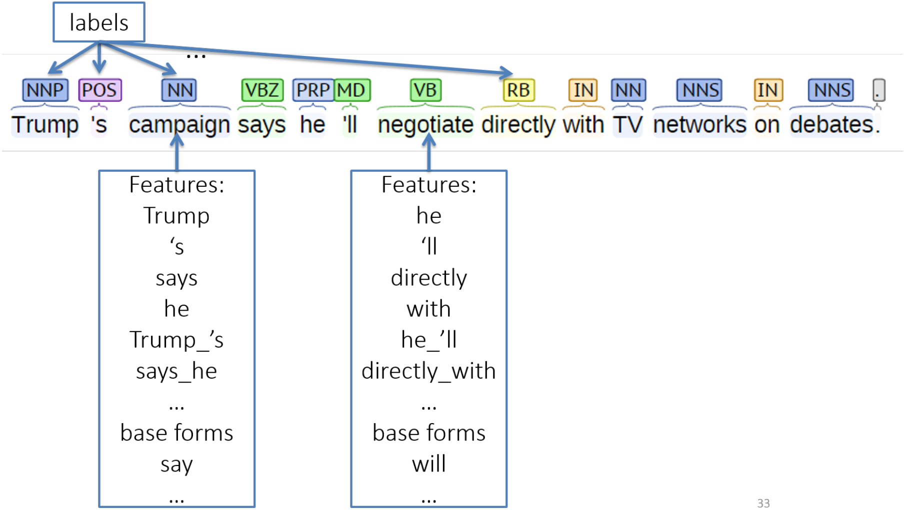
Course Topics



- Representation: language models, word embeddings, topic models, knowledge graphs
- Learning: supervised learning,unsupervised learning, semi-supervised learning, distant supervision, indirect supervision, sequence models, deep learning, optimization techniques
- Inference: constraint modeling, joint inference, search algorithms

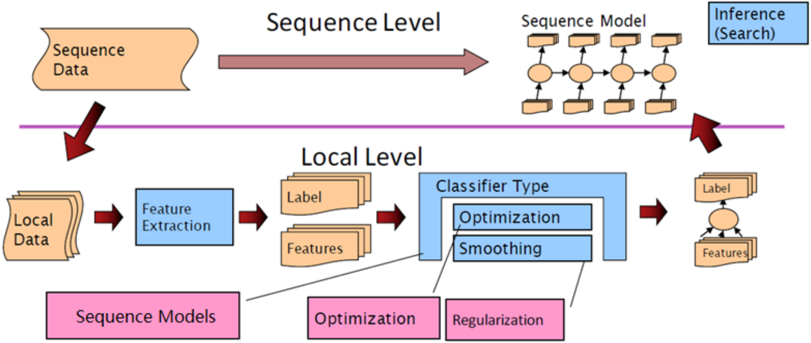
Overview

Classification Problem



The General Framework of Training and Testing

- Analogous to classification



Label and Feature Dependencies

- Current label may dependent on the previous one
  - Fed in "The Fed" is a Noun because it follows a Determiner
  - Fed in "I fed the.." is a Verb because it follows a Pronoun
- Sometimes more difficult: "I/PN can/MD can/VB a/DT can/NN."
- Two kinds of information incorporated in learning:
  - Some tag sequences are more likely than others. For instance, DT JJ NN is quite common, while DT JJ VBP is unlikely. ("a new book")
  - A word may have multiple possible POS, but some are more likely than others, e.g., "flour" is more often a noun than a verb
- The question is:
  - Given a word sequence

    $$\mathbf{x}_{1:N} \doteq \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N,$$

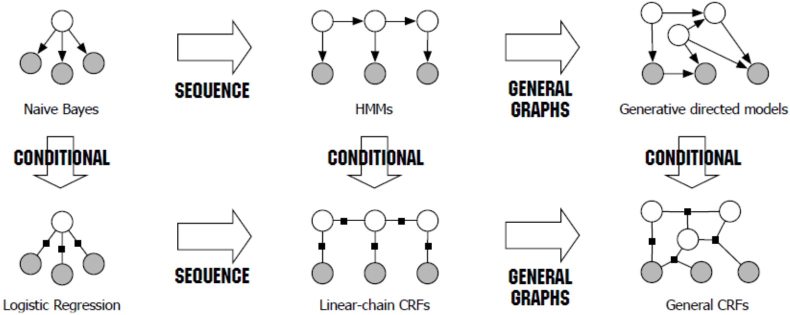
    how do we compute the most likely POS sequence

    $$y_{1:N} \doteq y_1, y_2, \ldots, y_N$$

  - One method is to use a Hidden Markov Model

Classifiers Feasible for Sequence Labeling

- Generative
  - Naive Bayes
  - Hidden Markov model (HMM)
- Discriminative models
  - Maximum entropy, logistic regression
  - Maximum Entropy Markov Model (MEMM)
  - Conditional random field (CRF)

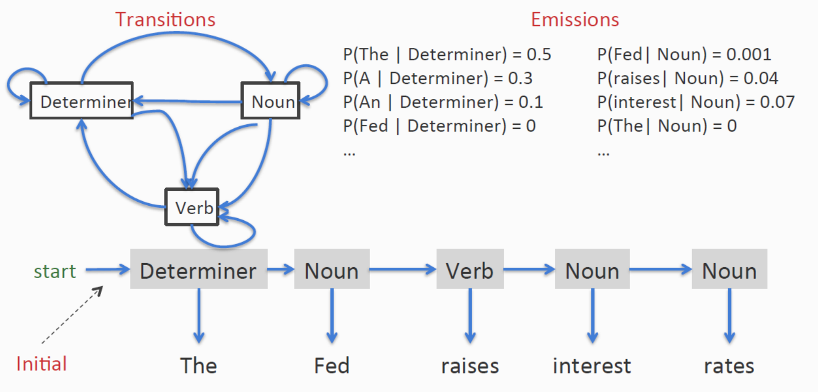


Hidden Markov Model

- Discrete Markov Model
  - States follow a Markov chain
  - Each state is an observation
- Hidden Markov Model
  - States follow a Markov chain
  - States are not observed
  - Each state stochastically emits an observation

A Toy Part-of-Speech Example

- Sentence "The Fed raises interest rates"



Most Likely State Sequence

- Input:
  - A hidden Markov model $\Theta = \{\boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\Phi}\}$
  - An observation sequence $\mathbf{x}_{1:N}$
- Output: A state sequence $y_{1:N}$ that corresponds to

$$\arg\max_{y_{1:N}} P(y_{1:N} | \mathbf{x}_{1:N}, \Theta)$$

  - This is maxinum a posteriori inference (MAP inference)
- Computationally a combinatorial optimization problem

MAP Inference

- We want $\arg\max_{y_{1:N}} P(y_{1:N}|\mathbf{x}_{1:N}, \Theta)$
- Note that $P(y_{1:N}|\mathbf{x}_{1:N}, \Theta) \propto P(y_{1:N}, \mathbf{x}_{1:N}|\Theta)$
  - And we don't care about $P(\mathbf{x}_{1:N})$ since we are maximizing over $y_{1:N}$
- So

$$\arg\max_{y_{1:N}} P(y_{1:N}|\mathbf{x}_{1:N}, \Theta) = \arg\max_{y_{1:N}} P(y_{1:N}, \mathbf{x}_{1:N}|\Theta)$$

- We have defined

$$P(\mathbf{x}_{1:N}, y_{1:N}|\Theta) = P(y_1|\boldsymbol{\pi})P(\mathbf{x}_1|y_1, \boldsymbol{\Phi}) \prod_{n=2}^{N} P(y_n|y_{n-1}, \mathbf{A})P(\mathbf{x}_n|y_n, \boldsymbol{\Phi})$$

- We omit the parameters for the ease of derivation

$$P(\mathbf{x}_{1:N}, y_{1:N}) = P(y_1)P(\mathbf{x}_1|y_1) \prod_{n=2}^{N} P(y_n|y_{n-1})P(\mathbf{x}_n|y_n)$$

How Many Possible Sequences?

The	Fed	raises	interest	rates
		List of allowed tags for each word		
Determiner	Verb Noun	Verb Noun	Verb Noun	Verb Noun
1	2	2	2	2

- In this simple case, we have 16 candidate sequences

$$(1 \times 2 \times 2 \times 2 \times 2)$$

How Many Possible Sequences?

- Output: one state per observation $y_n = s_k$

Observations	x_1	x_2	...	x_n
List of allowed states for each observation				
	s_1	s_1	...	s_1
	s_2	s_2		s_2
	s_3	s_2		s_3
	.	.		.
	.	.		.
	s_K	s_K		s_K

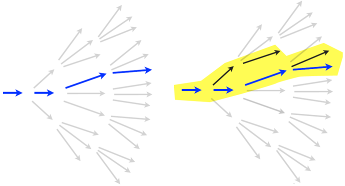
- We have K^n possible sequences to consider in $\arg\max_{y_{1:N}} P(y_{1:N}, \mathbf{x}_{1:N}|\Theta)$

Naive Approaches

- Try out every sequences
  - Score the sequence $y_{1:N}$ using $P(y_{1:N}, \mathbf{x}_{1:N} | \Theta)$
  - Return the highest scoring one
  - Correct but slow $O(K^N)$
- Greedy search
  - Construct the output left to right
  - For each n, elect the best y_n using y_{n-1} and $\mathbf{x}_n$
  - Incorrect but fast, $O(NK)$

Beam Search

- 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



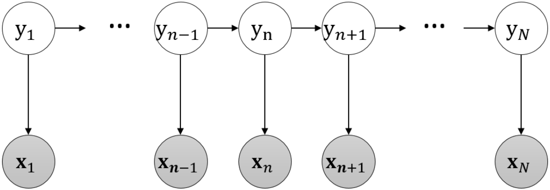
(a) Greedy (b) Beam Search

- 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

Optimal Solution: General Idea

- Dynamic programming
  - The best solution for the full problem relies on the best solution to the sub-problem
  - Memorize partial computation
- Examples
  - Viterbi algorithm
  - Dijkstra's shortest path algorithm
  - MDP value iteration
  - ...

Deriving the Recursion



$$\max_{y_{1:N}} P(\mathbf{x}_{1:N}, y_{1:N}) = \max_{y_{1:N}} P(y_1)P(\mathbf{x}_1|y_1)\prod_{n=1}^{N} P(y_n|y_{n-1})P(\mathbf{x}_n|y_n)$$

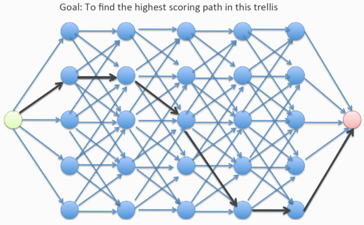
We reorganize it as

$$\max_{y_{1:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot P(\mathbf{x}_2|y_2)P(y_2|y_1) \cdot P(\mathbf{x}_1|y_1)P(y_1)$$

Deriving the Recursion

$$
\begin{aligned}
& \max_{y_{1:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot P(\mathbf{x}_2|y_2)P(y_2|y_1) \cdot P(\mathbf{x}_1|y_1)P(y_1) \\
= & \max_{y_{2:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot \max_{y_1} P(\mathbf{x}_2|y_2)P(y_2|y_1) \cdot P(\mathbf{x}_1|y_1)P(y_1) \\
= & \max_{y_{2:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot \max_{y_1} P(\mathbf{x}_2|y_2)P(y_2|y_1) \cdot score_1(y_1) \\
= & \max_{y_{3:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot \max_{y_2} P(\mathbf{x}_3|y_3)P(y_3|y_2) \\
& \cdot \max_{y_1} P(\mathbf{x}_2|y_2)P(y_2|y_1) \cdot score_1(y_1) \\
= & \max_{y_{3:N}} P(\mathbf{x}_N|y_N)P(y_N|y_{N-1}) \cdot \ldots \cdot \max_{y_2} P(\mathbf{x}_3|y_3)P(y_3|y_2) \cdot score_2(y_2) \\
= & \ldots \\
= & \max_{y_N} score_N(y_N)
\end{aligned}
$$

where we have $score_n(y_n) = \max_{y_{n-1}} P(y_n|y_{n-1})P(\mathbf{x}_n|y_n)score_{n-1}(y_{n-1})$



Complexity of Inference

- Complexity parameters
  - Input sequence length: N
  - Number of states: K
- Memory
  - Storing the table: NK (scores for all states at each position)
- Runtime
  - At each step, go over pairs of states
  - $O(NK^2)$

Summary of 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)

Summary

- Predicting sequences
  - As many output states as observations
- Markov assumption helps decompose the score
- Several algorithmic questions
  - Most likely state
  - Learning parameters: supervised, unsupervised (posterior, sum-product algorithm)
  - Probability of an observation sequence: sum over all assignments of states; replace max with sum in Viterbi
  - Inference: Viterbi (or max-product algorithm)

Outline

- Sequence Models
- Hidden Markov Models
  - Representation
  - Learning
  - Inference
- Conditional Models and Local Classifiers
- Global Models
  - Conditional Random Fields
  - Structured Perceptron for sequences
  - Structural SVM

Overview

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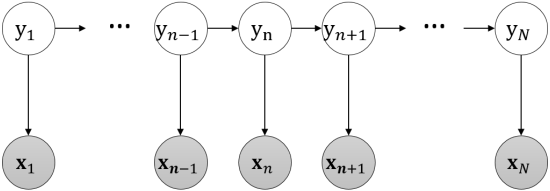
HMM Recap



- The joint probability is

$$P(\mathbf{x}_{1:N}, y_{1:N}|\Theta) = P(y_1|\boldsymbol{\pi})P(\mathbf{x}_1|y_1, \boldsymbol{\Phi}) \prod_{n=2}^{N} P(y_n|y_{n-1}, \mathbf{A})P(\mathbf{x}_n|y_n, \boldsymbol{\Phi})$$

- Training via maximum likelihood (supervised learning)

$$\Theta = \{\boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\Phi}\} = \arg\max_{\Theta} \prod_i P(\mathbf{x}^{(i)}_{1:N}, y^{(i)}_{1:N}|\Theta) = P(\mathbf{x}^{(i)}_{1:N}, y^{(i)}_{1:N}|\Theta)$$

where $\mathbf{x}^{(i)}_{1:N}, y^{(i)}_{1:N}$ is the i-th example (sequence)

HMM Recap

- In the training phase, we are optimizing joint likelihood of the input and the output for training

$$P(\mathbf{x}_{1:N}, y_{1:N}|\Theta)$$

- In the test phase, we are trying to find a state sequence $y_{1:N}$ that corresponds to

$$\arg\max_{y_{1:N}} P(y_{1:N}|\mathbf{x}_{1:N}, \Theta)$$

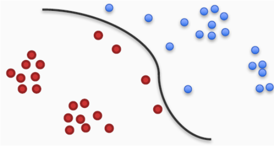
- Question:
  - Why not directly optimize this conditional likelihood instead in training phase?

Modeling Next-state Directly

- Instead of modeling the joint distribution $P(\mathbf{x}_{1:N}, y_{1:N})$, we only focus on $P(y_{1:N}|\mathbf{x}_{1:N})$
  - Which is what we care about eventually anyway
- For sequences, different formulations
  - Maximum Entropy Markov Model (McCallum et al. (2000))
  - Projection-based Markov Model (Punyakanok and Roth (2001))
  - Other names: discriminative/conditional Markov model, ...

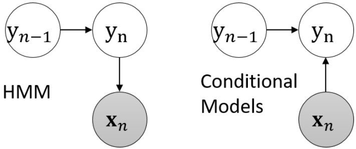
Generative vs Discriminative Models

- Generative models
  - Learn $P(\mathbf{x}, y)$
  - Characterize how the data is generated (both inputs and outputs)
  - E.g., Naive Bayes, Hidden Markov Model
- Discriminative models
  - Learn $P(y|\mathbf{x})$
  - Directly characterize the decision boundary only
  - E.g., Logistic Regression, Conditional models (several names)
- A generative model tries to characterize the distribution of the inputs, while a discriminative model doesn't care



Another Independence Assumption

$$P(y_n|y_{n-1}, y_{n-2}, \ldots, \mathbf{x}_n, \mathbf{x}_{n-1}, \mathbf{x}_{n-2}, \ldots) = P(y_n|y_{n-1}, \mathbf{x}_n)$$



- This assumption lets us write the conditional probability of the output as

$$P(y_{1:N}|\mathbf{x}_{1:N}) = \prod_n P(y_n|y_{n-1}, \mathbf{x}_n)$$

- Compared to HMM $P(y_{1:N}|\mathbf{x}_{1:N}, \Theta) \propto P(y_{1:N}, \mathbf{x}_{1:N}|\Theta)$
  - where we don't care about $P(\mathbf{x}_{1:N})$ since we are maximizing over $y_{1:N}$
  - We don't even need to model $P(\mathbf{x}_n|y_n)$ here
  - Very similar to logistic regression vs. naive Bayes

Modeling $P(y_n|y_{n-1}, \mathbf{x}_n)$

- Different approaches possible
  - Train a maximum entropy classifier
  - Or, ignore the fact that we are predicting a probability, we only care about maximizing some score. Train any classifier, using say the perceptron algorithm
- For both cases
  - Use rich features that depend on input and previous state
  - We can increase the dependency to arbitrary neighboring $\mathbf{x}_n$'s
    - E.g., Neighboring words influence this words POS tag

Overview

1. Hidden Markov Models
   - Representation
   - Learning
   - Inference
2. Conditional Models and Local Classifiers
   - Conditional Models for Predicting Sequences
   - Log-linear Models for Multiclass Classification
   - Maximum Entropy Markov Models
     - The Label Bias Problem

Detour: Log-linear Models for Multiclass

- Consider multiclass classification
  - Input: $\mathbf{x} \in \mathbb{R}^d$
  - Output: $y \in \{1, 2, \ldots, K\}$
  - Feature representation: $\phi(\mathbf{x}, y)$
    - We have seen this before
- Define probability of an input $\mathbf{x}$ taking a label y as

$$P(y|\mathbf{x}, \mathbf{w}) = \frac{\exp(\mathbf{w}^\top \phi(\mathbf{x}, y))}{\sum_{y'} \exp(\mathbf{w}^\top \phi(\mathbf{x}, y'))}$$

- A generalization of logistic regression to multiclass

Interpretation: Score for label, converted to a well-formed probability distribution by exponentiating + normalizing

Training a Log-linear Model

- Given a data set $\{\mathbf{x}^{(i)}, y^{(i)}\}$ (to be consistent here we use superscript to denote instance ids)
  - Apply the maximum likelihood principle

$$\max_{\mathbf{w}} \prod_i P(y^{(i)}|\mathbf{x}^{(i)}, \mathbf{w})$$

  where

$$P(y|\mathbf{x}, \mathbf{w}) = \frac{\exp(\mathbf{w}^\top \phi(\mathbf{x}, y))}{\sum_{y'} \exp(\mathbf{w}^\top \phi(\mathbf{x}, y'))}$$

  - With a regularizer

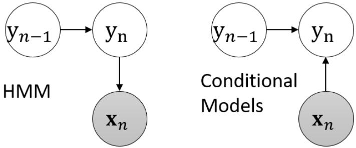
$$\max_{\mathbf{w}} -\frac{\lambda}{2}\mathbf{w}^\top \mathbf{w} + \sum_i \log P(y^{(i)}|\mathbf{x}^{(i)}, \mathbf{w})$$

- (Stochastic) gradient based methods to train $\mathbf{w}$
- Log-linear = Maximum Entropy distribution with feature constraints

Overview

The Next-state Model

$$P(y_n|y_{n-1}, y_{n-2}, \ldots, \mathbf{x}_n, \mathbf{x}_{n-1}, \mathbf{x}_{n-2}, \ldots) = P(y_n|y_{n-1}, \mathbf{x}_n)$$



- This assumption lets us write the conditional probability of the output as

$$P(y_{1:N}|\mathbf{x}_{1:N}) = \prod_n P(y_n|y_{n-1}, \mathbf{x}_n)$$

Modeling $P(y_n|y_{n-1}, \mathbf{x}_n)$

- Different approaches possible
  - Train a maximum entropy classifier
  - Or, ignore the fact that we are predicting a probability, we only care about maximizing some score. Train any classifier, using say the perceptron algorithm
- For both cases
  - Use rich features that depend on input and previous state
  - We can increase the dependency to arbitrary neighboring $\mathbf{x}_n$'s
    - E.g., Neighboring words influence this words POS tag

Modeling $\cancel{P(y_n|y_{n-1}, \mathbf{x}_n)}$ $P(y_n|y_{n-1}, \mathbf{x}_{1:N})$

- Different approaches possible
  - Train a maximum entropy classifier
    - Basically, a multinomial logistic regression
  - Or, ignore the fact that we are predicting a probability, we only care about maximizing some score. Train any classifier, using say the perceptron algorithm
- For both cases
  - Use rich features that depend on input and previous state
  - We can increase the dependency to arbitrary neighboring $\mathbf{x}_n$'s
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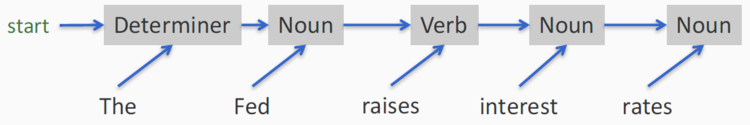
Maximum Entropy Markov Model (MEMM)

Goal: Compute $P(y_{1:N}|\mathbf{x}_{1:N}, \mathbf{w}) = \prod_n P(y_n|y_{n-1}, \mathbf{x}_{1:N})$ where

$$P(y_n|y_{n-1}, \mathbf{x}_{1:N}) \propto \exp\left(\mathbf{w}^\top \phi(\mathbf{x}, n, y_n, y_{n-1})\right)$$



The prediction task: Using the entire input and the current label, predict the next label

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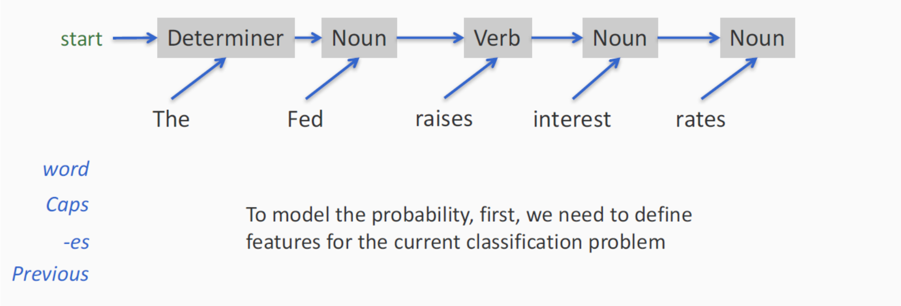

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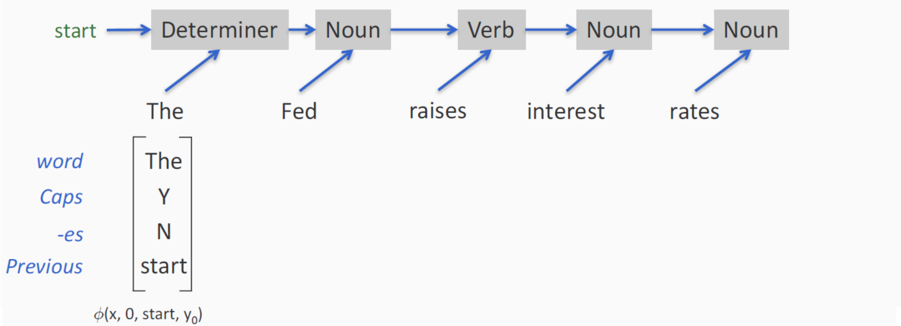

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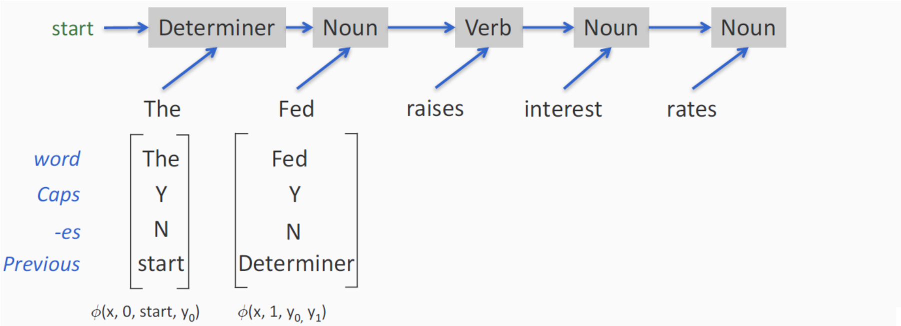

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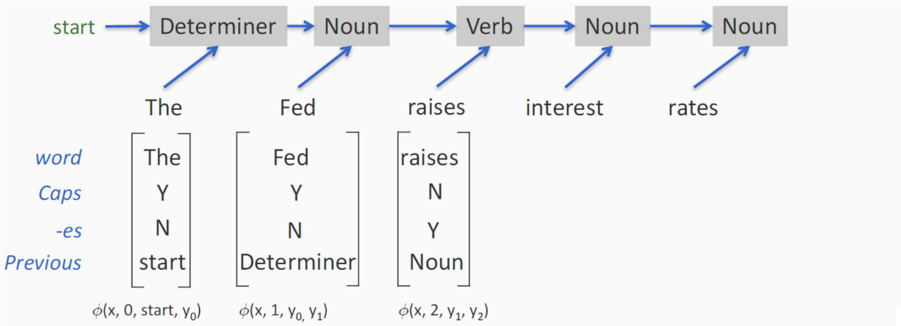

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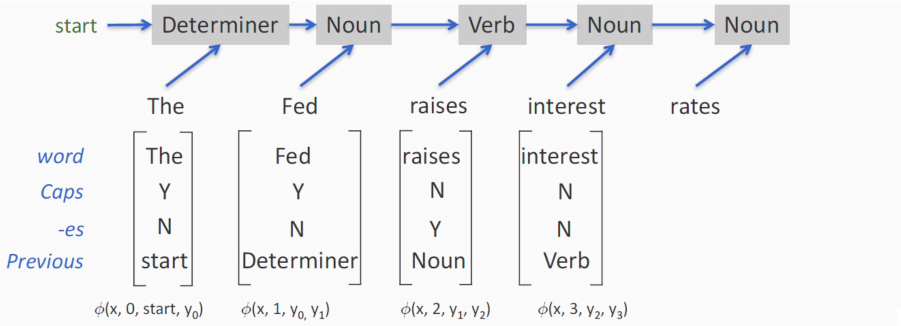

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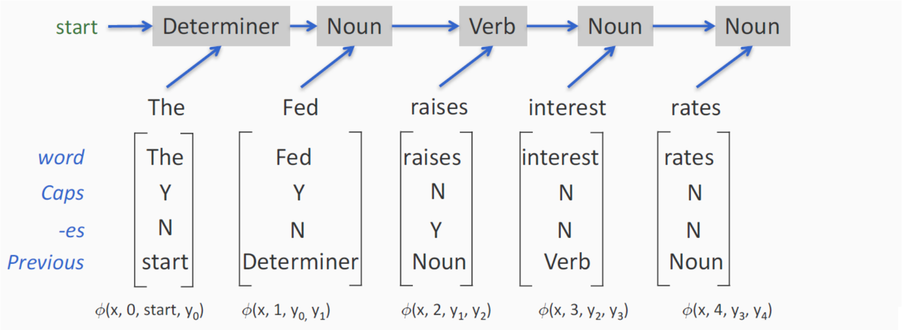

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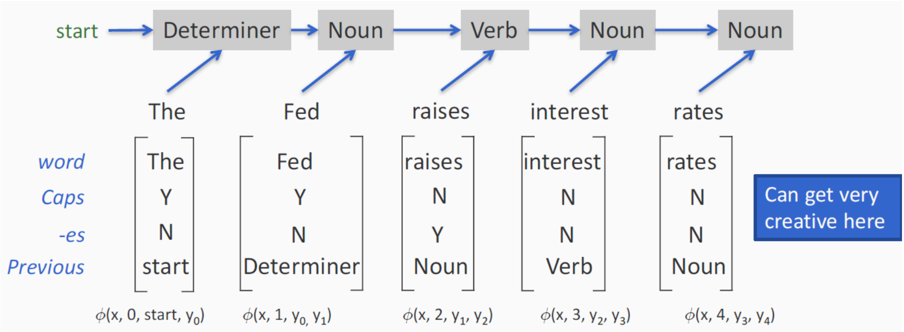
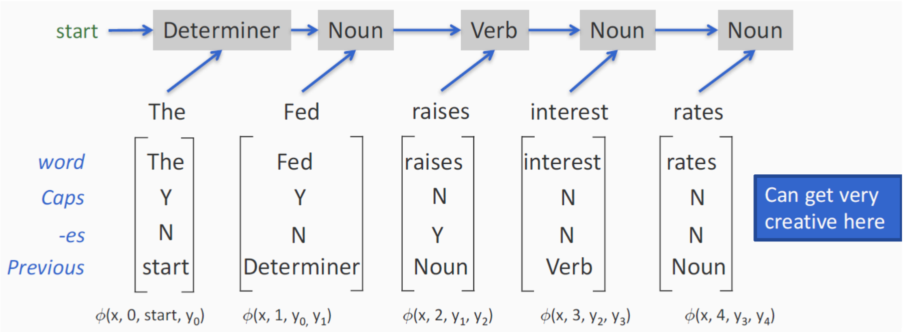
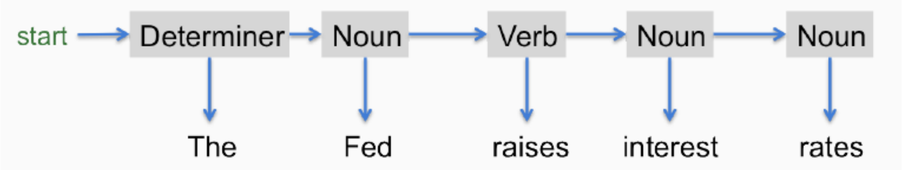


Compare MEMM and HMM

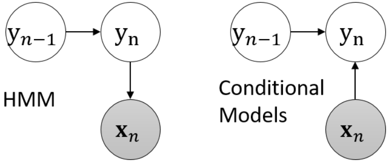


HMM: Only depends on the word and the previous tag



Using MEMM

- Training
  - Next-state predictor locally as maximum likelihood
  - Similar to any maximum entropy classifier
- Prediction/decoding
  - Modify the Viterbi algorithm for the new independence assumptions



  - In HMM, we use

$$score_n(y_n) = \max_{y_{n-1}} P(y_n|y_{n-1})P(\mathbf{x}_n|y_n)score_{n-1}(y_{n-1})$$

  - In MEMM, we use

$$score_n(y_n) = \max_{y_{n-1}} P(y_n|y_{n-1}, \mathbf{x}, n)score_{n-1}(y_{n-1})$$

Generalization: Any Multiclass Classifier

- Viterbi decoding: we only need a score for each decision
  - So far, probabilistic classifiers
- In general, use any learning algorithm to build get a score for the label y_n given y_{n-1} and $\mathbf{x}$
  - Multiclass versions of perceptron, SVM
  - Just like MEMM, these allow arbitrary features to be defined
- Viterbi needs to be re-defined to work with sum of scores rather than the product of probabilities

Comparison to HMM

What we gain

- Rich feature representation for inputs
    - Helps generalize better by thinking about properties of the input tokens rather than the entire tokens
    - E.g., If a word ends with es, it might be a present tense verb (such as raises). Could be a feature; HMM cannot capture this
- Discriminative predictor
    - Model $P(y|\mathbf{x})$ rather than $P(y, \mathbf{x})$
    - Joint vs conditional

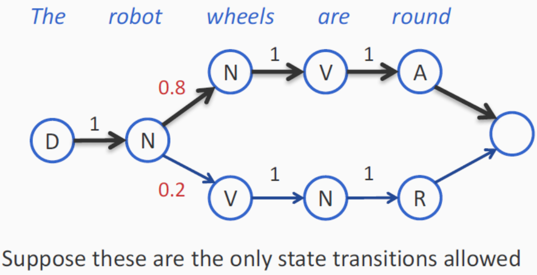
Overview

1. Hidden Markov Models
   - Representation
   - Learning
   - Inference
2. Conditional Models and Local Classifiers
   - Conditional Models for Predicting Sequences
   - Log-linear Models for Multiclass Classification
   - Maximum Entropy Markov Models
     - The Label Bias Problem

But ... Local Classifiers → Label Bias Problem

- Recall: the independence assumption ("Next-state" classifiers are locally normalized)

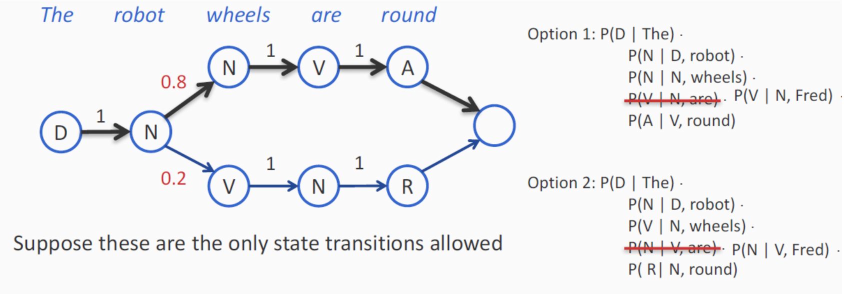
$$P(y_n|y_{n-1}, y_{n-2}, \ldots, \mathbf{x}_n, \mathbf{x}_n|y_{n-1}, \mathbf{x}_{n-2}, \ldots) = P(y_n|y_{n-1}, \mathbf{x}_n)$$



Option 1: P(D | The) ·
P(N | D, robot) ·
P(N | N, wheels) ·
P(V | N, are) ·
P(A | V, round)

Option 2: P(D | The) ·
P(N | D, robot) ·
P(V | N, wheels) ·
P(N | V, are) ·
P(R| N, round)

- The robot wheels Fred round



- The path scores are the same
- Even if the word Fred is never observed as a verb in the data, it will be predicted as one
- The input Fred does not influence the output at all

Label Bias

- States with a single outgoing transition effectively ignore their input
  - States with lower-entropy next states are less influenced by observations
- Why?
  - Because each the next-state classifiers are locally normalized
  - If a state has fewer next states, each of those will get a higher probability mass
    - and hence preferred
- Surprisingly doesn't affect some tasks
  - E.g., POS tagging

Summary: Local Models for Sequences

- Conditional models
- Use rich features in the mode
- Possibly suffer from label bias problem

References

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Punyakanok, V. and Roth, D. (2001). The use of classifiers in sequential inference. *CoRR*, cs.LG/0111003.