# Structured prediction

L101: Machine Learning for Language Processing

Andreas Vlachos

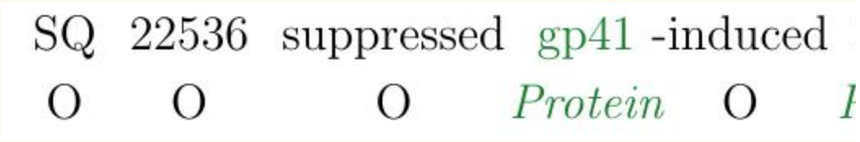
# Structured prediction in NLP?

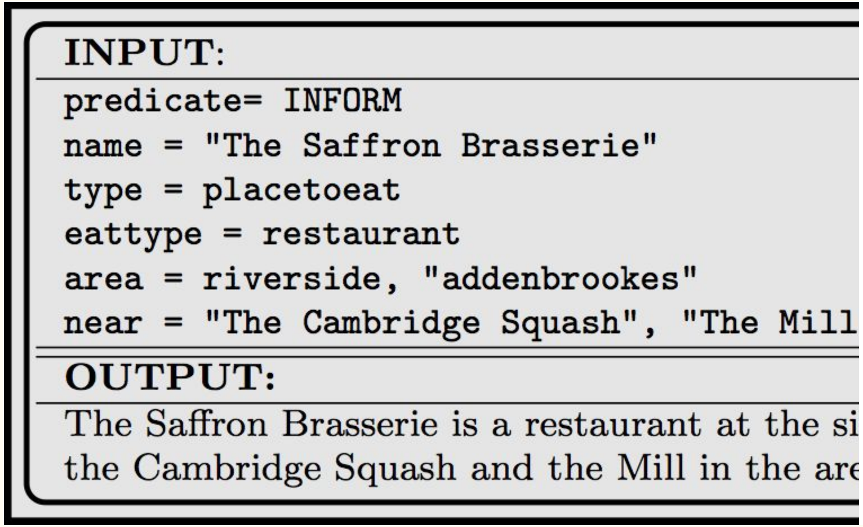
Given a piece of text, assign a *structured output*, typically a structure consisting of discrete labels

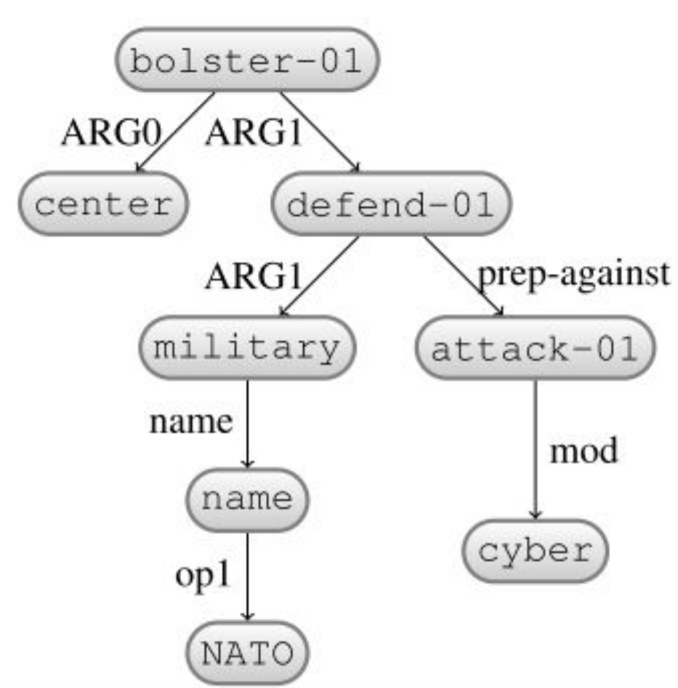
What could a structured output be?

- Sequence of part of speech tags
- Syntax tree
- SQL query
- Set of labels (a.ka. multi-label classification)
- Sequence of words (wait for the next lecture)
- etc.

# Structured prediction in NLP is everywhere




Sequences of labels, words and graphs combining them

# Structured prediction definition

Given an input ***x*** (e.g. a sentence) predict ***y*** (e.g. a PoS tag sequence):

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} score(x, y)$$

Where ***Y*** is rather large and often depends on the input (e.g. $\boldsymbol{L}^{|x|}$ in PoS tagging)

Is this large-scale classification?

- Yes, but with many, many classes
- Yes, but with classes not fixed in advance
- Yes, but with dependencies between parts of the output

Depending on how much the difference is, you might want to just classify

# Structured prediction variants

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} score(x, y)$$

Linear models (structured perceptron) $\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \Phi(x, y)$

Generative models (HMMs) $\hat{y} = \arg\max_{y \in \mathcal{Y}} P(x, y) = \arg\max_{y \in \mathcal{Y}} P(x|y)P(y)$

Discriminative probabilistic models (conditional random fields) $\hat{y} = \arg\max_{y \in \mathcal{Y}} P(y|x)$

Most of the above can use both linear and non-linear features, e.g. CRF-LSTMs

# Structured perceptron

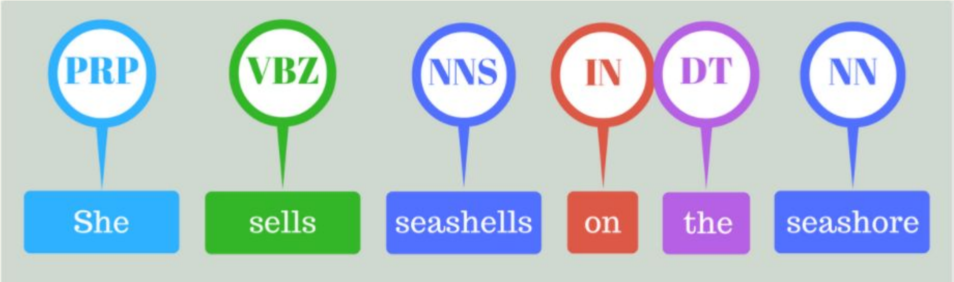
$$\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \Phi(x, y)$$

We need to learn ***w*** from training data

$$D = \{(x^1, y^1), \ldots (x^M, y^M)\}$$

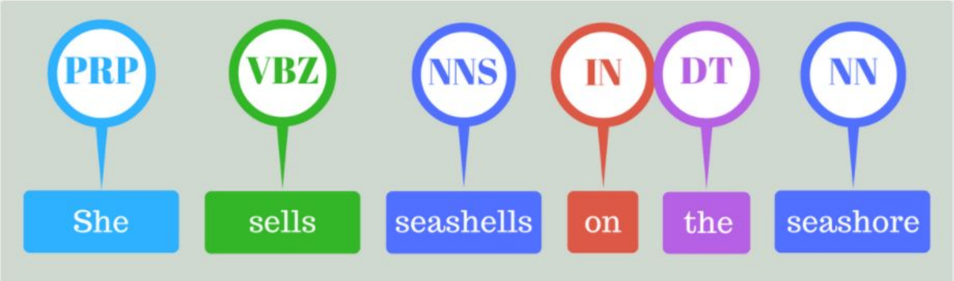
And define a joint feature map Φ***(x,y)***.

Ideas for PoS tagging?



# Structured perceptron features

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \Phi(x, y)$$




Two kinds of features:

- Features describing dependencies in the output (without these: classification)
- Features describing the match of the input to the output

Feature factorization, e.g. adjacent labels:

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \sum_i \phi(x, i, y_i, y_{i-1})$$

Does this restrict our modelling flexibility?

# Perceptron training (reminder)

**Input**: training examples $\mathcal{D} = \{(x^1, y^1), \ldots (x^M, y^M)\}$
Initialize weights $w = (0, ..., 0)$
**for** $(x, y) \in \mathcal{D}$ **do**
    Predict label $\hat{y} = sign(w \cdot \phi(x))$
    **if** $\hat{y} \neq y$ **then**
        Update $w = w + y\phi(x)$
    **end if**
**end for**

Learn compatibility between positive class and instance

# Structured Perceptron training (Collins, 2002)

**Input**: training examples $\mathcal{D} = \{(x^1, y^1), \ldots (x^M, y^M)\}$
Initialize weights $w = (0, \ldots, 0)$
**for** $(x, y) \in \mathcal{D}$ **do**
  Predict label $\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \Phi(x, y)$  Decoding
  **if** $\hat{y} \neq y$ **then**
    Update $w = w + \Phi(x, y) - \Phi(x, \hat{y})$  Feature differences
  **end if**
**end for**

Compatibility between input and output

Feature factorization accelerates both decoding and feature updating

Averaging helps

# Guess the features and weights (Xavier Carreras)

## Training Data

| PER | - | - |
|---|---|---|
| Maria | is | young |

| LOC | - | - |
|---|---|---|
| Athens | is | big |

| PER | - | - | LOC |
|---|---|---|---|
| Jack | went | to | Athens |

| LOC | - | - |
|---|---|---|
| Argentina | is | bigger |

| PER | PER | - | - | LOC | LOC |
|---|---|---|---|---|---|
| Jack | London | went | to | South | Pacific |

| ORG | - | - | ORG |
|---|---|---|---|
| Argentina | played | against | Chile |

# Some answers

## Training Data

- PER Maria, - is, - young
- LOC Athens, - is, - big
- PER Jack, - went, - to, LOC Athens
- LOC Argentina, - is, - bigger
- PER Jack, PER London, - went, - to, LOC South, LOC Pacific
- ORG Argentina, - played, - against, ORG Chile

## Weight Vector $\mathbf{w}$

$\mathbf{w}_{\langle \text{LOWER,-} \rangle} = +1$

$\cancel{\mathbf{w}_{\langle \text{UPPER,PER} \rangle} = +1}$

$\mathbf{w}_{\langle \text{UPPER,LOC} \rangle} = +1$

$\mathbf{w}_{\langle \text{WORD,PER,Maria} \rangle} = +2$

$\mathbf{w}_{\langle \text{WORD,PER,Jack} \rangle} = +2$

$\mathbf{w}_{\langle \text{NEXTW,PER,went} \rangle} = +2$

$\mathbf{w}_{\langle \text{NEXTW,ORG,played} \rangle} = +2$

$\mathbf{w}_{\langle \text{PREVW,ORG,against} \rangle} = +2$

$\ldots$

$\mathbf{w}_{\langle \text{UPPERBIGRAM,PER,PER} \rangle} = +100$

$\mathbf{w}_{\langle \text{UPPERBIGRAM,LOC,LOC} \rangle} = +100$

$\mathbf{w}_{\langle \text{UPPERBIGRAM,LOC,PER} \rangle} = -100$

$\mathbf{w}_{\langle \text{UPPERBIGRAM,PER,LOC} \rangle} = -100$

$\mathbf{w}_{\langle \text{NEXTW,LOC,played} \rangle} = -1000$

# Decoding

Assuming we have a trained model, decode/predict/solve the argmax/inference:

$$\hat{y} = \underset{y \in \mathcal{Y}}{\arg\max}\, score(x, y; \theta)$$

Isn't finding $\theta$ meant to be the slow part (training)?

Decoding is often necessary for training; you need to predict to update weights

Do you know a model where training is faster than decoding?

Hidden Markov Models! (especially if you don't do Viterbi)

Can be exact or inexact (to save computation)

# Dynamic programming

If we have a factorized the scoring function, we can reuse the scores (**optimal substructure** property), e.g.: $\hat{y} = \arg\max_{y \in \mathcal{Y}} w \cdot \sum_i \phi(x, i, y_i, y_{i-1})$

Thus changing one part of the output, doesn't change all/most scores

**Viterbi** recurrence:

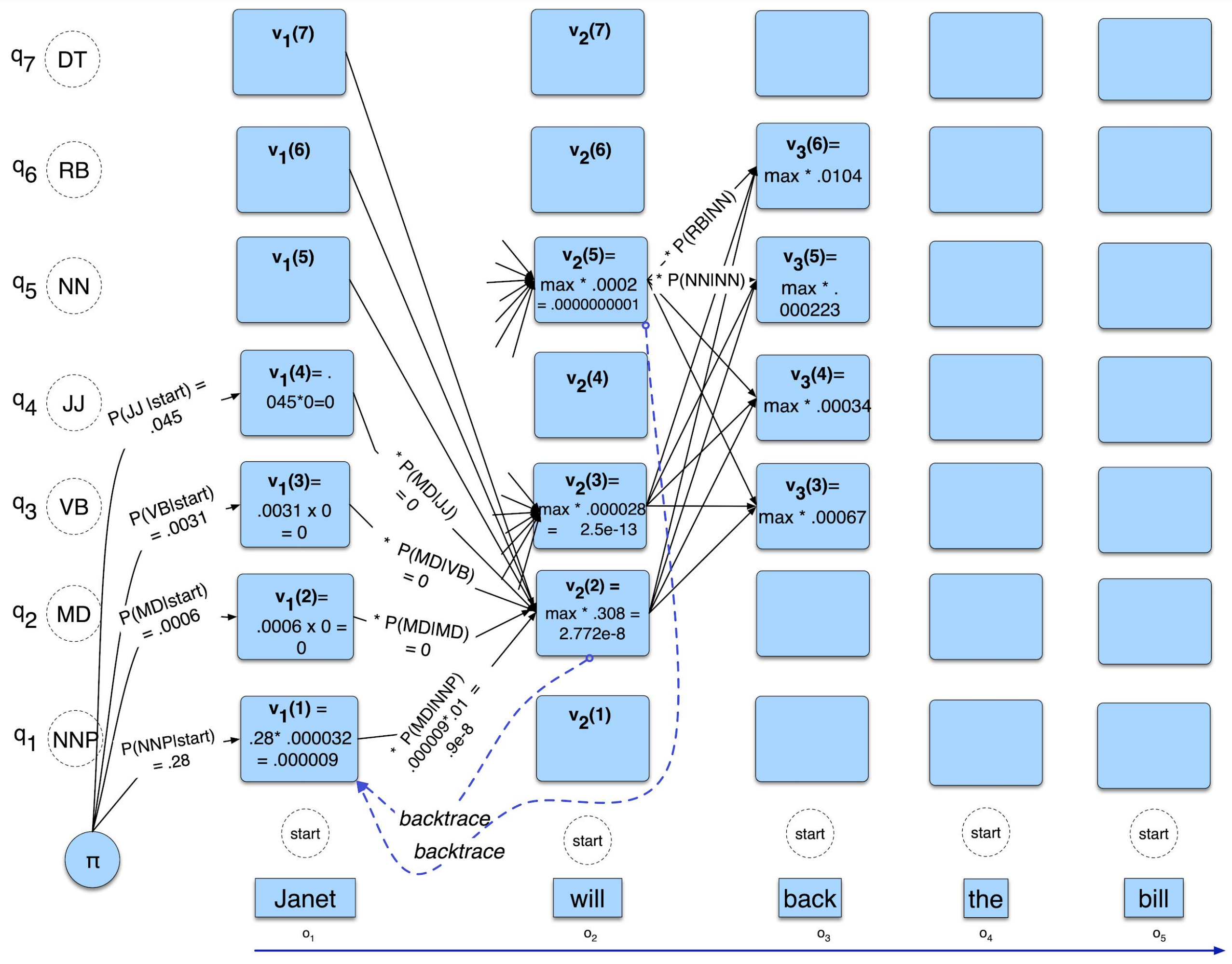
1. Assume we know for position $\boldsymbol{i}$ the best sequence ending with each possible $\boldsymbol{y_i}$
2. What is the best sequence up to position $\boldsymbol{i}$+1 for each possible $\boldsymbol{y_{i+1}}$?

An instance of shortest path finding in graphs

# Viterbi in action

Apart from the best scores (max), need to keep pointers to backtrace to the labels (argmax)

Higher than first order Markov assumption is possible, but more expensive




[Jurafksy and Martin]()

# Conditional random fields

Multinomial logistic regression reminder:

$$P(\hat{y} = y) = \frac{\exp(w_y \cdot \phi(x))}{\sum_{y' \in \mathcal{Y}} \exp(w_{y'} \cdot \phi(x))}$$

Conditional random field is a giant of the same type (softmax and linear scoring):

$$P(\hat{y} = y|x; w) = \frac{\exp(w \cdot \Phi(x, y))}{\sum_{y' \in \mathcal{Y}^{|x|}} \exp(w \cdot \Phi(x, y'))}$$

The denominator is independent of ***y***: needs to be calculated over all ***y***s!

Often referred to as the partition function

# Conditional random fields in practice

$$P(\hat{y} = y|x;w) = \frac{\exp(w \cdot \Phi(x,y))}{\sum_{y' \in \mathcal{Y}^{|x|}} \exp(w \cdot \Phi(x,y'))}$$

Factorize the scoring function:

$$w \cdot \Phi(x,y) = w \cdot \sum_i \phi(x, i, y_i, y_{i-1})$$

Dynamic programming to the rescue again: **forward-backward** algorithm

This allows us to train CRF by minimizing the convex negative log likelihood:

$$w^\star = \arg\min_w \sum_{(x,y)\in D} logP(y|x;w)$$

If you factorize the probability distribution: $P(\hat{y} = y|x;w) = \prod_{i=1}^{|x|} P(y_i|y_{i-1}, x; w)$

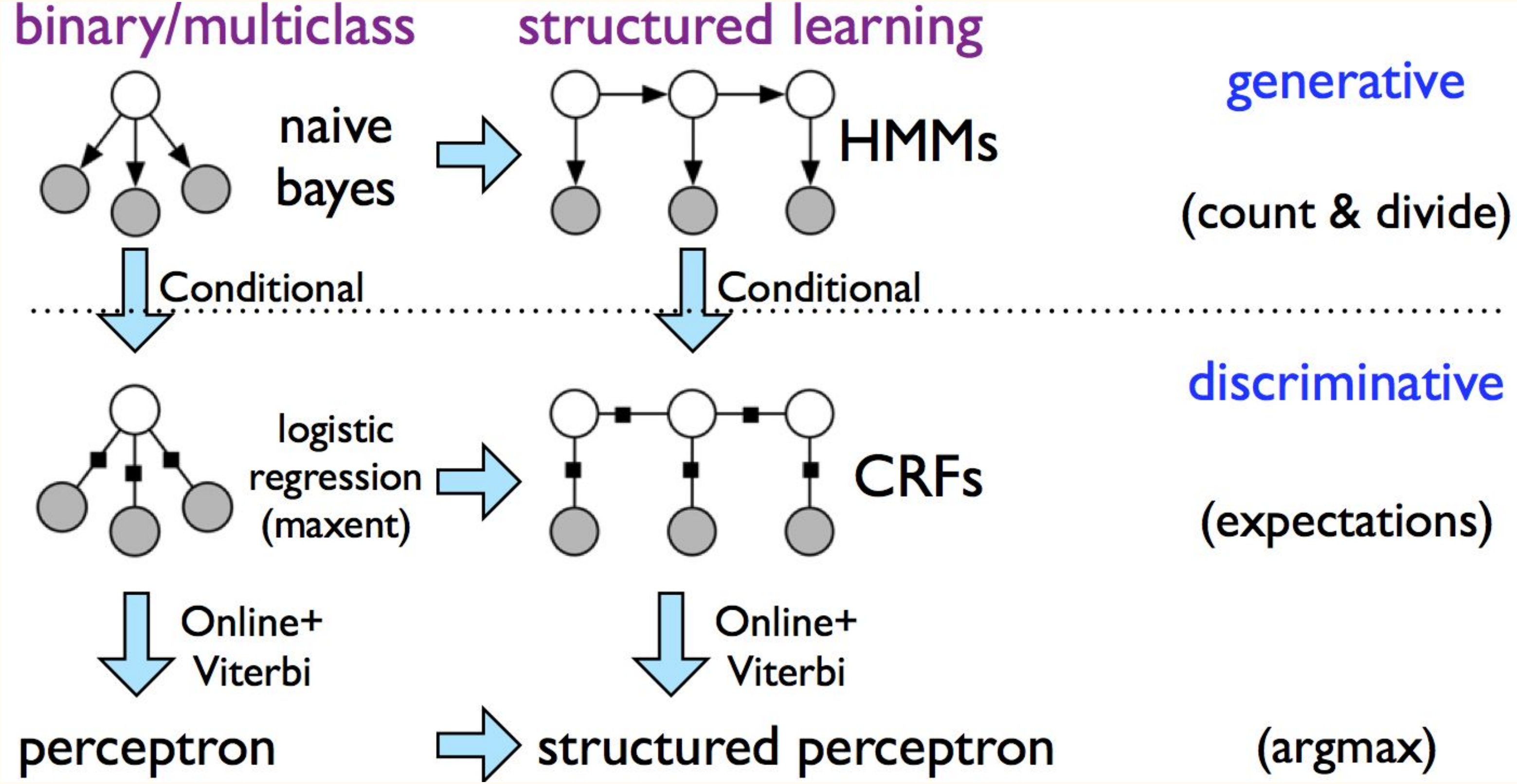
Maximum Entropy Markov Models: train logistic regression, Viterbi at inference

# An overview

Xavier Carreras
AthNLP2019

| Feature flexibility | input-output representation | Decoding | exact prediction? |
|---|---|---|---|
| classification — label classifiers | only individual labels | | yes |
| Lecture 7! — transition-based | full history of decisons | | no (greedy, beam search) |
| Most common — factored | label factors | | yes |
| Generalized binary classification — re-ranking | full | | limited to active set |

# Another overview!




[Sutton and McCallum (2011)]

# Things we didn’t cover

Latent variable structured prediction:

- Intermediate labels for which we don’t have annotation
- Can be thought of as hidden layers in NN (they are trained via “hallucinations”)

Constrained inference:

- Sometimes you can prune your search space (remove invalid outputs)
- Reduces the crude enumeration outputs but can make inference slower when using dynamic programming (e.g. here on enforcing valid syntax trees)
- Dual decomposition is often considered: split it into two (simpler) constrained inference problems and solve them to agreement

# Bibliography


- Noah Smith's book: good overview
- Sutton and McCallum (2011): everything you wanted to know about conditional random fields
- Xavier Carreras's AthNLP2019 slides and video
- Michael Collins's notes on HMMs and Viterbi
- A blog post on implementing Viterbi and CRFs on pytorch