# Language as a Sequence

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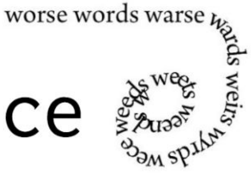
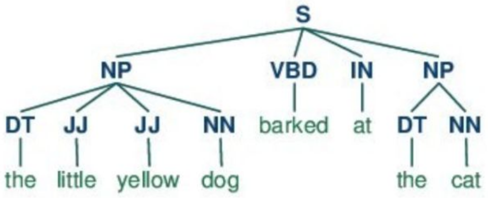
# NLP Viewpoints

* Bag-of-words

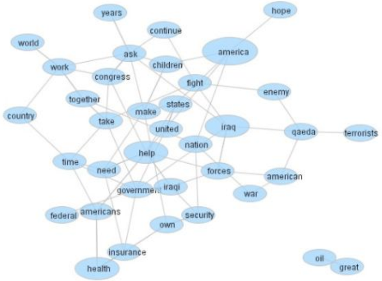
* Sequence


worse words warse wards weirs wyrds wece weeds weets weend ws

* Tree



* Graph



# Contents

1. Sequence labeling
2. Hidden Markov model
3. Logistic regression
4. Feature encoding
5. Conditional random fields
6. More about ngrams

# 1. Sequence Labeling

# Bag of words vs. sequence

Trump beat Clinton in the election.

= or ≠

Clinton beat Trump in the election.

# Sequence Labeling

Part-of-speech tagging:

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DT | NN | VBD | NNS | IN | DT | DT | NN | CC | DT | NN | . |
| The | pound | extended | losses | against | both | the | dollar | and | the | euro | . |

# Sequence Labeling

Named-entity recognition:

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| PER | O | PER | PER | PER | O | O | O | O | ORG | O |
| Fred | showed | Sue | Mengzui | Huang | ‘s | painting | in | the | Met | . |

# Sequence Labeling

Named-entity recognition:

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| B-PER | O | B-PER | B-PER | I-PER | O | O | O | O | B-ORG | O |
| Fred | showed | Sue | Mengzui | Huang | 's | painting | in | the | Met | . |

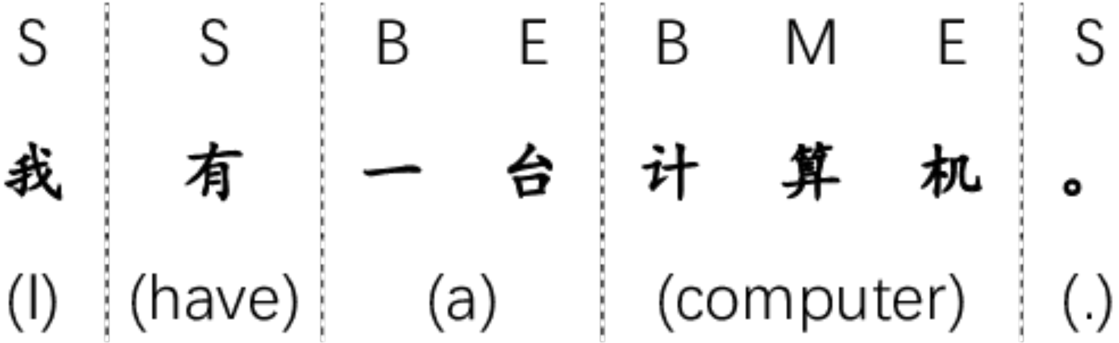
# Sequence Labeling

Error detection:

```
+  +     +   x        +    +       +    +     +     x       +
I  like  to  playing  the  guitar  and  sing  very  louder  .
```

# Sequence Labeling

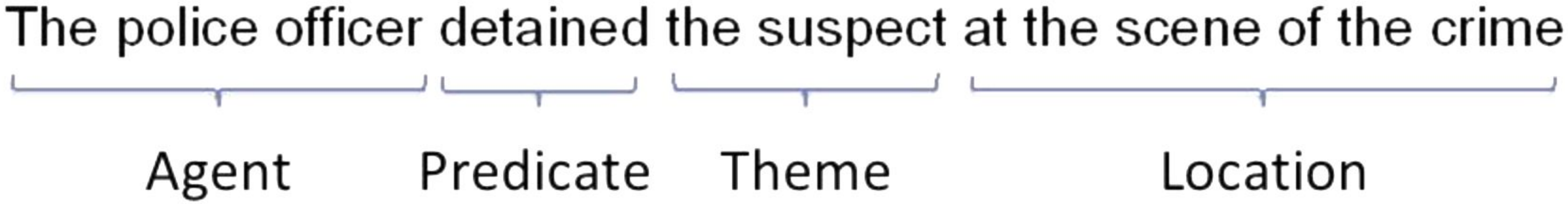
Word segmentation:



| | | | | | | | |
|---|---|---|---|---|---|---|---|
| S | S | B | E | B | M | E | S |
| 我 | 有 | 一 | 台 | 计 | 算 | 机 | 。 |
| (I) | (have) | (a) | | (computer) | | | (.) |

# Sequence Labeling

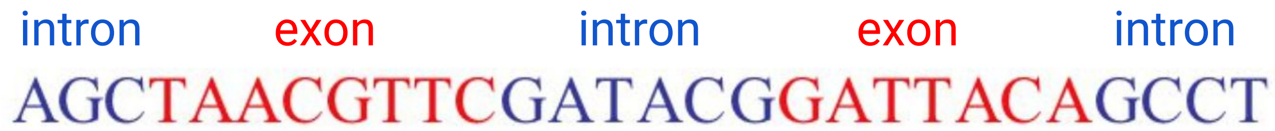
Semantic role labeling:



The police officer detained the suspect at the scene of the crime

# Sequence Labeling

Genome analysis:



intron exon intron exon intron

AGCTAACGTTCGATACGGATTACAGCCT

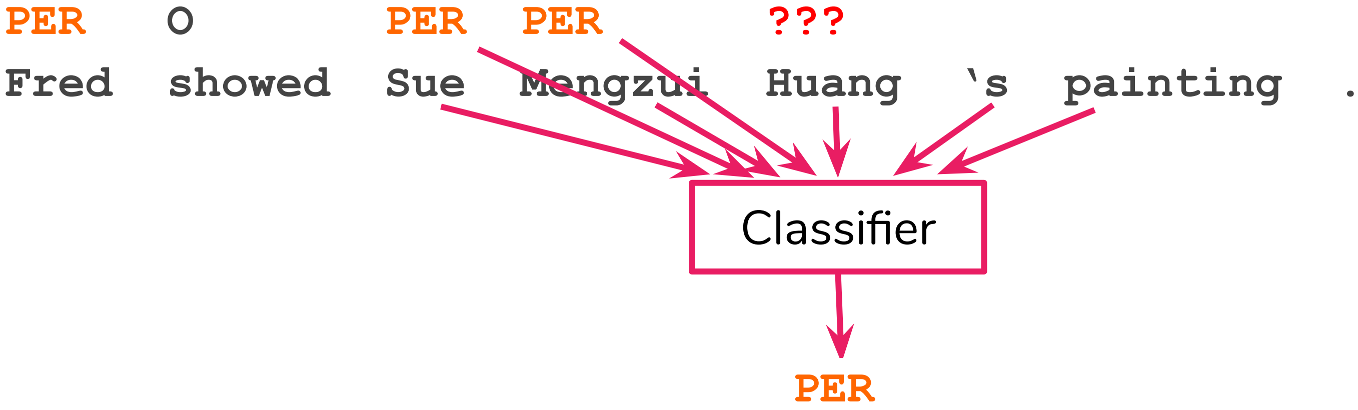
# Sequence Labeling

There’s more:

- dialogue act tagging
- lexical stress and pitch accent detection
- sentence segmentation
- chunking
- etc.

# Sequence Labeling

Sequence labeling is essentially a ***classification*** of each incoming element taking into account left and right context.



# Models for sequence labelling

- HMM - generative, classifies the whole sequence at once
  - $p(x, y)$
- MaxEnt - discriminative, classifies elements one by one
  - $p(y_i=1|x_i)$
- CRFs - discriminative, classifies the whole sequence at once
  - $p(y|x)$

# 2. Hidden Markov Model

# Hidden Markov Model

*HMM - a* ***generative*** *probabilistic sequence model used for:*

- *speech recognition*
- *segmentation (words, sentences, genomes)*
- *NER*
- *POS tagging*

# HMM for POS tagging

# HMM for POS tagging: notation

**V** - vocabulary

***T*** - POS tags

**x** - sentence (observation)

**y** - tag sequences (state)

**S** - all sentence/tag-sequence pairs $\{x_1 \ldots x_n, y_1 \ldots y_n\}$

- $n > 0$
- $x_i \in V$
- $y_i \in T$

# HMM for POS tagging: overview

**S** - all sentence/tag-sequence pairs $\{x_1 \ldots x_n, y_1 \ldots y_n\}$

| | | | | | | |
|---|---|---|---|---|---|---|
| **x:** | Chewie | , | we | 're | home | . |
| ***y*:** | NNP | , | PRP | VBP | RB | . |
| | NN | , | PRP | VBP | RB | . |
| | NNP | , | PRP | VBP | NN | . |
| | NN | , | PRP | VBP | NN | . |
| | … | | | | | |

**Aim:** find $\{x_1 \ldots x_n, y_1 \ldots y_n\}$ with the highest probability.

# Hidden Markov Model: assumptions

- Markov Assumption: "*The* ***future*** *is independent of the* ***past*** *given the* ***present***."
  - Trigram HMM: each state depends only on the previous two states in the sequence

- Independence assumption:
  - the state of $\mathbf{x}_i$ depends only on the value of $\mathbf{x}_i$, independent of the previous observations and states

# Hidden Markov Model: assumptions

**S** - all sentence/tag-sequence pairs $\{x_1 \ldots x_n, y_1 \ldots y_n\}$

| | | | | | | |
|---|---|---|---|---|---|---|
| **x:** | Chewie | , | we | 're | home | . |
| **y:** | NNP | , | PRP | VBP | ? | . |
| | … | | | | | |

# Trigram Hidden Markov Model: parameters

- q(s|u, v) - the probability of tag s after the tags (u, v)

$$q(s|u,v) = \frac{c(u,v,s)}{c(u,v)}$$

- e(x|s) - the probability of observation x paired with state s

$$e(x|s) = \frac{c(s \leadsto x)}{c(s)}$$

# Trigram Hidden Markov Model: parameters

$$p(x_1 \ldots x_n, y_1 \ldots y_{n+1}) = \prod_{i=1}^{n+1} q(y_i | y_{i-2}, y_{i-1}) \prod_{i=1}^{n} e(x_i | y_i)$$

# For example

| | | | | | | |
|---|---|---|---|---|---|---|
| x: | Chewie | , | we | 're | home | . |
| y: | *NNP* | *,* | *PRP* | *VBP* | *RB* | *.* |

**p(x, y)** = ?

# For example

| | | | | | | |
|---|---|---|---|---|---|---|
| x: | Chewie | , | we | 're | home | . |
| y: | NNP | , | PRP | VBP | RB | . |

**p(x, y)** = c(NNP,|,|,PRP) / c(NNP,|,|) * c(|,|,PRP, VBP) / c(|,|,PRP) *
c(PRP, VBP,RB) / c(PRP,VBP) * c(VBP,RB,|.|) / c(VBP,RB) * ...

# For example

| | | | | | | |
|---|---|---|---|---|---|---|
| x: | Chewie | , | we | 're | home | . |
| y: | NNP | , | PRP | VBP | RB | . |

**p(x, y)** = c(NNP,|,|,PRP) / c(NNP,|,|) * c(|,|,PRP, VBP) / c(|,|,PRP) *
c(PRP, VBP,RB) / c(PRP,VBP) * c(VBP,RB,|.|) / c(VBP,RB) *
c(NNP->Chewie) / c(NNP) * c(|,|->,) / c(|,|) *
c(PRP->we) / c(PRP) * c(VBP->’re) / c(VBP) *
c(RB->home) / c(RB) * c(|.|->.) / c(|.|)

# One thing missing

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| x: | | | Chewie | , | we | 're | home | . | |
| y: | <S> | <S> | NNP | , | PRP | VBP | RB | . | </S> |

**p(x, y)** = c(NNP,|,|,PRP) / c(NNP,|,|) * c(|,|,PRP, VBP) / c(|,|,PRP) *
c(PRP, VBP,RB) / c(PRP,VBP) * c(VBP,RB,|.|) / c(VBP,RB) *
c(<S>,<S>,NNP) / c(<S>,<S>) * c(<S>,NNP,|,|) / c(<S>,NNP) *
c(RB,|.|,</S>) / c(RB,|.|)* c(NNP->Chewie) / c(NNP) * c(|,|->,) / c(|,|) *
c(PRP->we) / c(PRP) * c(VBP->’re) / c(VBP) *
c(RB->home) / c(RB) * c(|.|->.) / c(|.|)

# HMM: problem 1

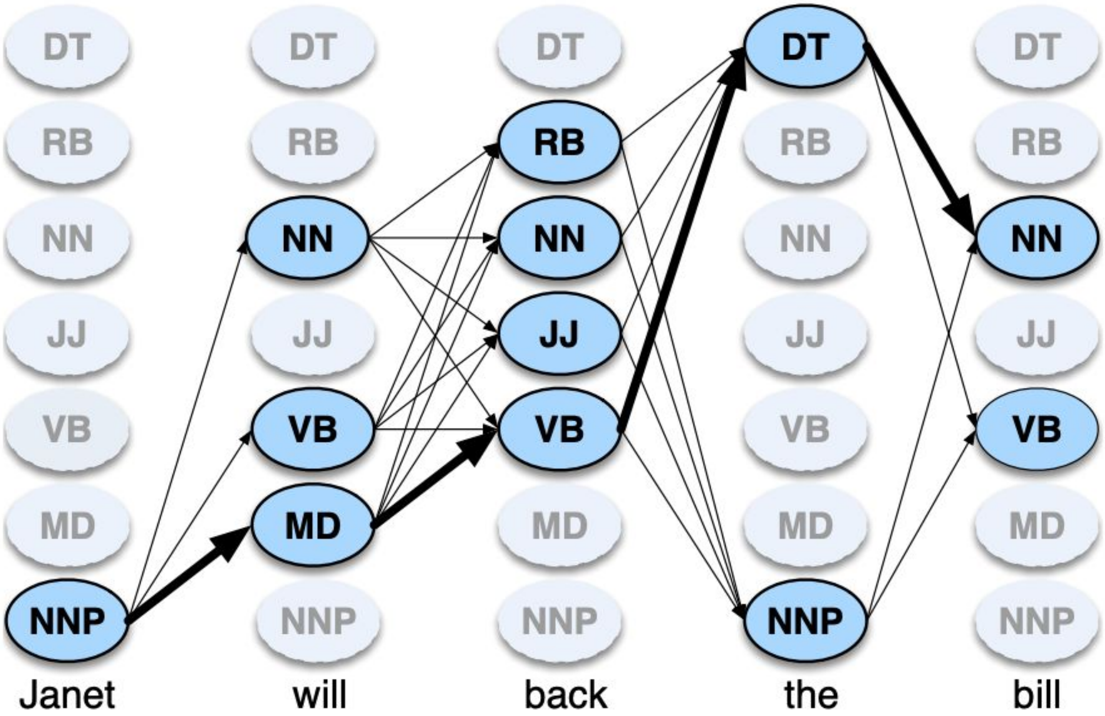
Enumerating all possible tag sequences is not feasible — $\boldsymbol{T^n}$.

44 tags ** 6-token sentence = 7,256,313,856 tag sequences

Solutions:

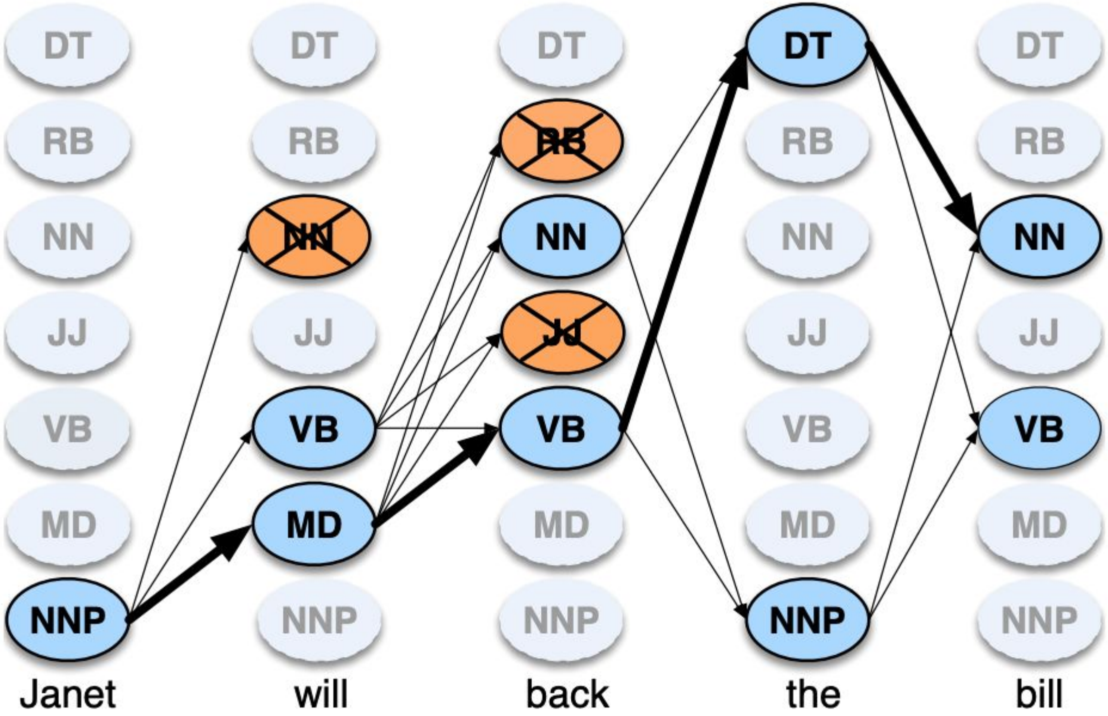
- use dynamic programming (the Viterbi algorithm) - $\boldsymbol{n*T^3}$
- limit the number of candidates with a dictionary - $\boldsymbol{n*8^3}$
- use beam search

# Viterbi algorithm



Borrowed from Dan Jurafsky: https://web.stanford.edu/~jurafsky/slp3/8.pdf

# Viterbi algorithm



Borrowed from Dan Jurafsky: https://web.stanford.edu/~jurafsky/slp3/8.pdf

# HMM: problem 2

Zero probabilities can occur because of OOV or rare words.

Solution: use *smoothing*

- ***add-1:*** pretend you saw each word (or each new word) one more time (also: **add-k**)
- ***Good-Turing:*** when the trigram count is near 0, rely on bigram
- ***Kneser-Ney:*** reallocate the probability of ngrams that occur *r+1* times to the ngrams that occur *r* times

# HMM: problem 3

Limited features taken into account:

- ***p(tag|word)*** could be informative
- incorporating lemmas, grammatical properties, spelling properties, etc. is hard

# HMM accuracy

- 96.7% for POS tagging of English
  - TnT tagger as tested on English and German
  - same quality as MaxEnt taggers but faster

# 3. Logistic Regression

# Logistic Regression

Logistic regression - a **discriminative** linear model used for binary classification.

- like Perceptron, it’s linear
- like NB, it extracts a set of weighted features, takes logs, and combines them linearly
- unlike NB, it’s discriminative

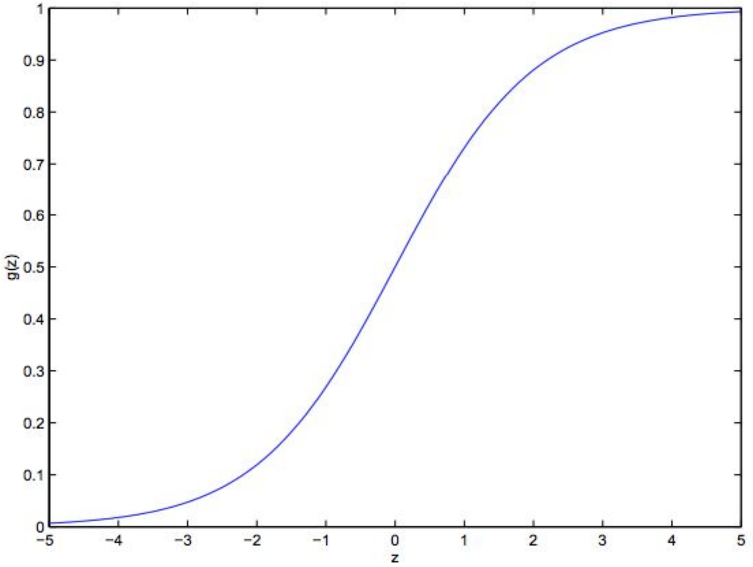
$$z = \left(\sum_{i=1}^{n} w_i x_i\right).$$

# Logistic Regression

A [0; 1] function would be handy: ***y* = 1** if ***p(y=1|x)* > 0.5**.

Sigmoid function:

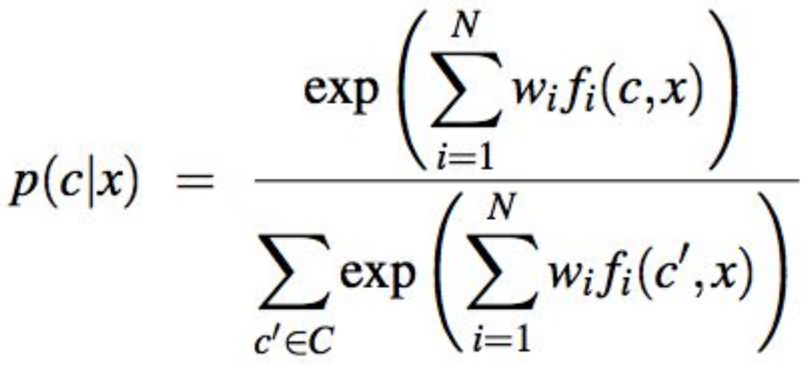
$$\begin{aligned} P(y=1) &= \sigma(w\cdot x+b) \\ &= \frac{1}{1+e^{-(w\cdot x+b)}} \end{aligned}$$



Borrowed from Andrew Ng: https://goo.gl/zGvb4W

# Logistic Regression

For multinomial logistic regression, use softmax:



$$p(c|x) = \frac{\exp\left(\sum_{i=1}^{N} w_i f_i(c,x)\right)}{\sum_{c' \in C} \exp\left(\sum_{i=1}^{N} w_i f_i(c',x)\right)}$$

# Logistic Regression: example

*Welcome to St . Paul ‘s Cathedral !*

[Is this period a sentence end?]

# Logistic Regression: example

Welcome to St . *Paul ‘s Cathedral !*

[Is this period a sentence end?]

**y**: *{is-end, is-not-end}*
**x**: {“w+1_is_cap”, “w+1=the”, “w-1=St”, “w-1=because”, “w-1_is_digit”}

# Logistic Regression: example

Welcome to St . Paul ‘s Cathedral !

[Is this period a sentence end?]

**y**: *{is-end, is-not-end}*
**x**: *{“w+1_is_cap”, “w+1=the”, “w-1=St”, “w-1=because”, “w-1_is_digit”}*

$\mathbf{x}_j$: *[1, 0, 1, 0, 0]*

# Logistic Regression: example

Welcome to St . *Paul* ‘s Cathedral !

[Is this period a sentence end?]

$\mathbf{y}$: *{is-end, is-not-end}*
$\mathbf{x}$: *{“w+1_is_cap”, “w+1=the”, “w-1=St”, “w-1=because”, “w-1_is_digit”}*

$\mathbf{x}_j$: *[1, 0, 1, 0, 0]*

$\mathbf{w}_{\text{is-end}}$: *[2.9, 0.6, -0.9, -1.3, 0]*
$\mathbf{w}_{\text{is-not-end}}$: *[0.5, 0.3, 2.9, 2.5, 1.7]*

# Logistic Regression: example

Welcome to St . Paul ‘s Cathedral !

[Is this period a sentence end?]

**y**: *{is-end, is-not-end}*
**x**: *{“w+1_is_cap”, “w+1=the”, “w-1=St”, “w-1=because”, “w-1_is_digit”}*

$\mathbf{x}_j$: *[1, 0, 1, 0, 0]*

$\mathbf{w}_{\textit{is-end}}$: [2.9, 0.6, -0.9, -1.3, 0]
$\mathbf{w}_{\textit{is-not-end}}$: [0.5, 0.3, 2.9, 2.5, 1.7]

$\mathbf{P(\textit{is-end}|x_j)} = e^{2.9-0.9} / (e^{2.9-0.9} + e^{0.5+2.9}) = 0.2$
$\mathbf{P(\textit{is-not-end}|x_j)} = e^{0.5+2.9} / (e^{2.9-0.9} + e^{0.5+2.9}) = 0.8$

# Logistic Regression: weights

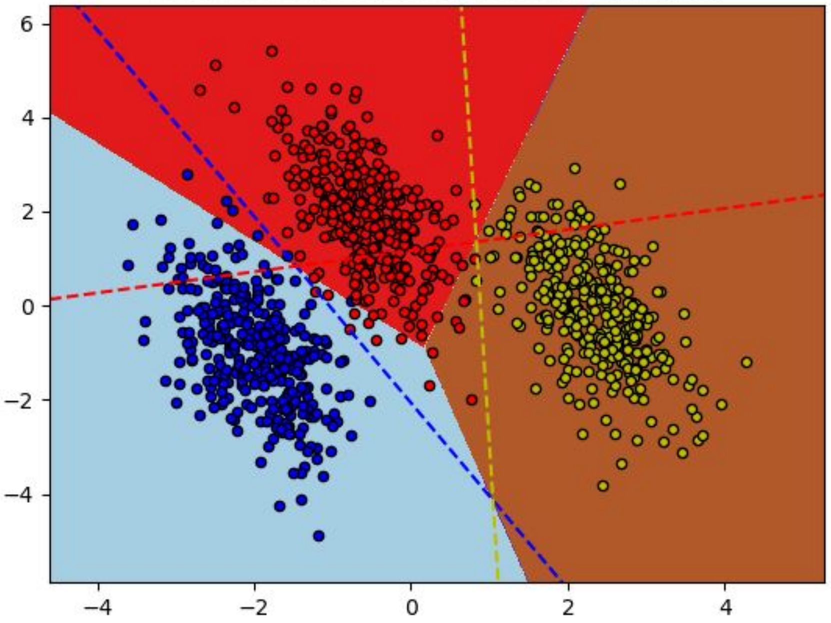
Learn weights:

- start with a vector of zeros or a random vector
- move towards the gradient
- to maximize the probability / minimize the loss function

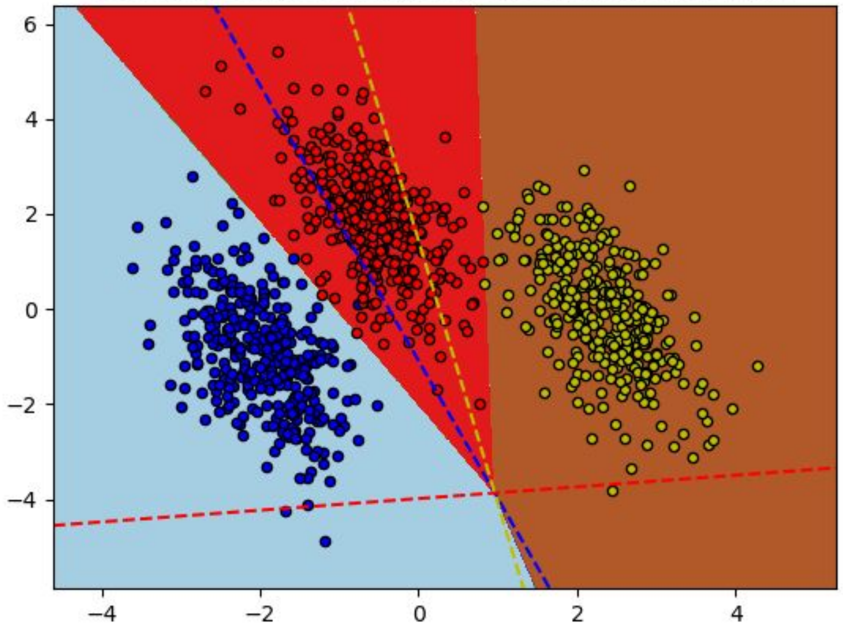
$$\hat{w} = \underset{w}{\operatorname{argmax}} \sum_{j} \log P(y^{(j)} | x^{(j)})$$

# Logistic Regression: multiclass and multilabel

one vs. rest



multinomial (MaxEnt)



http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_multinomial.html

# Multilabel classification

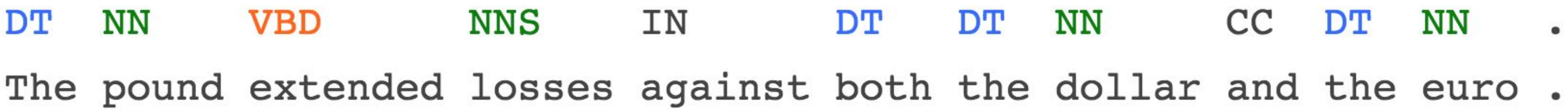
- Toxic Comment Classification
    - toxic
    - severe_toxic
    - obscene
    - threat
    - insult
    - identity_hate

# Multilabel classification

- Predicting movie genres
- Assignment of ICD-9-CM codes to radiology reports
- Sentiment or emotion analysis
- User reaction analysis
- Prediction of tags for blogs or news
- Any text classification by topic

# 4. Feature Encoding

# Encode neighbors: feature template



| DT | NN | VBD | NNS | IN | DT | DT | NN | CC | DT | NN | . |
|---|---|---|---|---|---|---|---|---|---|---|---|
| The | pound | extended | losses | against | both | the | dollar | and | the | euro | . |

**x: “losses”, y: NNS**

{“word-2”: “pound”,
 “word-1”: “extended”,
 “word+1”: “against”,
 “word+2”: “both”,

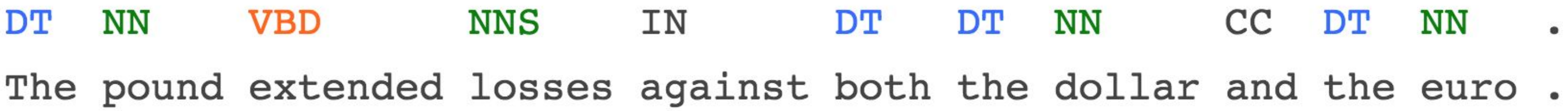
“tag-2”: “NN”,
“tag-1”: “VBD”}

# Encode neighbors: feature template

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DT | NN | VBD | NNS | IN | DT | DT | NN | CC | DT | NN | . |
| The | pound | extended | losses | against | both | the | dollar | and | the | euro | . |

| | | | | |
|---|---|---|---|---|
| *[* | *1,* | *1,* | *0,* | *...]* |
| | word-2=pound | word-1=extended | word+1=hello | |

# Encode neighbors: feature template

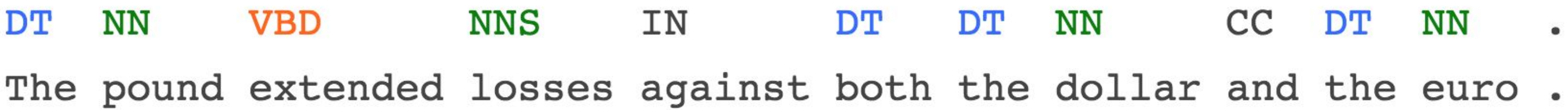


| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DT | NN | VBD | NNS | IN | DT | DT | NN | CC | DT | NN | . |
| The | pound | extended | losses | against | both | the | dollar | and | the | euro | . |

**x: “losses”, y: NNS**

{“wt-2”: “pound_NN”,
“wt-1”: “extended_VBD”,
“w+1”: “against”,
“w+2”: “both”}

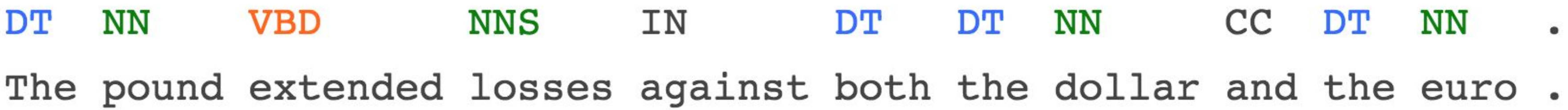
# What tag to use?



```
DT  NN    VBD      NNS    IN      DT   DT  NN     CC  DT  NN   .
The pound extended losses against both the dollar and the euro .
```

- *gold or predicted?*

# Encode context (ngrams)

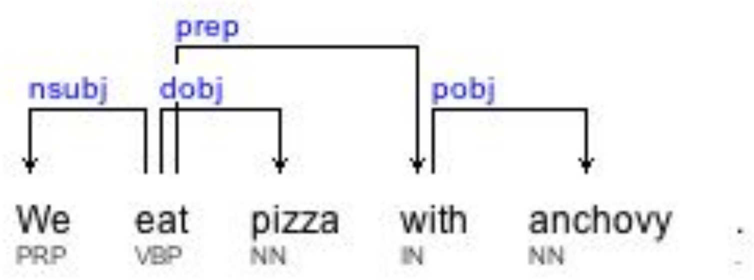


| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DT | NN | VBD | NNS | IN | DT | DT | NN | CC | DT | NN | . |
| The | pound | extended | losses | against | both | the | dollar | and | the | euro | . |

**x: “losses”, y: NNS**

*{“left-bigram”: “pound extended”,*
*“right-bigram”: “against both”,*
*“context”: “extended losses against both”}*

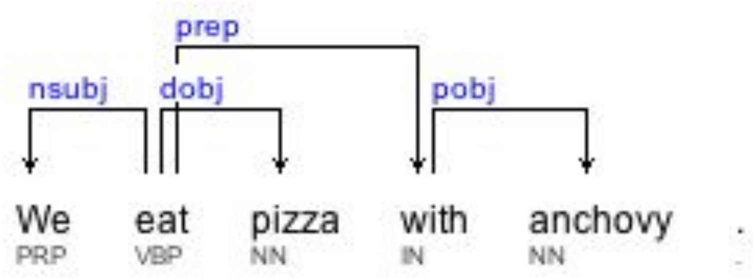
# Encode dependencies



**“eat”/VBP:**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *[ 1,* | *0,* | *0,* | *1,* | *0,* | *1,* | *0,* | *0,* | *…]* |
| *nsubj* | *acl* | *relcl* | *dobj* | *pobj* | *prep* | *punct* | *xcomp* | |

# Encode dependencies



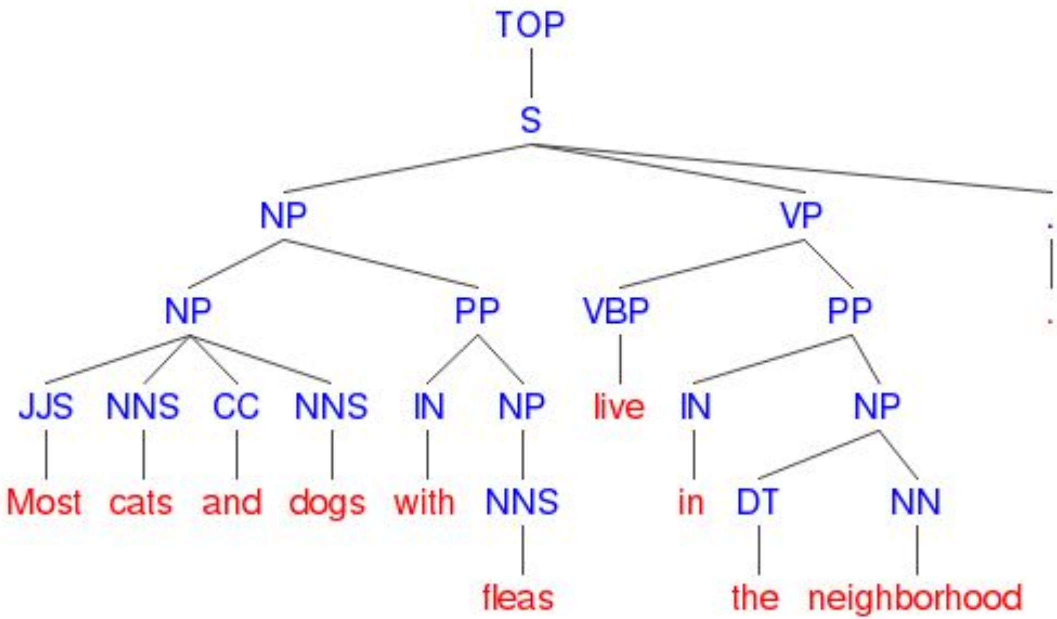
**“eat”/VBP:**

- *nsubj_We, dobj_pizza, prep_with*
- *nsubj_PRP, dobj_NN, prep_IN*
- *nsubj_We, dobj_pizza, prep_with_pobj_anchovy*

# Encode constituents

**“fleas”/NNS:**

{*“label”: “NP”,*
 *“anc-left”: ”PP”,*
 *“anc-right”: ”S”,*
 *“span-start”: 5,*
 *“span-end”: 6}*



# More features

- *capitalized?*
- *hyphenated?*
- *compound?*
- *lemma*
- *sense id*
- *number of senses in WordNet*
- *is in X dictionary*
- *has X as a synonym*
- …

# More features

- affixes
- coreference
- sentiment
- grammatical characteristics of various parts of speech:
    - countability of nouns
    - tense of verbs
    - degree of comparison of adjectives
    - pronoun type
    - conjunction type

# 5. Conditional Random Fields

# Conditional Random Fields

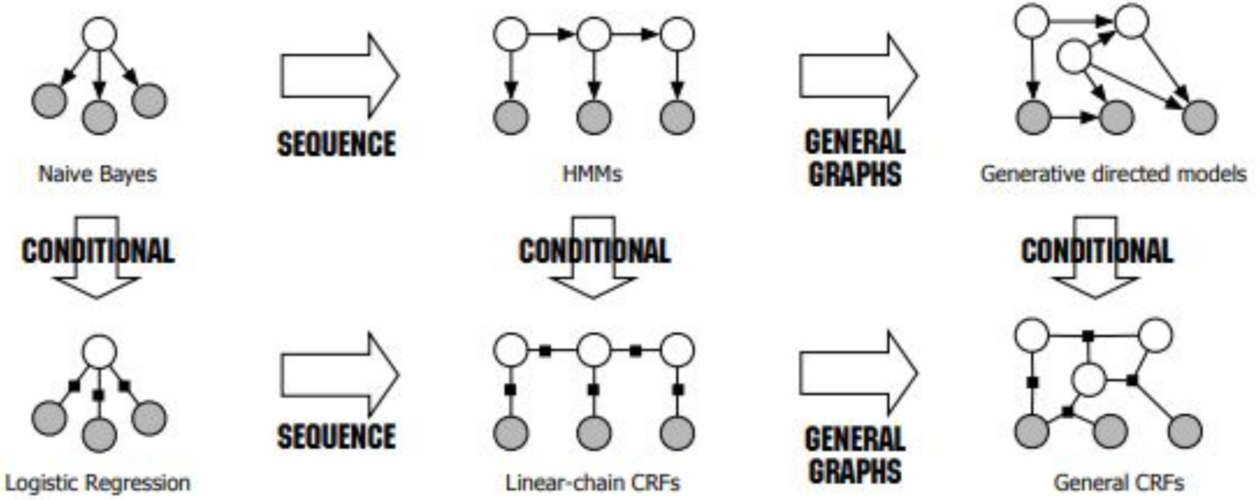


Fig. 2.3 Diagram of the relationship between naive Bayes, logistic regression, HMMs, linear-chain CRFs, generative models, and general CRFs.

# Conditional Random Fields

CRFs = MaxEnt + HMM

- HMM - generative, **classifies the whole sequence at once**
  - $p(x, y)$
- MaxEnt - **discriminative**, classifies elements one by one
  - $p(y_i=1|x_i)$
- CRFs - **discriminative, classify the whole sequence at once**
  - $p(y|x)$

# CRF Advantages

- Compared with HMM: Since CRF does not have as strict independence assumptions as HMM does, it can accommodate any context information. Its feature design is flexible (the same as ME).
- Compared with ME: CRF computes the joint probability distribution of the entire label sequence when an observation sequence intended for labeling is available, rather than defining the state distribution of the next state under the current state conditions given.

# CRF Disadvantage

CRF is highly computationally complex at the training stage of the algorithm. It makes it very difficult to re-train the model when newer data becomes available.

# Conditional Random Fields

- MaxEnt

$$p(c|x) = \frac{\exp\left(\sum_{i=1}^{N} w_i f_i(c,x)\right)}{\sum_{c' \in C} \exp\left(\sum_{i=1}^{N} w_i f_i(c',x)\right)}$$

- CRF also learns transitions

$$p(l|s) = \frac{exp(\sum_{j=1}^{m} \sum_{i=1}^{n} w_j f_j(s, i, l_i, l_{i-1}))}{\sum_{l'} exp(\sum_{j=1}^{m} \sum_{i=1}^{n} w_j f_j(s, i, l'_i, l'_{i-1}))}$$

# Conditional Random Fields

$$p(l|s) = \frac{exp(\sum_{j=1}^{m} \sum_{i=1}^{n} w_j f_j(s, i, l_i, l_{i-1}))}{\sum_{l'} exp(\sum_{j=1}^{m} \sum_{i=1}^{n} w_j f_j(s, i, l'_i, l'_{i-1}))}$$

*s* - sentence (list of words)
*l* - list of labels

*i* - index of a word in *s*
$l_i$ - label of the word *i*
$l_{i-1}$ - label of the word before *i*

# Linear Chain CRF

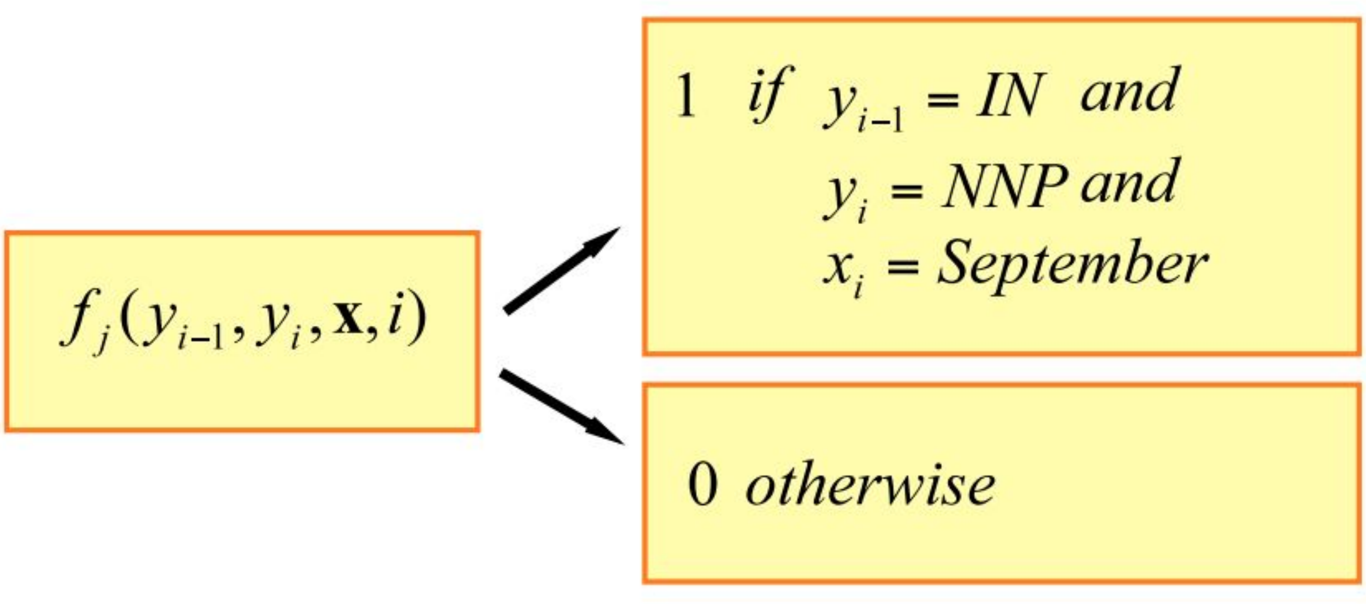
$$P(\mathbf{y} \mid \mathbf{X}) = \frac{\exp\left(\sum_{k=1}^{\ell} U(\mathbf{x}_k, y_k) + \sum_{k=1}^{\ell-1} T(y_k, y_{k+1})\right)}{Z(\mathbf{X})}$$

In *P(y|x;w)*, we can ignore the denominator *Z(x)* and exponent function in the numerator

which results i $\hat{w} = argmax_w \sum_{j=1}^{n} \sum_{i=1}^{m} w_i f_i(y_{j-1}, y_j, x, j)$

https://towardsdatascience.com/implementing-a-linear-chain-conditional-random-field-crf-in-pytorch-16b0b9c4b4ea

# Conditional Random Fields: feature function



$f_j(y_{i-1}, y_i, \mathbf{x}, i)$

1 *if* $y_{i-1} = IN$ *and*

$y_i = NNP$ *and*

$x_i = September$

0 *otherwise*

# 6. More about Ngrams

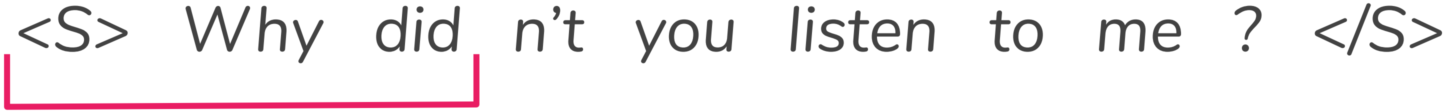
# What are ngrams

Ngram - a contiguous sequence of ***n*** items from a given text.

# What are ngrams

Ngram - a contiguous sequence of ***n*** items from a given text.

So, if ***n* = 3**:



*<S> Why did n’t you listen to me ? </S>*

# What are ngrams

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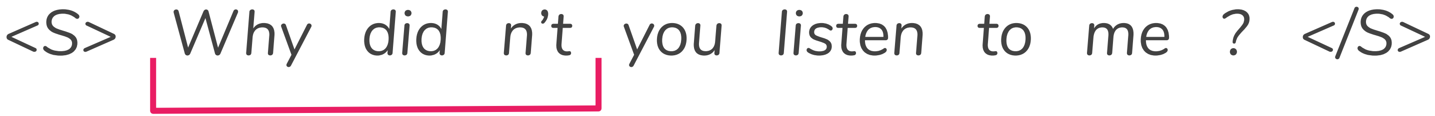

<S> *Why did n’t you listen to me ?* </S>

# What are ngrams

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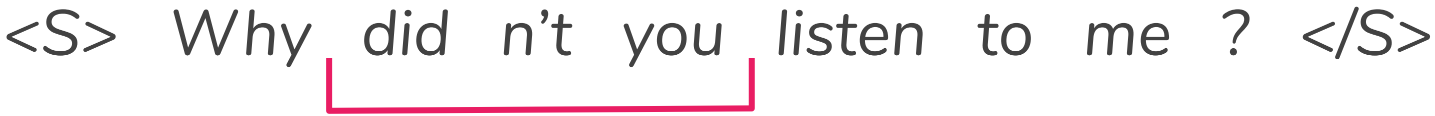

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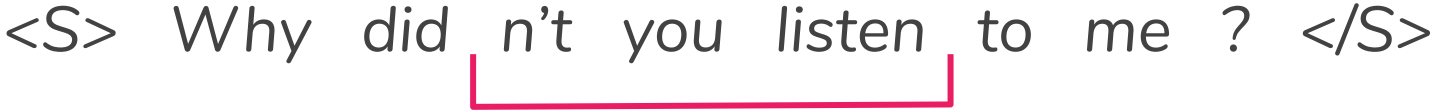

*<S>   Why   did   n't   you   listen   to   me   ?   </S>*

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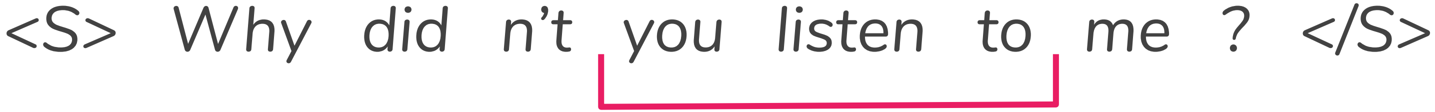

*<S>  Why  did  n’t  you  listen  to  me  ?  </S>*

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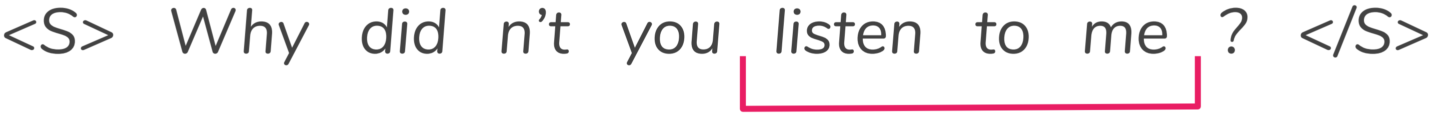

*<S> Why did n’t you listen to me ? </S>*

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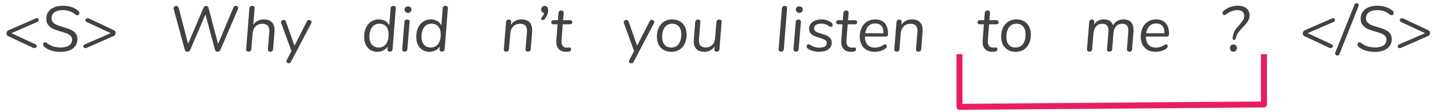

*<S> Why did n’t you listen to me ? </S>*

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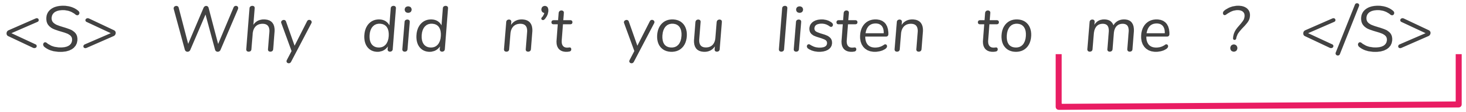


*<S> Why did n’t you listen to me ? </S>*

# Token ngrams

Usually 1 ≥ n ≥ 5.

*<S>   Why   did   n’t   you   listen   to   me   ?   </S>*

***n = 1***: *(<S>), (Why), (did), (n’t), (you), (listen), (to), (me), (?)…*

***n = 2***: *(<S> Why), (Why did), (did n’t), (n’t you), (you listen), (listen to)…*

***n = 3***: *(<S> Why did), (Why did n’t), (did n’t you), (you listen to)…*

…

# Character Ngrams

*<S> Why did n’t you listen to me ? </S>*

For words:

***n = 3***: *(<w> W h), (W h y), (h y </w>), (<w> d i), (d i d), (i d n), (d n ‘)…*

For sentences:

***n = 3***: *(W h y), (h y _), (y _ d), (_ d i), (d i d), (i d n), (d n ‘), (n ‘ t)…*

# POS Ngrams

|  |  |  |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|
| <S> | Why | did | n’t | you | listen | to | me | ? | </S> |
| <S> | WDT | VDB | RB | PRP | VB | TO | PRP | . | </S> |

POS:

***n = 3***: *(<S>, WDT, VBD), (WDT, VBD, RB), (VBD, RB, PRP), (RB, PRP, VB)…*

Token+POS:

***n = 2***: *(<S>_<S>, Why_WDT), (Why_WDT, did_VBD), (did_VBD, n’t_RB)…*

Token or POS:

***n = 3***: *(<S>, WDT, did), (WDT, did, RB), (did, RB, PRP), (RB, PRP, listen)…*

# Tree Ngrams

Head+dependency:

*listen_nsubj*

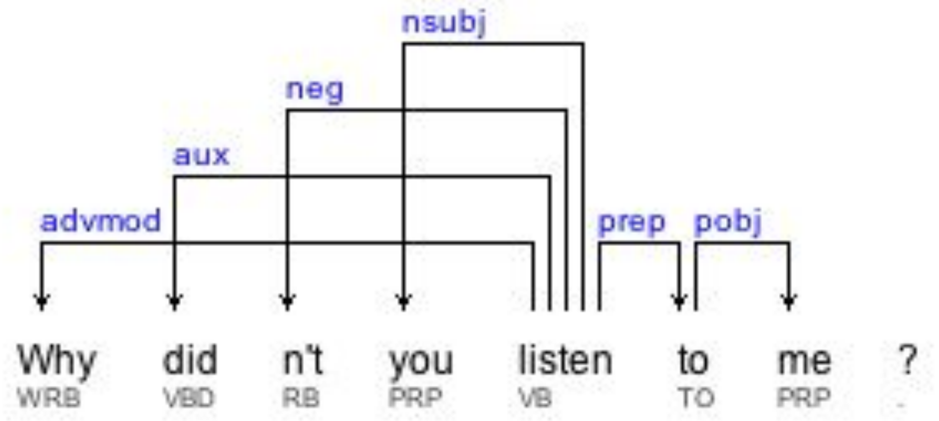
*listen_nsubj_you*

*listen_prep_to_pobj_me*

Head+POS+dependency:

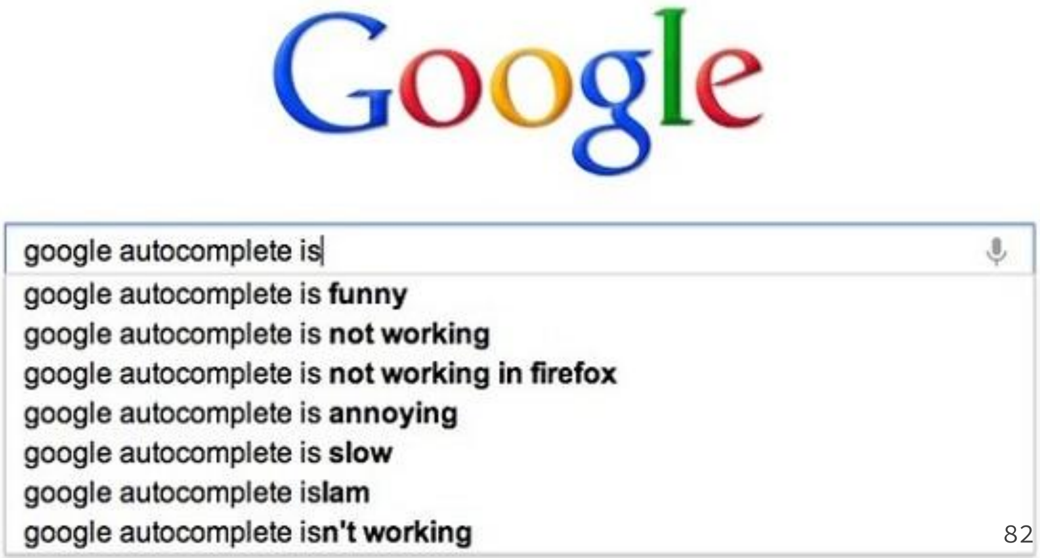
*listen/VB_nsubj*

*listen/VB_nsubj_you/PRP*



# Ngrams usage

1. Speech recognition
2. Autocompletion

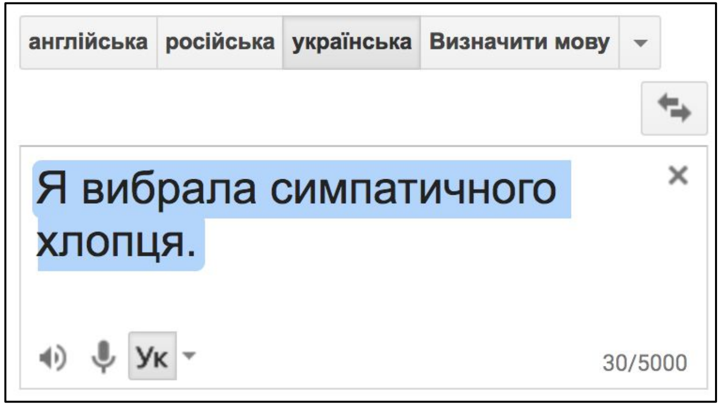


google autocomplete is

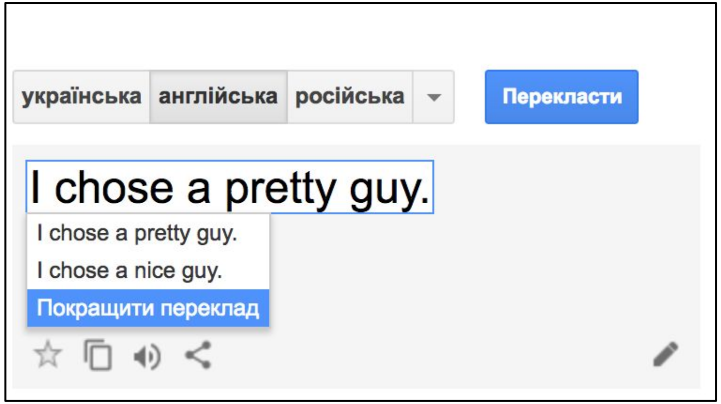
google autocomplete is **funny**
google autocomplete is **not working**
google autocomplete is **not working in firefox**
google autocomplete is **annoying**
google autocomplete is **slow**
google autocomplete is**lam**
google autocomplete is**n't working**

# Ngrams usage

1. Speech recognition
2. Autocompletion
3. Machine Translation



Я вибрала симпатичного хлопця.



I chose a pretty guy.

I chose a pretty guy.

I chose a nice guy.

Покращити переклад

# Ngrams usage

1. Speech recognition
2. Autocompletion
3. Machine Translation
4. Handwriting recognition
5. Spelling correction
6. (and GEC in general)

Borrowed from https://www.youtube.com/watch?v=l3pdGfKycz8

# Ngrams as a feature

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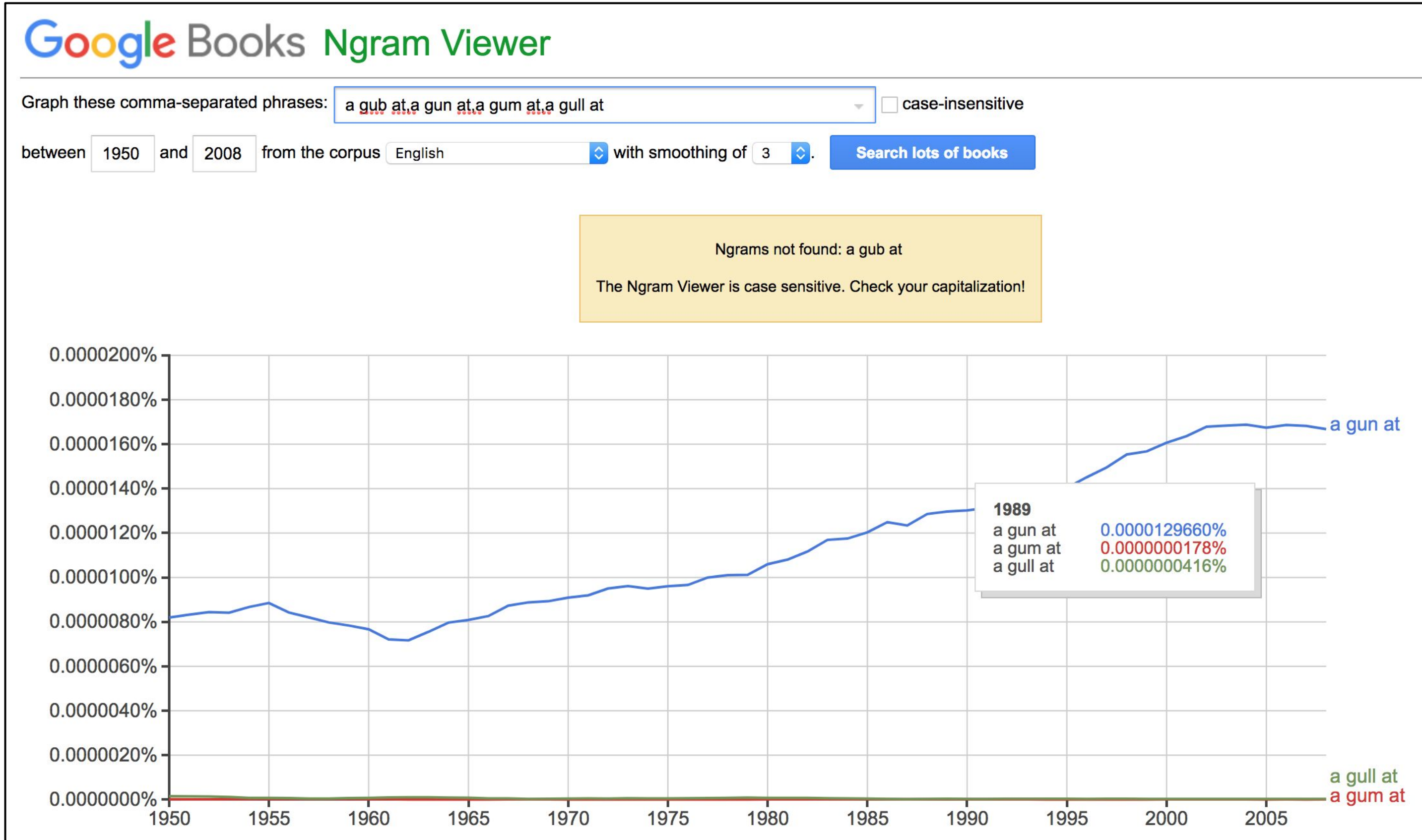
Frequency or probability:

a gub at

a gun at

a gum at

a gull at



Graph these comma-separated phrases: a gub at,a gun at,a gum at,a gull at □ case-insensitive

between 1950 and 2008 from the corpus English with smoothing of 3.

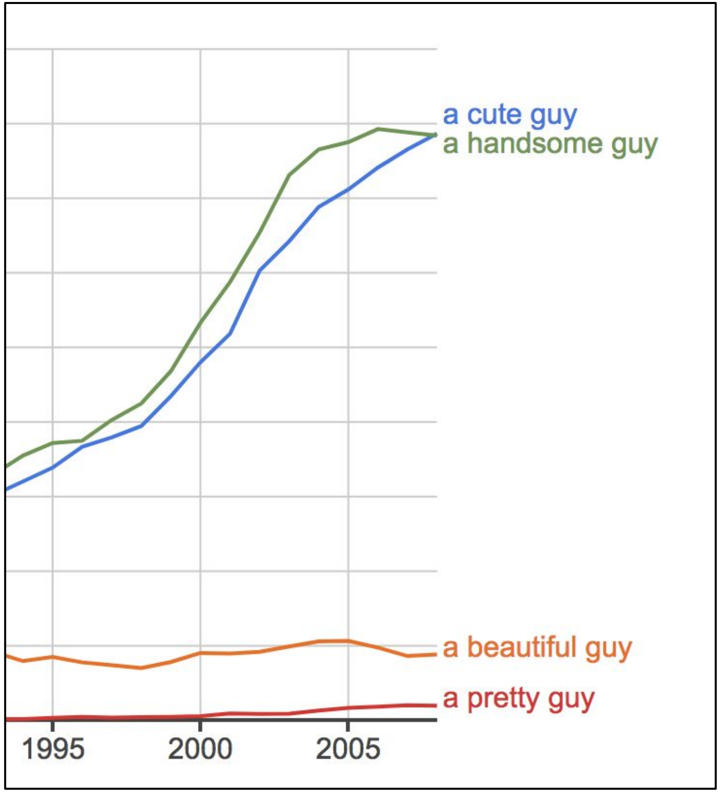
Ngrams not found: a gub at

The Ngram Viewer is case sensitive. Check your capitalization!

| 1989 | |
|---|---|
| a gun at | 0.0000129660% |
| a gum at | 0.0000000178% |
| a gull at | 0.0000000416% |

# Ngrams as a feature

Frequency / probability



# Ngrams as a feature

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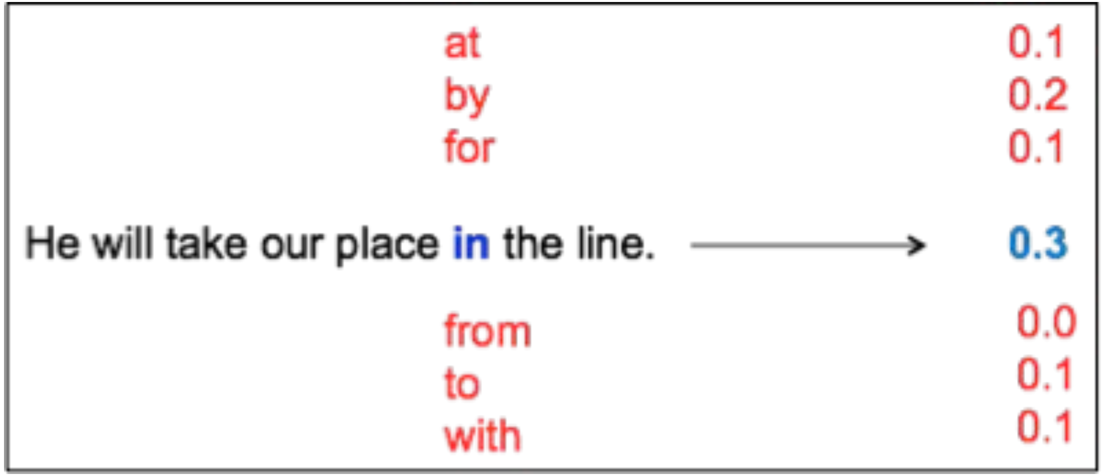
Frequency / probability



|  |  |
|---|---|
| at | 0.1 |
| by | 0.2 |
| for | 0.1 |
| He will take our place in the line. → | 0.3 |
| from | 0.0 |
| to | 0.1 |
| with | 0.1 |

# Ngrams as a feature

Conditional probability

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n)}{C(w_{n-1})}$$

*To be continued on the lecture about language modeling…*

# Where to get ngrams

- Google ngrams (and how to download)
- http://getmintbox.com/ (API for Google ngrams)
- Google syntactic ngrams
- https://phrasefinder.io/ (has an API)
- 1 mln of 2/3/4/5-ngrams from COCA for free
- collect on your own

# How to encode ngram frequencies

Ngrams:

“*met a cute*”: *3250*, “*a cute guy*”: *25289*, “*met a cute guy*”: 600, …
“*met a pretty*”: 2925, “*a pretty guy*”: *1159*, “*met a pretty guy*”: 0, …

- As additional vector to concatenate:
  - *[3250, 25289, 600, 2925, 1159, 0, …]*

- As part of the feature dictionary:
  - {“left-3gr”: 3250, “right-3gr”: 25289, “middle-4gr”: 600, “left-3gr-2”: 2925, “right-3gr-2”: *1159*, “middle-4gr-2”: 0, …}

# References

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3. Introduction to Conditional Random Fields by Edwin Chen (2012)
4. Conditional Random Fields: An Introduction by Hanna M. Wallach (2004)
5. A Comparative Analysis of Sequence Modeling Methods (HMM, CRF)
6. Sequence labeling by Raymond J. Mooney (2016)
7. Multiclass and Multi-label Classification by Prof. Michael Paul (2017)