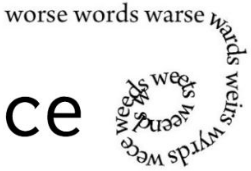
Language as a Sequence

Mariana Romanyshyn
Grammarly, Inc.

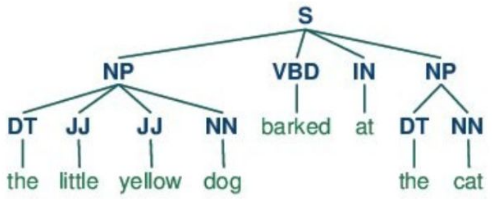
NLP Viewpoints

* Bag-of-words

* Sequence



* Tree



* Graph

Contents

---

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   .
```

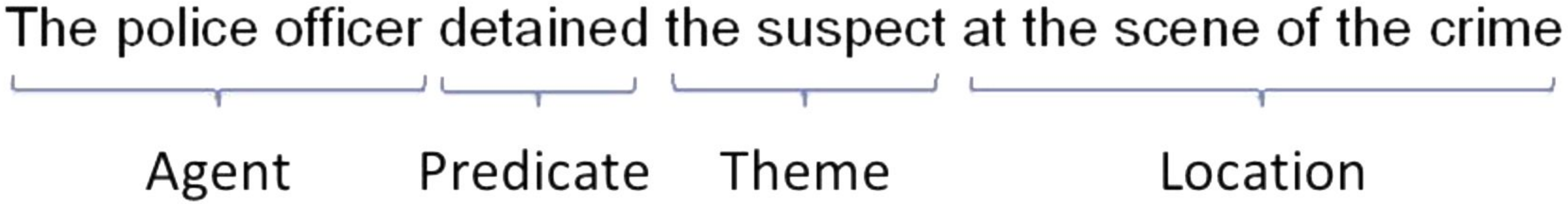
Sequence Labeling

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:



Sequence Labeling

Genome analysis:

intron exon intron exon intron

AGCTAACGTTCGATACGGATTACAGCCT

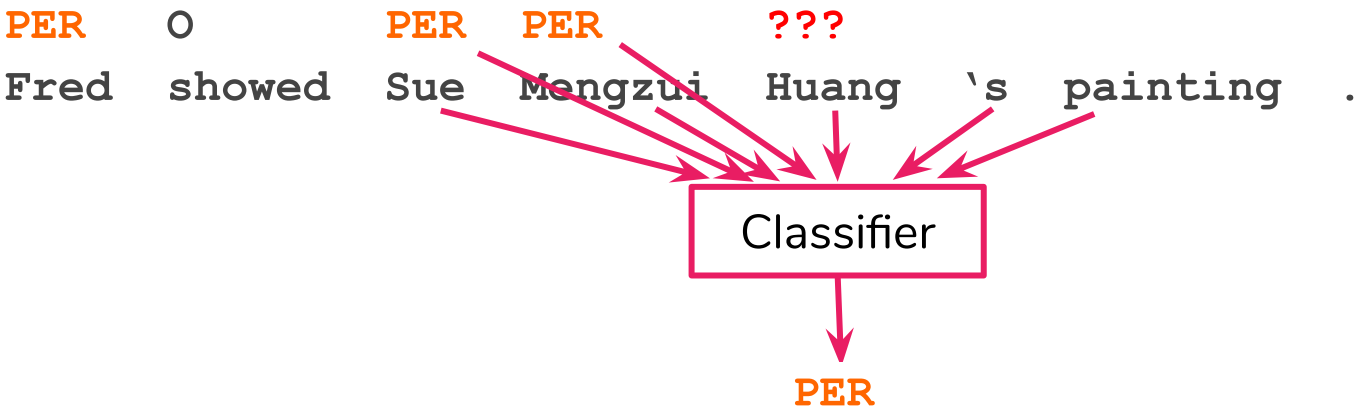
Sequence Labeling

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	.

$\mathbf{p(x, y)} = ?$

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

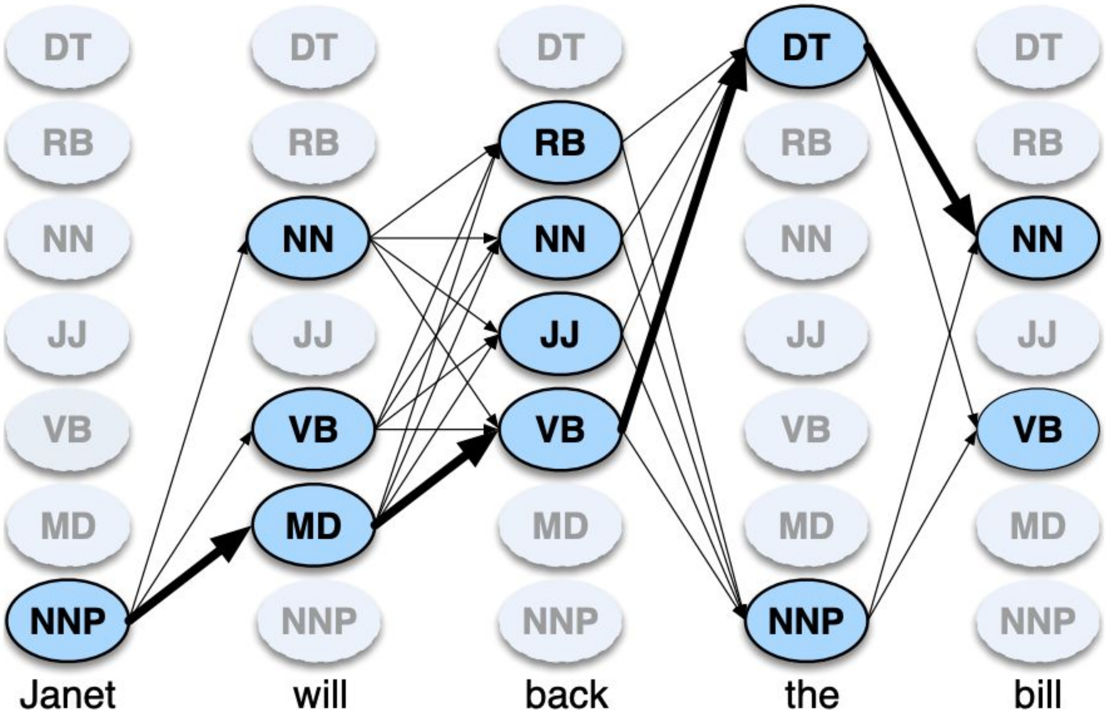
Enumerating all possible tag sequences is not feasible — $\boldsymbol{T^n}$.

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

Solutions:

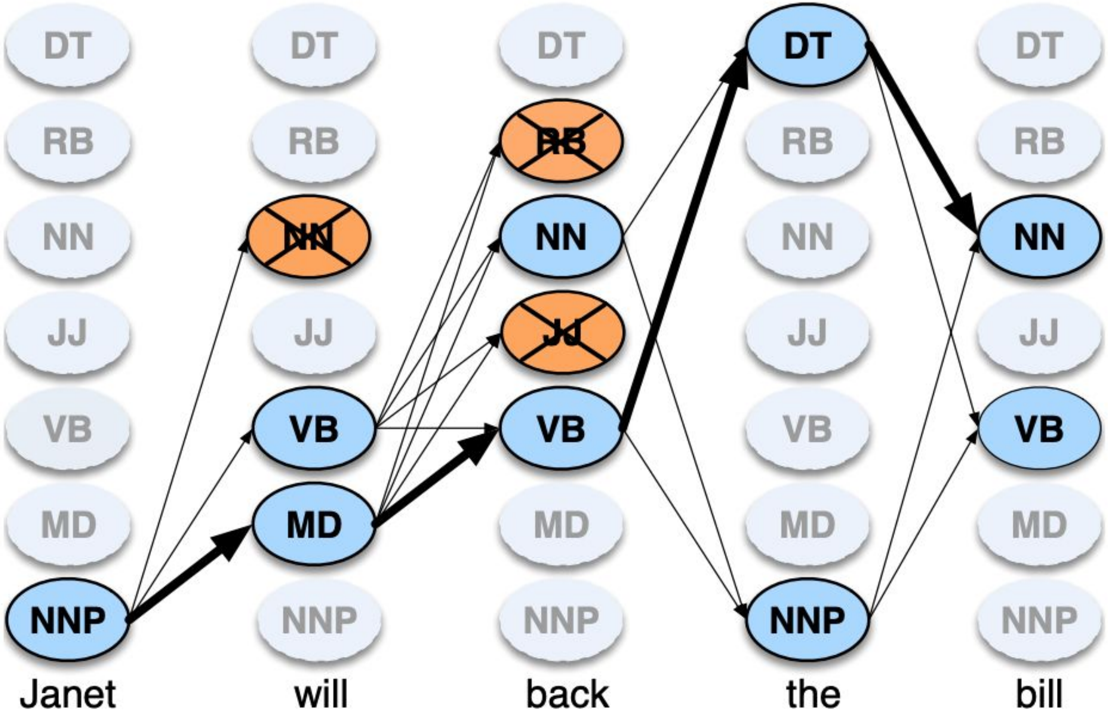
- use dynamic programming (the Viterbi algorithm) - $\boldsymbol{n*T^3}$
- limit the number of candidates with a dictionary - $\boldsymbol{n*8^3}$
- use beam search

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

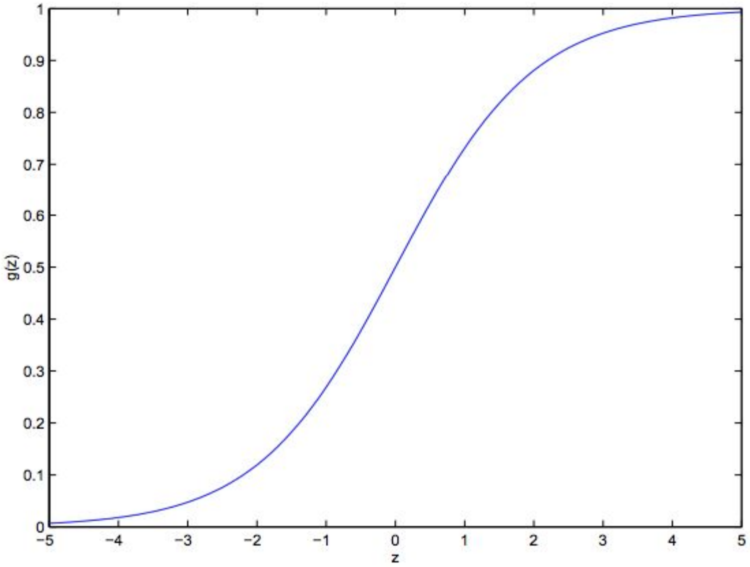
$$z = \left(\sum_{i=1}^{n} w_i x_i\right).$$

Logistic Regression

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

Sigmoid function:

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



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]*

$\mathbf{w}_{\text{is-end}}$: *[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]*

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

Logistic Regression: weights

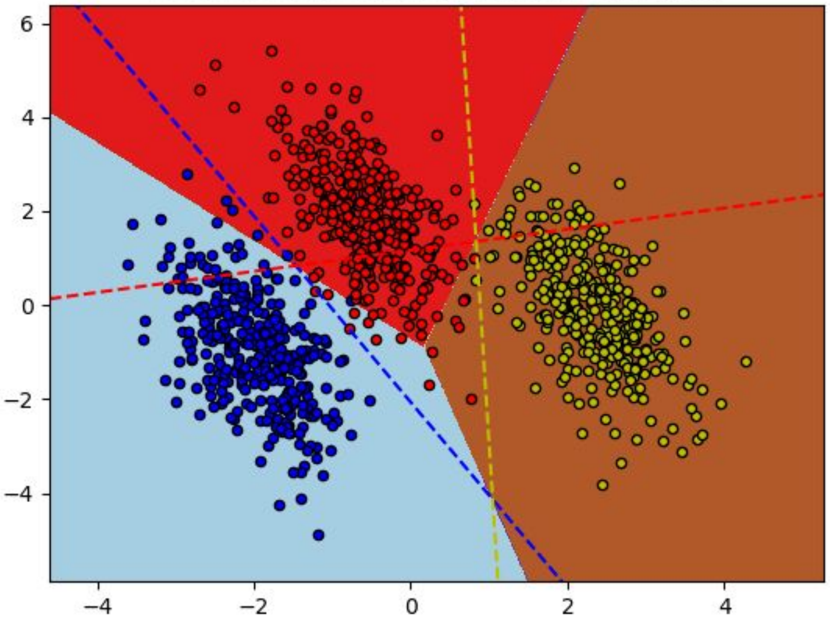
Learn weights:

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

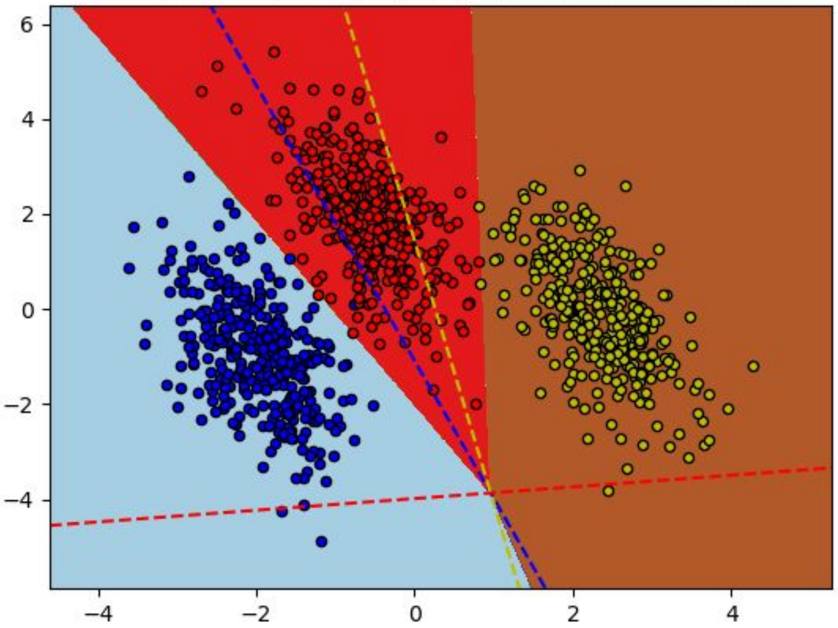
$$\hat{w} = \operatorname*{argmax}_{w} \sum_{j} \log P(y^{(j)} | x^{(j)})$$

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?*

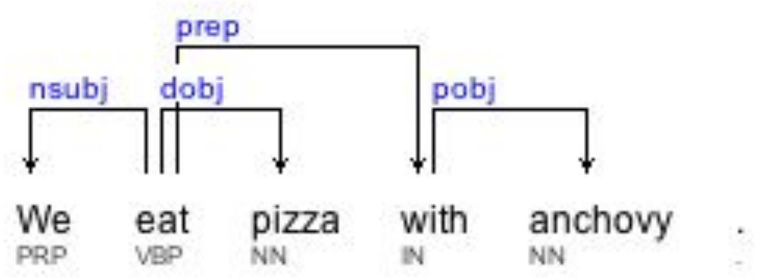
Encode context (ngrams)

```
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”}

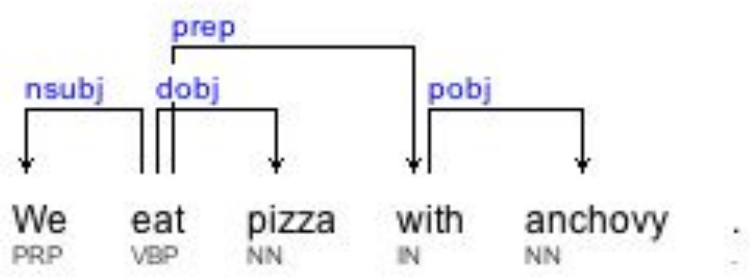
Encode dependencies



“eat”/VBP:

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

Encode dependencies



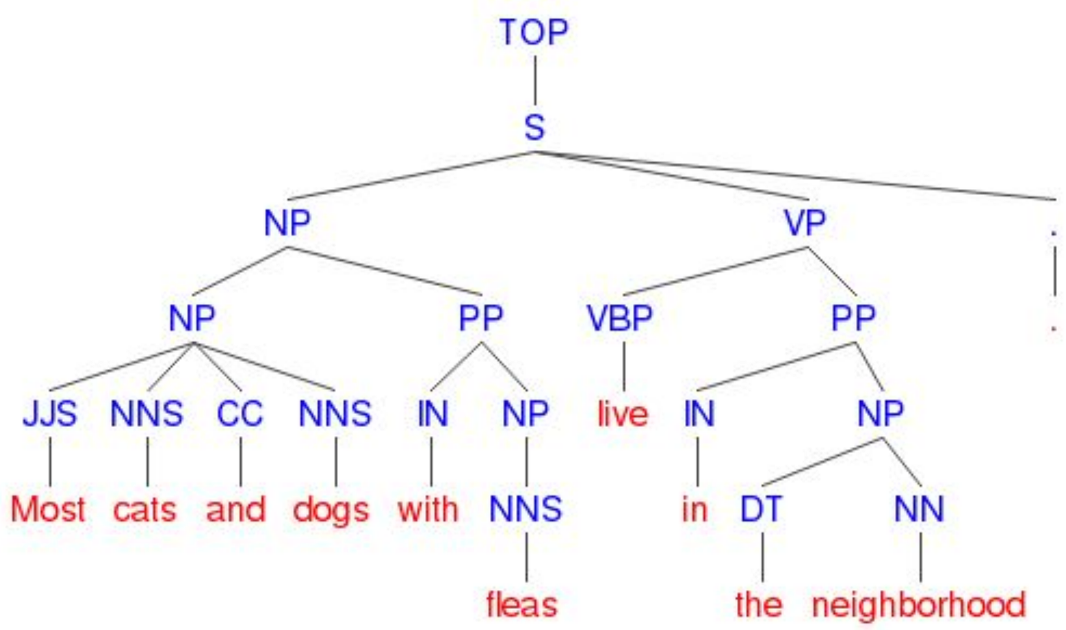
“eat”/VBP:

- *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

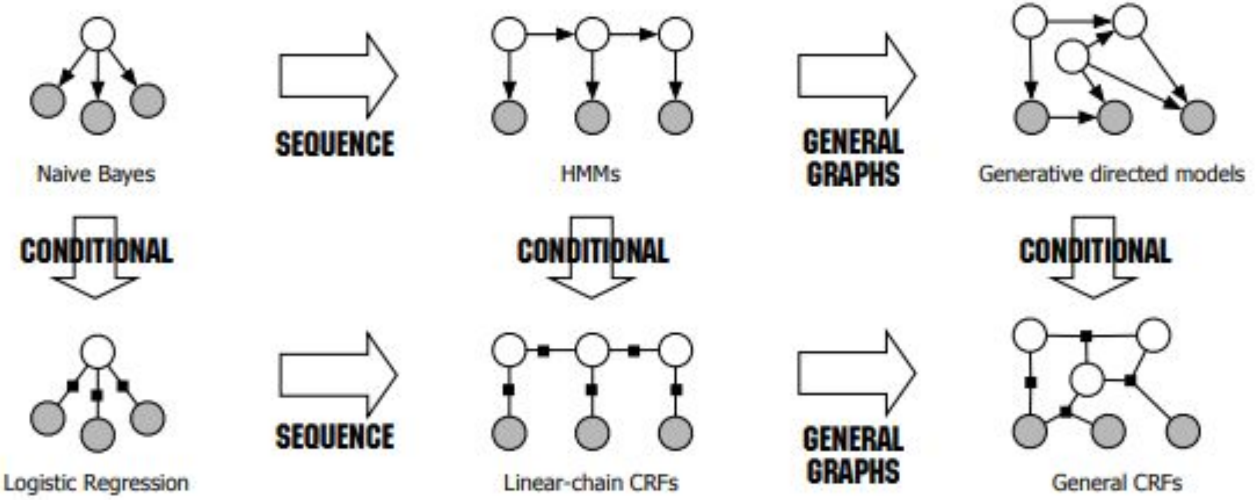


Fig. 2.3 Diagram of the relationship between naive Bayes, logistic regression, HMMs, linear-chain CRFs, generative models, and general CRFs.

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: feature function

$$f_j(y_{i-1}, y_i, \mathbf{x}, i) \rightarrow \begin{cases} 1 \;\; \mathit{if} \;\; y_{i-1} = IN \;\; \mathit{and} \\ \qquad\quad y_i = NNP \;\; \mathit{and} \\ \qquad\quad x_i = September \\ 0 \;\; \mathit{otherwise} \end{cases}$$

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

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

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

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

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

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

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

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

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>

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

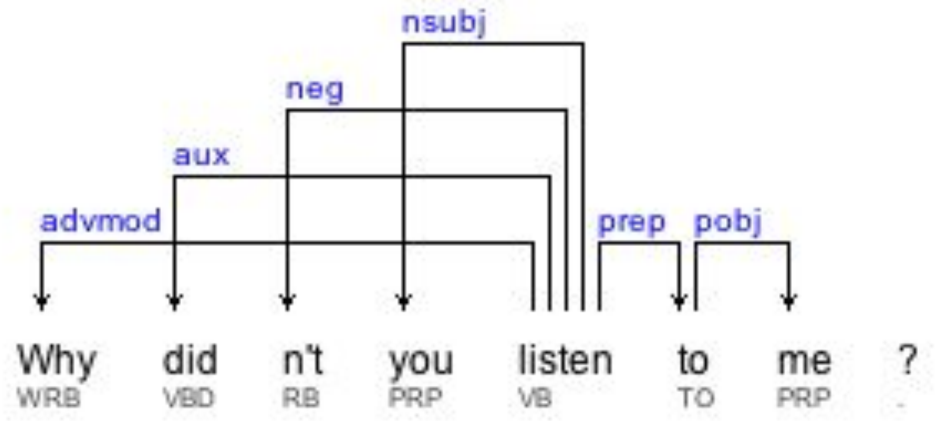
listen_nsubj_you

listen_prep_to_pobj_me

Head+POS+dependency:

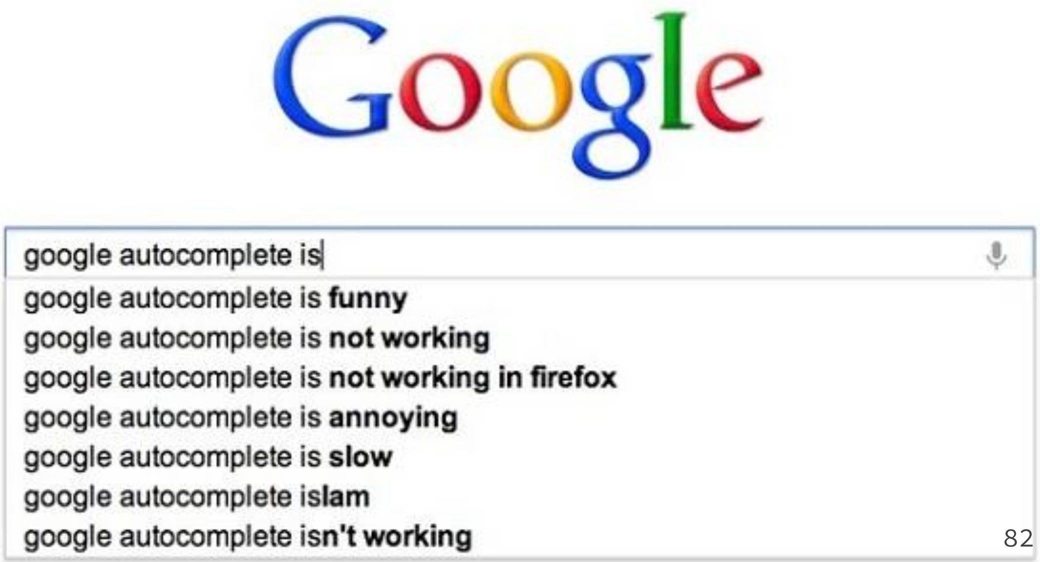
listen/VB_nsubj

listen/VB_nsubj_you/PRP



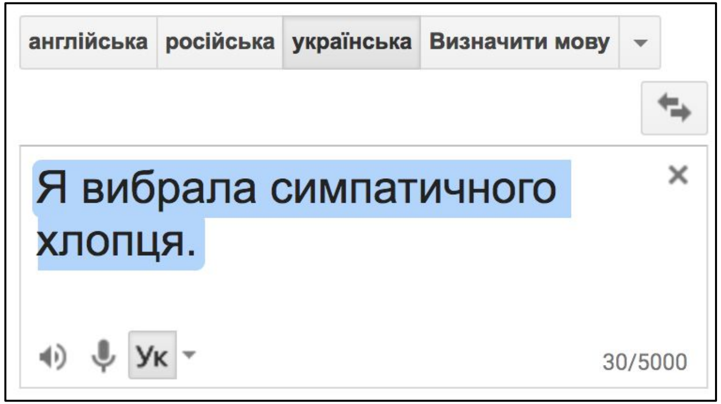
Ngrams usage

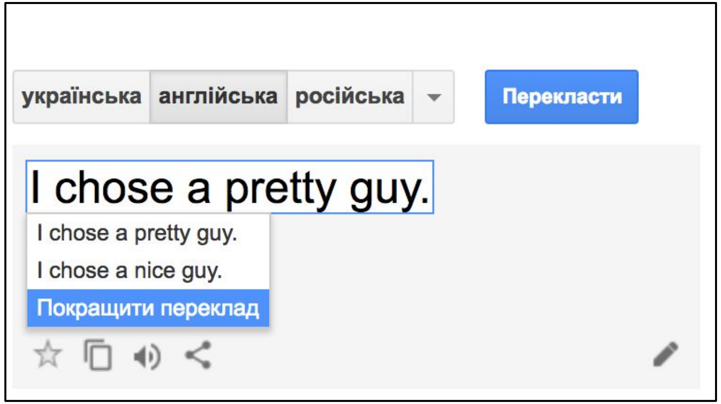
1. Speech recognition
2. Autocompletion



Ngrams usage

1. Speech recognition
2. Autocompletion
3. Machine Translation





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

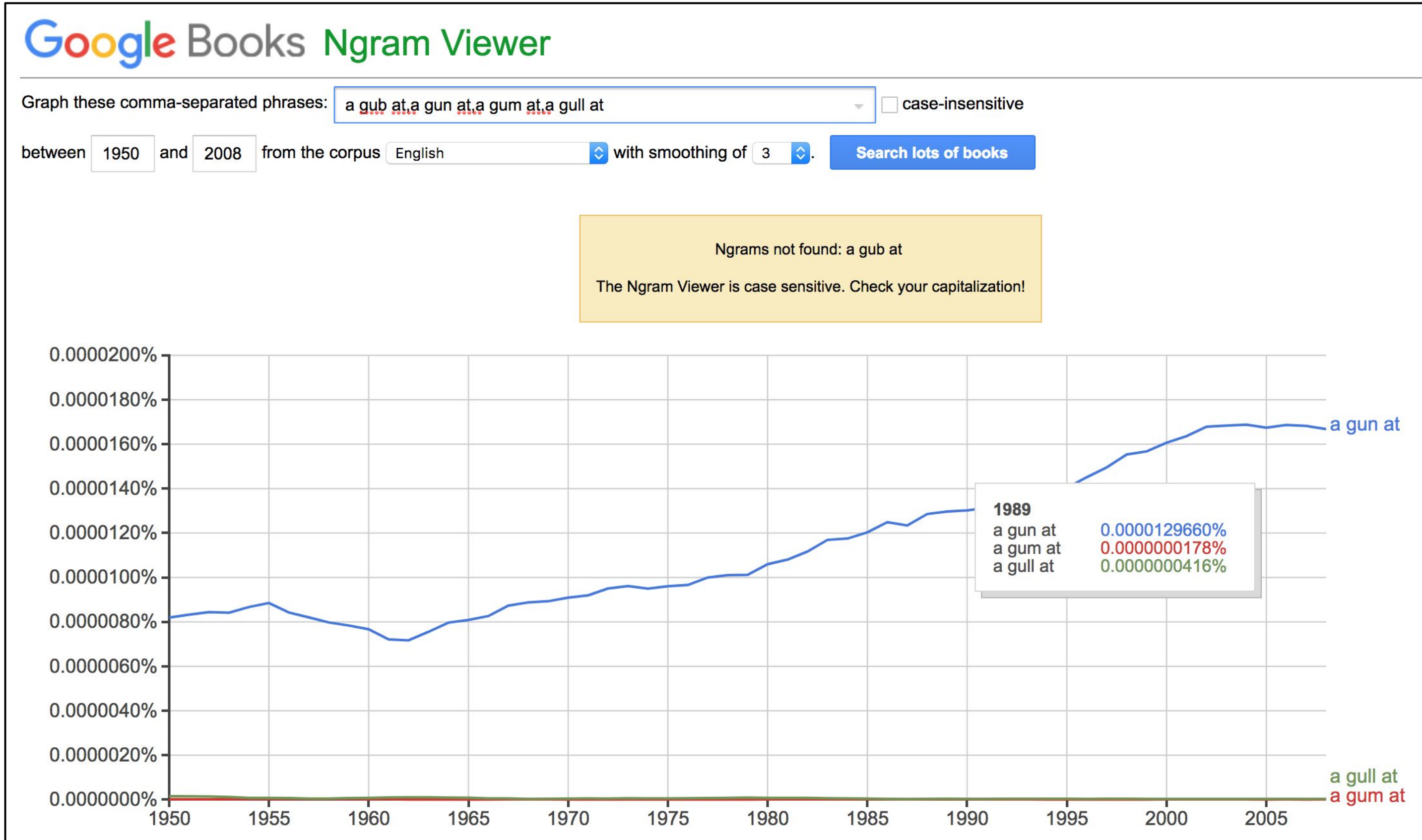
Frequency or probability:

a gub at

a gun at

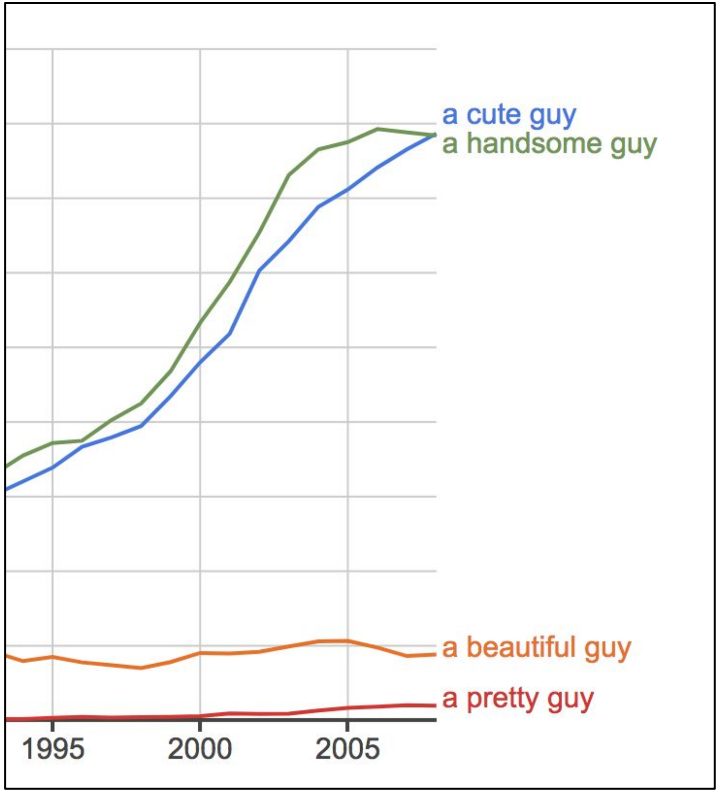
a gum at

a gull at



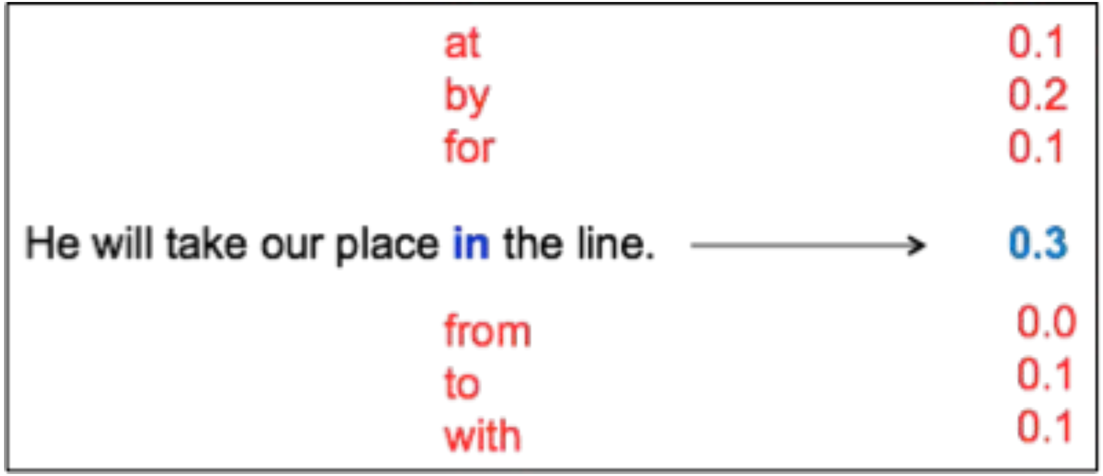
Ngrams as a feature

Frequency / probability



Ngrams as a feature

Frequency / probability



Ngrams as a feature

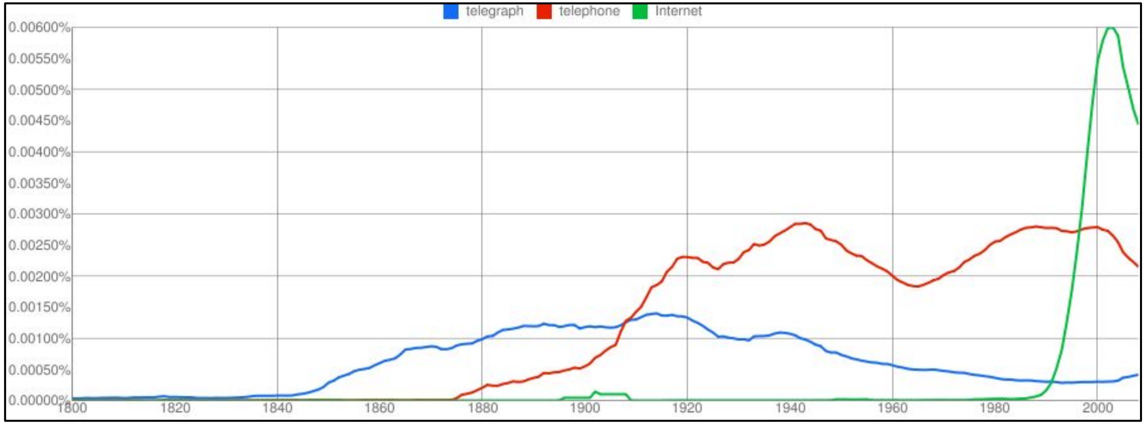
Conditional probability

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

To be continued on the lecture about language modeling…

Where to get ngrams

- 1 mln of 2/3/4/5-ngrams from COCA for free
- Google ngrams (and how to download)
- Google syntactic ngrams
- 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

1. Logistic Regression *in Speech and Language Processing* by *D. Jurafsky and J. H. Martin (2019)*
2. Hidden Markov Models in *Speech and Language Processing* by *D. Jurafsky and J. H. Martin (2019)*
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)