7. Language as a Sequence

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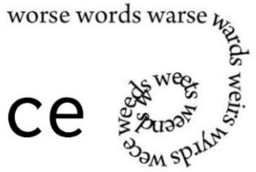
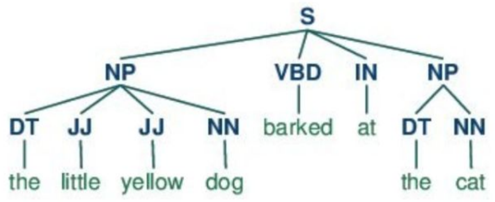
NLP Viewpoints

* Bag-of-words

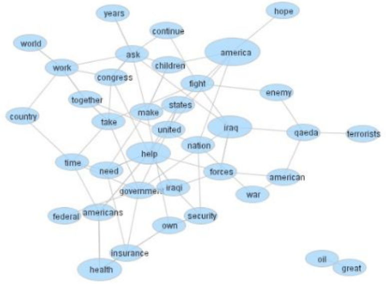
* Sequence



* 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   .
```

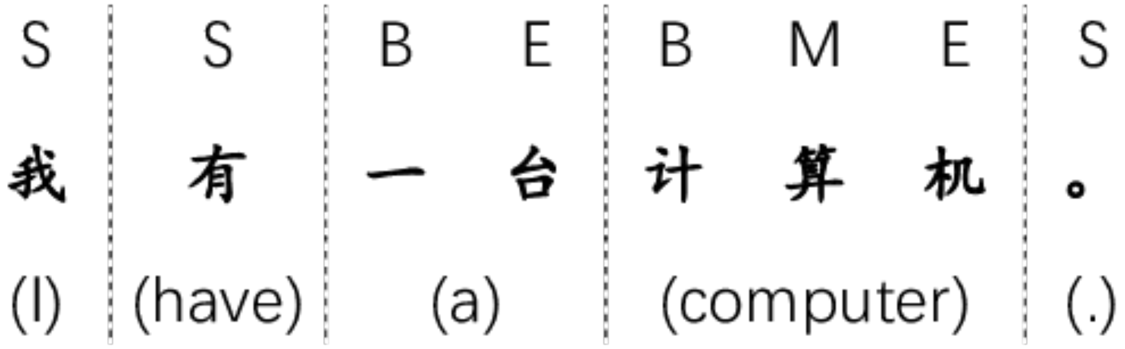
Sequence Labeling

Error detection:

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

Sequence Labeling

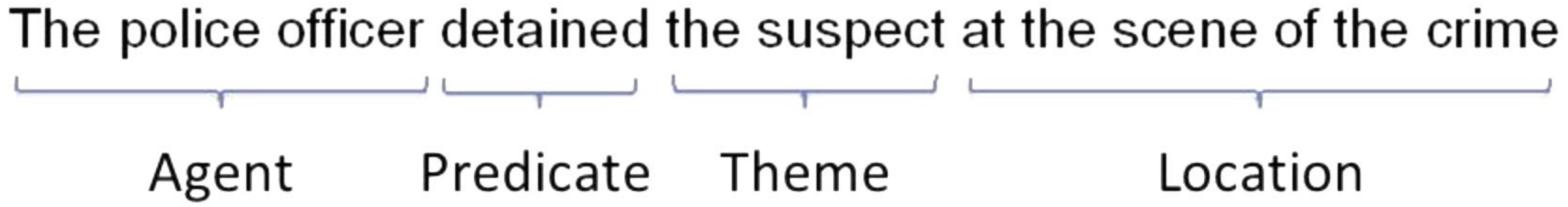
Word segmentation:



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

Sequence Labeling

Semantic role labeling:


The police officer detained the suspect at the scene of the crime
Agent
Predicate
Theme
Location

Sequence Labeling

Genome analysis:

intron exon intron exon intron

AGCTAACGTTCGATACGGATTACAGCCT

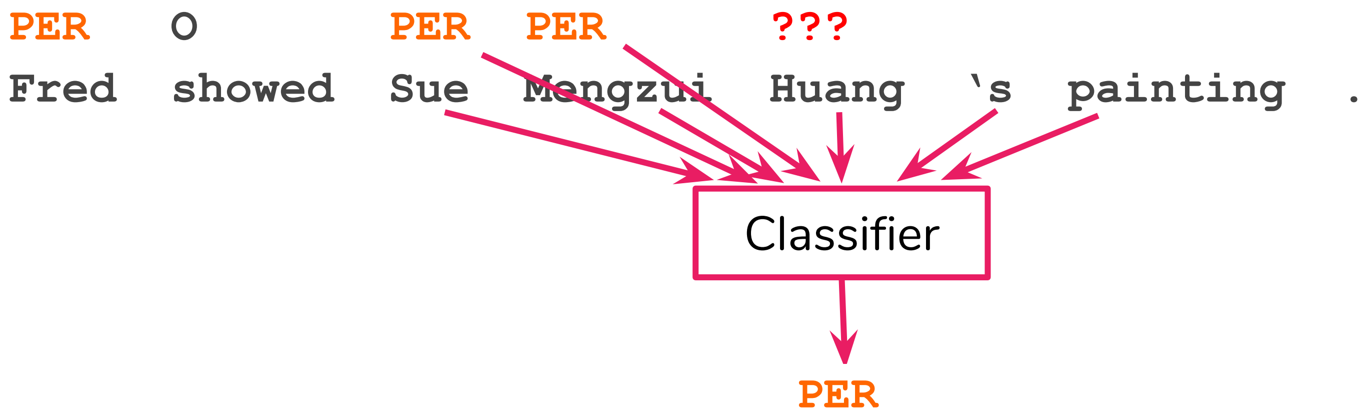
Sequence Labeling

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: 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

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

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

Aim: find $\{x_1 \dots x_n, y_1 \dots y_n\}$ 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 $\{x_1 \dots x_n, y_1 \dots y_n\}$

x:	Chewie	,	we	're	home	.
y:	NNP	,	PRP	VBP	?	.
	NN	,	PRP	VBP	?	.
	…					

Trigram Hidden Markov Model: parameters

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

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

- e(x|s) - the probability of observation x paired with state s
  - x ∈ V, s ∈ T

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

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

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

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

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

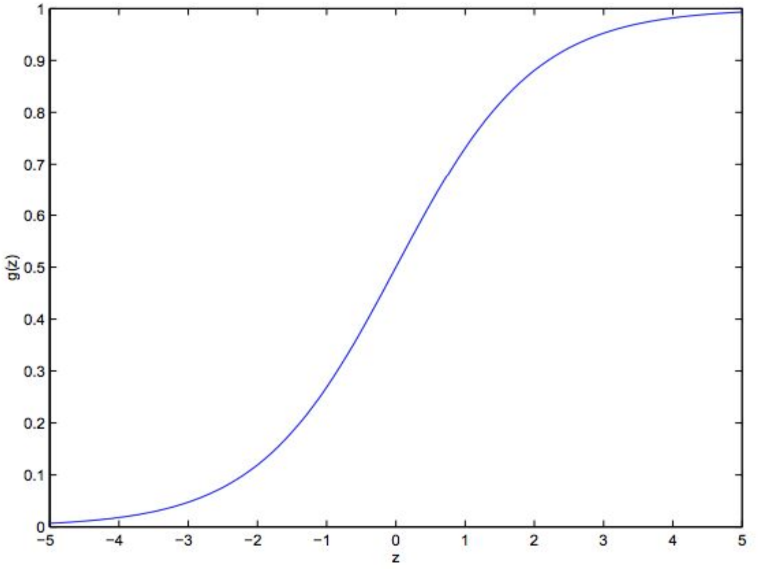
$$z = \left(\sum_{i=1}^{n} w_i x_i\right).$$

Logistic Regression

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

Sigmoid function:

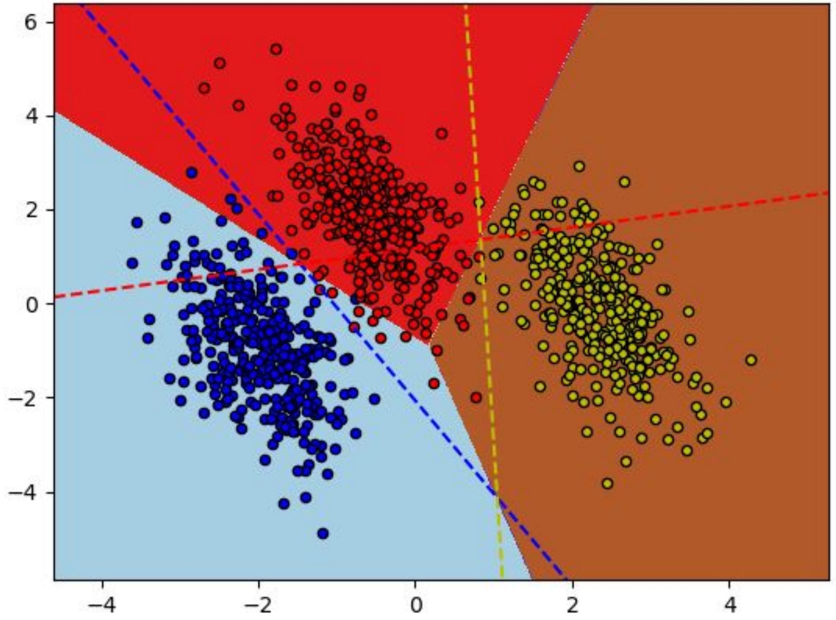
$$\begin{aligned} P(y=1) &= \sigma(w \cdot x + b) \\ &= \frac{1}{1+e^{-(w \cdot x + b)}} \end{aligned}$$



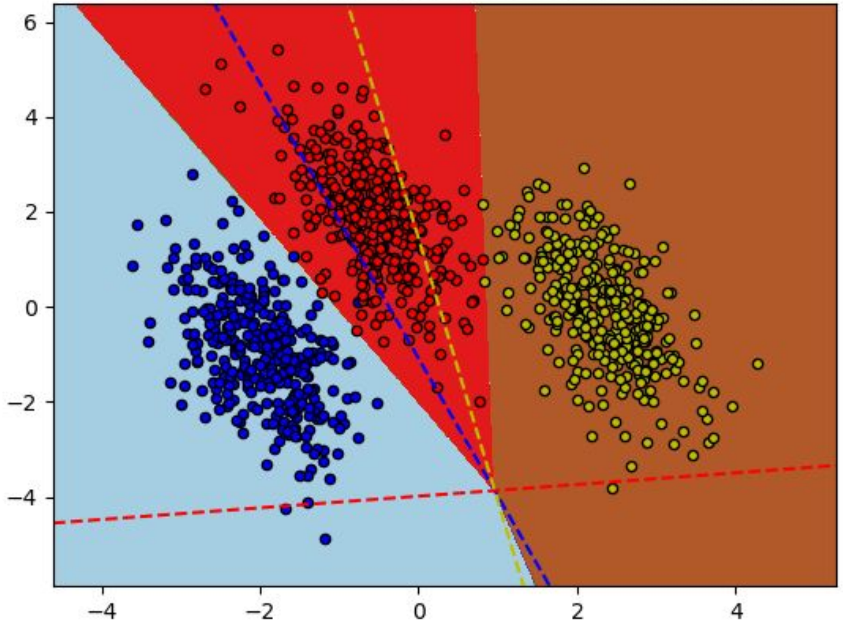
Borrowed from Andrew Ng: https://goo.gl/zGvb4W

Logistic Regression: multiclass

one vs. rest



multinomial (MaxEnt)



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

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: {“word+1_is_cap”, “word-1=kittens”, “word-1=St”, *“tag-1=PRP”, “tag+1=JJ”}*

Logistic Regression: example

Welcome to St . *Paul* ‘s Cathedral !

[Is this period a sentence end?]

y: *{is-end, is-not-end}*
x: {“word+1_is_cap”, “word-1=kittens”, “word-1=St”, “*tag-1=PRP*”, “*tag+1=JJ*”}

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

Logistic Regression: example

Welcome to St . Paul ‘s Cathedral !

[Is this period a sentence end?]

y: *{is-end, is-not-end}*
x: {“word+1_is_cap”, “word-1=kittens”, “word-1=St”, “tag-1=PRP”, “tag+1=JJ”}

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

$\mathbf{w}_{\text{is-end}}$: *[2.9, 2.5, -0.9, 0, 0]*
$\mathbf{w}_{\text{is-not-end}}$: *[0.5, -0.7, 2.9, 0, 0]*

Logistic Regression: example

Welcome to St . Paul ‘s Cathedral !

[Is this period a sentence end?]

y: *{is-end, is-not-end}*
x: {“word+1_is_cap”, “word-1=kittens”, “word-1=St”, “tag-1=PRP”, “tag+1=JJ”}

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

$\mathbf{w}_{\text{is-end}}$: [2.9, 2.5, -0.9, 0, 0] **P(is-end|x$_j$)** $= e^{2.9-0.9} / (e^{2.9-0.9} + e^{0.5+2.9}) = 0.2$
$\mathbf{w}_{\text{is-not-end}}$: [0.5, -0.7, 2.9, 0, 0] **P(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
- move towards the gradient
- to maximize the probability / minimize the loss function

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

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	.

“losses”/NNS:

{“word-2”: “pound”,
“word-1”: “extended”,
“word+1”: “against”,
“word+2”: “both”,
“tag-2”: “NN”,
“tag-1”: “VBD”,
“tag+1”: “IN”,
“tag+2”: “DT”}

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

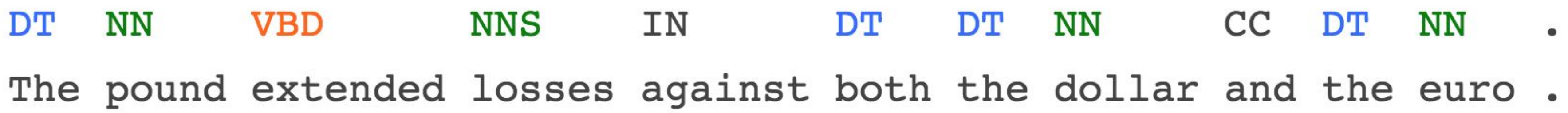
Encode neighbors: feature template

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

“losses”/NNS:

{“wt-2”: “pound_NN”,
 “wt-1”: “extended_VBD”,
 “wt+1”: “against_IN”,
 “wt+2”: “both_DT”}

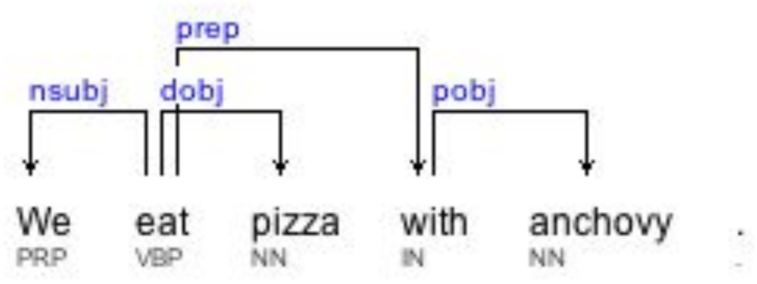
Encode context (ngrams)



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

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

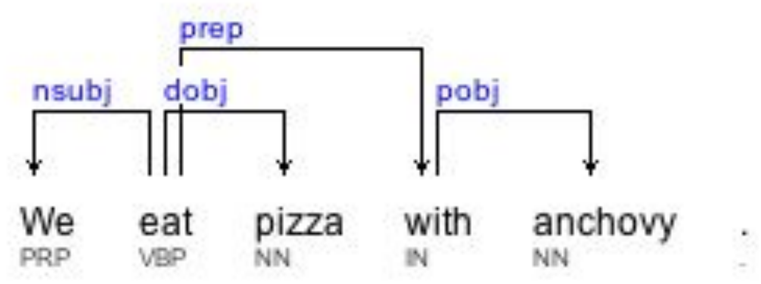
Encode dependencies



“eat”/VBP:

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

Encode dependencies



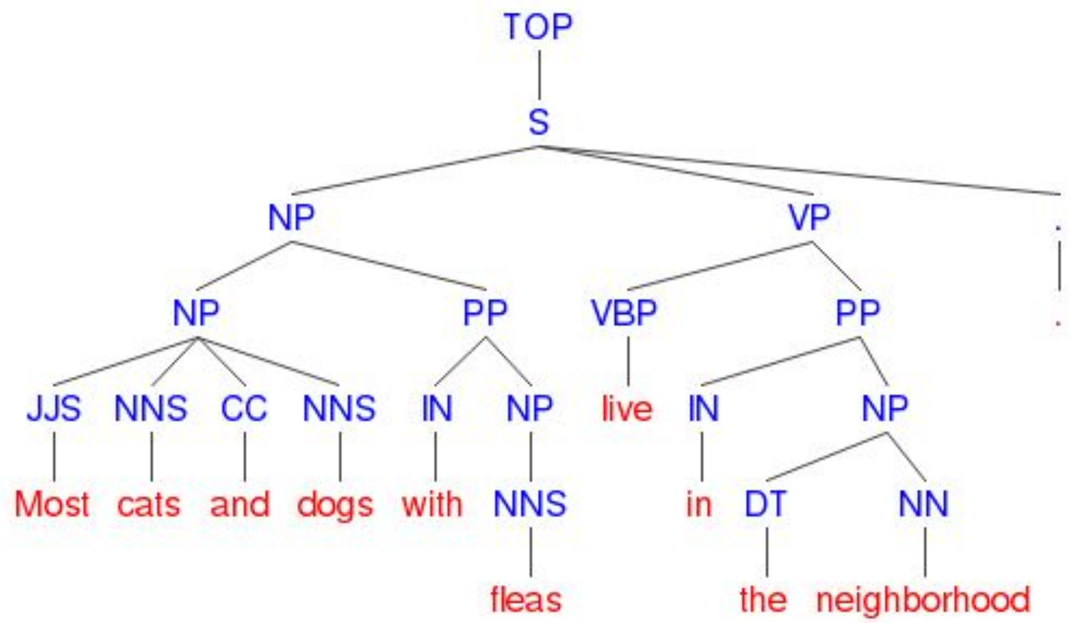
“eat”/VBP:

- *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

- 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

More features

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

What features 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?*

5. Conditional Random Fields

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**
    - $p(y|x)$

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*

Conditional Random Fields: feature function

$$\begin{tikzcd}
 & \boxed{\begin{array}{ll} 1 \ \ \mathit{if} & y_{i-1} = IN \ \ \mathit{and} \\ & y_i = NNP \ \mathit{and} \\ & x_i = \mathit{September} \end{array}} \\
\boxed{f_j(y_{i-1}, y_i, \mathbf{x}, i)} \arrow[ur] \arrow[dr] & \\
 & \boxed{0 \ \ \mathit{otherwise}}
\end{tikzcd}$$

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**:

$\underbrace{\textit{<S> Why did}}$ *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> $\underbrace{\textit{Why did n't}}$ *you listen to me ? </S>*

What are ngrams

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

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

$$\textit{<S>}\quad \textit{Why}\quad \underbrace{\textit{did}\quad \textit{n't}\quad \textit{you}}\quad \textit{listen}\quad \textit{to}\quad \textit{me}\quad \textit{?}\quad \textit{</S>}$$

What are ngrams

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

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

<S> Why did $\underbrace{\textit{n't} \quad \textit{you} \quad \textit{listen}}$ *to me ? </S>*

What are ngrams

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

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

$\textit{<S>}\quad \textit{Why}\quad \textit{did}\quad \textit{n't}\quad \underbrace{\textit{you}\quad \textit{listen}\quad \textit{to}}\quad \textit{me}\quad \textit{?}\quad \textit{</S>}$

What are ngrams

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

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

<S> Why did n’t you $\underbrace{\textit{listen to me}}$ *? </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 $\underbrace{\textit{to me ?}}$ *</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 $\underbrace{\textit{me ? </S>}}$

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

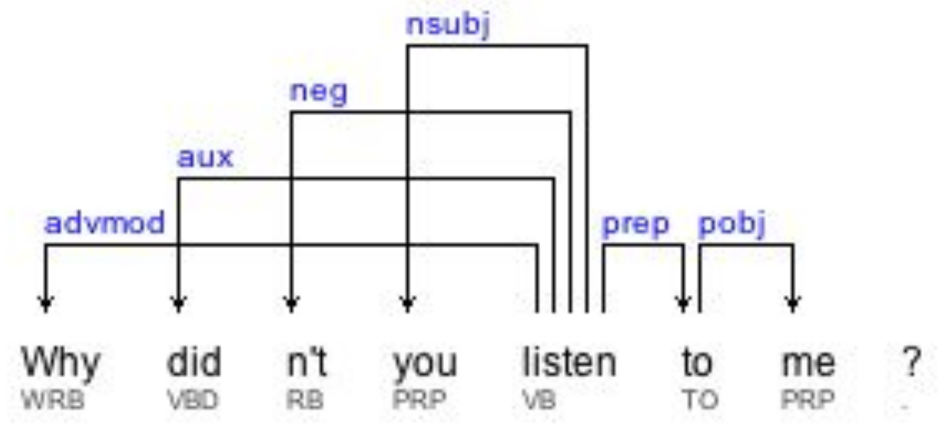
listen_nsubj_you

listen_prep_to_pobj_me

Head+POS+dependency:

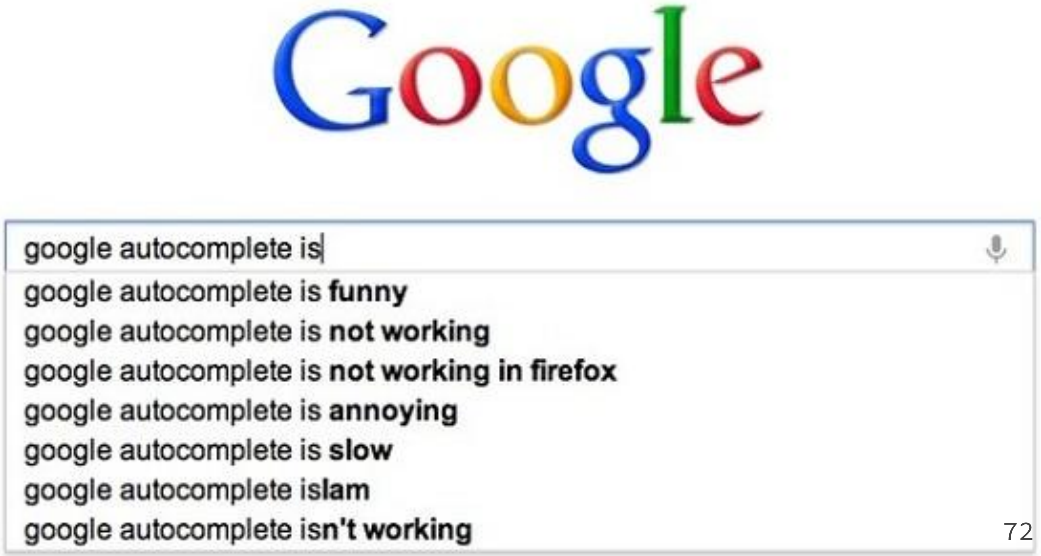
listen/VB_nsubj

listen/VB_nsubj_you/PRP



Ngrams usage

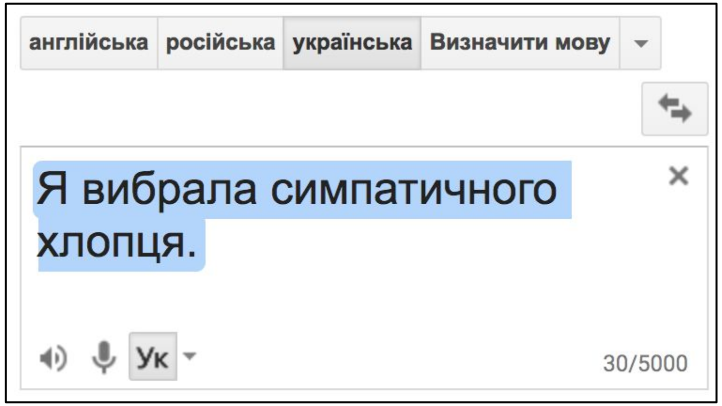
1. Speech recognition
2. Autocompletion



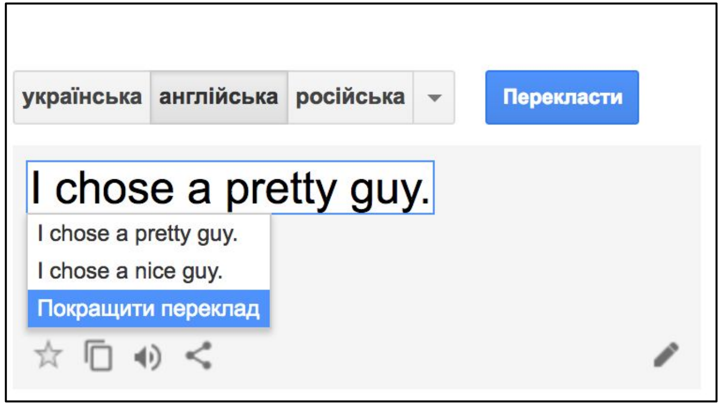
google autocomplete is
google autocomplete is **funny**
google autocomplete is **not working**
google autocomplete is **not working in firefox**
google autocomplete is **annoying**
google autocomplete is **slow**
google autocomplete is**lam**
google autocomplete is**n't working**

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.

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

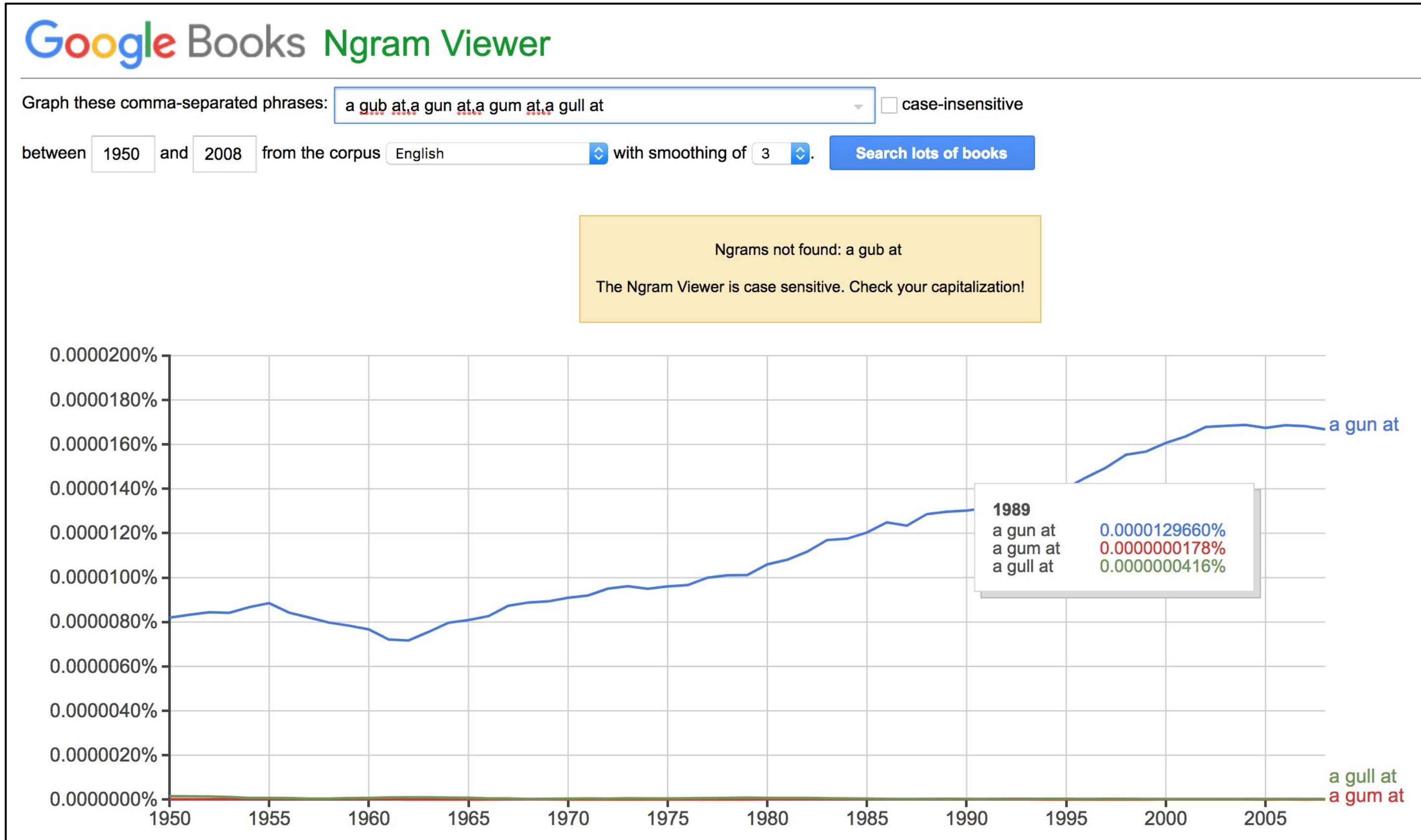
Frequency or probability:

a gub at

a gun at

a gum at

a gull at


Google Books Ngram Viewer

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. Search lots of books

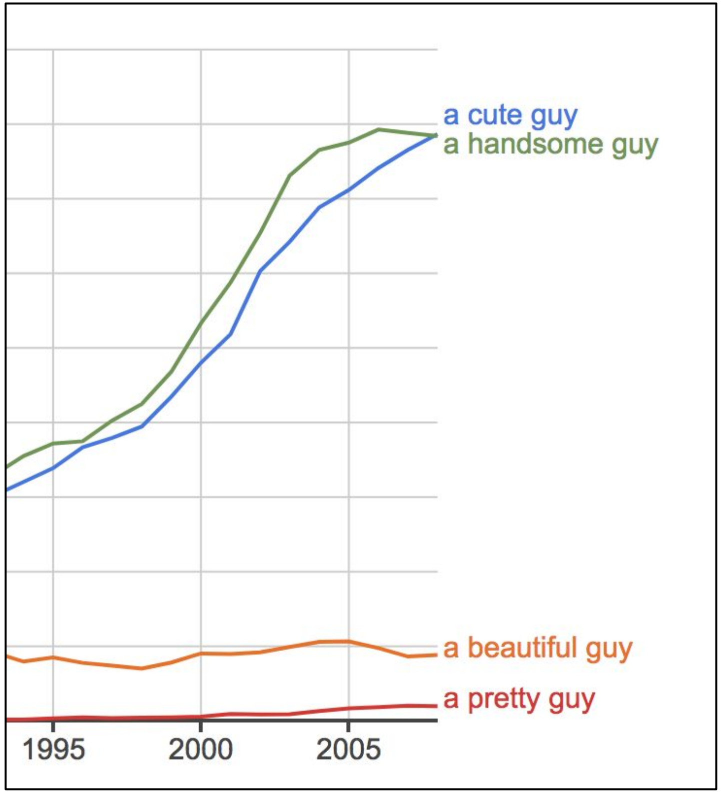
Ngrams not found: a gub at

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%

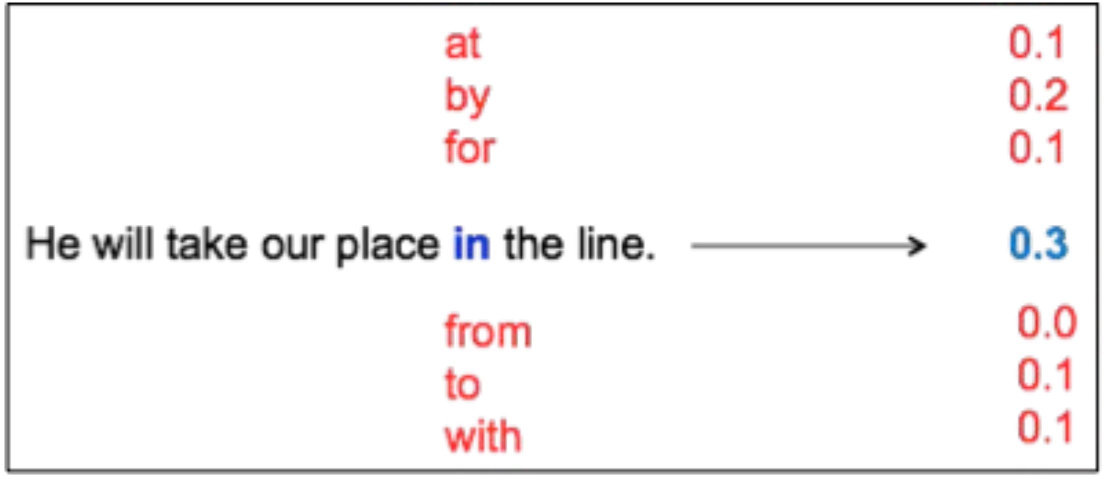
Ngrams as a feature

Frequency / probability



Ngrams as a feature

Frequency or probability



at	0.1
by	0.2
for	0.1
He will take our place **in** the line. $\longrightarrow$	0.3
from	0.0
to	0.1
with	0.1

Ngrams as a feature

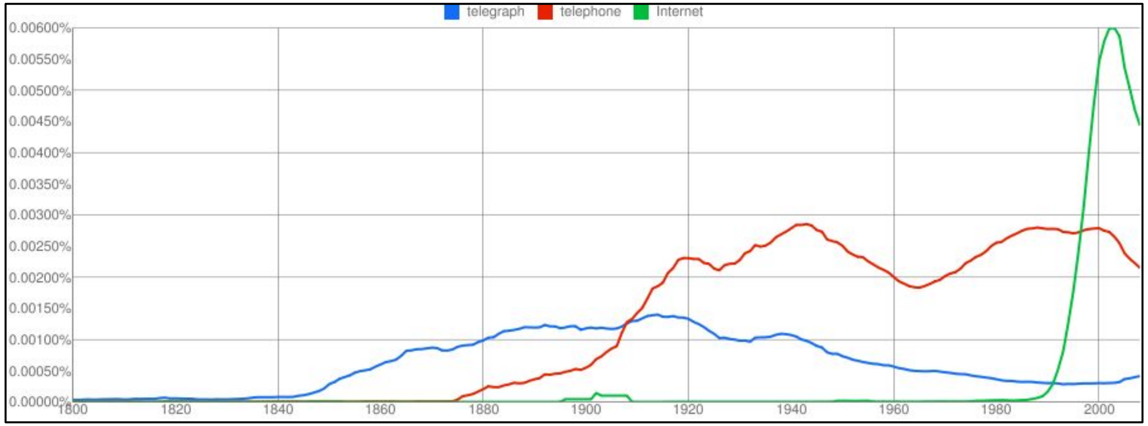
Conditional probability

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

To be continued on the lecture about language modeling…

Where to get ngrams

- 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 (2017)*
2. Hidden Markov Models in *Speech and Language Processing* by *D. Jurafsky and J. H. Martin (2017)*
3. Introduction to Conditional Random Fields by Edwin Chen (2012)
4. Conditional Random Fields: An Introduction by Hanna M. Wallach (2004)
5. Sequence labeling by Raymond J. Mooney (2016)
6. Multiclass and Multi-label Classification by Prof. Michael Paul (2017)