# Feature engineering in NLP

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#### **Contents**

- 1. Presentation of text in NLP
- 2. Feature engineering
- 3. Feature encoding
- 4. A few words about ngrams (optional)
- 5. Logistic regression (optional)
- 6. Error correction use case

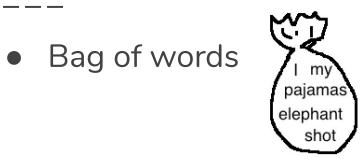
## Are these sentences equal?

\_\_\_\_

Trump beat Clinton in the election.

?

Clinton beat Trump in the election.



Bag of words



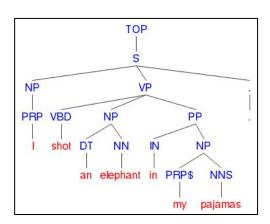
Sequence

I shot an elephant in my pajamas.

Bag of words



Tree



Sequence

I shot an elephant in my pajamas.

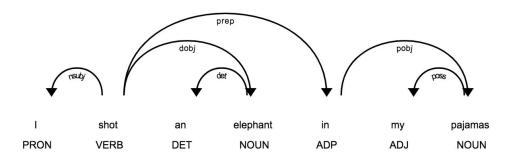
Bag of words



Sequence

I shot an elephant in my pajamas.

Tree



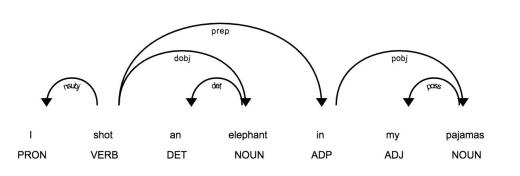
Bag of words



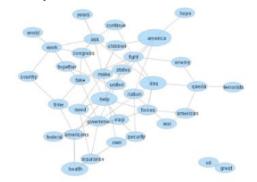
Sequence

I shot an elephant in my pajamas.

Tree



Graph



Bag of words

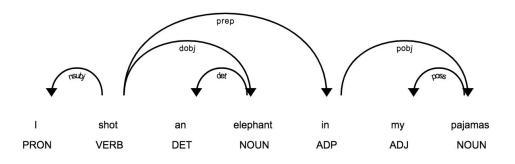


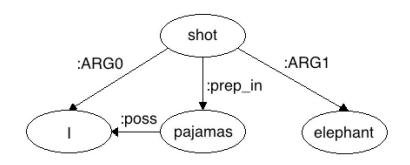
Sequence

I shot an elephant in my pajamas.

Tree

Graph





#### Think of different NLP tasks

How would you view the text if you need...

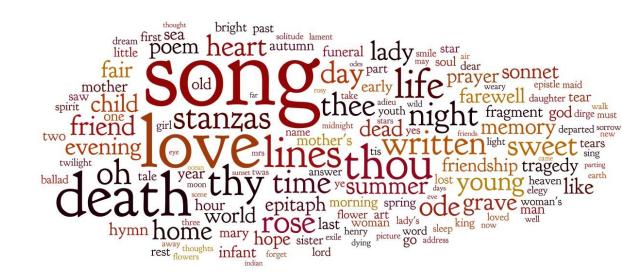
- classification of news articles by topic?
- named-entity recognition?
- sentiment assignment to objects in the text?
- abstractive text summarization?

## 2. Feature engineering

#### The Word

A word is its...

- 1. form
- 2. function
- 3. meaning



### The Form

\_\_\_\_

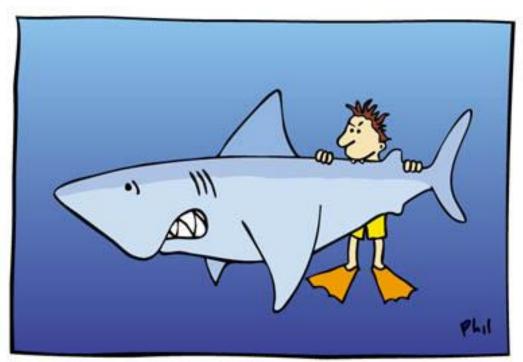
The form — how the word is written.

#### Form Features

- Capitalization, hyphenation, apostrophes
- Lemma or stem
- Number of stems
- Number and types of affixes
- Length of the word/lemma/stem
- Number of tokens, position of a token
- Number of syllables in a word
- Ratio of vowels vs. consonants
- Voiced vs. voiceless consonants
- All possible frequencies

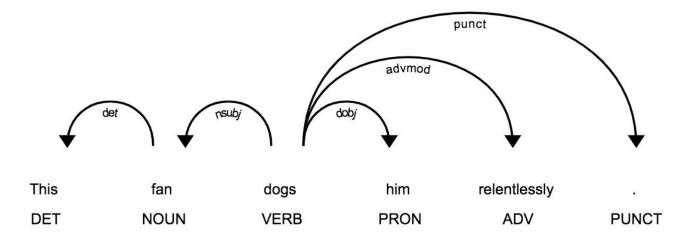
#### Form Features

a man-eating shark vs. a man eating shark



#### The Function

The function — what the word does and how it interacts with other words in the text.



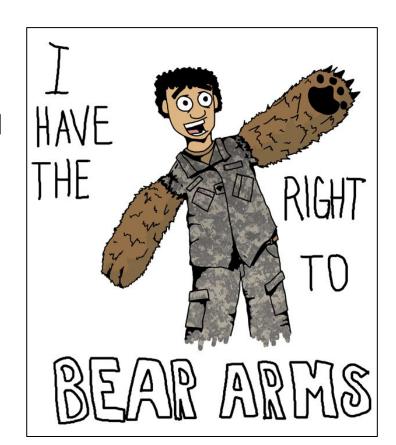
#### **Function Features**

- Part of speech
- Morphological properties:
  - o gender, animacy, number, person, case
  - aspect, voice, tense, degree of comparison
- Constituents
  - o parents, children, spans
- Direct and indirect dependencies
  - o parents, children, type of relation
- Depth of the syntactic tree
- Statistics: POS+word, POS ngrams, syntactic ngrams

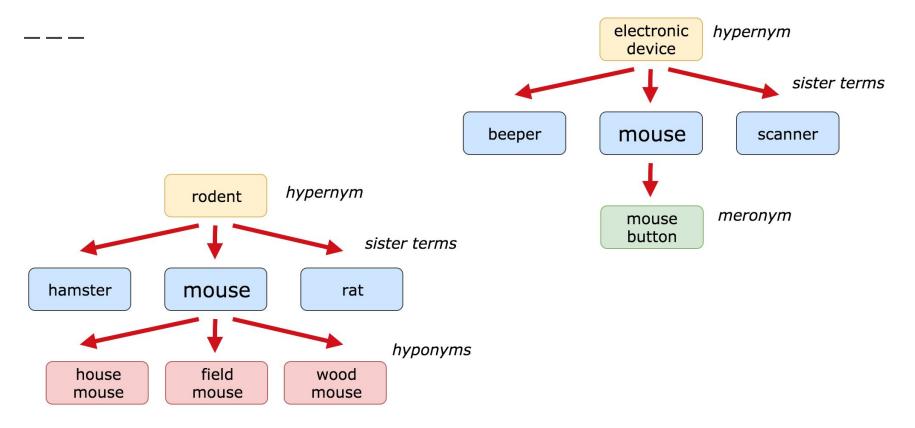
## The Meaning

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The meaning — the sense that the word obtains in the context and how it correlates with other words and senses.



#### **Lexical Semantics in WordNet**



## **Entailment (or inference)**

#### Entailment examples:

- Mom slices a cucumber. => A woman cuts a vegetable.
- Her husband was snoring. => Her husband was sleeping.
- A jogger was spotted. => Someone was jogging.
- The king of France is bald. => There exists a king of France.

## **Meaning Features**

- Word sense
- Number of senses
- Shortest path to another word sense
- Similarity to another sense
- Synonyms/antonyms, hyponyms/hypernyms, meronyms/holonyms
- Entailment
- Semantic role

## 3. Feature encoding

## Encode as a bag of words: boolean

The pound extended losses against both the dollar and the euro .

## Encode as a bag of words: count

The pound extended losses against both the dollar and the euro .

## Encode as a bag of words: tf-idf

\_\_\_\_

The pound extended losses against both the dollar and the euro .

[ 0.1, 0.7, 0, 0, 0.4, 0, ...] the dollar hello pirate losses run

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-1": "extended", "tag-1": "VBD",
    "word-2": "pound", "tag-2": "NN",
    "word+1": "against", "tag+1": "IN",
    "word+2": "both", "tag+2": "DT"}
```

DT NN VBD NNS IN DT DT NN CC DT NN .

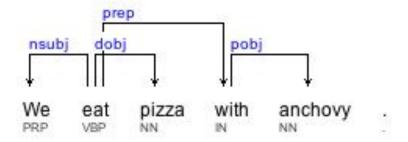
The pound extended losses against both the dollar and the euro .

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"}

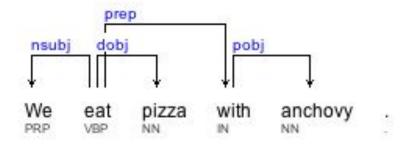
\_\_\_\_



#### "eat"/VBP:

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

\_\_\_



#### "eat"/VBP:

- nsubj\_We, dobj\_pizza, prep\_with
- nsubj\_PRP, dobj\_NN, prep\_IN
- nsubj\_We, dobj\_pizza, prep\_with\_pobj\_anchovy

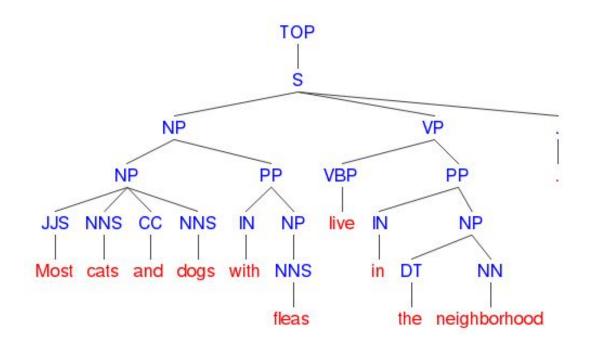
#### "fleas"/NNS:

```
{"label": "NP",

"anc-left": "PP",

"anc-right": "S",

"span-width":1}
```



## **Example**

https://bit.ly/2KNsiLJ

or

https://github.com/mariana-scorp/esscass-2019-nlp/blob/master/ 2-features/feature-encoding.ipynb

## 4. A few words about ngrams (optional)

## What are ngrams

\_\_\_\_

Ngram - a contiguous sequence of  $\mathbf{n}$  items from a given text.

## What are ngrams

\_\_\_\_

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So, if **n = 3**:

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

\_\_\_\_

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So, if n = 3:

\_\_\_\_

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

So, if n = 3:

### Token ngrams

\_\_\_\_

Usually  $1 \ge n \ge 5$ .

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

n = 1: (<S>), (Why), (did), (n't), (you), (listen), (to), (me), (?)...

 $\mathbf{n} = \mathbf{2}$ : (<S> Why), (Why did), (did n't), (n't you), (you listen), (listen to)...

 $\mathbf{n} = \mathbf{3}$ : (<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 ?

#### 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> WDT VDB RB PRP VB TO PRP .
```

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)... 46

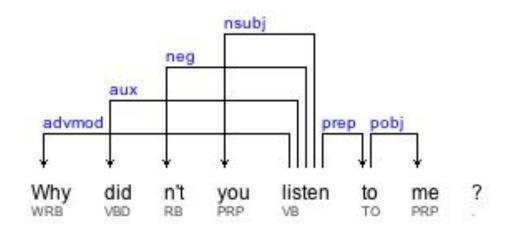
### Tree Ngrams

\_\_\_\_

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

- Speech recognition
- Text generation
- 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 islam
google autocomplete isn't working
```

#### Ngrams usage

\_\_\_\_

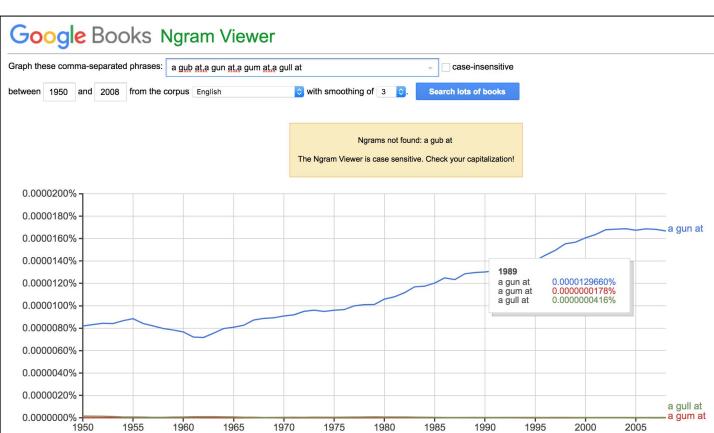
- Speech recognition
- Text generation
- Autocompletion
- Handwriting recognition
- Spelling correction
- (and GEC in general)



#### Ngrams as a feature

Frequency or probability:

a gub at
a gun at
a gum at
a gull at



#### Ngrams as a feature

\_\_\_\_

Frequency or probability

#### Ngrams as a feature

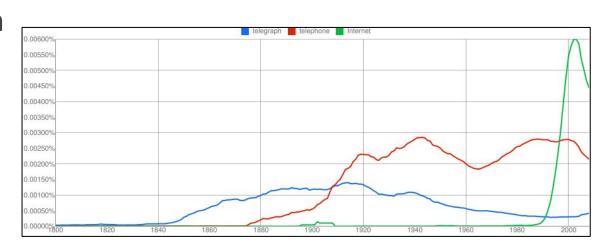
\_\_\_\_

Conditional probability

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

#### 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



# 5. Logistic Regression (optional)

#### **Logistic Regression**

\_\_\_\_

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

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

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

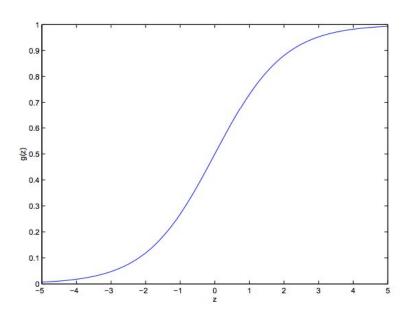
#### **Logistic Regression**

\_\_\_\_

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

Sigmoid function:

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



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#### **Logistic Regression: multiclass**

multinomial (MaxEnt) one vs. rest

http://scikit-learn.org/stable/auto\_examples/linear\_model/plot\_logistic\_multinomial.html

### **Logistic Regression**

\_\_\_\_

For multinomial logistic regression, use softmax:

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

Welcome to St. Paul 's Cathedral!

[Is this period a sentence end?]

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"}

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]

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"}
x<sub>j</sub>: [1, 0, 1, 0, 0]
w<sub>is-end</sub>: [2.9, 2.5, -0.9, 0, 0]
w<sub>is-not-end</sub>: [0.5, -0.7, 2.9, 0, 0]
```

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]  $\mathbf{P}(\text{is-end}|\mathbf{x}_{j}) = e^{2.9-0.9} / (e^{2.9-0.9} + e^{0.5+2.9}) = 0.2$   $\mathbf{w}_{\text{is-not-end}}$ : [0.5, -0.7, 2.9, 0, 0]  $\mathbf{P}(\text{is-not-end}|\mathbf{x}_{j}) = e^{0.5+2.9} / (e^{2.9-0.9} + e^{0.5+2.9}) = 0.8$ 

#### **Logistic Regression: weights**

#### Learn weights:

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

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

### 6. Error correction use case

#### Error correction use case

https://bit.ly/31GFZmd

or

https://github.com/mariana-scorp/esscass-2019-nlp/blob/master/ 2-features/adjective-vs-adverb.ipynb

### Thank you! Any kwestions?