



Introduction to Natural Language Processing

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Agenda

- NLP tasks
- Basics of Computational Linguistics
- Raw text pre-processing
- Text classification
- Topic modelling and text clustering
- Vector representation of words
- Python examples



Major NLP tasks

- Machine translation
- Sentiment analysis
- Text summarization
- Topic segmentation
- Named Entity Recognition
- Text-to-speech



NLP problematics

- Context-free grammar
- Different linguistic typologies (subject, object, verb): *SOV, SVO, VSO, VOS, others*
- Different writing systems: *Arabic, Latin, Cyrillic, Chinese, others*

Word order	Example in English	Languages
SOV	She him loves.	<i>Sanskrit, Hindi, Ancient Greek, Latin, Japanese</i>
SVO	She loves him.	<i>English, French, Indonesian, Malay, Mandarin, Russian</i>
VSO	Loves she him.	<i>Arabic, Irish, Filipino, Welsh</i>

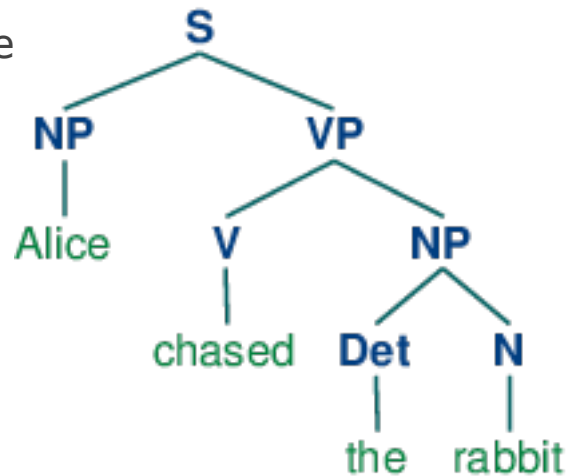
Corpora

- **Brown Corpus:** *500* examples, *15* genres, *2000* words with POS tags.
- **Quranic Arabic Corpus:** *77 430* words present in Quran with morphological and syntactic annotations.
- **WordNet:** *155 287* words organized into *117 659* synsets and *206 941* word-sense pairs.



Treebank

- text corpus with annotated syntactic and semantic structure
- based on top of corpus with annotated POS tags
- in practice usually used to determine relations between objects in a sentence
- more than 20 treebanks for majority of languages
wikipedia.org/wiki/Treebank



Pre-processing: stop words

- most common words in a language
- bring a little value to the sense of a text
- there is no universal list of stop words
- typical examples: ***a, the, of, it, as, in, at***



Pre-processing: tokenization

- **Word tokenization** – split raw text into a set of words, typically using white space.
- **Sentence tokenization** – split raw text in to a set of sentences, typically using period.

Typical problems:

- word tokenization: *Let's visit New York.* → [*Let's*, *visit*, *New*, *York*]
- sentence tokenization: *It was Mr. Holmes.* → [*'It was Mr.'*], [*'Holmes.'*]



Pre-processing: stemming & lemmatization

- **Stem** – part of the word that never changes even when morphologically inflected.

swimming → *swim*

university → *univers*

- **Lemma** – the base form of the word.

went → *go*

- Python NLTK stemmers: *PorterStemmer*, *SnowballStemmer*
- Python NLTK lemmatization: *WordNetLemmatizer*



Pre-processing: n-grams

- Example: *It was raining in Dubai yesterday.*

- 1-grams or **unigrams**:


$[(It,), (was,), (raining,), (in,), (Dubai,), (yesterday,)]$

- 2-grams or **bigrams**:

$[(It, was), (was, raining), (raining, in), (in, Dubai), (Dubai, yesterday)]$



Part-of-speech tagging

- **Verb** - show an action or a state of being: *go, write, exist, be*
 - **Noun** - refer to people, animals, objects, states, events: *John, lion, table, freedom, love*
 - **Adjective** - used to describe or specify a noun or pronoun: *good, beautiful, nice, my*
 - **Adverb** - used to modify a verb, adjective and other adverbs: *completely, never, there*
 - Others: **Pronoun, Preposition, Conjunction, Interjection.**
- 

Part-of-speech tagging workflow

- Get manually annotated corpus with POS tags for each word.
- Derive features which will be used to predict POS tag for word ω_i :
 - previous k words: $\omega_{i-1} \dots \omega_{i-k}$
 - POS tags of previous k words: $t_{i-1} \dots t_{i-k}$
 - next k words: $\omega_{i+1} \dots \omega_{i+k}$
 - POS tags of previous k words: $t_{i+1} \dots t_{i+k}$
- Use one of the classification algorithms to train model:
Hidden Markov Models, Neural Network, etc.



Bag-of-words

- **Main idea:** use word frequencies as features to classify text.
- Go through N documents in our dataset and build a dictionary of words used in a dataset
- Build matrix of frequencies with size $N \times M$
- Run classifier using frequencies matrix



Bag-of-words: matrix example

1. Place was really good.
2. We had a good time.
3. Spent a great time there.

$$X \begin{pmatrix} \textit{place} & \textit{was} & \textit{really} & \textit{good} & \textit{we} & \textit{had} & \textit{time} & \textit{spent} & \textit{great} & \textit{there} \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{pmatrix}$$



tf-idf

- term frequency–inverse document frequency
- one of the most popular term-weighting algorithms
- increases proportionally along with the word frequency
- adjusted to reduce importance of frequent words in general

$$tfidf(t, d, D) = f_{t,d} \cdot \log \frac{N}{n_t}$$



Bayes theorem

$$P(B | A) = \frac{P(A | B) \cdot P(B)}{P(A)}$$

- $P(A)$ and $P(B)$ are the probabilities to observe events A and B in our overall data
- $P(A | B)$ is a probability of observing event A given the fact that B is true
- $P(B | A)$ is a probability of observing event B given that A is true



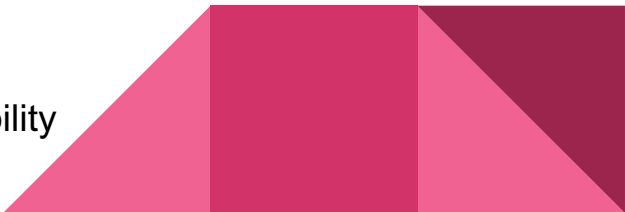
Naïve Bayes

- assume independence between predictors
- suitable for a large datasets

$$P(\text{Positive}, [\text{good} = 1, \text{bad} = 0]) = \frac{P([\text{good} = 1, \text{bad} = 0], \text{Positive}) \cdot P(\text{Positive})}{P([\text{good} = 1, \text{bad} = 0])}$$

Diagram illustrating the Naïve Bayes formula with labels and arrows:

- Posterior probability** points to $P(\text{Positive}, [\text{good} = 1, \text{bad} = 0])$.
- Likelihood** points to $P([\text{good} = 1, \text{bad} = 0], \text{Positive})$.
- Class prior probability** points to $P(\text{Positive})$.
- Evidence prior probability** points to $P([\text{good} = 1, \text{bad} = 0])$.



Latent Dirichlet allocation

- unsupervised statistical model
- represents documents as mixtures of topics
- each topic is represented by a set of weighted words

Topic 1		Topic 2		Topic 3	
word	weight	word	weight	word	weight
politics	3245	university	5443	environment	4554
government	2334	education	4435	pollution	3442
affairs	1545	degree	4322	ecosystem	1245



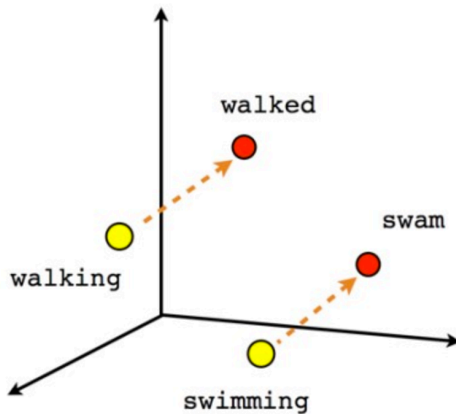
Latent Dirichlet allocation

- Assume that documents are produced from a mixture of topics. Topics generate words based on their probability distribution.
- Determine the number of words in a document. Let's say our document has 50 words.
- Determine the mixture of topics in that document. For example, the document might contain 1/2 the topic ***education*** and 1/2 the topic ***politics***.
- Using each topic's multinomial distribution, output words to fill the document's word slots.

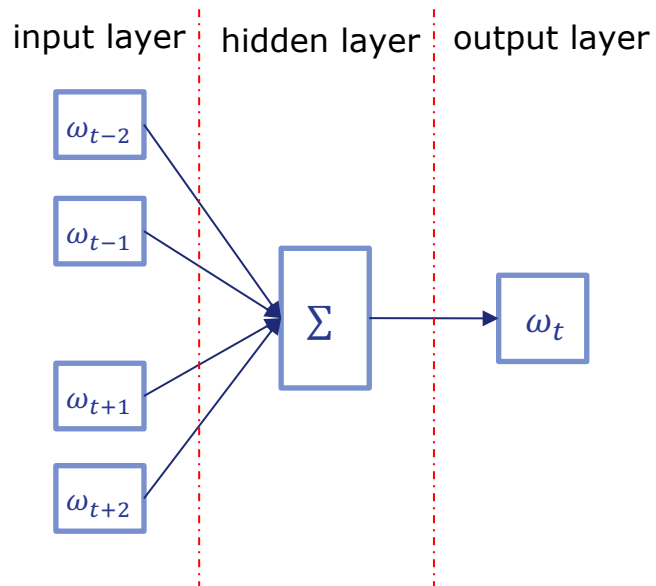


Vector representation of words

- build a vector for each word taking in account context in which particular word occurs
- don't require labeled data
- simple feedforward neural network under the hood
- popular implementations: **word2vec**, **GloVe**

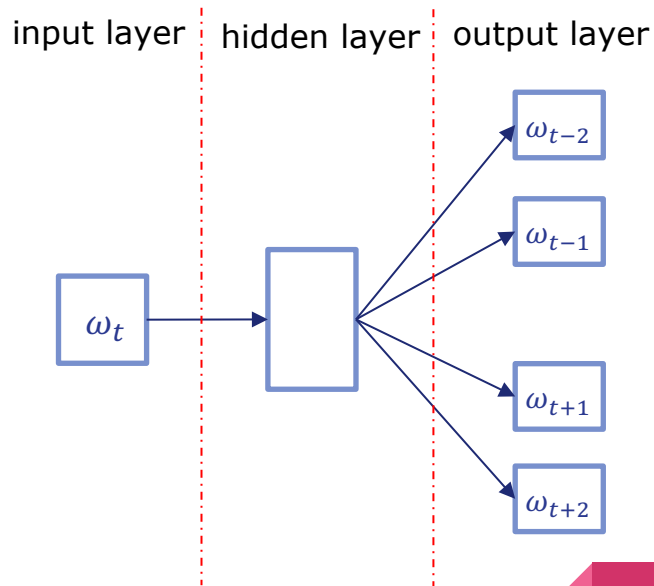


Vector representation of words



CBOW

Continuous Bag-of-Words



skip-gram

Common NLP tools

- NLTK – nltk.org
- gensim – radimrehurek.com/gensim
- SpaCy – spacy.io
- OpenNLP – opennlp.apache.org
- Stanford CoreNLP – stanfordnlp.github.io/CoreNLP



Python examples



github.com/root-ua/nlp-intro-meetup



Thanks!

