Natural Language Processing from Scratch

https://github.com/DataForScience/NLP

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www.data4sci.com

Question

- Where are you located?
    - Europe
    - Asia
    - Africa
    - US
    - Canada
    - Latin America
    - Oceania

Question

- What's your job title?
    - Data Scientist
    - Statistician
    - Data Engineer
    - Researcher
    - Business Analyst
    - Software Engineer
    - Other

Question

- How experienced are you in Python?
    - Beginner (<1 year)
    - Intermediate (1-5 years)
    - Expert (5+ years)

Lesson 1:
Text Representations

Lesson 1.1:
Represent words and Numbers

Words and Numbers

- How can computers represent, analyze and understand a piece of text?
- Computers are really good at crunching numbers but not so much when it comes to words.
- Perhaps we can substitute words with numbers?
    - Unfortunately, computers assume that numbers are sequential.
- Vectors work much better!
    - Each word corresponds to a unique dimension.

1	a
2	about
3	above
4	after
5	again
6	against
7	all
8	am
9	an
10	and
11	any
12	are
13	aren't
14	as
…	…

Lesson 1.2:
Use One-hot Encoding

One-hot Encoding

$$v_{after} = (0, 0, 0, 1, 0, 0, \cdots)^T$$
$$v_{above} = (0, 0, 1, 0, 0, 0, \cdots)^T$$

One-hot encoding

- What about full texts instead of single words?
- The vector representation of a text is simply the vector sum of all the words it contains:

Mary had a little lamb, little lamb,
little lamb, Mary had a little lamb
whose fleece was white as snow.
And everywhere that Mary went
Mary went, Mary went, everywhere
that Mary went
The lamb was sure to go.

$$v_{text} = (2, 4, 1, 2, 2, 1, 1, 2, 6, 1, 5, 1, 2, 1, 1, 1, 1, 4, 1)^T$$

0	had	10	lamb
1	went	11	as
2	and	12	that
3	a	13	sure
4	was	14	whose
5	to	15	go
6	snow	16	the
7	everywhere	17	little
8	mary	18	white
9	fleece		

One-hot Encoding

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$$v_{text} = (2, 4, 1, 2, 2, 1, 1, 2, 6, 1, 5, 1, 2, 1, 1, 1, 1, 4, 1)^T$$

0	had	10	lamb
1	went	11	as
2	and	12	that
3	a	13	sure
4	was	14	whose
5	to	15	go
6	snow	16	the
7	everywhere	17	little
8	mary	18	white
9	fleece		

Lesson 1.3:
Implement Bag of Words

Bag of Words

- In practice it's much more convenient to use a dictionary instead of an actual vector

- This is known as a bag-of-words, and word order is discarded.

Mary had a little lamb, little lamb,
little lamb, Mary had a little lamb
whose fleece was white as snow.
And everywhere that Mary went
Mary went, Mary went, everywhere
that Mary went
The lamb was sure to go.

$$v_{text} = (2, 4, 1, 2, 2, 1, 1, 2, 6, 1, 5, 1, 2, 1, 1, 1, 1, 4, 1)^T$$

had	2	lamb	5
went	4	as	1
and	1	that	2
a	2	sure	1
was	2	whose	1
to	1	go	1
snow	1	the	1
everywhere	2	little	4
mary	6	white	1
fleece	1		

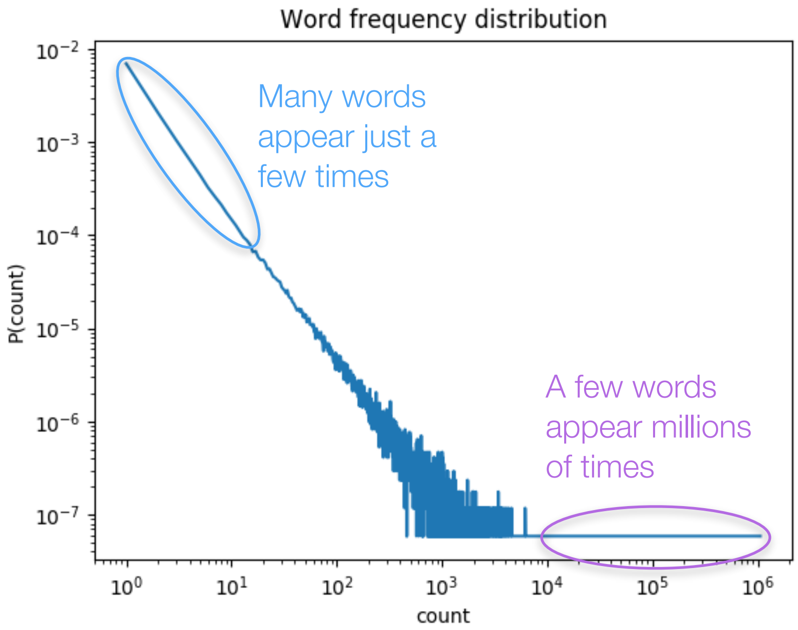
Lesson 1.4: Apply Stopwords

Word Frequency

- Some words are much more common than others.
- While most words are very rare.
- The most common words in a corpus of 17M words:

the	1061396
of	593677
and	416629
one	411764
in	372201
a	325873
to	316376
zero	264975
nine	250430
two	192644

- These are known as "stopwords", words that carry little meaning and can be discarded.



Stopwords

- After removing the most common words we go from 17M words to just 9M, without significantly losing any information!
- In practice, stopwords aren't simply the most common words but rather curated lists of common and non-informative words.
- Computational linguists have published lists of stop words that can easily be found online, and that were curated for different languages and purposes.
- Stopwords in 40 languages: https://www.ranks.nl/stopwords

Stopwords

- NLTK also includes stopwords from the 14 languages listed here: http://anoncvs.postgresql.org/cvsweb.cgi/pgsql/src/backend/snowball/stopwords/ plus Romanian (http://arlc.ro/resources/) and Kasakh.

- And perhaps there is a better way to quantify how much information is carried by a word, other than just the number of times it is used in a single document?

- How can we compare different documents?

Lesson 1.5: Understand TF/IDF

Term Frequency

- We already saw that some words are much more common than others
- The number of times that a word appears in a document is known as the "term frequency" (TF)
- After the removal of stopwords, the term frequency is a good indicator of what words are most important. A book on Python programming will likely have words like "code", "script", "print", "error", etc much more frequently than a book on football.

the	1061396
of	593677
and	416629
one	411764
in	372201
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to	316376
zero	264975
nine	250430
two	192644

Inverse Document Frequency

- TF gives us an idea of how popular a specific term is within a document, but how can we compare across documents within a corpus?

- The inverse document frequency (IDF) tells us how unusual it is for a document to include that word. The idea is that words that appear in more documents are less meaningful.

the	1061396
of	593677
and	416629
one	411764
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a	325873
to	316376
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nine	250430
two	192644

TF/IDF

- Mathematically there are several possible definitions for both TF and IDF

TF

IDF

Number of times term t occurs in document d

$$N_{t,d}$$

$$\frac{N_{t,d}}{\sum_{t'} N_{t',d}}$$

$$1 + \log\left(N_{t,d}\right)$$

$$\log\left(\frac{N}{N_t}\right)$$

$$\log\left(1 + \frac{N}{N_t}\right)$$

Number of documents

Number of documents in which term t appears

- TF-IDF is the product of these two quantities and is useful for finding terms that are important for the specific document (high TF) and uncommon in the corpus as a whole (large IDF/ small DF).

TF/IDF

- In particular, a term that occurs in every document is meaningless when it comes to distinguishing between documents.
- Stopwords, are naturally weighed down due to appearing in all documents.

Lesson 1.6: Understand Stemming

Word variants

- So far we have seen multiple techniques to represent words and to reduce the number of words we have to deal with.
- But what about word variants? Verb conjugations, plurals, nouns and adverbs?

love

loved

loves

loving

lovingly

…

- In some cases they should just be represented by the same stem or root.

Word variants

- So far we have seen multiple techniques to represent words and to reduce the number of words we have to deal with
- But what about word variants? Verb conjugations, plurals, nouns and adverbs?

love
loved
loves love
loving
lovingly
...

- In some cases they should just be represented by the same stem or root.

Stemming

- Stemming is a series of techniques to automatically identify the stem or root of a word
- Naturally, the rules that must be applied depend on the grammar of the specific language being used
- For English, the most common algorithm is called Porter stemmer

Porter Stemmer Algorithm

- Let V be a set of one or more vowels (a, e, i, o, u, y) and C be a set of one of more consonants (b, c, d, f, …).
- Any word in the English language is of the form:

$$[C](VC)^m[V]$$

where the contents of the $[]$ are optional and $m \geq 0$ is known as the measure, the number of times that the sequence VC repeats.

Porter Stemmer Algorithm

- The Porter stemmer algorithm develops over the course of several steps, by the successive application of hand-crafted rules of the form:

  $$(condition)\ old\_suffix \rightarrow new\_suffix$$

  where $condition$ is a boolean expression evaluated on the stem. Each rule can be read as “if $condition$ is True, then replace old_suffix by new_suffix .
- Rules are grouped together and applied in a greedy fashion, such that the longest matching old_suffix takes precedence.
- new_suffix can be an empty string and $condition$ can be null.

Porter Stemmer Algorithm

- For example, the rule:

$$(m > 0)\ eed \rightarrow ed$$

would transform

$$agreed \rightarrow agree$$
$$feed \rightarrow feed$$

since

$$measure\left('\mathrm{agr}'\right) = 1$$

$$measure\left('f'\right) = 0$$

- Of course, not all $conditions$ rely only on the value of $measure$

Porter Stemmer Algorithm

- Other expressions commonly used in $condition$ are:
  - $*S$ - The stem ends with the letter S (or any other specified)
  - $*v*$ - The stem contains a vowel
  - $*d$ - The stem ends in a double consonant (-tt, -ss, etc)
  - $*o$ - The stem ends in cvc where the second c is not W, X, or Y
- Expressions can be combined using the usual boolean operators and, or, not, grouped using parenthesis, etc.
- For example

$$\left(*d \text{ and not} \left(*L \text{ or } *S \text{ or } *Z \right) \right)$$

represents a stem ending with a double consonant other than L, S or Z.

Questions?

Lesson 2:
Topic Modeling

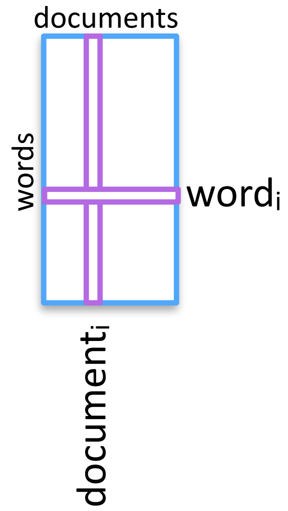
Lesson 2.1:
Find Topics in Documents

Topics

- A common application of NLP is to Search and Information Extraction.
- Can we automatically define the subject of a document?
- We saw in the previous lesson that some words are more meaningful than others.
- Based on the importance of each word for a specific document, it should be possible to characterize its topic.

Term-Document Matrix

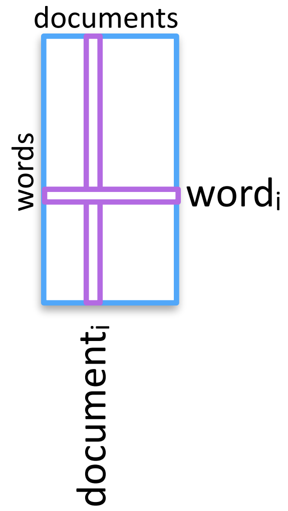
- We already know how to represent documents in terms of the TFIDF weights of each of their words.
- If we similarly use a vector representation where each element corresponds to a specific word, we can represent a corpus of documents as a matrix where each column is a document.
- Conversely, each word can be thought of as being represented by a row vector defined by its importance over all documents.



Lesson 2.2:
Perform Explicit Semantic Analysis

Explicit Semantic Analysis

- In the term document matrix, each word is defined, explicitly, by its contribution for each document.
- We can infer the meaning of each word by the concepts (documents) it contributes to.
- Typically, the English Wikipedia is used as the knowledge base (corpus).
- Using the TD matrix we can represent any (other) document by the sum (or average) over all the words it contains. This is similar to what we did with one-hot encodings to define bag-of-words.



Explicit Semantic Analysis

- The similarity of words or new documents can be measured using the cosine similarity:

$$\text{sim}\left(\vec{u}, \vec{v}\right) = \frac{\vec{u} \cdot \vec{v}}{||\vec{u}|| \, ||\vec{v}||}$$

- Explicit semantic analysis, despite its simplicity, has been shown to improve the performance of different kinds of systems for search.
- The main disadvantage of ESA is that it requires the use of a large knowledge base corpus (the entire English Wikipedia!), resulting in high dimensional representations of words and documents.

Lesson 2.3: Understand Document clustering

Document Clustering

- Using the cosine similarity:

$$\text{sim}\left(\vec{u}, \vec{v}\right) = \frac{\vec{u} \cdot \vec{v}}{||\vec{u}|| \, ||\vec{v}||}$$

  we can easily measure the similarity between every pair of documents in our corpus to generate a square similarity matrix.
- There is a large literature on clustering algorithms for matrices.
- The simples approach is to impose a minimum similarity cutoff and consider any pair of documents with higher similarity to be part of the same cluster.

Hierarchical Document Clustering

- Algorithm
    - Assign each document to its own cluster.
    - Calculate the similarity matrix between all clusters.
    - Identify the two most similar clusters and merge them.
    - Recompute the similarity matrix for this reduced set of clusters.
    - Repeat until we reach the desired number of clusters.
- Library implementations will usually merge all the clusters until there is just one left so that any cutoff can be imposed a posteriori.

Lesson 2.4: Implement Latent Semantic Analysis

Singular Value Decomposition (SVD)

- Any matrix M, such as the TD matrix seen above, can be decomposed into three matrices of the form:

$$\underset{m \times n}{M} = \underset{m \times m}{U} \; \underset{m \times n}{\Sigma} \; \underset{n \times n}{V^{\dagger}}$$

where

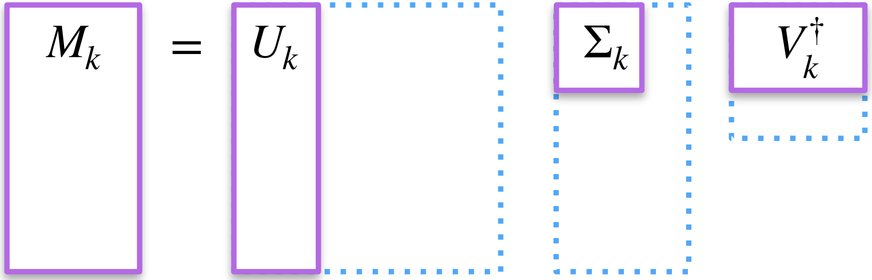
U is a unitary matrix ($UU^{\dagger} = 1$)

Σ is diagonal with non-negative elements

$V^{\dagger}$ is a unitary matrix

Singular Value Decomposition (SVD)

- The diagonal elements of Σ, σ_i are called the singular values of the matrix M and are conceptually similar to eigenvalues in the case of square matrices.
- σ_i are sorted from largest to smallest.
- The original matrix M can be approximated by keeping only the top k dimensions of the SVD decomposition.



- Naturally, the larger the value of k the better the approximation.

Latent Semantic Analysis (LSA)

- While ESA explicit defines each word based on the documents in contributes to in the knowledge base, LSA tries to implicitly determine a “latent” representation for each word and document.
- LSA defines the term-document matrix for the corpus under consideration (as opposed to an external knowledge base).
- The DT matrix is approximated using a k dimensional singular value decomposition
- Each of the k latent dimensions used represents a latent dimension (topic) of the underlying dataset.

Latent Semantic Analysis (LSA)

- The U_k represents the distribution of each topic among the words in our vocabulary, while the V_k matrix describes the distribution of each document across topics.
- Documents and words can be more effectively clustered in the singular space.
- New documents (or queries) can be mapped into the singular space using:

$$\hat{v} = \Sigma_k^{-1} U_k^{\dagger} v$$

where v is the column vector representing the original query and $\hat{v}$ the transformed document vector.

Lesson 2.5: Implement Non-negative Matrix Factorization

Non-Negative Matrix Factorization

- Matrix factorization methods, like SVD, have a long history of application to natural language processing.
- Another common factorization method used to identify a latent structure to a dataset is non-negative matrix factorization (NMF).

$$\underset{m \times n}{M} = \underset{m \times k}{W} \; \underset{k \times n}{H}$$

- NMF directly approximates the matrix M for a given value of k.

Non-Negative Matrix Factorization

- In this formulation, it has the advantage of being easily interpretable:
    - Columns of W are the underlying basis vectors for each topic.
    - Columns of H are the contribution of each topic to a specific document.

Non-Negative Matrix Factorization

- The value of W and H are found through an optimization procedure where we minimize the error of the approximation:

$$\min_{W,H} ||V - WH||_F^2$$

- One simple way to do this is given by:

$$h_{ij} \leftarrow h_{ij} \frac{\left(W^\dagger V\right)_{ij}}{\left(W^\dagger WH\right)_{ij}} \qquad w_{ij} \leftarrow w_{ij} \frac{\left(VH^\dagger\right)_{ij}}{\left(WHH^\dagger\right)_{ij}}$$

- And we initiate the process by assigning random non-negative values to W and H.
- We stop updating the values of h_{ij} and w_{ij} when the cost function converges.

Questions?

Lesson 3:
Sentiment Analysis

Lesson 3.1: Quantify words and feelings

Positive and Negative Words

- We often use words to describe how we are feeling or how we feel about something
- People associate specific connotations and meanings to words
- Some are obvious:
  - Love, yes, friendship, good, … transmit positive feelings
  - Hate, no, animosity, bad, … transmit negative feelings
- Others less so:
  - Blue, maybe, indifference, …

Positive and Negative Texts

- We can use the words in a text to determine the sentiment behind the text
- The simplest approach:
    - count positive P and negative N words
    - define sentiment as:

$$\text{sentiment} = \frac{P - N}{P + N}$$

- This effectively weighs positive words as +1 and negative words as -1 and defines sentiment as how dominant one sentiment is over another
- Despite it's simplicity, this approach is surprisingly powerful

Word Valence

- Many lexicons of positive and negative words are available online:
  - Opinion Lexicon: https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html
  - Opinion Finder: https://mpqa.cs.pitt.edu/opinionfinder/
- Even commercial products use similar approaches:
  - Linguistic Inquiry and Word Count (LIWC) http://liwc.wpengine.com/
  - Valence Aware Dictionary and sEntiment Reasoner (VADER) https://github.com/cjhutto/vaderSentiment

Lesson 3.2:
Use negations and modifiers

Negations and Modifiers

- So far, our approach to sentiment analysis has relied on considering just individual words
- However it's clear that context matters.
- "not pretty" is very different from "pretty"
- n-grams are a natural extension, but increase significantly the memory requirements
- An intermediate approach is to consider modifier words like "not", "much", "little", "very", etc.
- By keeping track of the modifiers we can generate n-grams on the fly

Modifiers

- While sentiment words contribute additively to the sentiment score, modifiers have a multiplicative effect
- If we define the weights of each modifier

not	-1
very	1.5
somewhat	1.2
pretty	1.5
…	…

- We just have to check the previous word whenever we encounter one of the sentiment words in our lexicon
- Special care must be taken whenever a modifier word can also be a sentiment word (such as "pretty").

Modifiers

- We must keep two separate dictionaries of words: modifiers and valence words.
- For each word we encounter, we first check whether it is a modifier and only then whether it is valence word.
- Words that are in neither list act as a signal to end the current n-gram
- With this simple approach we can handle even long sequences of modifiers, double negatives, etc.

Lesson 3.3: Understanding corpus-based approaches

Corpus-based Approaches

- Sentiment analyses often rely on dictionaries of words and valences
- In many cases, these lists are curated manually with varying degrees of care
- Can we automatically generate them?
- With the advent of the Web, large corpora of product reviews became available
- Each review associates a piece of text with a numerical evaluation (typically 1-5 stars)

Corpus-based Approaches

- Corpus based approaches to sentiment analysis rely on these datasets to generate the lexicons used
- These approaches leverage sophisticated supervised machine learning techniques to automatically determine the weight that should be assigned to each word
- Modifiers can be identified using Part-of-Speech (POS) tagging
- The details of these techniques are beyond the scope of this introductory course, but it's important to understand their advantages and disadvantages

Corpus-based Approaches

- Hand curated lexicons are naturally subjective and potentially incomplete
- Lexicons generated automatically from large corpora can cover a wider range of languages and subjects
- Hand curation is more powerful when only smaller datasets are available
- Automatic generation relies on large datasets and their inherent biases. They are typically only applicable to specific domains and may appear to be more objective.
- Your results will only be as good as your lexicon. Make sure to understand its biases and limitations.

Questions?

Lesson 4: Applications

Lesson 4.1: Understand Word2vec word embeddings

Distributional hypothesis

- We already saw various way in which to represent word in a vectorial form, but never in a way that was semantically meaningful.
- The distributional hypothesis in linguistics states that words with similar meanings should occur in similar contexts.
- In other words, from a word we can get some idea about the context where it might appear.

___ ___ house __ ____.
___ ___ car __ _______.

$$\max p\left(C|w\right)$$

- And from the context we have some idea about possible words.

The red _____ is beautiful.
The blue _____ is old.

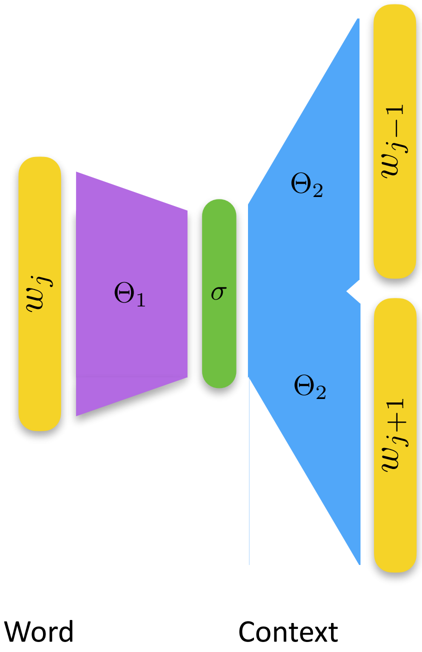
$$\max p\left(w|C\right)$$

word2vec

Mikolov 2013

Skipgram

$$\max p\left(C|w\right)$$



Θ_1 word embeddings

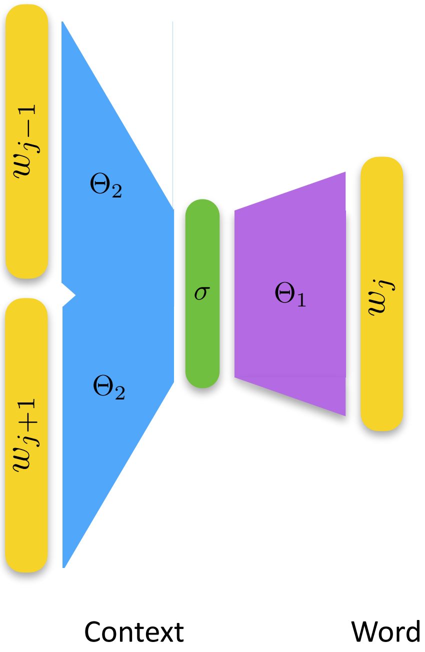
Θ_2 context embeddings

w_j one hot vector

σ activation function

Continuous Bag of Words

$$\max p\left(w|C\right)$$



word2vec variations

- Hierarchical Softmax:
  - Approximate the softmax using a binary tree
  - Reduces the number of calculations per training example from V to $\log_2 V$ and increases performance by orders of magnitude.
- Negative Sampling:
  - Under sample the most frequent words by removing them from the text before generating the contexts
  - Similar idea to removing stop-words — very frequent words are less informative.
  - Effectively makes the window larger, increasing the amount of information available for context

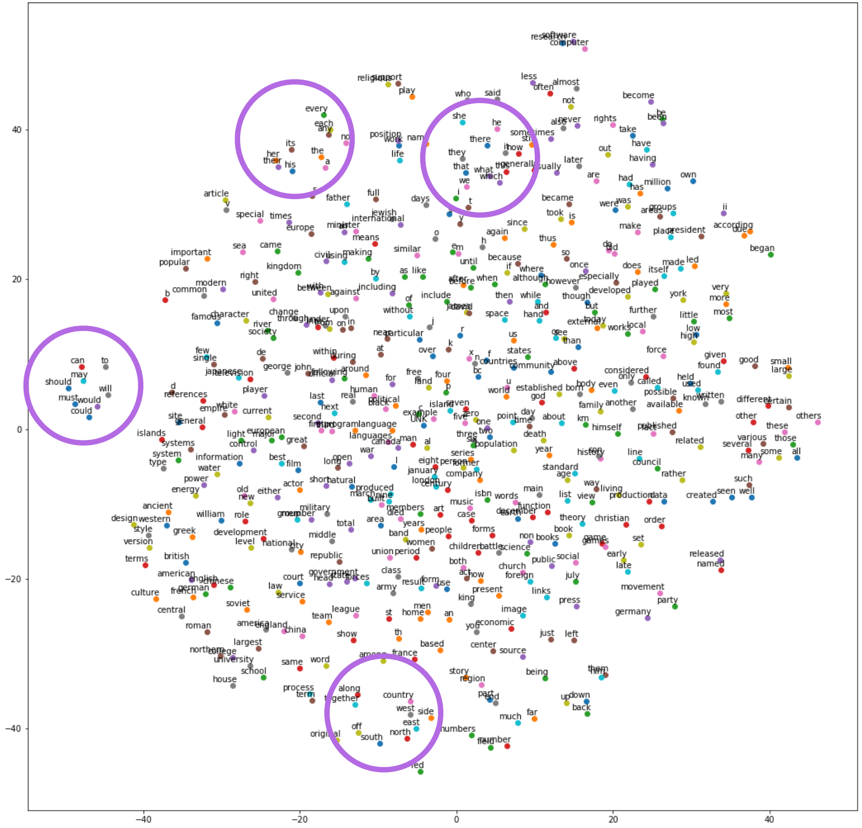
word2vec details

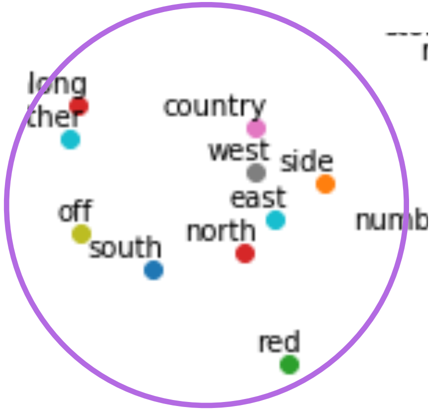
- The output of this neural network is deterministic:
  - If two words appear in the same context ("blue" vs "red", for e.g.), they will have similar internal representations in Θ_1 and Θ_2
  - Θ_1 and Θ_2 are vector embeddings of the input words and the context words respectively
- Words that are too rare are also removed.
- The original implementation had a dynamic window size:
  - for each word in the corpus a window size k' is sampled uniformly between 1 and k

Reference implementations

- C - https://code.google.com/archive/p/word2vec/ (the original one)
- Python/tensorflow - https://www.tensorflow.org/tutorials/word2vec
- Python/gensim - https://radimrehurek.com/gensim/models/word2vec.html
- Pretrained embeddings:
  - 30+ languages, https://github.com/Kyubyong/wordvectors
  - 100+ languages trained using wikipedia: https://sites.google.com/site/rmyeid/projects/polyglot

Visualization





Analogies

- The embedding of each word is a function of the context it appears in:

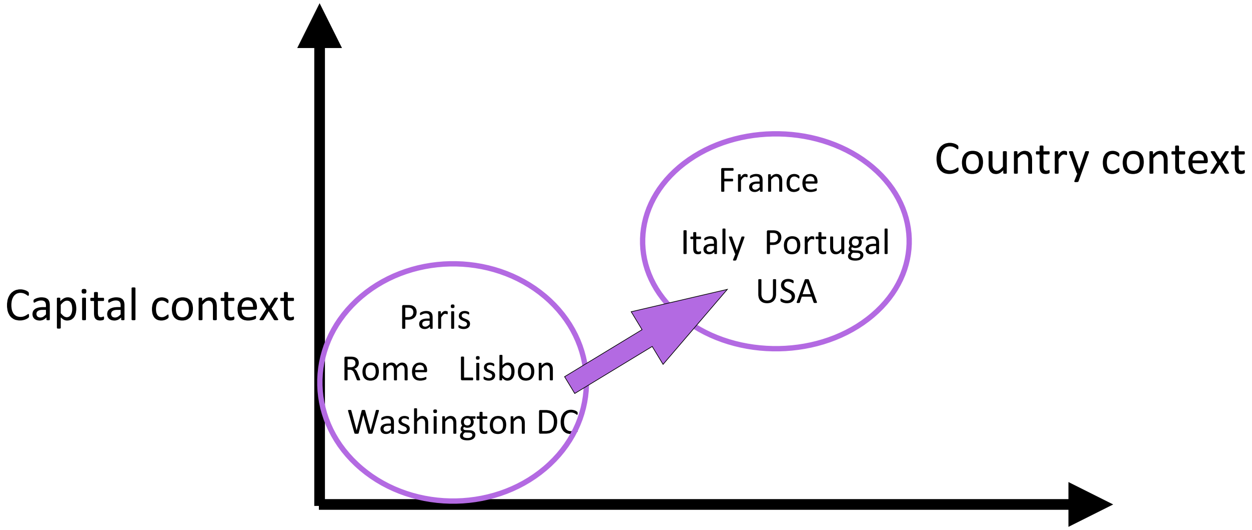
$$\sigma\left(red\right) = f\left(context\left(red\right)\right)$$

- words that appear in similar contexts will have similar embeddings:

$$context\left(red\right) \approx context\left(blue\right) \implies \sigma\left(red\right) \approx \sigma\left(blue\right)$$

- "Distributional hypotesis" in linguistics

Analogies



$$\sigma\left(France\right) - \sigma\left(Paris\right) + \sigma\left(Rome\right) = \sigma\left(Italy\right)$$

$$\vec{b} - \vec{a} + \vec{c} = \vec{d}$$

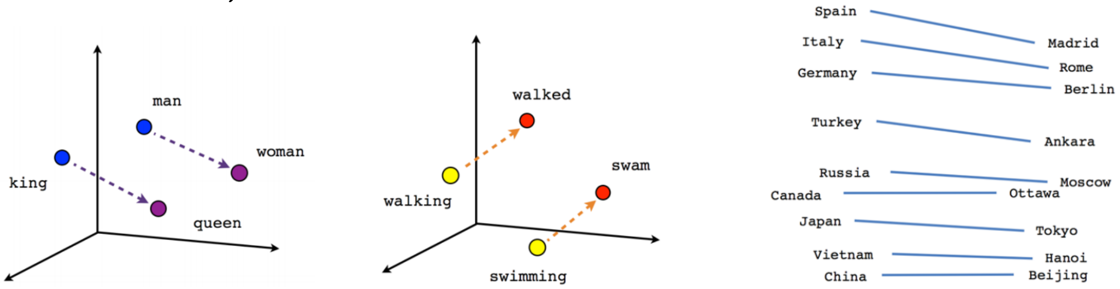
Analogies

$$\vec{b} - \vec{a} + \vec{c} = \vec{d}$$

$$d^{\dagger} = \underset{x}{\operatorname{argmax}} \frac{\left(\vec{b} - \vec{a} + \vec{c}\right)^{T}}{\left\|\vec{b} - \vec{a} + \vec{c}\right\|} \vec{x}$$

What is the word d that is most similar to b and c and most dissimilar to a?

$$d^{\dagger} \sim \underset{x}{\operatorname{argmax}} \left(\vec{b}^{T} \vec{x} - \vec{a}^{T} \vec{x} + \vec{c}^{T} \vec{x}\right)$$



Male-Female

Verb tense

Country-Capital

Lesson 4.2: Define GloVe

Global Vectors (GloVe)

- An alternative to word2vec developed by the Stanford NLP Group in 2014
- Explicitly models word cooccurrences by a cooccurrence matrix X where rows correspond to input words and columns to context words
- X_{ij} is the number of times word i occurred with context word j
- Contexts are defined through a sliding window

Global Vectors (GloVe)

- Embedding vectors for word i is defined as:

$$w_i^T \tilde{w}_k + b_i + \tilde{b}_k = \log\left(X_{ik}\right)$$

- Embedding vectors are found through an optimization procedure with a cost function of the form:

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_k - log\left(X_{ij}\right)\right)^2$$

$$f\left(X_{ij}\right) = \begin{cases} \left(\frac{X_{ij}}{X_{max}}\right) & \text{if } \mathrm{X_{ij}} < \mathrm{x_{max}} \\ 1 & \text{otherwise} \end{cases}$$

Global Vectors (GloVe)

- $f\left(X_{ij}\right)$ prevents common word pairs from skewing our cost function
- Explicitly considers the context in which each word appears
- Word-context matrix is large, but sparse
- Relatively fast to train
- Highlights the importance of relative frequency of words
- Impractical to use as a language model (to explicitly calculate the value of $\max p\left(w|C\right)$)

Resources

- The original implementation: https://nlp.stanford.edu/projects/glove/
- Python package: https://pypi.org/project/glove/
- Pre-trained vectors: https://github.com/stanfordnlp/GloVe

Lesson 4.3:
Apply Language detection

Language Detection

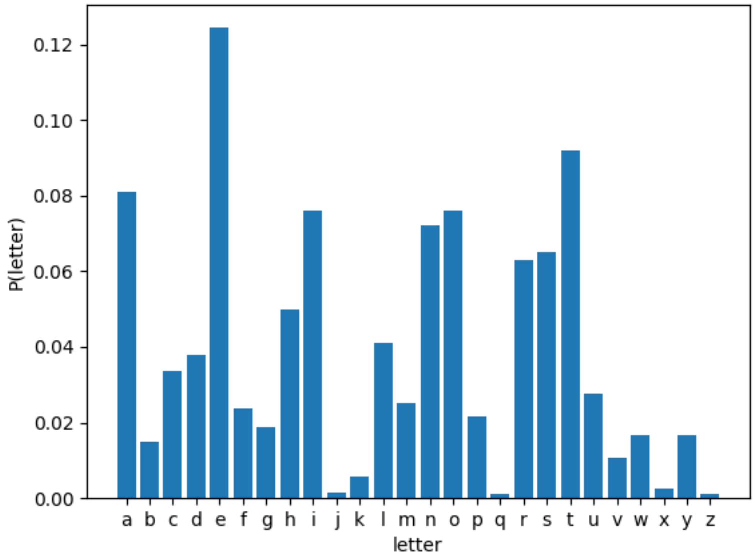
- Sometimes a given corpus will contain documents written in different languages (comment boxes in international websites, for example)
- We intrinsically assumed that each individual documents is comparable with all others.
- When multiple languages are present within the same corpus (on Twitter, in the comment boxes of an international website, etc) this is no longer true.

Language Detection

- One way to handle this would be to cluster documents, as documents in the same language will naturally cluster together. However:
    - there might be multiple clusters using the same language
    - We might not be interested in doing all this work for languages other than, say, English
- Language detection allows us to preprocess our corpus so that we can focus on specific languages, sort documents by language (to use different stopword lists), etc.
- Languages can be characterized by their character (letter) distribution.

Character distributions

- The character level distribution for English, obtained using Google Books 1-gram dataset is:



Character distributions

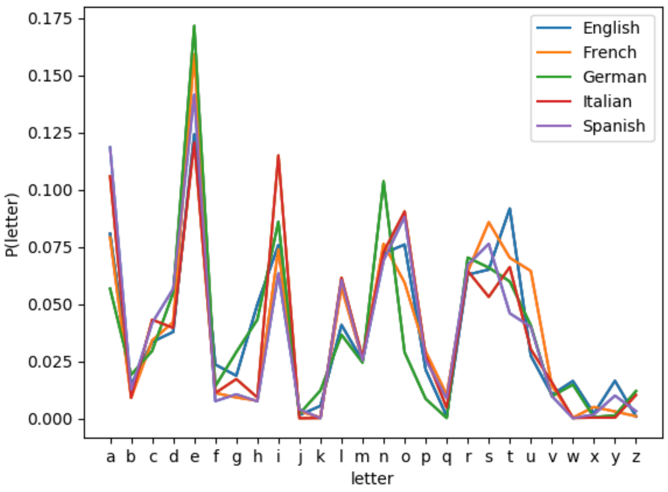
- We measured the probability distribution of letters in the english language. In effect, we calculated: $P\left(letter|english\right)$

- The probability of seeing a specific letter given that the text is in English. If we do this for a few other languages we can have a table of the form: $P\left(letter|language\right)$

- Google Books covers several different languages, among which we an find 5 different European languages: English, French, German, Italian and Spanish.

Character distributions

- Character distributions for different languages look different in at least a few of the characters due to the idiosyncrasies of each language, even in the case of closely related languages.



Conditional Probabilities

- Using these conditional probabilities, and Bayes Theorem, we can easily build a language detector. For that we just need to calculate:

$$P\left(language|text\right)$$

- Which we can rewrite as:

$$P\left(language|letter_1, letter_2, \cdots, letter_n\right)$$

- If we treat each letter independently, we obtain:

$$P\left(language|letter_1, letter_2, \cdots, letter_n\right) = \prod_i P\left(language|letter_i\right)$$

Naive Bayes

- This is known as the Naive Bayes Approach and is an obvious oversimplification: It completely ignores correlations present in the sequence of letters.
- All we have to do now is apply Bayes Theorem to our original table:

$$P\left(language|letter\right) = \frac{P\left(letter|language\right)P\left(language\right)}{P\left(letter\right)}$$

- And if we assume that all languages are equally probable (non-informative prior):

$$P\left(language\right) = \frac{1}{N_{langs}}$$

Naive Bayes

- Naive Bayes approaches (and many others) use terms of the form:

$$\prod_i P\left(A|B_i\right)$$

- which implies multiplying many small numbers. To avoid numerical complications, it is best to use, instead:

$$\sum_i \log P\left(A|B_i\right)$$

- Which is commonly referred to as the "Log-Likelihood". Our expression then becomes:

$$\mathcal{L}\left(language|letter_1, letter_2, \cdots, letter_n\right) = \sum_i \log\left[\frac{P\left(letter_i|language\right)P\left(language\right)}{P\left(letter_i\right)}\right]$$

Language detection

- Or more simply:

$$\mathcal{L}\left(language|text\right)=\sum_i \log\left[\frac{P\left(letter_i|language\right)P\left(language\right)}{P\left(letter_i\right)}\right]$$

- And finally:

$$\mathcal{L}\left(language|text\right)=\sum_i \mathcal{L}\left(language|letter_i\right)$$

- Providing us with a quick and easy way to determine which language is more likely to be the correct one.

Questions?

Other Tutorials

Data Visualization with matplotlib and seaborn

- Jun 4, 2019 8am-12pm (PST)

Deep Learning from Scratch

- Jul 2, 2019 5am-9pm (PST)

Natural Language Processing (NLP) from Scratch

- Aug 5, 2019 5am-9pm (PST)

Deep Learning from Scratch

- Sept 24, 2019 - Strata NYC

END