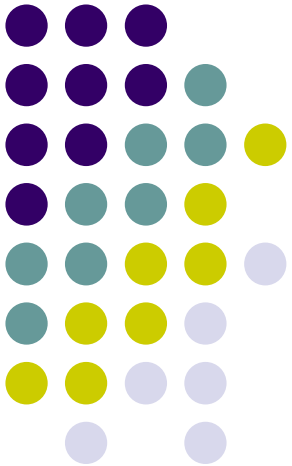
Big Data Analytics

Lecture 10:

Word Embedding Models.

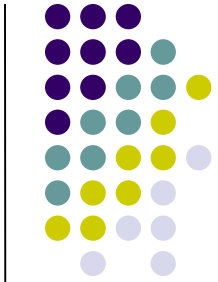
A non-technical introduction



References

- ✓ Rodriguez Pedro L. and Spirling Arthur (2022). Word Embeddings: What works, what doesn't, and how to tell the difference for applied research, *Journal of Politics*, 84(1), 101-115
- ✓ Rudkowsky Elena, et al. (2018). More than Bags of Words: Sentiment Analysis with Word Embeddings. *Communication Methods and Measures*. 12:2-3, 140-157

Beyond bag-of-words



Bag-of-words representation of texts

- ✓ Focusing on frequency of features
- ✓ Ignoring context, grammar, word order

Bag-of-words approach discards therefore much linguistic information regarding the **surrounding syntactic and semantic context** of a given word in a sentence

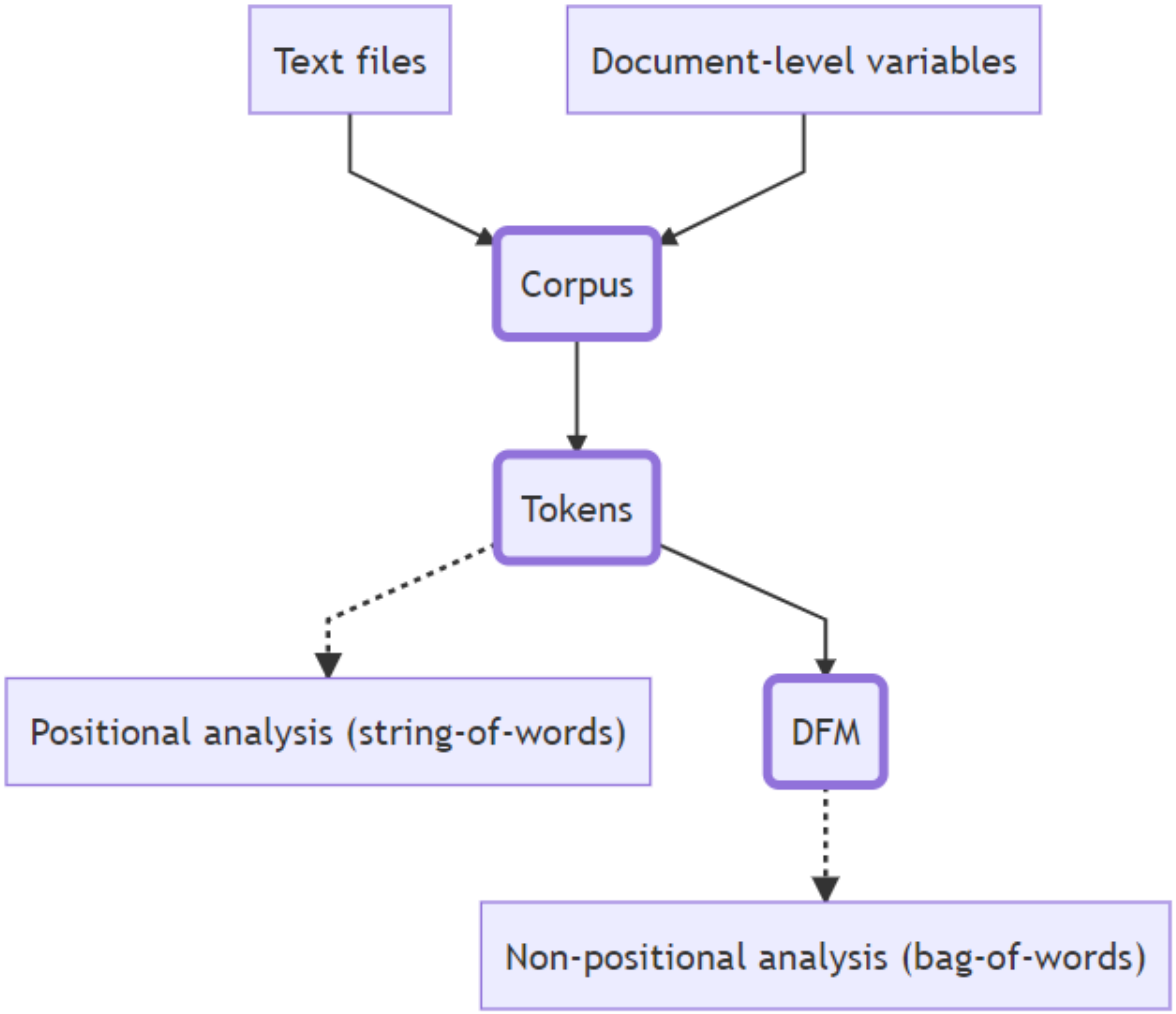
This is wrong, but often useful!

How bringing back the context in which a word appears?

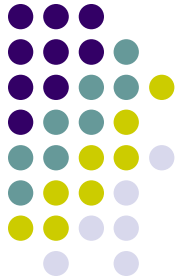
One alternative: **word embeddings (WE)**

WE approach allows us to move from non-positional to positional text-analysis

Beyond bag-of-words



What is word-embedding?

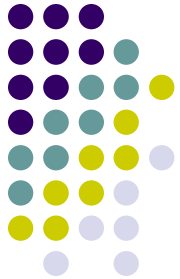


It's all began with…: "*You shall know a word by the company it keeps*" (Firth, 1957)

More concretely, a word's meaning can be garnered from its *contextual information*: literally, the other words that appear near it in text

Here, a "context" means a *symmetric window* of terms around the word of interest

What is word-embedding?



Let's consider the following three sentences:

1. Kitty likes milk

2. Cat likes milk

3. Lion eats meat

Let's create a **co-occurrence matrix**

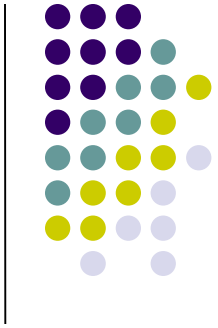
If there are kk features, a **co-occurrence matrix** (COM) is a KK x KK matrix, where each cell tells us how frequently $word_i$ occurs with $word_j$ in some window

In such instance the *window-size* determines the number of words, on either side of the focus word, to be included in its context

Let's consider a window size of 2

In Quanteda the command for doing it is `fcm`

What is word-embedding?



	kitty	likes	milk	cat	lion	eats	meat
kitty	0	1	1	0	0	0	0
likes	1	0	2	1	0	0	0
milk	1	2	0	1	0	0	0
cat	0	1	1	0	0	0	0
lion	0	0	0	0	0	1	1
eats	0	0	0	0	1	0	1
meat	0	0	0	0	1	1	0

The semantically similar words will have similar looking vectors (i.e., similar looking rows) to each other (at least more similar looking than the semantically dissimilar words) – compare for example cat, kitty and lion here. This usually becomes more evident as we increase our corpus size

- ✓ Formalizing this idea, the "*distributional hypothesis*" suggests that words which appear in similar contexts are likely to share similar meanings (Harris, 1970)

What is word-embedding?

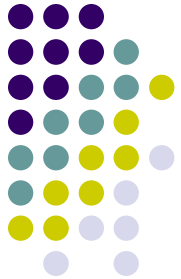
Compare it with a bag-of-words approach. In our case we would have generated the following document feature matrix (DfM) via the command `dfm` in Quanteda:

	kitty	likes	milk	cat	lion	eats	meat
text 1	1	1	1	0	0	0	0
text 2	0	1	1	1	0	0	0
text 3	0	0	0	0	1	1	1

The main difference between a DfM and a COM is the **type of contextual information** they use

- A DfM use *documents as contexts*
- A co-occurrence matrix instead use *words as contexts*, which can be considered as more natural from a linguistic perspective

What is word-embedding?



But what should we do with a COM?

We could perform some matrix factorization technique (a Factor Analysis or a Principal Component Analysis for example) on it to reduce its *dimensionality*

The outcome would be that now each word will have a *vector* of numeric values to represent it

For example, if we extract 4-dimensions out of a COM, the word “like" now will be represented as a 4-dimensional vector which may look like (-0.4, 0.3, 0.6, -0.3). And this is true for each other word included in our corpus

The length of this vector corresponds to the nature and complexity of the multidimensional space in which we are seeking to **embed** the word (more on this later on)

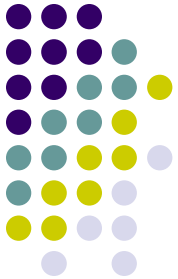
What is word-embedding?

Instead of using vectors of word counts (i.e., our traditional bag-of-words approach), words are therefore now represented as **positions on a latent multidimensional vector space**

In such space, words that are mapped closer to each other have similar meaning (remember the *Distributional hypothesis*: words that appear in the same context – i.e., sharing a similar vector in the COM - share semantic meaning!)

Through that, we can give a more meaningful numeric representation of a text that contains both information regarding the word itself as well as information regarding the *linguistic context* of that word

What is word-embedding?



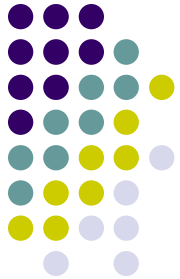
Word embeddings give us therefore a way to use an efficient, dense representation in which similar words have a similar encoding

`GloVe` (“Global VEctors of words”) uses a more sophisticated approach to construct word vectors compared to PCA or FA

More in details, `GloVe` is a count-based model

Count-based models learn vectors by doing once again dimensionality reduction on a COM

What is word-embedding?

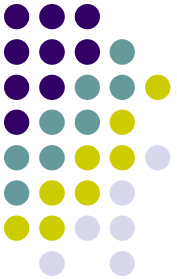


This is achieved by minimizing a "**reconstruction loss**" which looks for lower-dimensional representations that can explain most of the variance in the high-dimensional data

More in details, `GloVe`'s objective is to **minimize the difference** between the product of a given word pair's embeddings and the log of their global co-occurrence count

If in fact the intuition motivating `GloVe` is correct, namely that meaning is strongly connected to co-occurrence ratios, **optimizing the correspondence** between the embedding vectors (that are supposed to capture semantic meaning after all) and the global co-occurrence statistics appears to be a very reasonably thing after all!

What is word-embedding?



More in details, `GloVe` aims to minimize the following loss function:

$$\sum_{i \in V} \sum_{j \epsilon V} h(x_{ij}) \left(\boldsymbol{u}_j \boldsymbol{v}_{\boldsymbol{i}} + b_i + c_j - \log x_{ij} \right)^2$$

where: *i* is the center word; *j* is the context word (within a given window)

V is the size of the vocabulary within COM

$\boldsymbol{u}_j$ and $\boldsymbol{v}_{\boldsymbol{i}}$ are the word vectors for the two words

x_{ij} is the global co-occurrence count of word *j* (as the context word) and word *i* (as the center word) in the same context window in the entire corpus

b_i and c_j are two scalar bias terms associated with words *i* and *j*, respectively

What is word-embedding?

$$\sum_{i \in V} \sum_{j \epsilon V} h(x_{ij}) \left(\boldsymbol{u}_j \boldsymbol{v}_i + b_i + c_j - \log x_{ij} \right)^2$$

Finally $h(x_{ij})$ is a weight function that takes into account that co-occurrences that happen rarely or never are noisy and carry less information than the more frequent ones

The typical class of weighting functions can be parameterized as:

$$f(x) = \begin{cases} (x/x_{max})^{\alpha} \text{ if } x < x_{max} \\ 1 \text{ otherwise} \end{cases}$$

where: x_{max} (i.e., maximum number of co-occurrences) is a parameter that can be chosen by the researcher; α is .75

What is word-embedding?

$$\sum_{i \in V} \sum_{j \epsilon V} h(x_{ij}) \left(\boldsymbol{u}_j \boldsymbol{v}_i + b_i + c_j - \log x_{ij} \right)^2$$

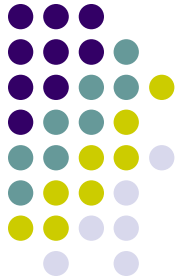
Note the following: if word *i* appears in the context window of word *j*, then *vice versa*. Therefore, $x_{ij} = x_{ji}$

However in practice, owing to different initialization values, the same word may still get different values in these two vectors after training

As a result of that, `GloVe` learns two sets of word vectors

While both of word-vectors matrices can be used as result it could be a good idea to average or take a sum of main and context vector

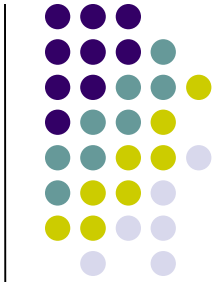
What is word-embedding?



The technical details related to *GloVe* are not (too much) important for applied users to benefit from them

The aim remains the usual same: building a low-dimensional vector representation out of a COM, which preserves the contextual similarity of words, such that the **semantically similar** words are mapped close to each other

What is word-embedding?



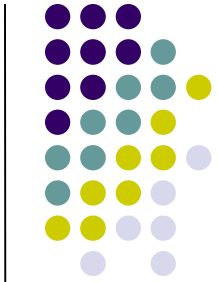
`word2vec` is the main alternative to `GloVe` among the context independent algorithms (more on this later…)

`word2vec` is however a *predictive model*: it uses a neural net model to estimate the probability that a word is "close" to another given word in a given window

In predictive models, the word vectors are learnt by trying to improve on the predictive ability, i.e., minimizing the loss between the target word and the context word

For example, in our COM above initially *kitty* and *cat* could have been randomly assigned as too distant. However in order to minimize its loss with the context words ("*like*" and "*milk*"), both words will have to be close to each other in the vector space

What is word-embedding?



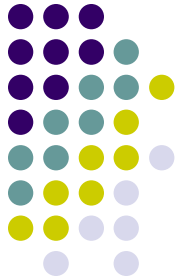
Two options: the CBOW (continuous bag-of-words) or the continuous skip-gram model

CBOW model: it predicts the middle/focus word based on surrounding context words (included in our window). The training objective is to maximize the conditional probability of observing the actual output word (the focus word) given the input context words

In our example above, given the input (“kitty”, “milk”, “cat”) we want to maximize the probability of getting “likes” as the output

This architecture is called a bag-of-words model as the order of words in the context is not important (as far the words are included in the context!)

What is word-embedding?

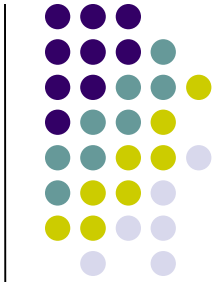


Two options: the CBOW (continuous bag-of-words) or the continuous skip-gram model

Continuous skip-gram model: predicts words within a certain range before and after the current word in the same sentence

That is, while the CBOW model predicts a word given the neighboring context, a skip-gram model predicts the context (or neighbors) of a word, given the word itself

What is word-embedding?



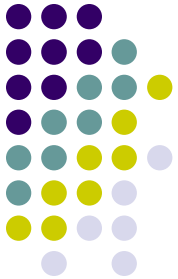
Contrary to `GloVe`, that works directly on the entire co-occurrence matrix, `word2vec` follows therefore an *online learning approach*, that is, the model is trained as the local window is moved from word to word along the corpus

That is, `GloVe` captures the counts of overall statistics how often it appears, while `word2vec` captures co-occurrence one window at a time

Despite this difference, the two approaches are not mathematically very different

This should not be all that surprising since the number of times `word2vec` will observe a given target-context pair once the moving window has covered the entire corpus is exactly equal to the total co-occurrence count used in `GloVe`

What is word-embedding?



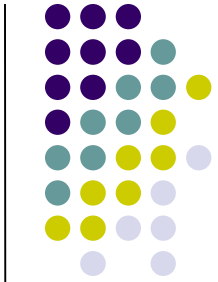
Any so which one to choose?

According to Rodriguez and Spirling (2022), `Word2Vec` is likely to be less “robust,” i.e., embeddings will tend to be more corpus specific, than `GloVe`

Moreover, to properly understand the logic behind `Word2Vec` we should go in greater details into the architecture of a neural networks (something we haven’t discussed in class, such as hidden layers, nodes, weights, etc.)

So we will focus on it in the lab (plus: it is more easy to implement within `Quanteda`…)

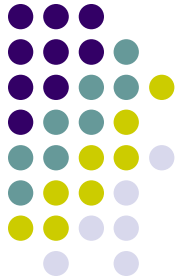
Parameter Choices



You should be called, at the very least, to decide about 3 parameters in any embedding model:

1. how large a **window size** you want the model to use
2. how **large an embedding** you wish to use to represent your words (i.e., the number of extracted dimensions)
3. whether to fit the embedding models **locally**, or to use **pre-trained embeddings** fit to some other (hopefully related) corpus

Window-size



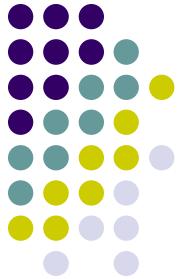
Window-size determines the number of words, on either side of the focus word to be included in its context

Intuitively, larger windows provide more information to discriminate between different words

Take, for example, the following two sentences: “cows eat grass” and “lions eat meat”. A window-size of 1 does not provide enough information to distinguish between cows and lions (we know they both eat, but we don’t know what) whereas a window size of 2 does

Larger windows (usually 5 or above) tend therefore to produce better quality embeddings although with decreasing returns

Embedding dimensions

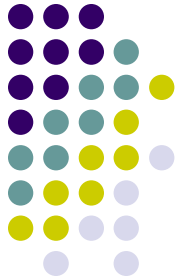


This parameter determines the **dimensions** of the embedding vectors which usually range between 50-500

We can think of these dimensions as capturing different aspects of “meaning” or semantics that can be used to organize words

Though none of the dimensions of the estimated vector are named, the “loading” of each term on the dimensions indeed often captures substantively important relationships

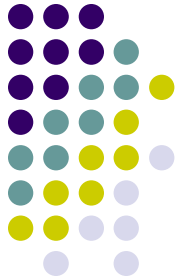
Embedding dimensions



For instance, the words “king” and “queen” might have a similar concentration on a dimension that seems to relate to the concept of royalty, but deviate on a dimension that seems to relate to gender

The coordinates of the dimensional-vector represent in other words **distinct topics**

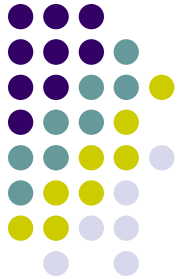
Embedding dimensions



Too few dimensions - imagine the extreme of 1 - and there can be no meaningful separability of words; too many, and some dimensions are likely to be redundant (go unused)

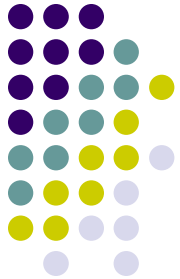
Factors such as vocabulary size and topical specificity of the corpus are likely to play a role, although theoretical work in this area remains scant

Advice to Practitioners



- ✓ Window-size and embedding dimensions: with the possible exception of small corpora, one should avoid using very few dimensions (below 100) and small window-sizes (< 5)
- ✓ While performance improves with larger window-sizes and more dimensions, both exhibit decreasing returns: i.e., improvements are marginal beyond 300 dimensions and window-size of 6
- ✓ Given the trade-off between more dimension/larger window-size and computation time, the choice of 5 or 6 (window-size) and between 100 and 300 (dimensions) seems therefore reasonable

Pre-Trained Versus Going Local



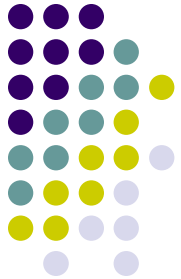
Embedding models can be data hungry, meaning they need a lot of data to produce ‘useful’ results

Consequently, researchers with small corpora rather than building word-embeddings **locally** out of their corpus, can decide to use generic pre-trained embeddings trained on much larger corpora

These off-the-shelf embedding corpora can be used like dictionaries, but instead of translations or meanings, they return vector embeddings for the requested words

Therefore, the usage of pre-trained embeddings does not require any further computing time

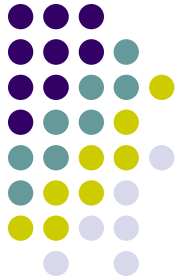
Pre-Trained Versus Going Local



For example, pre-trained word vectors are available that have been estimated from large corpora, such as that trained on six billion tokens from Wikipedia and the "Gigiword" corpus (Pennington, Socher and Manning, 2014)

This allows a researcher to represent his or her texts not just from the corpus at hand, but also augmented with quantitative measures of the words' semantic representations fitted from other contexts

Pre-Trained Versus Going Local



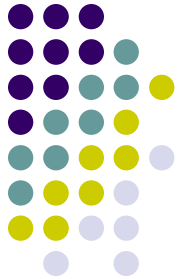
However, there are some trade-offs

Intuitively, we would want to use pre-trained embeddings trained on a corpus generated by a similar “language model” to that which generated our corpus of interest

The more similar the two language models, the more similar the underlying semantics

For a highly specific local corpus - a corpus in Old English for example - generic pre-trained embeddings may not be all that useful!

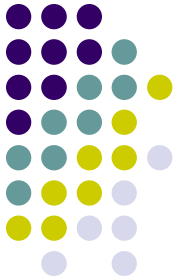
What for Word embedding models?



Operations with word-vectors are meaningful per-se, i.e., embeddings can be a **direct object of interest** for studying word usage and meaning

For example, **similarities** between word embeddings may be substantively informative: if the distance between “immigrants” and “hardworking” is smaller for liberals than for conservatives, we learn something about their relative worldviews!

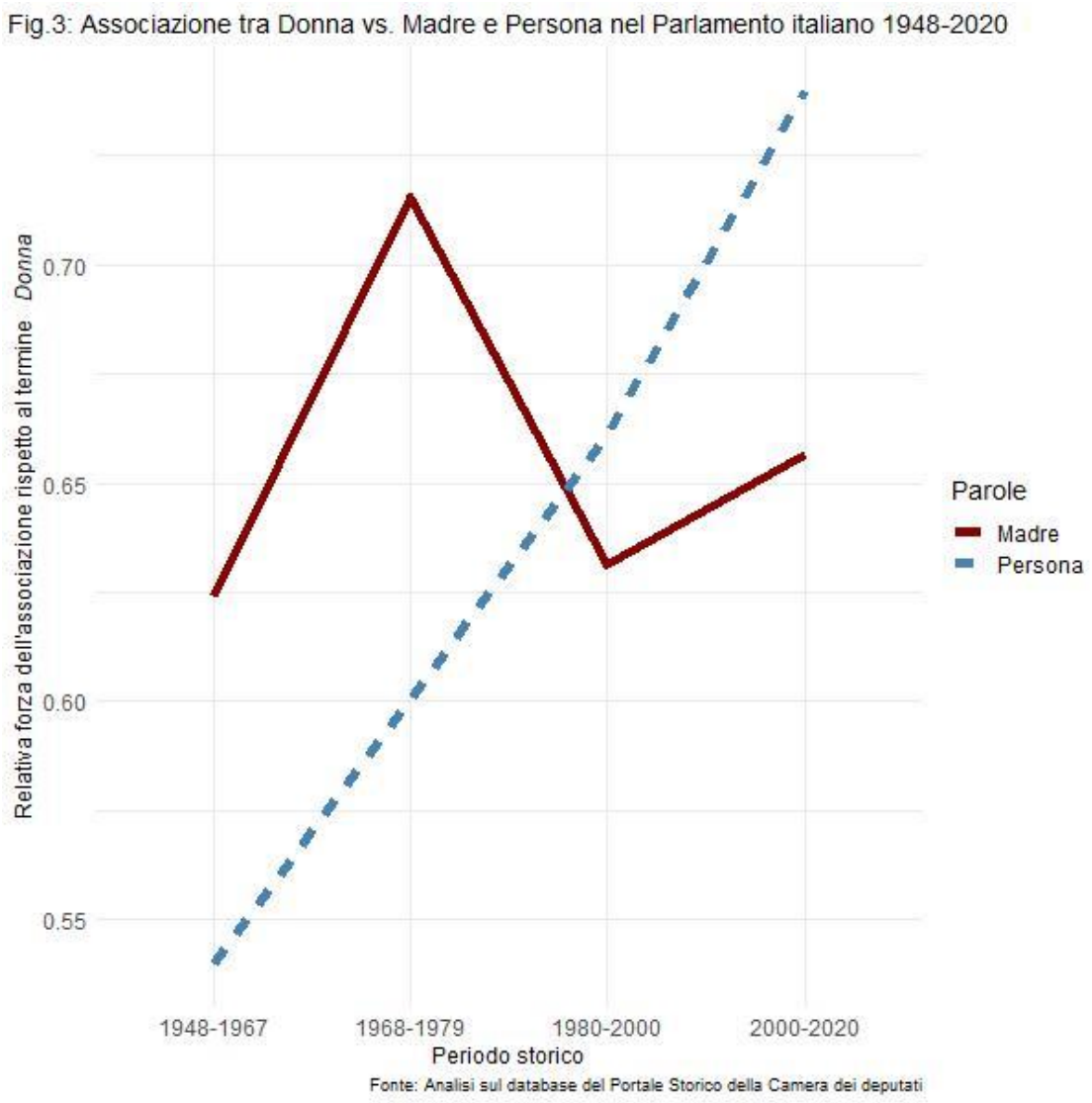
What for Word embedding models?



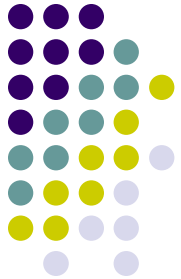
This also allows us to explore the possible existence of societal *stereotypes* encoded in the language

To take an example, if you analyze the Italian legislative speeches since 1948 to nowadays, the most similar word to “woman” in the ‘50s was “mother” and “wife”; then over the years it changed to “worker” and “person”

What for Word embedding models?



What for Word embedding models?



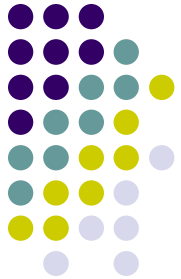
You can also do addition in a word embeddings framework to explore *analogies*

Analogies are **equations** of the form *A is to B as C is to D*

Given the terms A, B, C, the model must return the word that correctly stands for D in the given analogy

A classic example is the following one: «King - male + female ~ queen». That is, “man is to king as woman is to queen”. Why?

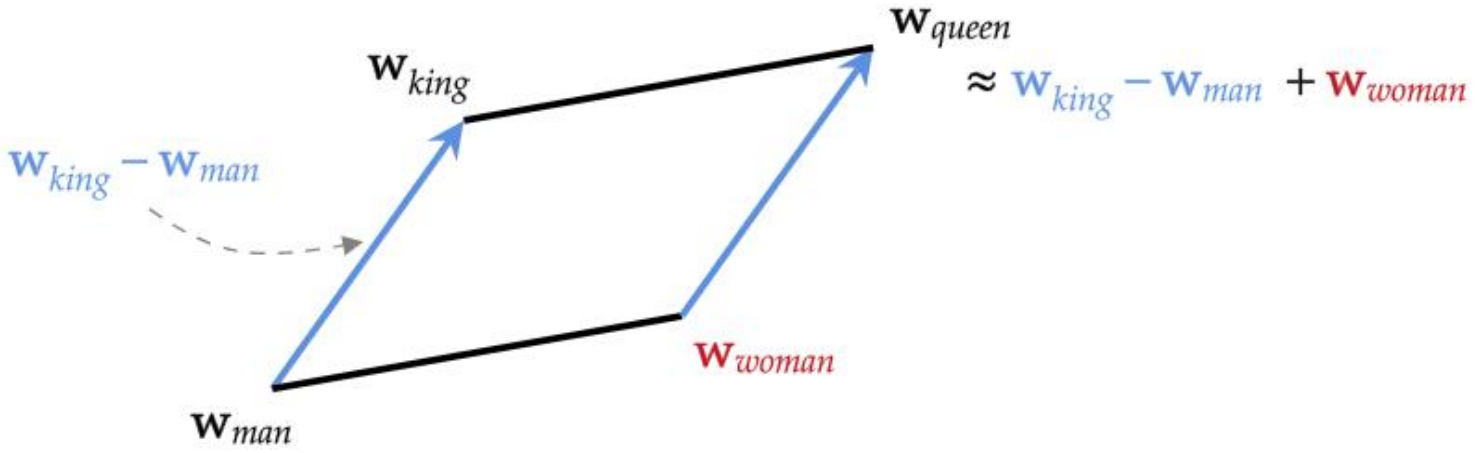
What for Word embedding models?



As the difference between vector *king* and vector *queen* is similar to the difference between vector *male* and vector *female*, then "King - queen ~ male - female", therefore, "King - male + female ~ queen”

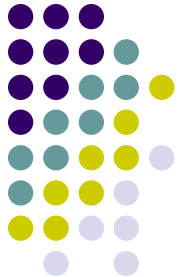
Subtracting the **man** vector from the **king** vector and adding **female**, the most similar word to this would be **queen**

What for Word embedding models?



word	D_1	D_2	D_3	. . .	D_N
man	0.46	0.67	0.05	. . .	. . .
woman	0.46	-0.89	-0.08	. . .	. . .
king	0.79	0.96	0.02	. . .	. . .
queen	0.80	-0.58	-0.14	. . .	. . .

What for Word embedding models?

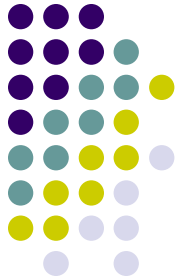


It may be surprising that you are able to get these results, without any label on the meaning of words

"*Co-occurrence*" is however the key here! It is in fact the only information that you are using

By building a sense of one word's proximity to other similar words, which do not necessarily contain the same letters, we can move beyond hard tokens to a smoother and more general sense of meaning

What for Word embedding models?



Word embedding models can be however thought not simply as a **method on their own** for analyzing text as data, but also as extremely **useful complements to representations of text as data based on word counts**

How?

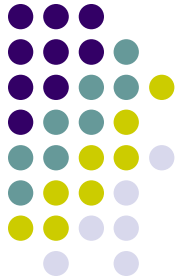
The advantages of Embeddings

In a bag-or-words approach (i.e., in a context-blind approach) features are completely independent from one another (remember?). The feature word “dog” is as dissimilar to word “war” than it is to word “cat”

One the contrary, using a word embeddings approach, each feature is embedded into a *d* dimensional space, and represented as a vector in that space

And as we have already discussed, similar features will have similar vectors – i.e., information is shared between similar features (“dog” will be reasonably spatially much closer to “cat” than to “war”)

The advantages of Embeddings



What's the implication of that?

Let's suppose that we summarize the position of each text in our corpus by calculating its *mean vector* over each of the dimensions in which its words are embedded

i.e., if a text includes 3 words and the size of the dimensions of the embedding is 20, we will take the average of the vectors of these 3 words in each of the 20 dimensions to represent the text in the same embedding world than the words

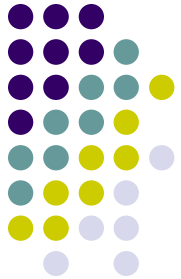
The advantages of Embeddings

As a result, a text that includes that word “dog”, ceteris paribus, will report a mean vector in the embedded world more similar to a text including the word “cat” than it is to a text including the word “war”

Let’s further suppose that in a training-set we have a text including the word “dog” but not the word “cat”

Moreover, let’s also suppose that the mean vector of the text including the word “dog” is important in affecting the prediction of our SVM algorithm for the class “positive” for example

The advantages of Embeddings



Now our SVM can take advantage of the word “dog” during the prediction stage to classify a text as “Positive”, although the word “dog” wasn’t included in the training set!

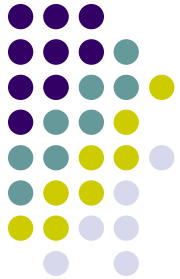
This is because “dog” is spatially closer to “cat”, and as a result, the mean vector of a text including the word “dog” is going also to be spatially closer, ceteris paribus, to the mean vector of a text including the word “cat”

The advantages of Embeddings

The main benefit of a *dense real-valued vector of number representation* (such as the one we obtain via word-embedding), rather than a *sparse matrix (*such as the one we obtain via BoW) lies therefore in its **generalization power**

- ✓ if we believe some features may provide similar clues, it is worthwhile to provide a representation that is able to capture these similarities

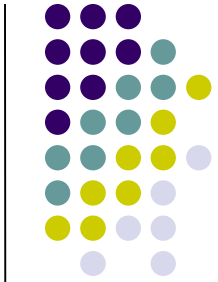
The advantages of Embeddings



Through that, WE may increase the accuracy of classification models as they also provide information (i.e., vector representations) on words **that are not represented** in the training data based on their similarity with other words

This is of course impossible in a bag-of-words approach in which new words encountered in the texts of the test-set are a *nuisance*

What for Word embedding models?

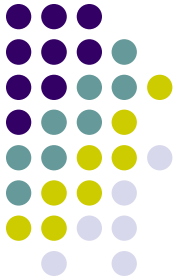


WE can also be very useful to expand *existing dictionaries*

Imagine you want to expand a dictionary of uncivil words

By looking for other words with semantic similarity to each of the terms included in the original dictionary, we can identify words that we may not have thought of in the first place, either because they're slang, new words or just misspellings of existing words

What for Word embedding models?

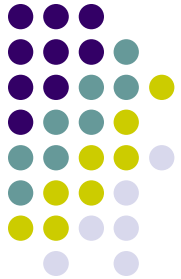


An example:

Douglas R. Rice and Christopher Zorn. Corpus-based dictionaries for sentiment analysis of specialized vocabularies, *Political Science Research and Methods* (2021), 9, 20–35

Replication data:
https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/4EKHFM

What for Word embedding models?

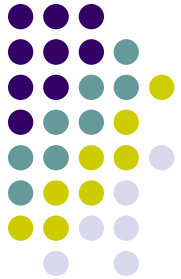


Similarly, we can use WE to estimate a semi-supervised scaling algorithm

For example Watanabe (2021) propose a Latent semantic scaling based on WE

- ✓ first you have to identify a list of seed words related to the two polarity of a unidimensional scale you are interested about (say positive/negative)
- ✓ then you are going to assign a polarity score to each word included in a given text based on the semantic proximity between words in a corpus and the seed words employing precisely word-embedding techniques
- ✓ Once you have a score for each word, you can locate documents on the previous unidimensional scale

What for Word embedding models?

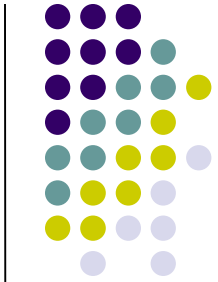


Watanabe, K. (2021). Latent semantic scaling: A semisupervised text analysis technique for new domains and languages. *Communication Methods and Measures*, 15(2), 81-102.

The nice thing is that there is a package that you can run within Quanteda that implements such method:

```
library(LSX)
```

Evaluation

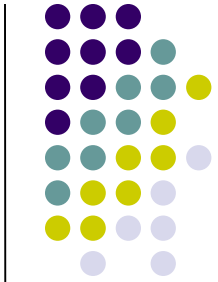


How to evaluate embedding models? Two possible evaluation tasks: *intrinsic* and *extrinsic*

These correspond to the two main use cases of embeddings: as models of semantics and as feature inputs

Such evaluation tasks allow you not only to evaluate one single WE, but also to choose between different WE settings (i.e., with different window-size or different dimensions), similarly to what you do via a grid-search

Evaluation

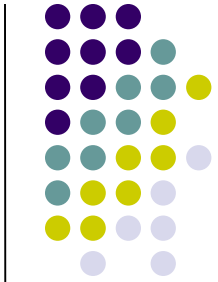


Intrinsic tasks evaluate embeddings as models of semantics

These include: comparing if the WE estimated retrieve some very well known *word analogy*; or if they provide meaningful *word similarities* (including comparing similarity—pairs of words along with their human provided similarity ratings vs. similarity ratings computed using WE)

These tasks require human generated data

Evaluation



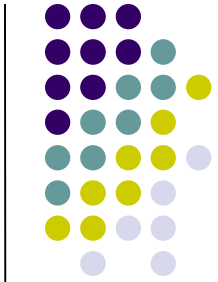
Extrinsic tasks evaluate embeddings generally via supervised approaches

For example, if you want to use WE as an input for a ML classification, you can compare different WE (for example, with a different number of dimensions / window-size) via cross-validation on the training-set!

See Rodriguez and Spirling (2021) for some further alternatives in this respect

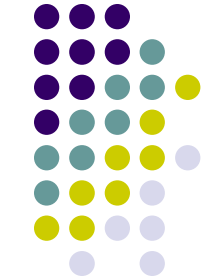
Of course, note two things: a) evidence of good performance need not generalize (it is corpus specific!), b) performance in extrinsic tasks need not translate into good performance in intrinsic tasks (and vice-versa)

Evaluation



Another possible metric to compare different models is focusing on the **prediction loss** at the point of convergence and selecting that model (i.e., combination of # dimensions and window size) that minimizes it

Recent advancements



`GloVe` (as well as `word2vec`) embeddings are *context independent* - these models output just one embedding for each word, combining all the different senses of the word into one single vector *regardless* of where the words occurs in a sentence and *regardless* of the different meanings they may have

For instance, after we train `GloVe` on a corpus we get as output one vector representation for, say the word "cell"

So even if we had a sentence like "He went to the prison cell with his cell phone to extract blood cell samples from inmates", where the word cell has different meanings based on the sentence context, these models just collapse them all into one vector for "cell" in their output

Recent advancements

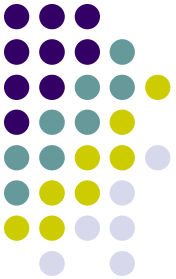
New WE algorithms (such as `ELMo` or `BERT`) can generate different word embeddings for a word that captures the *context of a word* - that is its **position** in a sentence

For instance, for the same example above, such algorithms would generate different vectors for the three vectors for cell

The first cell (prison cell case), for instance would be plausibly closer to words like incarceration, crime etc. whereas the second “cell” (phone case) would be plausibly closer to words like iPhone, Android, etc..

This difference arises cause `GloVe` and `word2vec` do not take into account word order in their training, while `ELMo` and `BERT` does

Recent advancements



An implication of this difference is that we can use `GloVe` vectors trained on a corpus directly for some tasks. All we need is the vectors for the words. There is no need for the model itself that was used to train these vectors

However, in the case of *ELMo* and *BERT*, since they are context dependent, we need the model that was used to train the vectors even after training, since the models generate the vectors for a word based on context

R pakcages to install

install.packages("text2vec", repos='http://cran.us.r-project.org')

install.packages("lsa", repos='http://cran.us.r-project.org')

install.packages("readr", repos='http://cran.us.r-project.org')

install.packages("Rtsne", repos='http://cran.us.r-project.org')

install.packages("htmlwidgets", repos='http://cran.us.r-project.org')

install.packages("plotly", repos='http://cran.us.r-project.org')

install.packages("tsne", repos='http://cran.us.r-project.org')

install.packages("knitr", repos='http://cran.us.r-project.org')

install.packages("quanteda.textplots", repos='http://cran.us.r-project.org')