Social Data Science

Word embeddings II

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Plan

1. Course updates
2. Word embeddings
3. Contextualized embeddings

Course updates

- Project proposals due 5pm Friday
  - Submit form on Canvas

Recap

- Language models are probabilistic models for language understanding and generation
  - Auto-complete, search suggestions, etc.
- N-gram language models
  - Probabilistic models predicting words based on previous N words used

Language models

Neural language models

- Recent advances in both the availability of large corpora of text *and* the development of neural network models have resulted in new ways of computing language models.
- By using machine-learning techniques, particularly neural networks, to train a language model, we can construct better vector representations

Word embeddings

Intuition

- We use the context in which a word occurs to train a language model
  - The model learns by viewing millions of short snippets of text (e.g 5-grams)
- This model outputs a vector representation of each word in k-dimensional space, where $k << |V|$.
  - Like LSA, these vectors are *dense*
    - Each element contains a real number and can be positive or negative

Word embeddings

Word2vec: Skip-gram and continuous bag-of-words (CBOW)

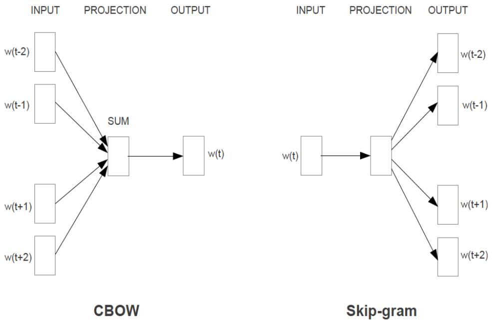


Figure 1: New model architectures. The CBOW architecture predicts the current word based on the context, and the Skip-gram predicts surrounding words given the current word.

Word embeddings

Word2vec: CBOW intuition

- We start with a string where the focal word is known, but hidden from the model, but we know the context within a window, in this case two words on either side of the focal word
  - e.g. "The cat ? on the", where ? = "sat"
- The model is trained using a process called *negative sampling*, where it must distinguish between the true sentence and "fake" sentences where ? is replaced with another token.
  - Each "guess" allows the model to begin to learn the correct answer
- By repeating this for millions of text snippets the model is able to "learn" which words go with which contexts

Word embeddings

Word2vec: Skip-gram intuition

- We start with a string where the focal is known, but the context within the window is hidden
  - e.g. "$?_1$ $?_2$ sat $?_3$ $?_4$"
- The model tests different words in the vocabulary to predict the missing context words
  - Each "guess" allows the model to begin to learn the correct answer
- By repeating this for millions of text snippets the model is able to "learn" which contexts go with which words

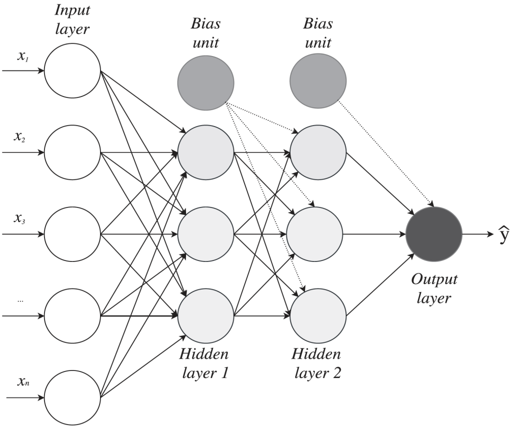
Word embeddings

Word2vec: Model

- Word2vec uses a shallow neural-network to predict a word given a context (CBOW) or a context given a word (skip-gram)
  - But we do not care about the prediction itself, only the *weights* the model learns
- It is a self-supervised method since the model is able to update using the correct answers
  - e.g. In CBOW the model knows when the prediction is wrong and updates the weights accordingly

Word embeddings

Word2vec: Feed-forward neural network



This example shows a two-layer feed-forward neural network.

Word embeddings

Word2vec: Estimation procedure

- Batches of strings are passed through the network
  - After each batch, weights are updated using *back-propagation*
    - The model updates its weights in the direction of the correct answer (the objective is to improve predictive accuracy)
    - Optimization via *stochastic gradient descent*

Word embeddings

Vector representations of words

- Each word is represented as a vector of weights learned by the neural network
  - Each element of this vector represents how strongly the word activates a neuron in the hidden layer of the network
  - This represents the association between the word and a given dimension in semantic space

Word embeddings

Distributional semantics

- The word vectors in the embedding space capture information about the context in which words are used
  - Words with similar meanings are situated close together in the embedding space
- This is consistent with Ludwig Wittgenstein's *use theory of meaning*
  - "the meaning of a word is its use in the language", *Philosophical Investigations* (1953)
- *Distributional semantics* is the theory that the meaning of a word is derived from its context in language use
  - "You shall know a word by the company it keeps", J.R. Firth (1957)

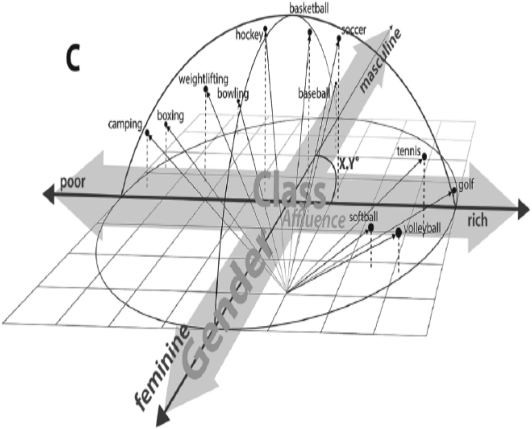
Word embeddings

Analogies

- The most famous result from the initial word embedding paper is the ability of these vectors to capture analogies:
  - $king - man + woman \approx queen$
  - $Madrid - Spain + France \approx Paris$

Word embeddings

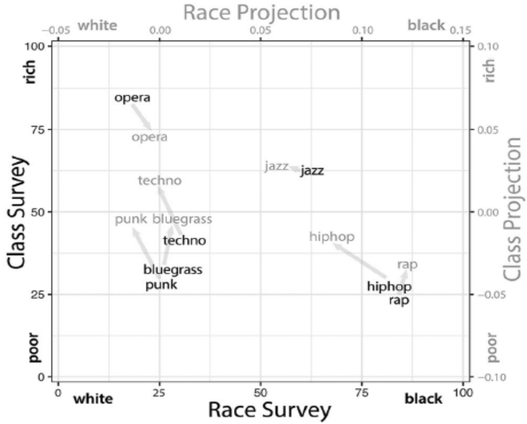
Applications: Understanding social class



Kozlowski, Austin C., Matt Taddy, and James A. Evans. 2019. "The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings." American Sociological Review, September, 000312241987713. https://doi.org/10.1177/0003122419877135.

Word embeddings

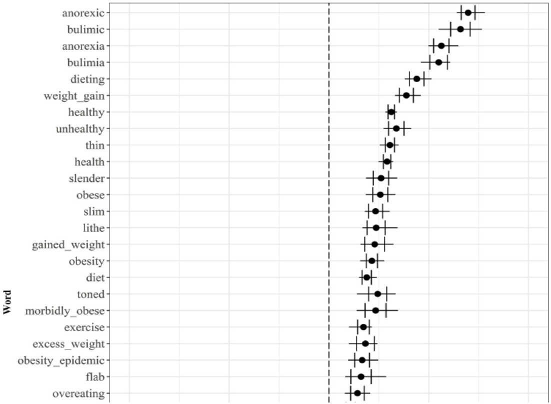
Applications: Understanding social class



Word embeddings

Applications: Understanding cultural schematas

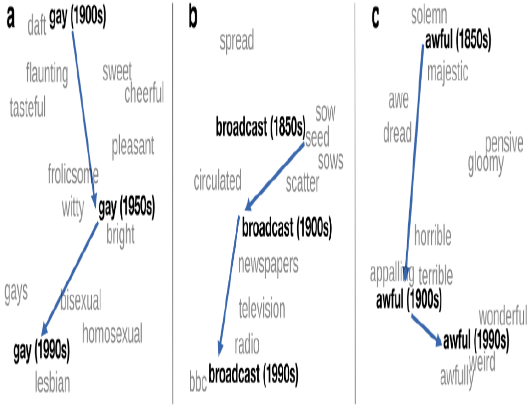
Figure 4: Gendering of Obesity-Related Words



Arseniev-Koehler, Alina, and Jacob G. Foster. 2020. "Machine Learning as a Model for Cultural Learning: Teaching an Algorithm What It Means to Be Fat." Preprint. *SocArXiv*. https://doi.org/10.31235/osf.io/c9yj3.

Word embeddings

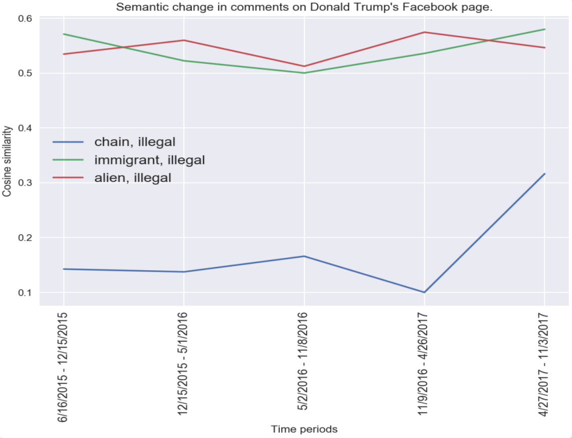
Applications: Semantic change



Hamilton, William L., Jure Leskovec, and Dan Jurafsky. 2016. "Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change." In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics*, 1489–1501.

Word embeddings

Applications: Semantic change



Davidson 2017, unpublished.

Word embeddings

Pre-trained word embeddings

- In addition to `word2vec` there are several other popular variants including `GloVe` and `Fasttext`
  - Pre-trained embeddings are available to download so you don't necessarily need to train your own
- When to train your own embeddings?
  - You have a large corpus of text ($>$ tens of thousands of documents)
  - You think the underlying language model / data generating process may differ from that represented by existing corpora
    - e.g. A word embedding trained on newspapers may not be very useful for studying Twitter since online language use differs substantially from written news media

Word embeddings

Loading a corpus

```
library(janeaustenr)
library(dplyr)
library(stringr)

original_books <- austen_books() %>%
  group_by(book) %>%
  mutate(linenumber = row_number(),
         chapter = cumsum(str_detect(text,
                                     regex("^chapter [\\divxlc]",
                                           ignore_case = TRUE)))) %>%
  ungroup()
```

Code from https://www.tidytextmining.com/tidytext.html

Word embeddings

Word embeddings in R

We're going to use the library `word2vec`. The library is a R wrapper around a `C++` library. The the original library can be found here and the R version wrapper here.

```
#install.packages("word2vec")
library(word2vec)
set.seed(987654321) # random seed
```

Word embeddings

Word embeddings in R

Let's train a model on the Jane Austen texts.

```
model <- word2vec::word2vec(x = original_books$text,
                  type="cbow",# continuous bag of words
                  dim=100, # 100-dim output vectors
                  window = 3L, # window size 3
                  iter = 100L, # train over 100 iterations
                  negative= 10L) # 10 negative samples for each positiv
```

Word embeddings

Getting embeddings for words

We can use the `predict` function to find the nearest words to a given term.

```
predict(model, c("love"), type = "nearest", top_n = 10)
```

```
## $love
##    term1       term2 similarity rank
## 1   love       world  0.6711781    1
## 2   love    attached  0.6663648    2
## 3   love       fault  0.6638469    3
## 4   love  compassion  0.6536404    4
## 5   love     plagued  0.6534255    5
## 6   love     believe  0.6479680    6
## 7   love    deceived  0.6476627    7
## 8   love  acquainted  0.6447310    8
## 9   love     pleased  0.6430528    9
## 10  love       heart  0.6382179   10
```

Word embeddings

Getting embeddings for words

We can also get the embedding matrix and try to do reasoning by analogy. We can see the model doesn't perform very well. This is because it has only been trained on a small corpus of text.

```r
emb <- as.matrix(model)
vector <- emb["King", ] - emb["man", ] + emb["woman", ]
predict(model, vector, type = "nearest", top_n = 10)
```

```
##          term similarity rank
## 1     Bennets  0.8147888    1
## 2        Grey  0.7775009    2
## 3    Carteret  0.7692646    3
## 4  inimitable  0.7684274    4
## 5     Fairfax  0.7575922    5
## 6        Nash  0.7566887    6
## 7     Andrews  0.7508329    7
## 8    Williams  0.7483135    8
## 9       Owens  0.7464975    9
## 10   Crawford  0.7462509   10
```

Word embeddings

Getting embeddings for words

Let's try another example.

```
vector <- emb["queen", ] - emb["woman", ] + emb["man", ]
predict(model, vector, type = "nearest", top_n = 10)
```

```
##          term similarity rank
## 1      Amelia  0.7126954    1
## 2    thorough  0.6816552    2
## 3         wet  0.6648111    3
## 4  difference  0.6529062    4
## 5       doubt  0.6453437    5
## 6   ourselves  0.6293879    6
## 7   indignity  0.6283700    7
## 8    goodness  0.6261469    8
## 9    greatest  0.6253009    9
## 10      dream  0.6240788   10
```

Word embeddings

Loading a pre-trained embedding

Let's try another example. I downloaded a pre-trained word embedding model trained on a much larger corpus of English texts. The file is 833MB in size. Following the documentation we can load this model into R.

```
model.pt <- read.word2vec(file = "data/sg_ns_500_10.w2v", normalize = T
```

Word embeddings

Similarities

Find the top 10 most similar terms to "love" in the embedding space.

```
predict(model.pt, c("love"), type = "nearest", top_n = 5)
```

```
## $love
##   term1   term2 similarity rank
## 1  love   loves  0.8190995    1
## 2  love romance  0.7833382    2
## 3  love  loving  0.7823190    3
## 4  love   adore  0.7729287    4
## 5  love   loved  0.7710815    5
```

Word embeddings

Similarities

Find the top 10 most similar terms to “hamlet” in the embedding space.

```
predict(model.pt, c("hamlet"), type = "nearest", top_n = 5)
```

```
## $hamlet
##    term1       term2 similarity rank
## 1 hamlet     laertes  0.7913417    1
## 2 hamlet  fortinbras  0.7826205    2
## 3 hamlet shakespeare  0.7587951    3
## 4 hamlet       osric  0.7433756    4
## 5 hamlet    polonius  0.7390884    5
```

Word embeddings

Re-trying the analogy test

Let's re-try the analogy test. We still don't go great but now queen is in the top 5 results.

```
emb <- as.matrix(model.pt)
vector <- emb["king", ] - emb["man", ] + emb["woman", ]
predict(model.pt, vector, type = "nearest", top_n = 10)
```

```
##            term similarity rank
## 1          king  0.9663149    1
## 2        alveda  0.7624112    2
## 3     leonowens  0.7437726    3
## 4       sobhuza  0.7369328    4
## 5         queen  0.7323185    5
## 6        chakri  0.7305732    6
## 7    chulabhorn  0.7290710    7
## 8    sirindhorn  0.7239375    8
## 9        khesar  0.7216632    9
## 10      namgyel  0.7201231   10
```

Word embeddings

Re-trying the analogy test

Let's try another analogy. The "correct' answer is second. Not bad.

```
vector <- emb["madrid", ] - emb["spain", ] + emb["france", ]
predict(model.pt, vector, type = "nearest", top_n = 10)
```

```
##                term similarity rank
## 1            france  0.9215138    1
## 2             paris  0.9075408    2
## 3            madrid  0.8657743    3
## 4         marseille  0.8486081    4
## 5          charléty  0.8464751    5
## 6          nicollin  0.8420396    6
## 7   superpuissances  0.8416948    7
## 8          moustoir  0.8402181    8
## 9          surplace  0.8379595    9
## 10           juvisy  0.8375083   10
```

Word embeddings

Re-trying the analogy test

Let's try another slightly more complex analogy. Not bad overall.

```
vector <- (emb["new", ] + emb["jersey", ])/2 - emb["trenton", ] + emb["
predict(model.pt, vector, type = "nearest", top_n = 10)
```

```
##        term similarity rank
## 1    albany  0.9643639    1
## 2       new  0.9062052    2
## 3      york  0.8031820    3
## 4   mceneny  0.7575994    4
## 5   upstate  0.7556026    5
## 6      wgdj  0.7479031    6
## 7     cuomo  0.7402880    7
## 8    jersey  0.7357954    8
## 9    brunos  0.7214818    9
## 10   panynj  0.7166725   10
```

Word embeddings

Representing documents

Last week we focused on how we could represent documents using the rows in the DTM. So far we have just considered how words are represented in the embedding space. We can represent a document by averaging over its composite words.

```
descartes <- (emb["i", ] +
                emb["think", ] +
                emb["therefore", ] +
                emb["i", ] +
                emb["am", ])/5
predict(model.pt, descartes, type = "nearest", top_n = 10)
```

```
##             term similarity rank
## 1              i  0.8336274    1
## 2          think  0.7580560    2
## 3         myself  0.7498994    3
## 4             we  0.7494881    4
## 5         really  0.7459691    5
## 6    [criticism]  0.7449573    6
```

Word embeddings

Representing documents

The package has a function called `doc2vec` to do this automatically. This function includes an additional scaling factor (see documentation) so the results are slightly different.

```
descartes <- doc2vec(model.pt, "i think therefore i am")
predict(model.pt, descartes, type = "nearest", top_n = 10)
```

```
## [[1]]
##              term similarity rank
## 1               i  0.9500304    1
## 2           think  0.8639066    2
## 3          myself  0.8546111    3
## 4              we  0.8541421    4
## 5          really  0.8501323    5
## 6     [criticism]  0.8489791    6
## 7              am  0.8417951    7
## 8       obviously  0.8406690    8
## 9              so  0.8392198    9
## 10           [am]  0.8369783   10
```

Word embeddings

Visualizing high-dimensional embeddings in low-dimensional space

- There are various algorithms available for visualizing word-embeddings in low-dimensional space
  - `PCA`, `t-SNE`, `UMAP`
- There are also browser-based interactive embedding explorers
  - See this example on the Tensorflow website

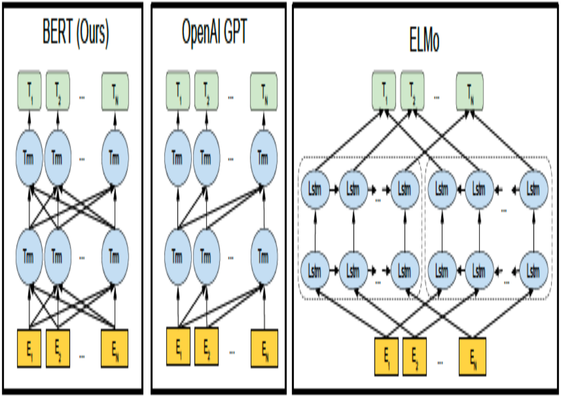
Contextualized embeddings

Limitations of existing approaches

- Word2vec and other embedding methods run into issues when dealing with *polysemy*
  - e.g. The vector for "crane" will be learned by averaging across different uses of the term
    - A bird
    - A type of construction equipment
    - Moving one's neck
  - "She had to crane her neck to see the crane perched on top of the crane".
- New methods have been developed to allow the vector for "crane" to vary according to different contexts
- The intuition here is that we want to take more context into account when constructing vectors

Contextualized embeddings

Architectures



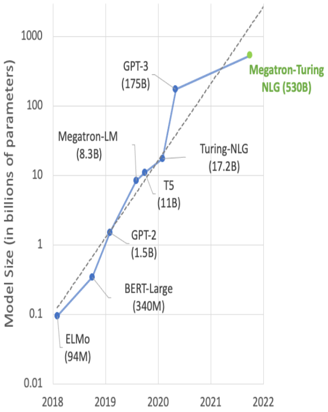
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. "BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding." In Proceedings of NAACL-HLT 2019, 4171–86. ACL.

Contextualized embeddings

Methodological innovations

- More complex, deeper neural networks
  - *Attention* mechanisms, *LSTM* architecture, *bidirectional transformers*
- Optimization over multiple tasks (not just a simple prediction problem like Word2vec)
- Character-level tokenization and embeddings
- Much more data and enormous compute power required
  - e.g. BERT trained on a 3.3 billion word corpus over 40 epochs, taking over 4 days to train on 64 TPU chips (each chip costs ~$10k).

Very large language models



See Nvidia blog on Megatron-Turing NLG.

Contextualized embeddings

On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?

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ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GPT-2/3, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art

alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (§2), we ask whether enough thought has been put into the potential risks associated with developing them and strategies to mitigate these risks.

We first consider environmental risks. Echoing a line of recent

Bender, Emily M, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?" In Conference on Fairness, Accountability, and Transparency (*FAccT '21*).

Contextualized embeddings

Fine-tuning

- One of the major advantages of BERT and other approaches is the ability to "fine-tune" a model
  - We can train the model to accomplish a new task or learn the intricacies of a new corpus without retraining the mode
    - Although this can still take time and require quite a lot of compute power
- This means we could take an off-the-shelf, pre-trained BERT model and fine-tune it to an existing corpus
  - See this notebook for a Python example of fine-tuning BERT

Contextualized embeddings

Using contextualized embeddings in R

- Most contextualized embeddings require specialized programming languages optimized for large matrix computations like `PyTorch` and `Tensorflow`
- Once installed, I recommend using `keras`, a high-level package that can be used to implement various neural network methods without directly writing `Tensorflow` code.
- It is possible to work with these models in R, but you might be better off learning Python!

Summary

- Word embeddings use a neural language model to better represent texts as dense vectors
  - Distributional semantics
  - Analogical reasoning
  - Sociological analysis of meaning and representations
- Recent methodological advances better incorporate context
  - Better semantic representations but huge financial and environmental costs