Advanced Text Analysis

Day 5 / Session 1

Petro Tolochko

Embeddings

Embeddings

- a dense numerical representation of objects in a continuous vector space

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- a numerical representation of objects in a continuous vector space
- words, sentences, documents, etc.

Embeddings

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Embeddings

- embeddings aim to capture the essence of an object by mapping it to a lower-dimensional vector space, where proximity in the vector space reflects similarity or relatedness

Continuous Vector Space

- embeddings map objects to a continuous vector space, typically of lower dimensionality compared to the original space
-

Continuous Vector Space

- embeddings map objects to a continuous vector space, typically of lower dimensionality compared to the original space
- each dimension in the vector space represents a learned feature or property of the object
- proximity or distance between vectors in the embedding space captures the similarity or dissimilarity between the corresponding objects
- representing objects as vectors, various mathematical operations and computations can be performed on the embeddings for prediction and/or inference

Word Embeddings

- words are represented as dense vectors in the embedding space, where words with similar meanings or contexts are located closer to each other
- word embeddings can capture semantic relationships
- sentiment analysis
- machine translation
- document classification
- Etc.

Machine Learning

- Supervised
- Unsupervised

Machine Learning

- Supervised
- ***Unsupervised***

Word2Vec

Efficient Estimation of Word Representations in Vector Space

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Continuous Bag-of-Words Model

Continuous Skip-gram Model

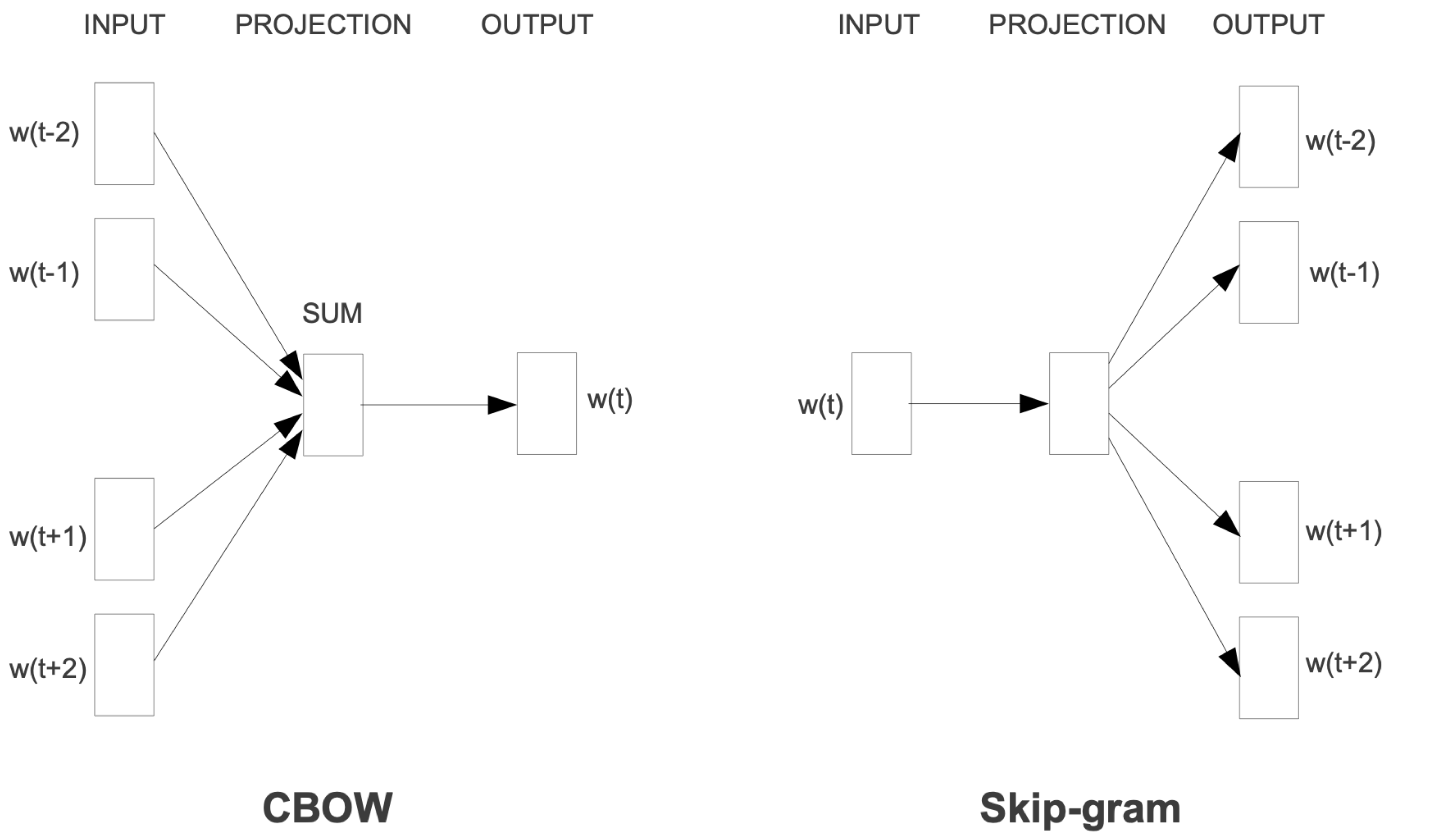

Figure 1: New model architectures. The CBOW architecture predicts the current word based on the context, and the Skip-gram predicts surrounding words given the current word.

Continuous Bag-of-Words Model

$$word_1, word_2, word_3, \ldots, word_n$$

$$-, word_2, word_3, \ldots, word_n$$

$$\_\_, word_2, word_3, \ldots, word_n$$

$$\underline{word_1, \_\_ , word_3,} \ldots, word_n$$

$$word_1, \underline{word_2, \_\_\, , \ldots ,}\, word_n$$

Continuous Skip-gram Model

$$word_1, \_\_ , \_\_ , \ldots$$

$$\_\_, \ word_2, \ \_\_, \ldots$$

Training Objective

- The objective of Word2Vec is to maximize the likelihood of predicting the context words or target word given the input words.
- For CBOW, the model maximizes the average log probability of the target word given the context words.
- For Skip-gram, the model maximizes the average log probability of the context words given the target word.

Training Process

- during training, a sliding window is used to define the context words around each target word.
- the words are represented as one-hot encoded
- stochastic gradient descent
- the weights of the ***hidden layer***, which represent the word embeddings, are learned by adjusting the model's parameters to improve the prediction accuracy.

GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning
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GloVe

- Global Vectors for Word Representation
- focuses on learning word embeddings by leveraging co-occurrence statistics and factorizing a word co-occurrence matrix

GloVe

- co-occurrence matrix that captures the frequency of word co-occurrences in a large corpus
- each entry in the co-occurrence matrix represents the number of times two words co-occur within a specified context window
- size of the context window determines the range of words considered as context words for each target word

Objective Function

- custom objective function
- objective function is designed to capture the ratio of co-occurrence probabilities of words
- the aim is to find word embeddings that preserve semantic relationships based on the observed co-occurrence statistics

Contextualized BERT word embeddings

- captures the contextual meaning of words within a given sentence or text
- pretrained on a large corpus of text using a masked language modeling objective and next sentence prediction objective
- during MLM, random words in the input text are masked
- NSP training involves predicting whether two sentences appear consecutively or not, enabling BERT to understand relationships between sentences

Transformer Architecture

Tokenization

- tokenizes input text into subword units (WordPiece or SentencePiece)
- subword token is associated with an embedding vector, and the embeddings of multiple subwords form the representation for a given word
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Contextualized Word Representations

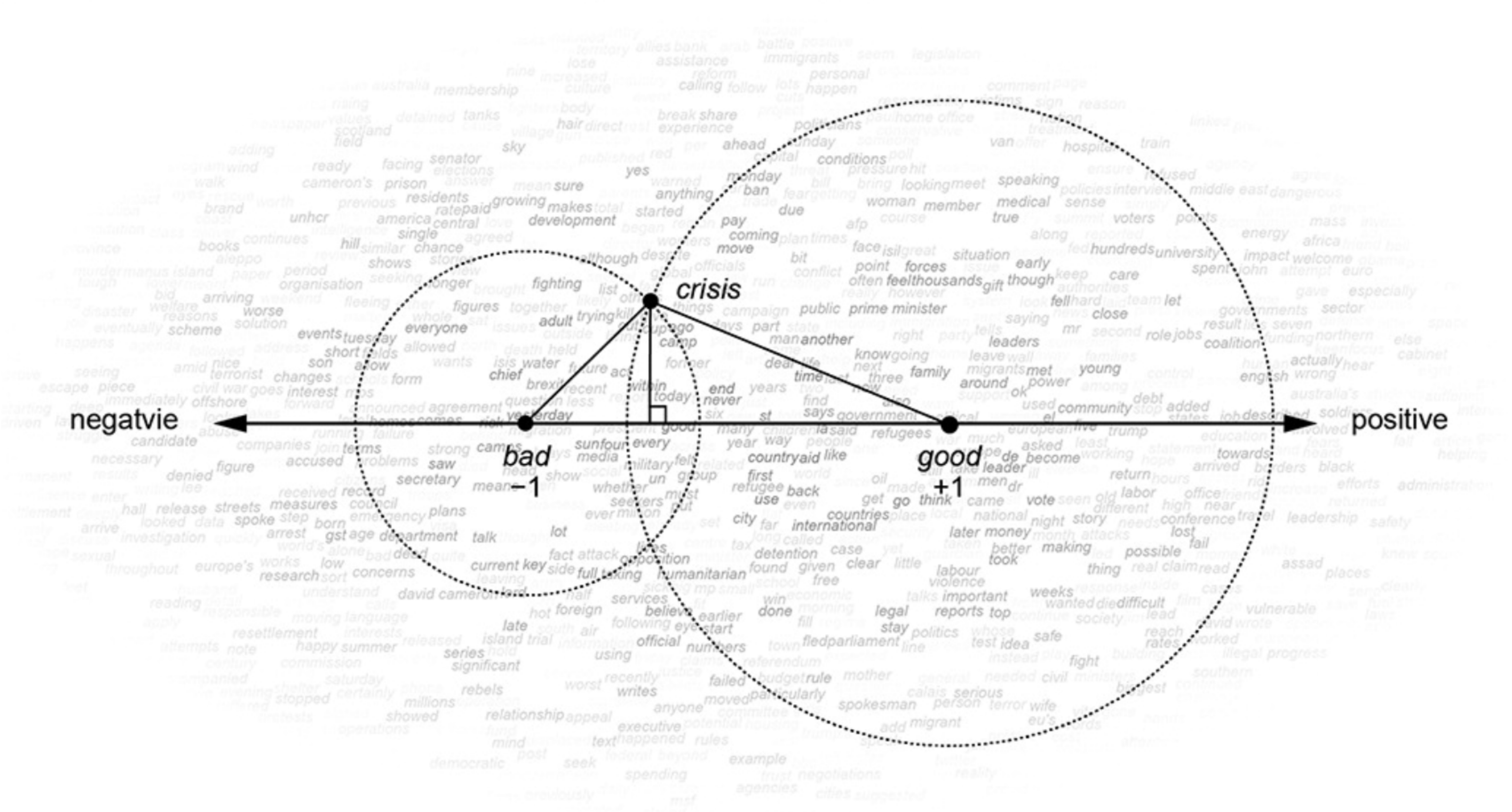
- entire sentence or text is fed into the model
- compute contextualized representations for each subword token based on its surrounding context in the sentence
- contextual meaning

Limitations

- Semantic Shifts
- Difficulty in Handling Out-of-Vocabulary Words
- Lack of Interpretability
- Limited Handling of Syntax and Word Order
- Polysemy and Homonymy

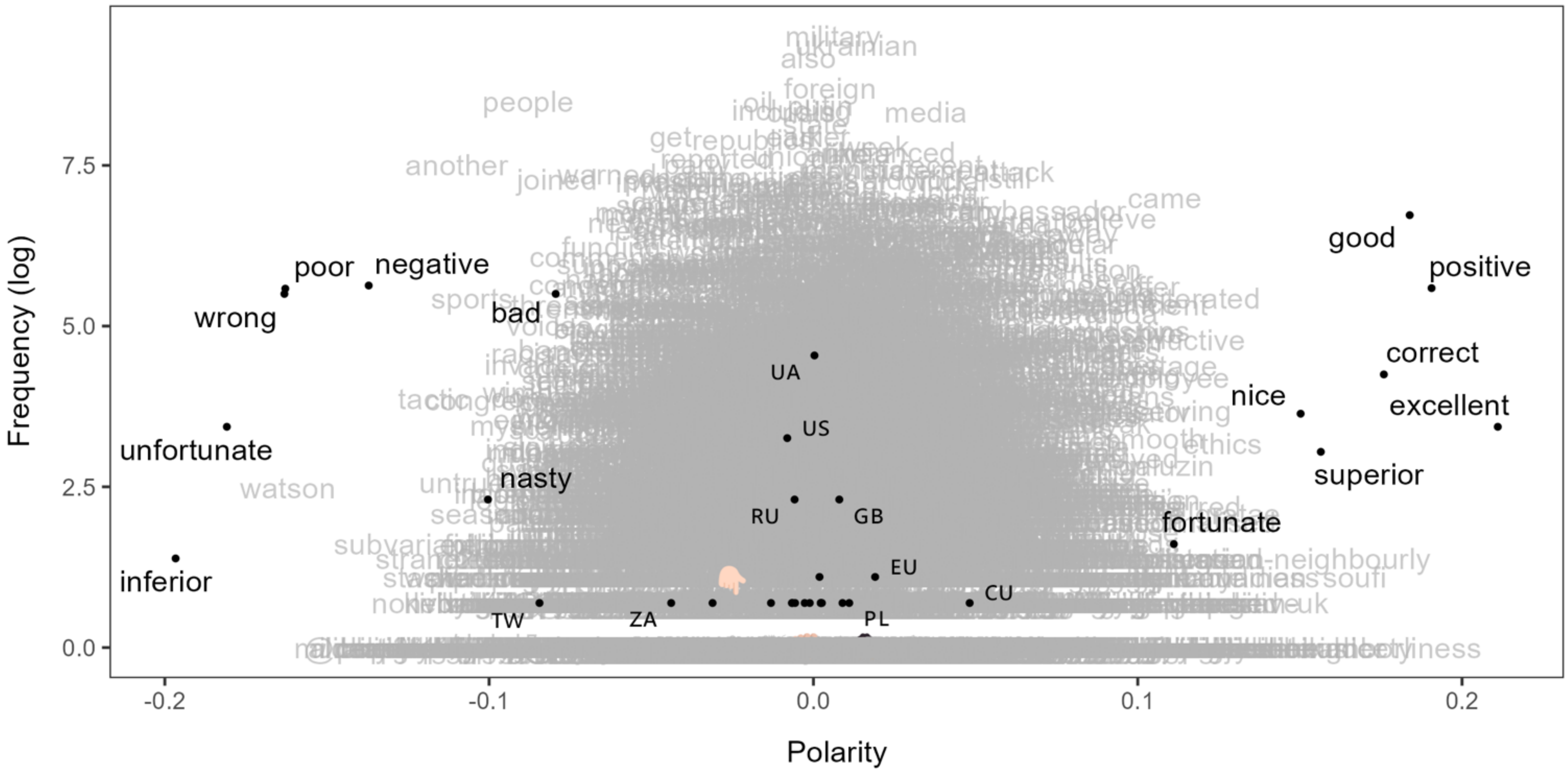
Latent Semantic Scaling

Latent Semantic Scaling



Latent Semantic Scaling

- choose “seed words” that represent your dimensions
- calculate the polarity of words based on their proximity to seed words
    - e.g., cosine similarity
- predict polarity scores of documents by weighting word polarity scores by their frequency in the documents



Frequency (log)
7.5
5.0
2.5
0.0
-0.2
-0.1
0.0
0.1
0.2
Polarity
good
positive
correct
nice
excellent
superior
fortunate
poor
negative
wrong
bad
unfortunate
nasty
inferior
UA
US
RU
GB
EU
CU
TW
ZA
PL
military
also
foreign
people
media
another
came
watson

Check for updates

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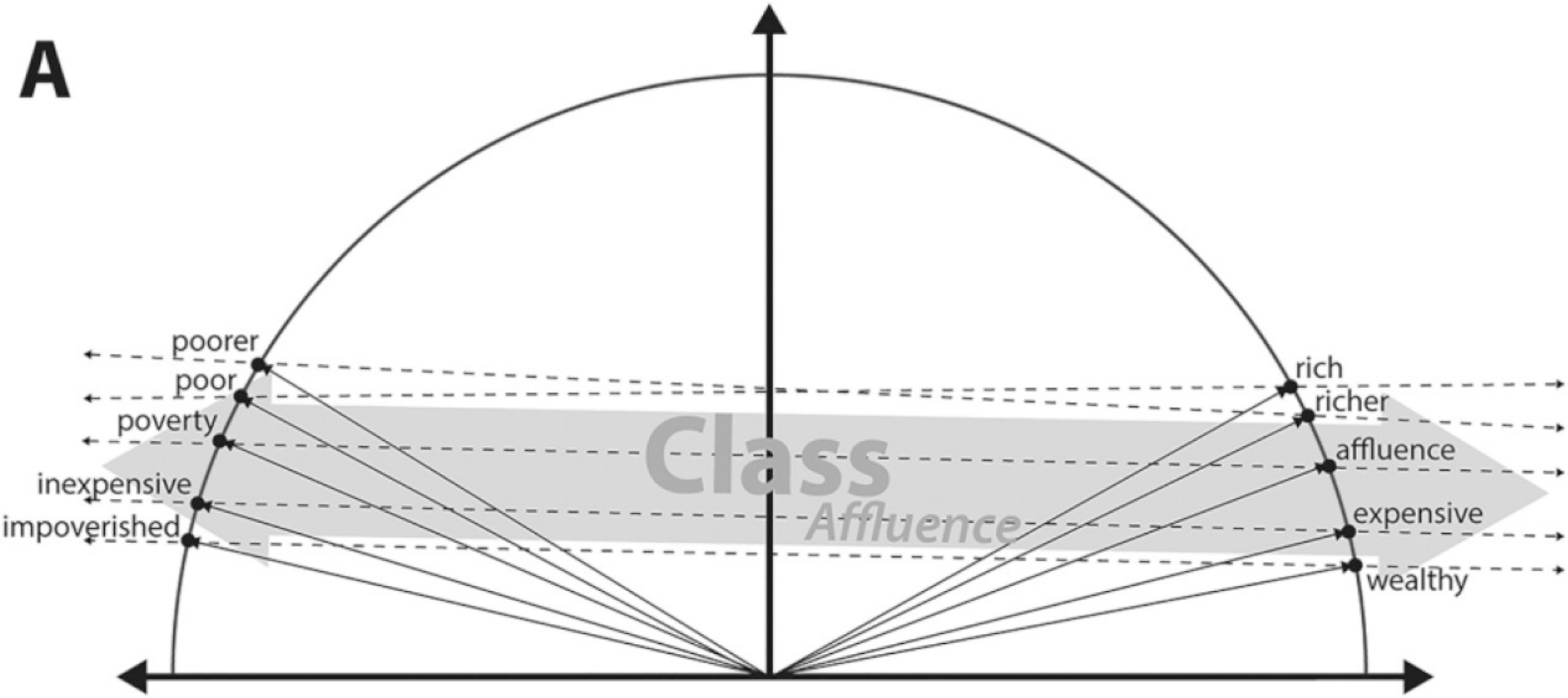
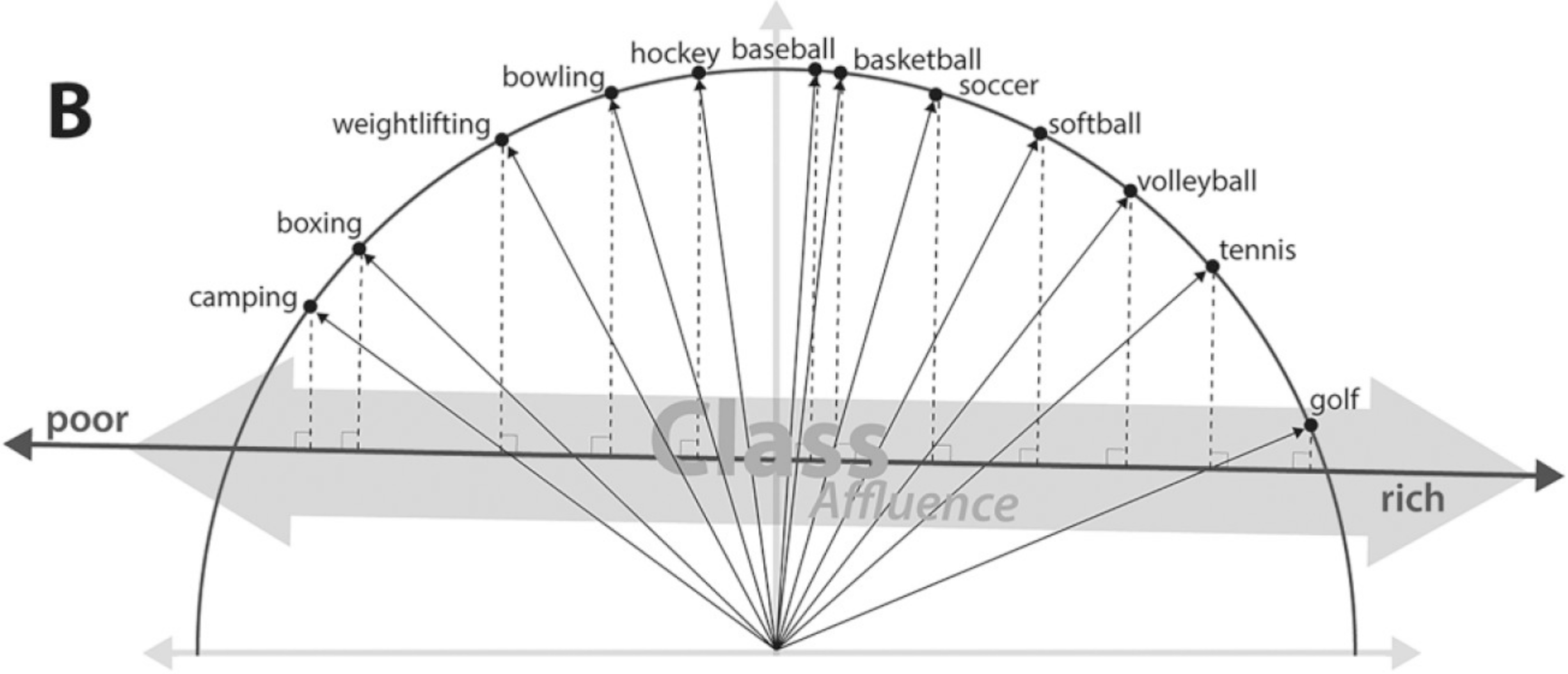
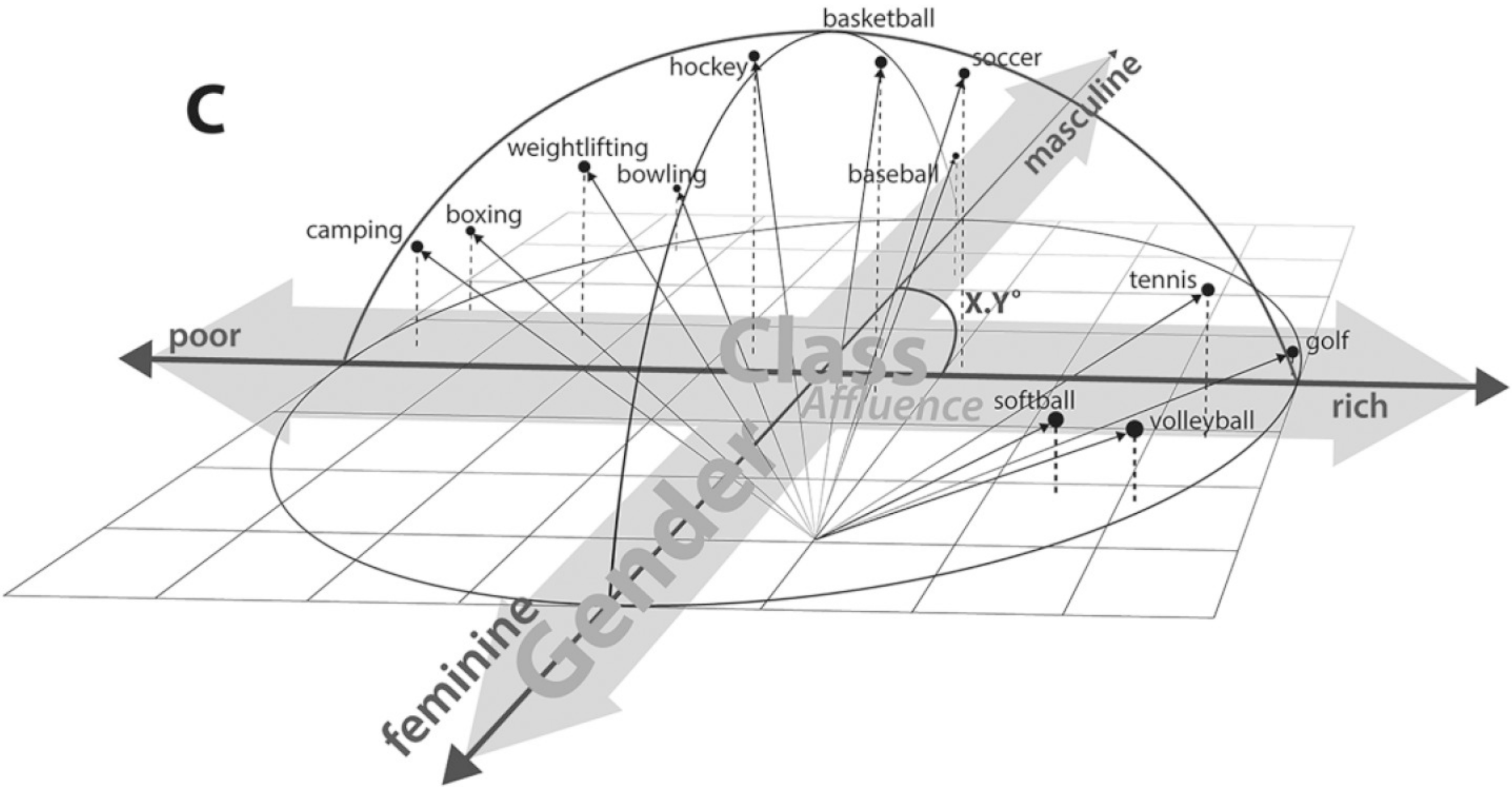
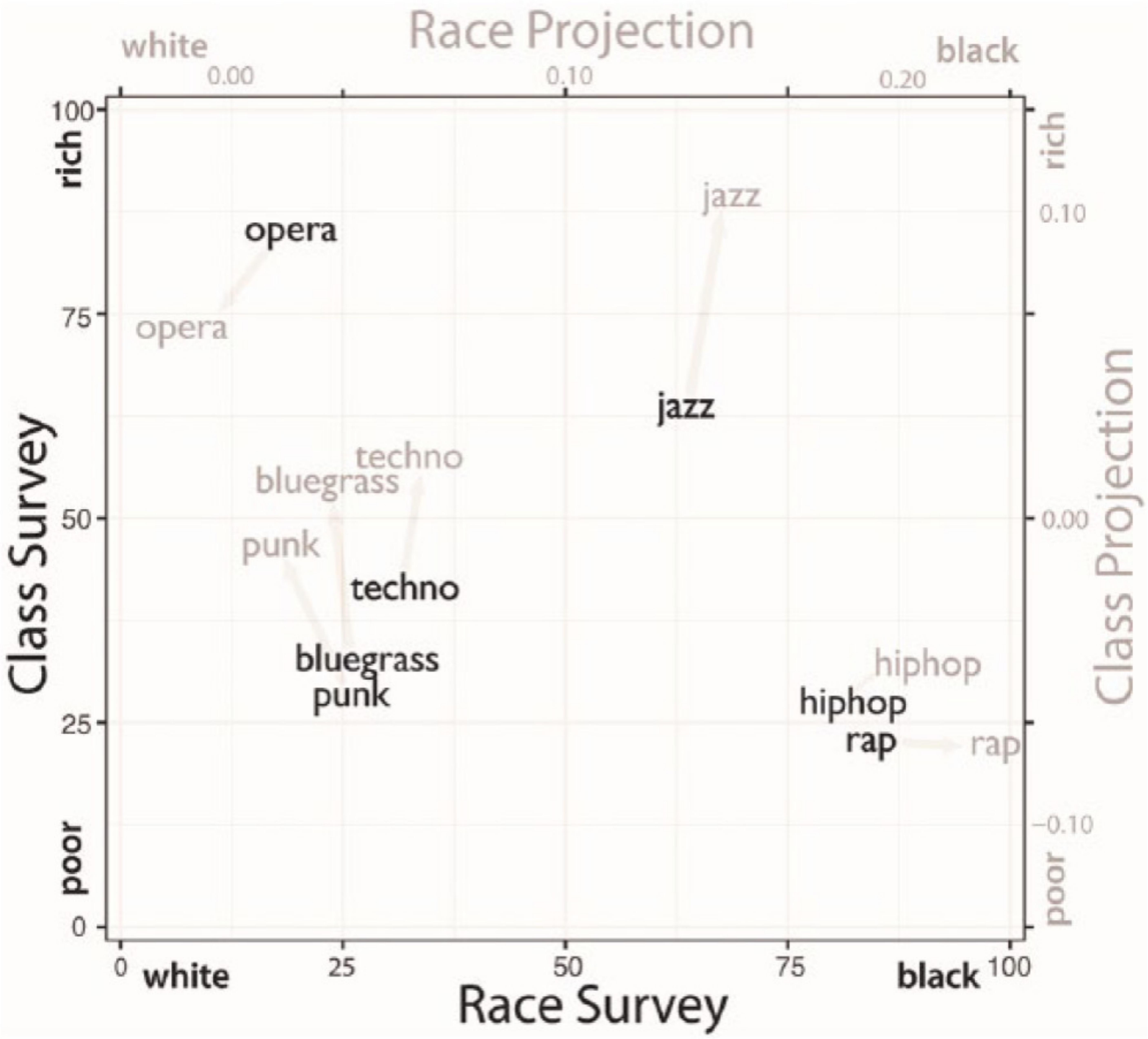
The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings

Austin C. Kozlowski,[a] Matt Taddy,[b] and James A. Evans[a,c]


A
poorer
poor
poverty
inexpensive
impoverished
Class
Affluence
rich
richer
affluence
expensive
wealthy


B
hockey
baseball
basketball
bowling
soccer
weightlifting
softball
volleyball
boxing
tennis
camping
golf
poor
Class
Affluence
rich


C
basketball
hockey
soccer
weightlifting
bowling
baseball
boxing
camping
masculine
X.Y°
tennis
poor
Class
golf
Affluence
softball
rich
volleyball
Gender
feminine


Race Projection
white
black
0.00
0.10
0.20
Class Survey
rich
poor
100
75
50
25
0
Class Projection
rich
poor
0.10
0.00
−0.10
opera
opera
jazz
jazz
techno
bluegrass
punk
techno
bluegrass
punk
hiphop
hiphop
rap
rap
0
white
25
50
75
black
100
Race Survey

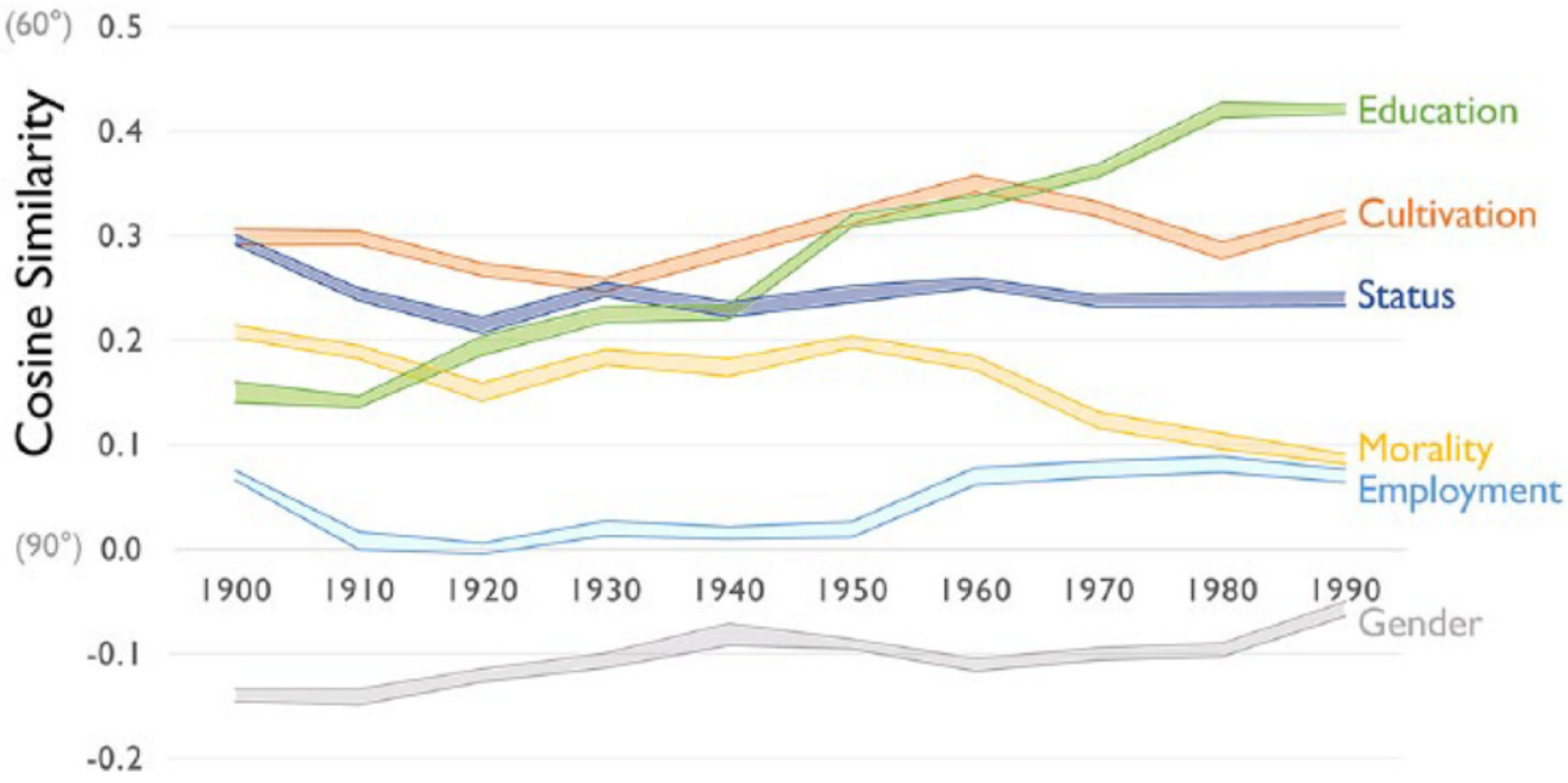


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

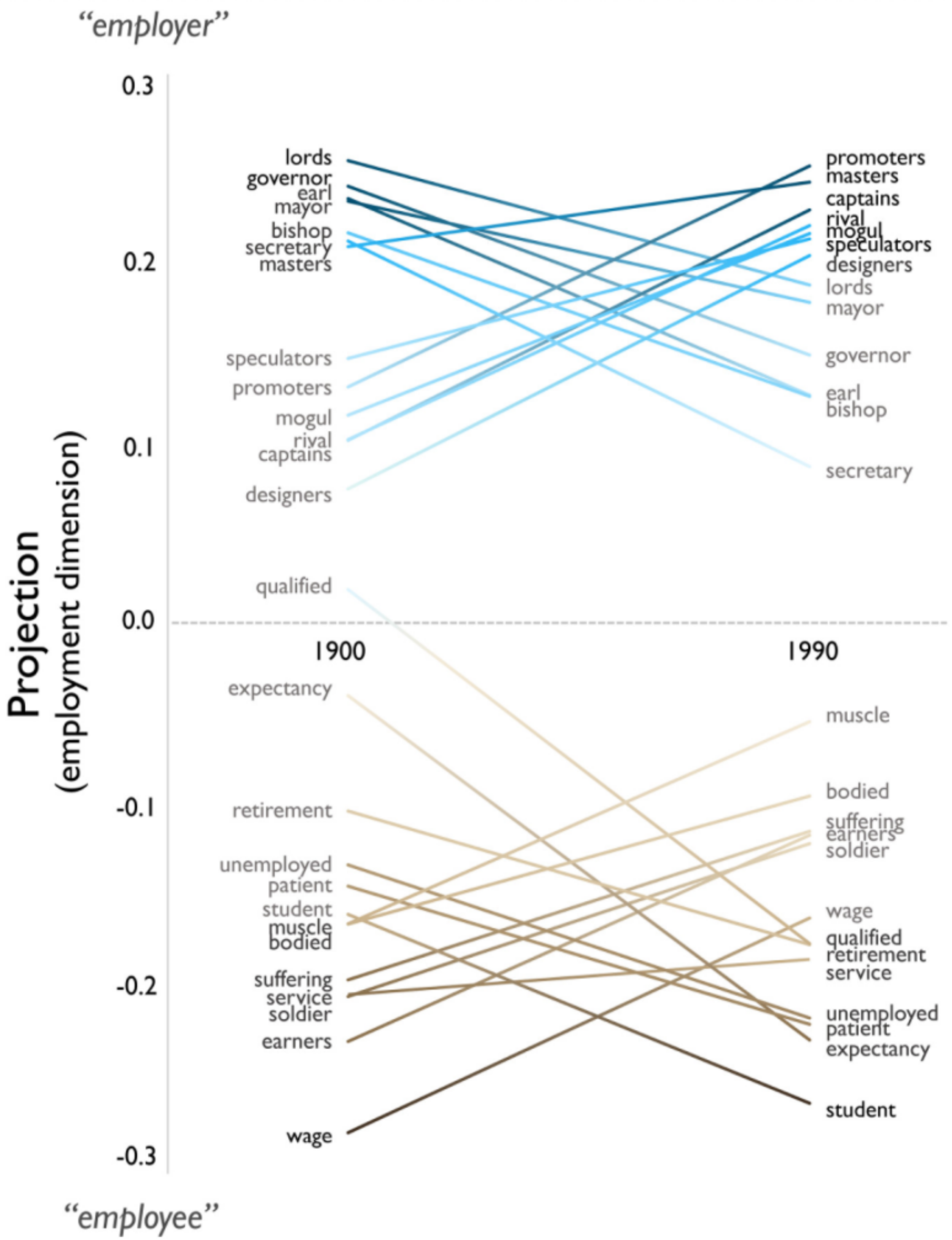


Figure 10. Words That Project High and Low on the Employment Dimension of Word Embedding Models Trained on Texts Published at the Beginning and End of the Twentieth Century; 1900–1919 and 1980–1999 Google Ngrams Corpus

Final Paper (+ 2ECTS)

- Task: application of one or several automated text analysis methods on a topic related to the Bachelor/Master/PhD thesis or a topic of free choice
- Required contents: short motivation, analysis (commented code), description and interpretation of results (about 5-7 pages)
- Format: R Markdown
- Deadline: July 31st, 2023

Course Evaluation

- You should have received an email?


That's all Folks!