Word Embeddings II: Properties and Applications

Sandeep Soni

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From last class

- Distributional hypothesis: Words used in similar contexts have similar meanings (and therefore similar representations)
- Many different ways to transform words into vectors

From last class

	d_1	d_2	d_3	…	d_m
w_1	2				1
w_2		3			
w_3	1				
…					
w_n			5		

Term-Document Matrix

	w_1	w_2	w_3	…	w_m
w_1	2				1
w_2		3			
w_3	1				
…					
w_n			5		

Cooccurrence Matrix

w_1	0.1				1.06
w_2		0.14			
w_3	-0.2				
…					
w_n			0.75		

Word Embedding Matrix

Methodologically simple

High-dimensional and sparse word vectors

High-dimensional and sparse word vectors

Transformations to convert counts into scores

Learned vectors from data

Fixed dimensional dense vectors

From last class

- Instead of counting, word2vec or GloVe are methods to learn vectors by predicting which words will co-occur together

x	y
wine	cold
wine	sweet
wine	spirit
wine	drink

x	y
wine	cold
wine	sweet
wine	spirit
wine	drink

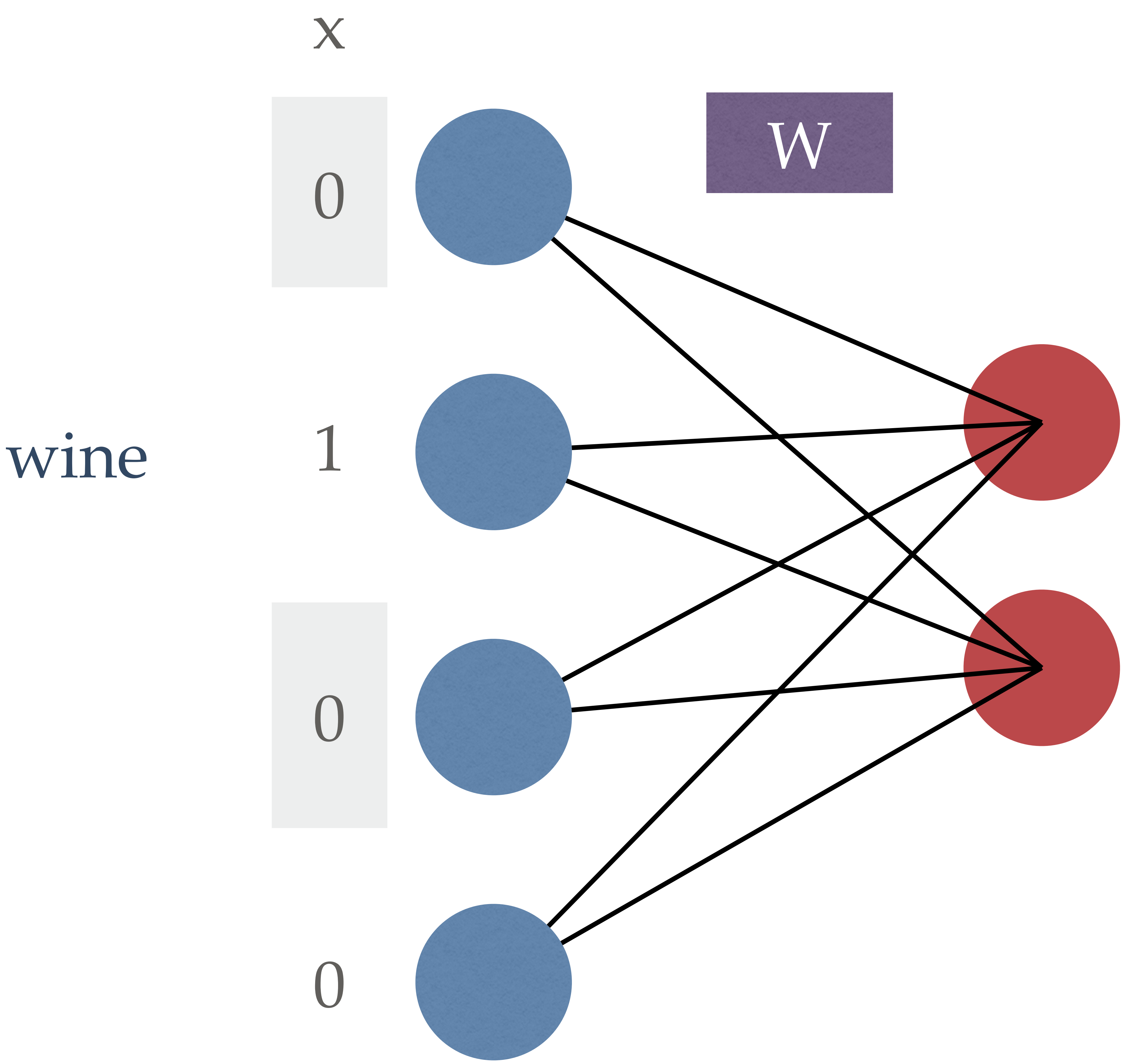
wine

x	y
wine	cold
wine	sweet
wine	spirit
wine	drink

x
0
1
0
0

wine

x	y
wine	cold
wine	sweet
wine	spirit
wine	drink



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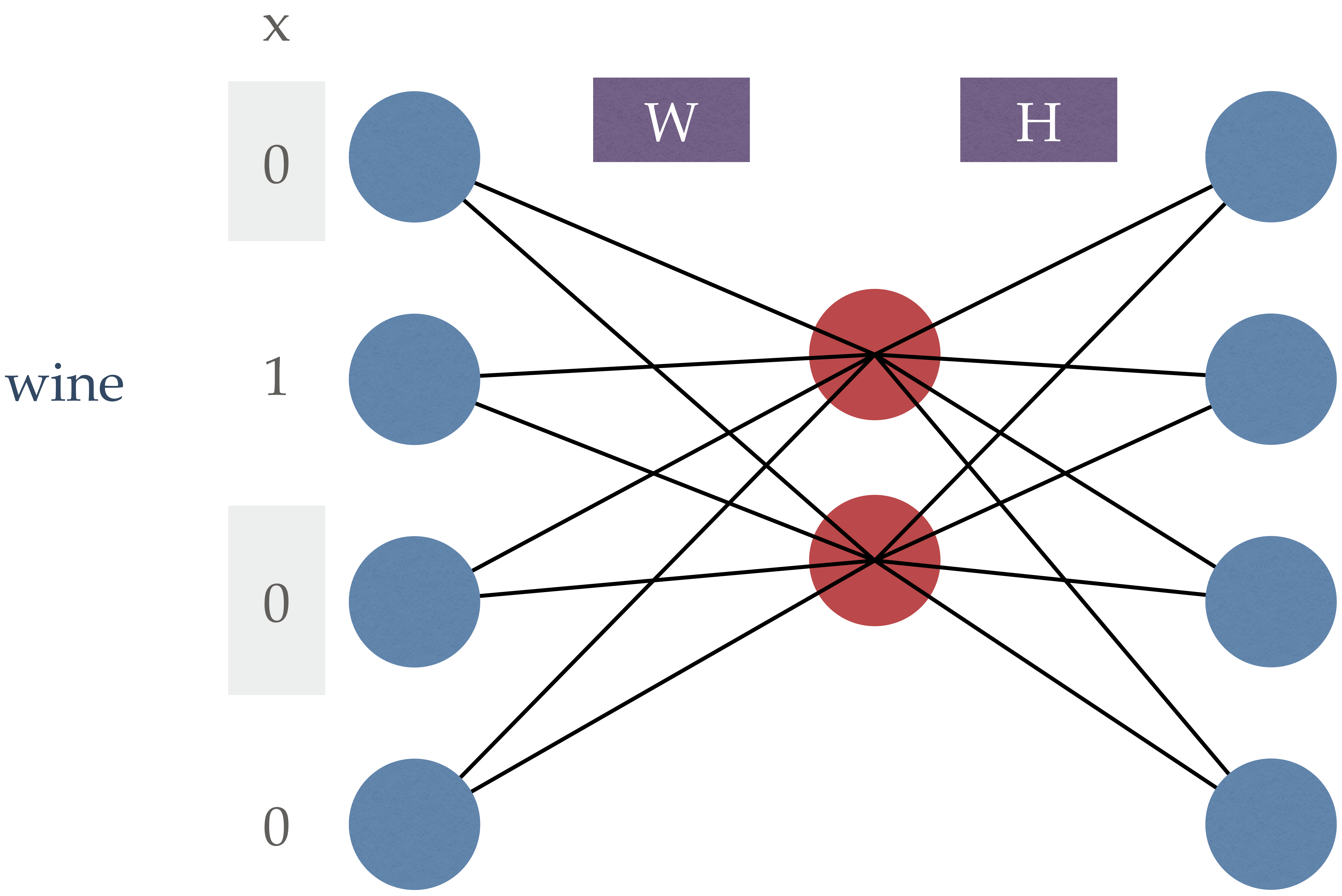

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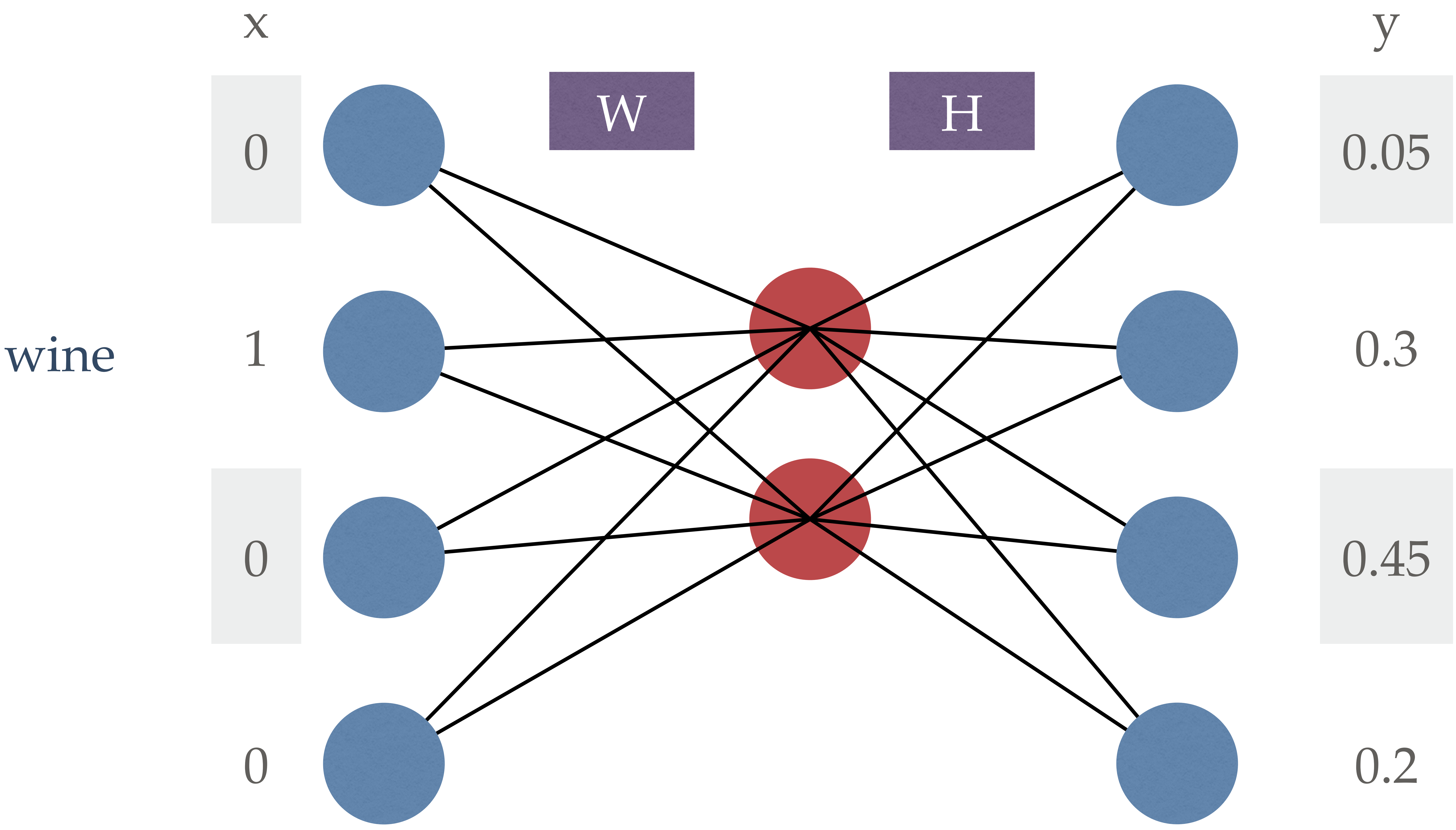

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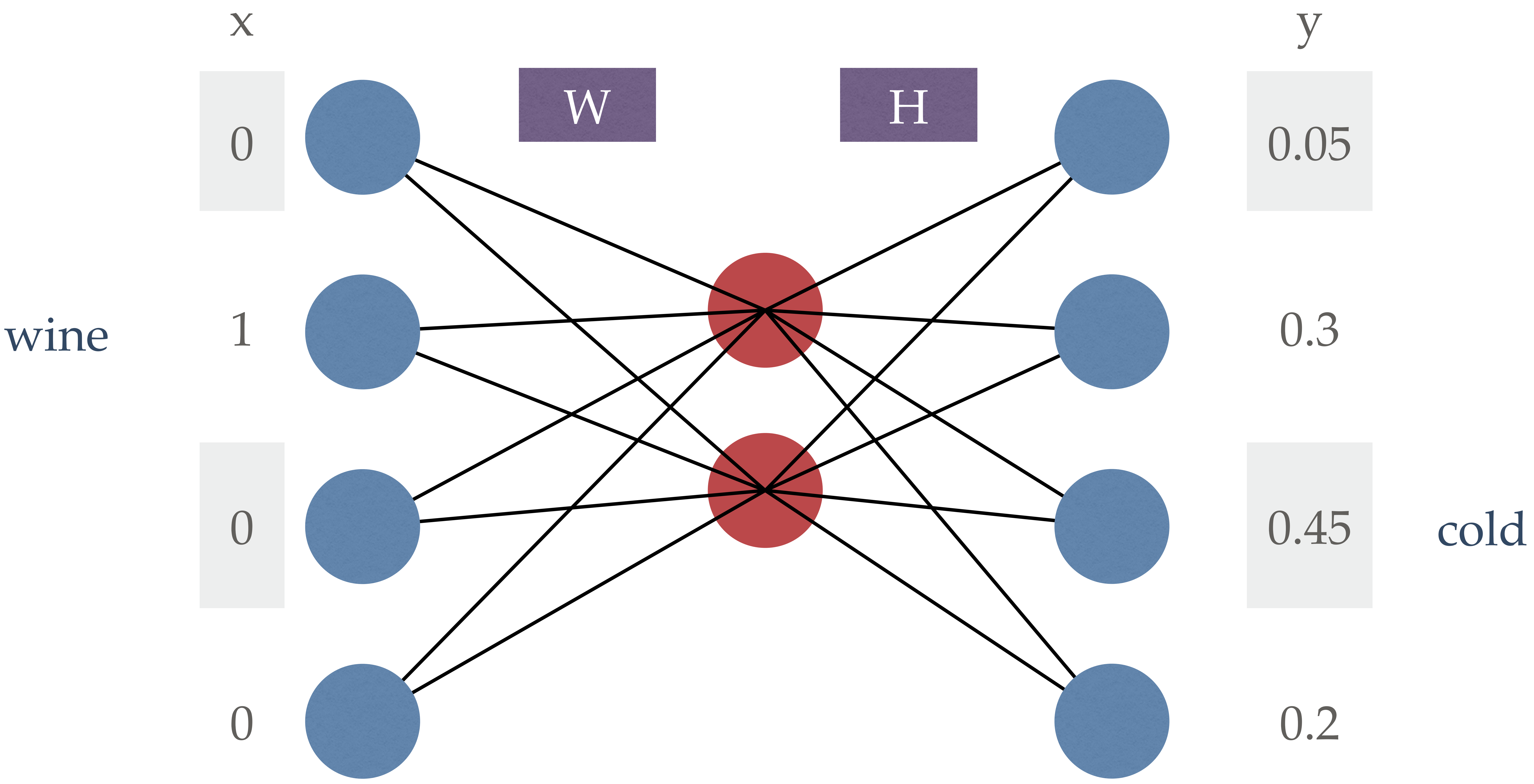

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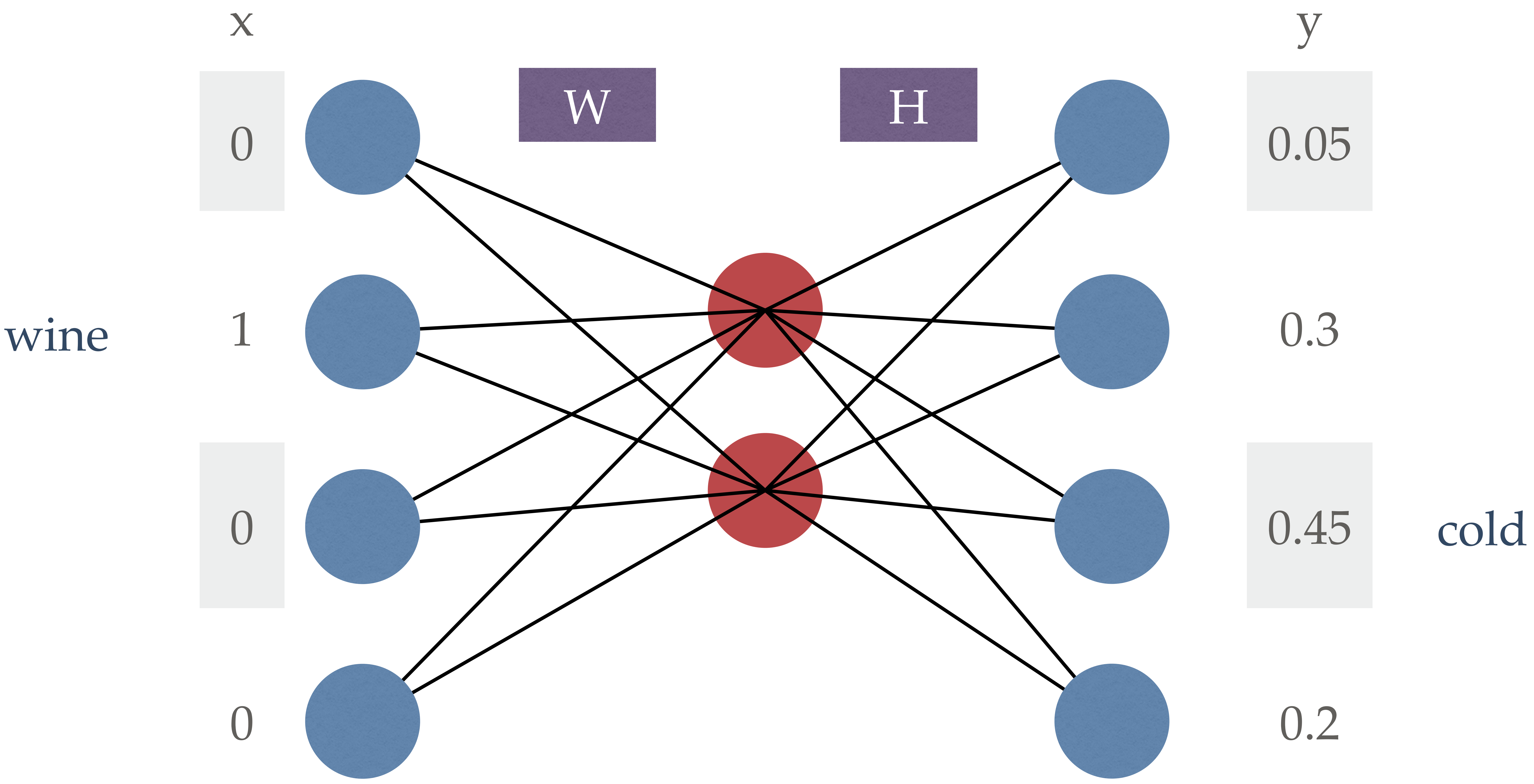
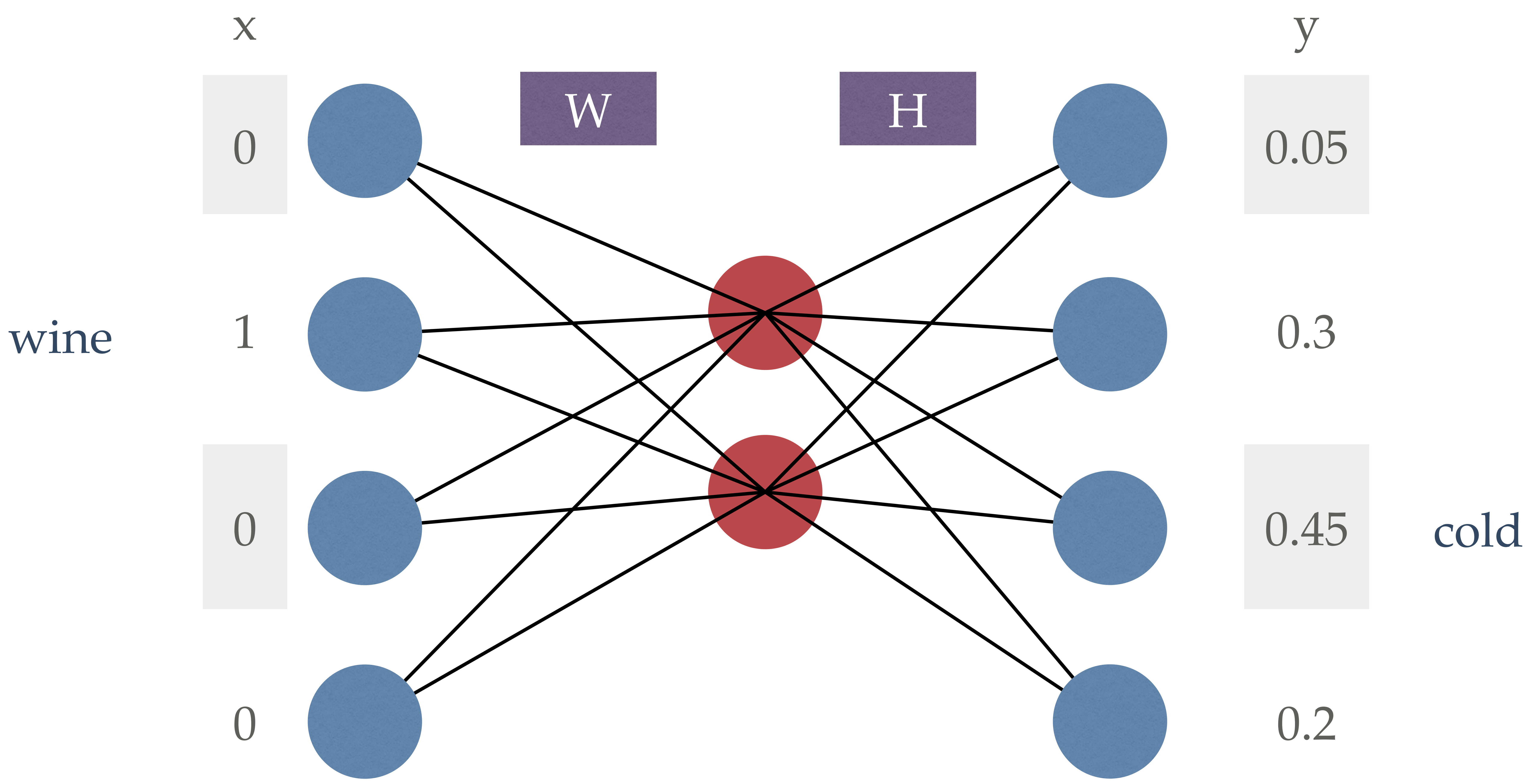


x	y
wine	cold
wine	sweet
wine	spirit
wine	drink

Word embeddings as columns

W

-0.3	1.2	0.5	-0.6
0.2	0.9	0.1	-0.4



x	y
wine	cold
wine	sweet
wine	spirit
wine	drink

Word embeddings as columns

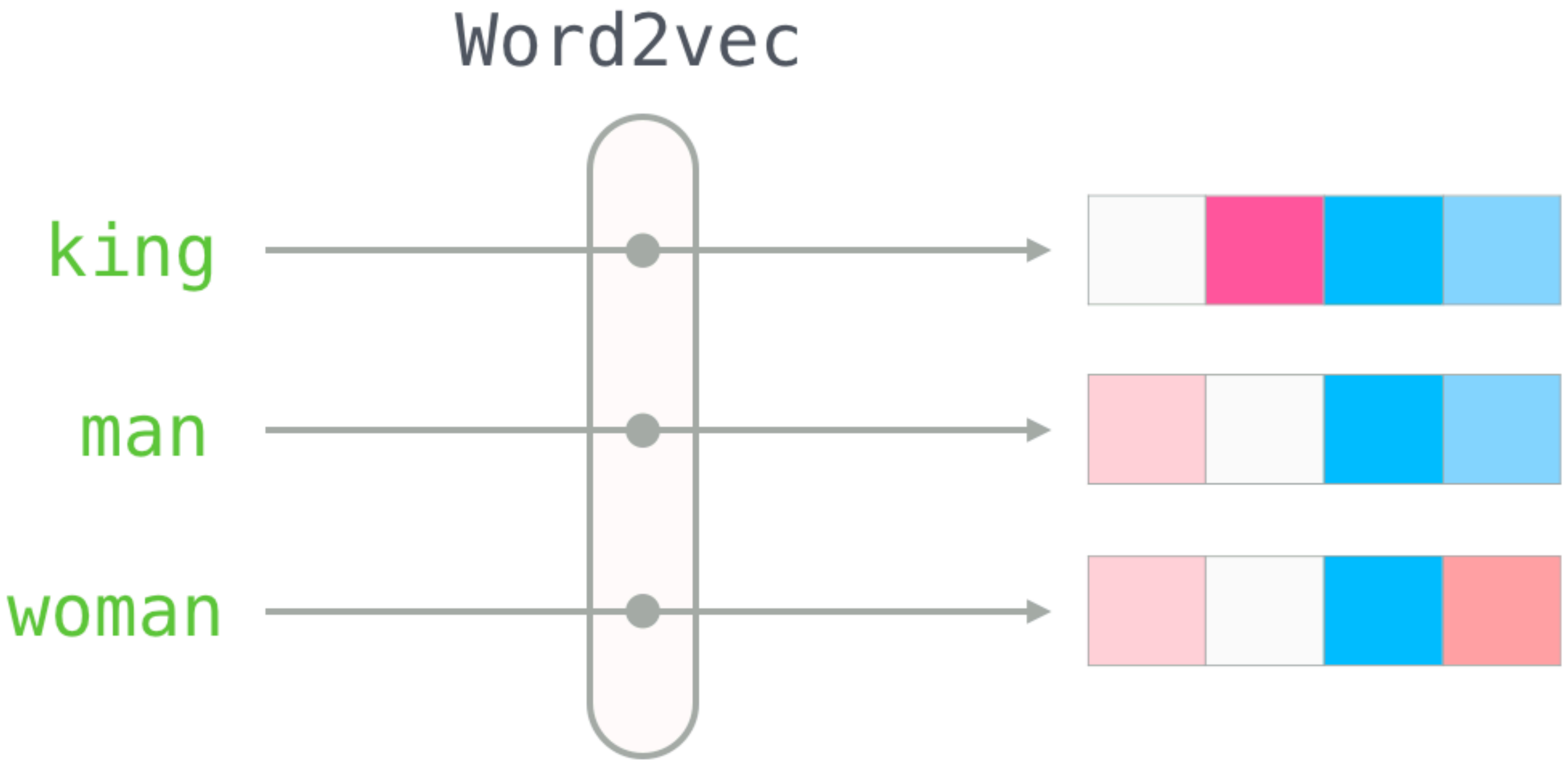
W

-0.3	1.2	0.5	-0.6
0.2	0.9	0.1	-0.4

Context embeddings as rows

H

0.1	-0.4
0.4	-0.5
0.3	-0.1
0.2	0.1



http://jalammar.github.io/illustrated-word2vec/

Question for the day

"What do word embeddings encode and what can we do with them?"

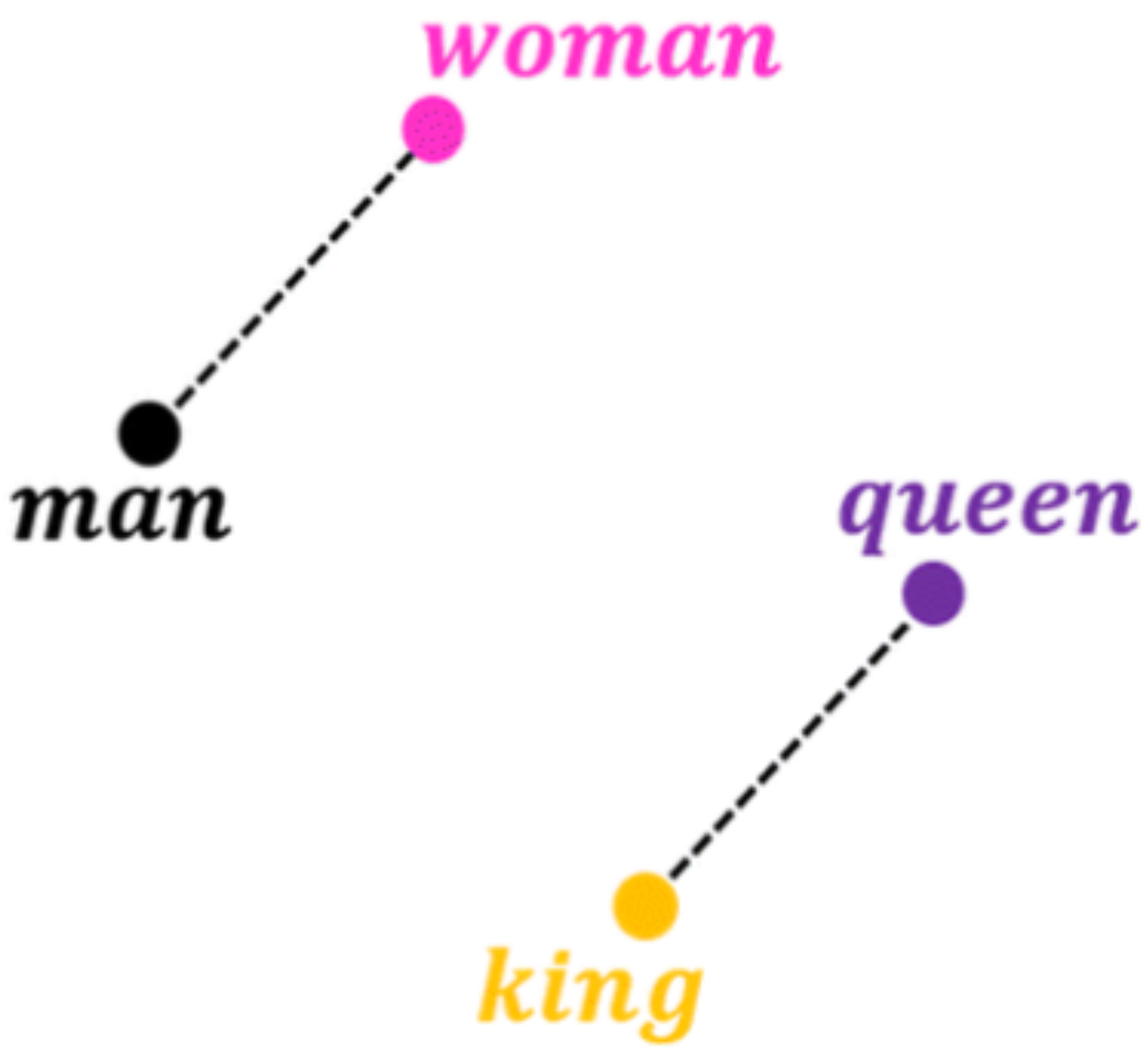
Word Embeddings

- What is the geometry of word embeddings?
- What is their use as predictors?
- Can they be used to explain something about the world?

Geometry

man:woman::king:queen

v(“man”)-v(“woman”)+v(“king”) ≈ v(“queen”)



Mikolov et. al. 2013 Linguistic Regularities in Continuous Space Word Representations

Prediction

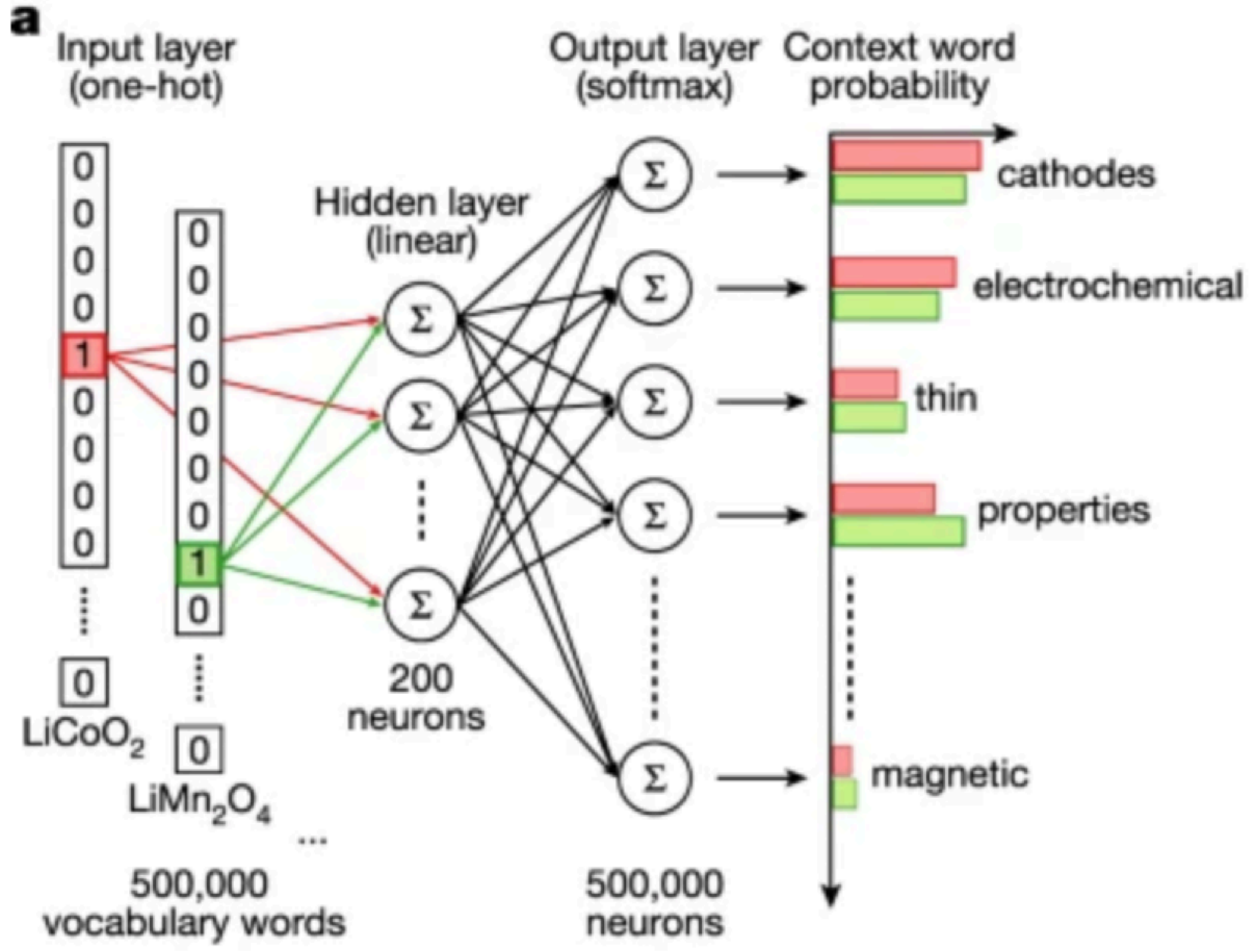
Prediction

$$\text{ferromagnetic} - \text{NiFe} + \text{IrMn} \approx \text{antiferromagnetic}$$

Oxides $\quad Zr - ZrO_2 \approx Cr - Cr_2O_3 \approx Ni - NiO$

Structure $\quad Zr - HCP \approx Cr - BCC \approx Ni - FCC$

Embeddings can be used to construct knowledge bases that can lead to new discoveries



Tshitoyan, Vahe, et al. "Unsupervised word embeddings capture latent knowledge from materials science literature." *Nature* 571.7763 (2019): 95-98.

Prediction

Are Word Embedding-based Features Useful for Sarcasm Detection?

Aditya Joshi[1,2,3] **Vaibhav Tripathi**[1] **Kevin Patel**[1]
Pushpak Bhattacharyya[1] **Mark Carman**[2]
[1]Indian Institute of Technology Bombay, India
[2]Monash University, Australia
[3]IITB-Monash Research Academy, India
{adityaj,kevin.patel,pb}@cse.iitb.ac.in, mark.carman@monash.edu

	Word2Vec	**LSA**	**GloVe**	**Dep. Wt.**
+S	0.835	0.86	0.918	**0.978**
+WS	**1.411**	0.255	0.192	1.372
+S+WS	**1.182**	0.24	0.845	0.795

Table 4: Average gain in F-Scores obtained by using intersection of th four word embeddings, for three word embedding feature-types, aug mented to four prior works; Dep. Wt. indicates vectors learned fron dependency-based weights

Word Embedding	**Average F-score Gain**
LSA	0.452
Glove	0.651
Dependency	1.048
Word2Vec	1.143

Table 5: Average gain in F-scores for the four types of word embed dings; These values are computed for a subset of these embedding consisting of words common to all four

Bias

man:woman::king:?

man:woman::waiter:?

man:woman::doctor:?

`man:woman::king:?`	queen	okay
`man:woman::waiter:?`	waitress	okay
`man:woman::doctor:?`	nurse	huh

man:woman::king:? queen okay

man:woman::waiter:? waitress okay

man:woman::doctor:? nurse huh

RESEARCH

REPORT

COGNITIVE SCIENCE

Semantics derived automatically from language corpora contain human-like biases

Aylin Caliskan,[1*] Joanna J. Bryson,[1,2*] Arvind Narayanan[1*]

Machine learning is a means to derive artificial intelligence by discovering patterns in existing data. Here, we show that applying machine learning to ordinary human language results in human-like semantic biases. We replicated a spectrum of known biases, as measured by the Implicit Association Test, using a widely used, purely statistical machine-learning model trained on a standard corpus of text from the World Wide Web. Our results indicate that text corpora contain recoverable and accurate imprints of our historic biases, whether morally neutral as toward insects or flowers, problematic as toward race or gender, or even simply veridical, reflecting the status quo distribution of gender with respect to careers or first names. Our methods hold promise for identifying and addressing sources of bias in culture, including technology.

Bias

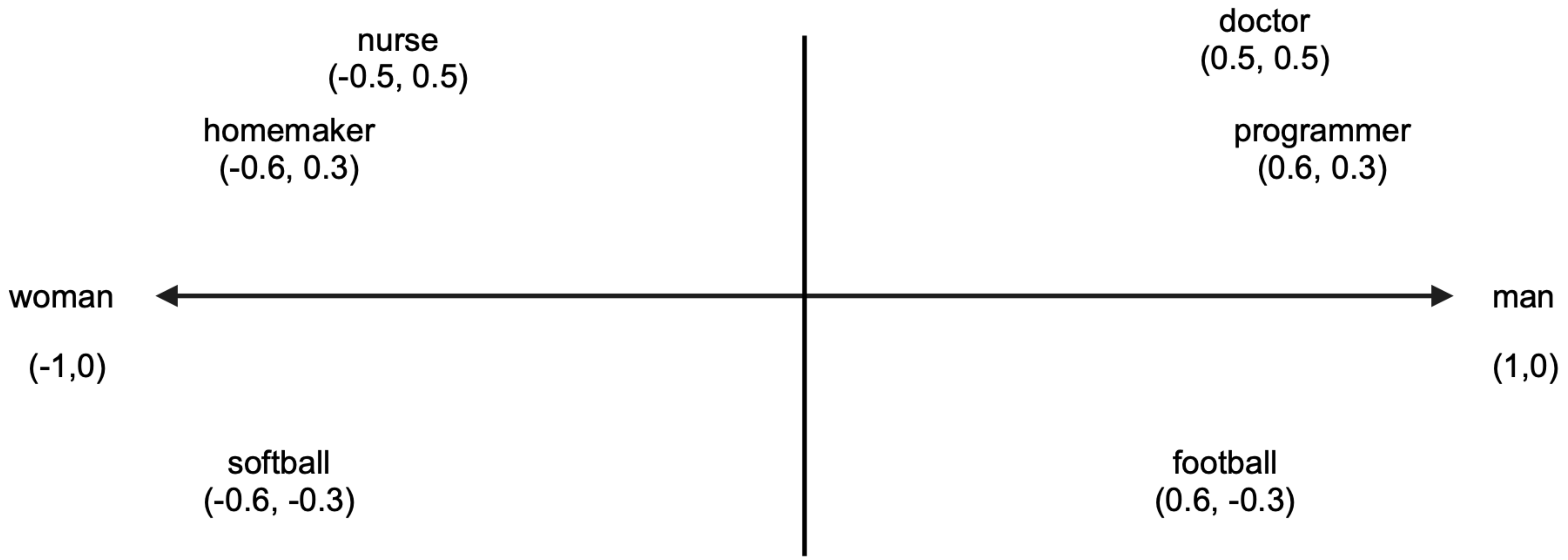
- Allocation harms: Systems should not allocate resources to groups unfairly
- Representational harms: Systems should not misrepresent groups unfairly

- Su Lin Blodgett, Solon Barocas, Hal Daumé III, and Hanna Wallach. 2020. Language (Technology) is Power: A Critical Survey of "Bias" in NLP. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5454–5476, Online. Association for Computational Linguistics.

Projection of embeddings on a subspace

$$\vec{b} = \overrightarrow{\text{man}} - \overrightarrow{\text{woman}}$$

$$\vec{p} = (\vec{v} \cdot \vec{b})\vec{b}$$



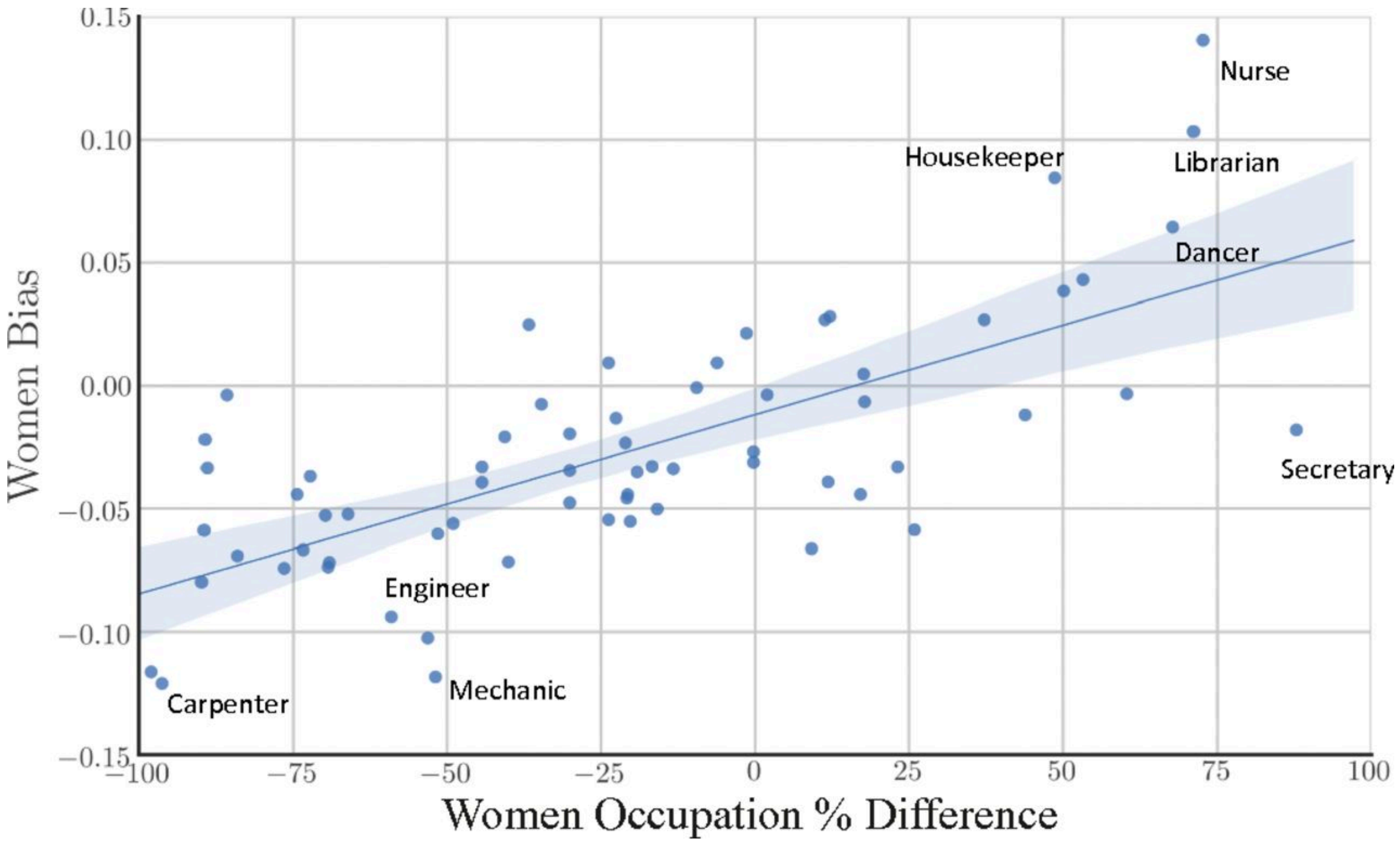


Image from Garg et. al. (2018)

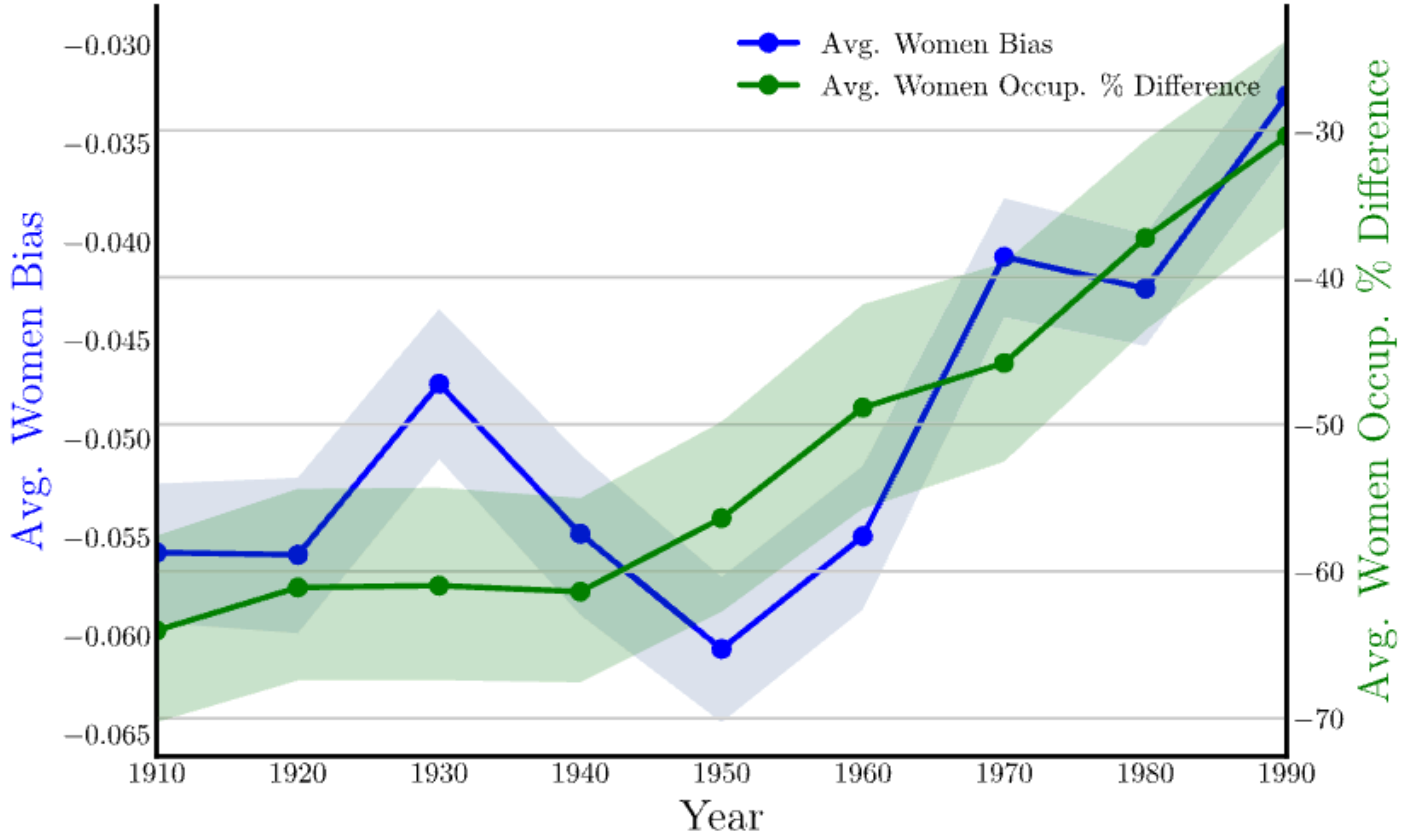


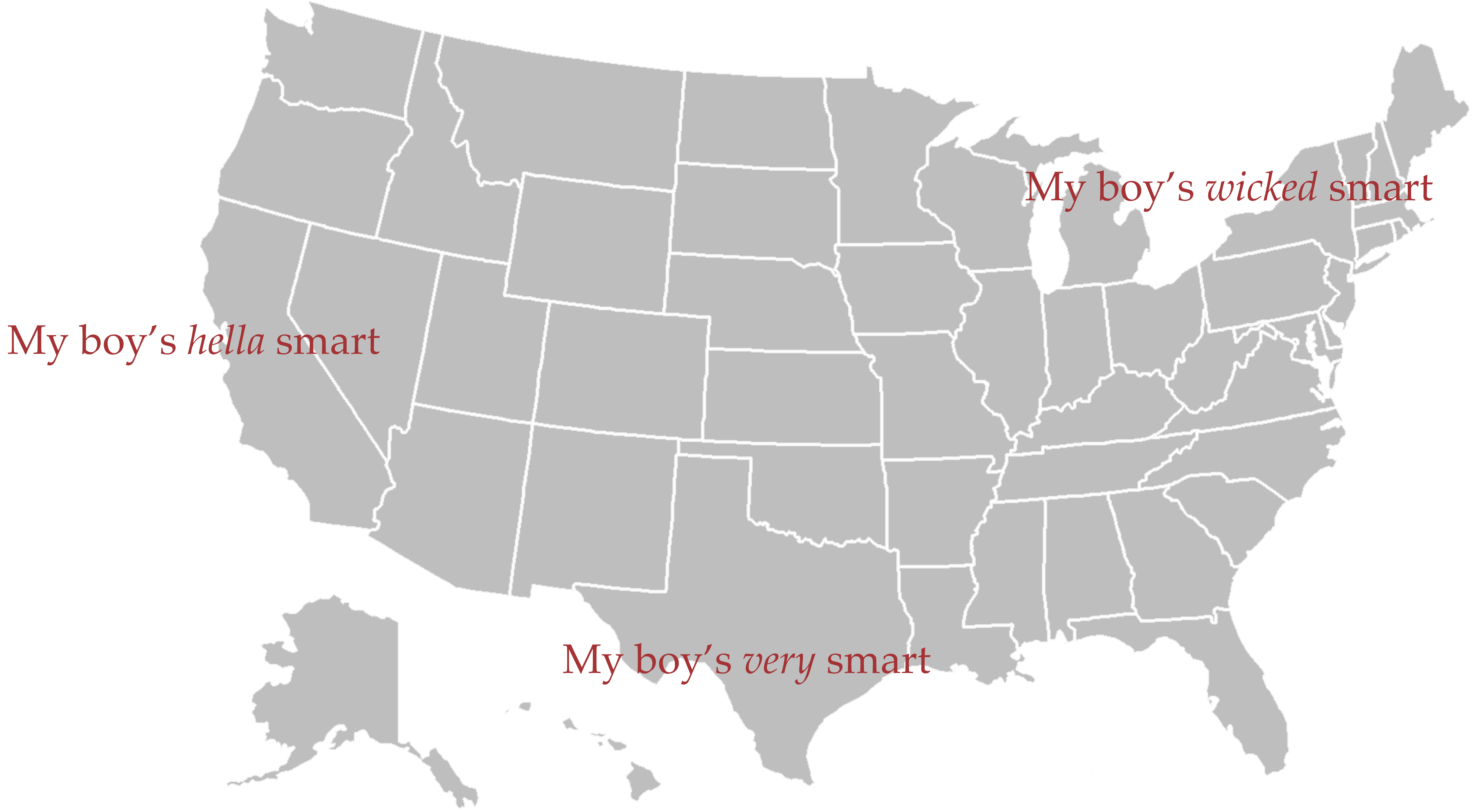
Image from Gary et. al. (2018)

Change and Variation

My boy’s *hella* smart

My boy’s *wicked* smart

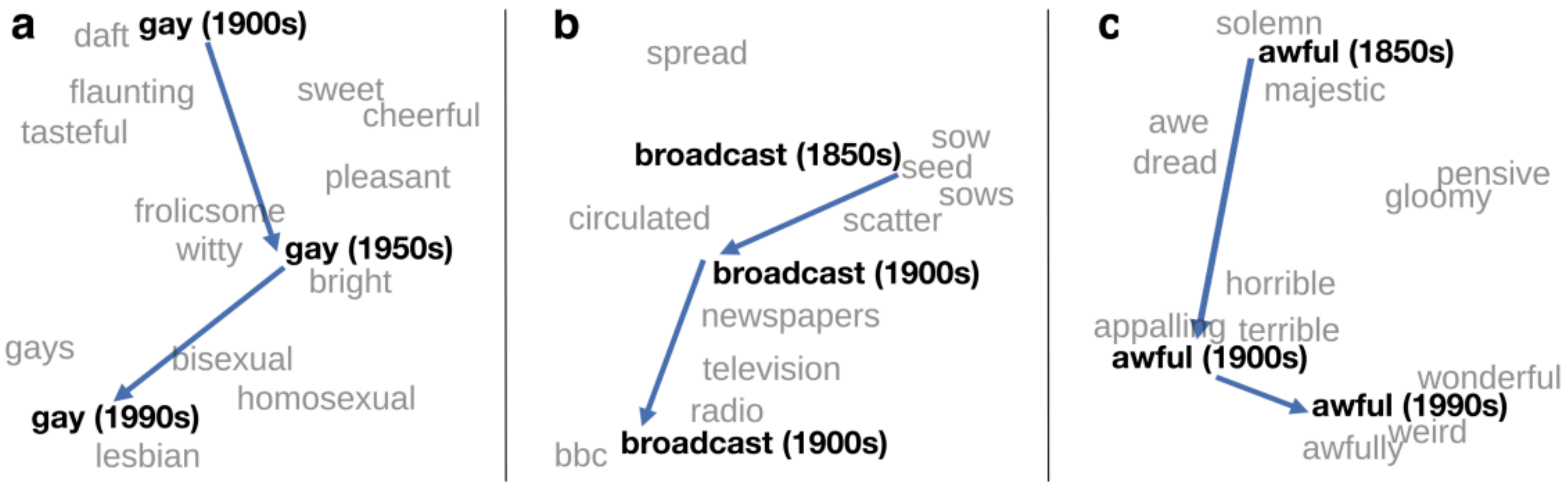
My boy’s *very* smart



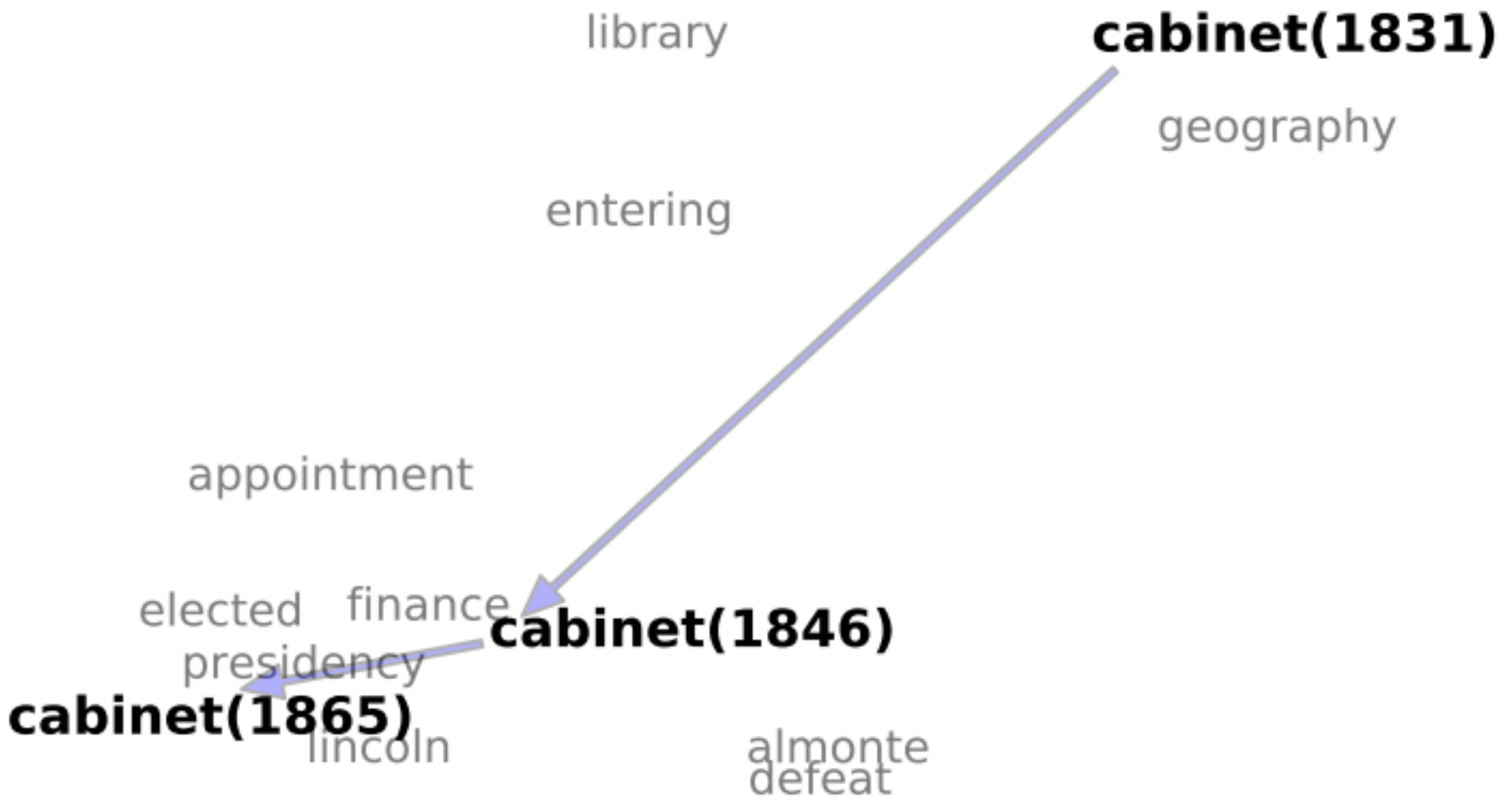
- David Bamman, Chris Dyer, and Noah A. Smith. 2014. Distributed Representations of Geographically Situated Language. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 828–834, Baltimore, Maryland. Association for Computational Linguistics.

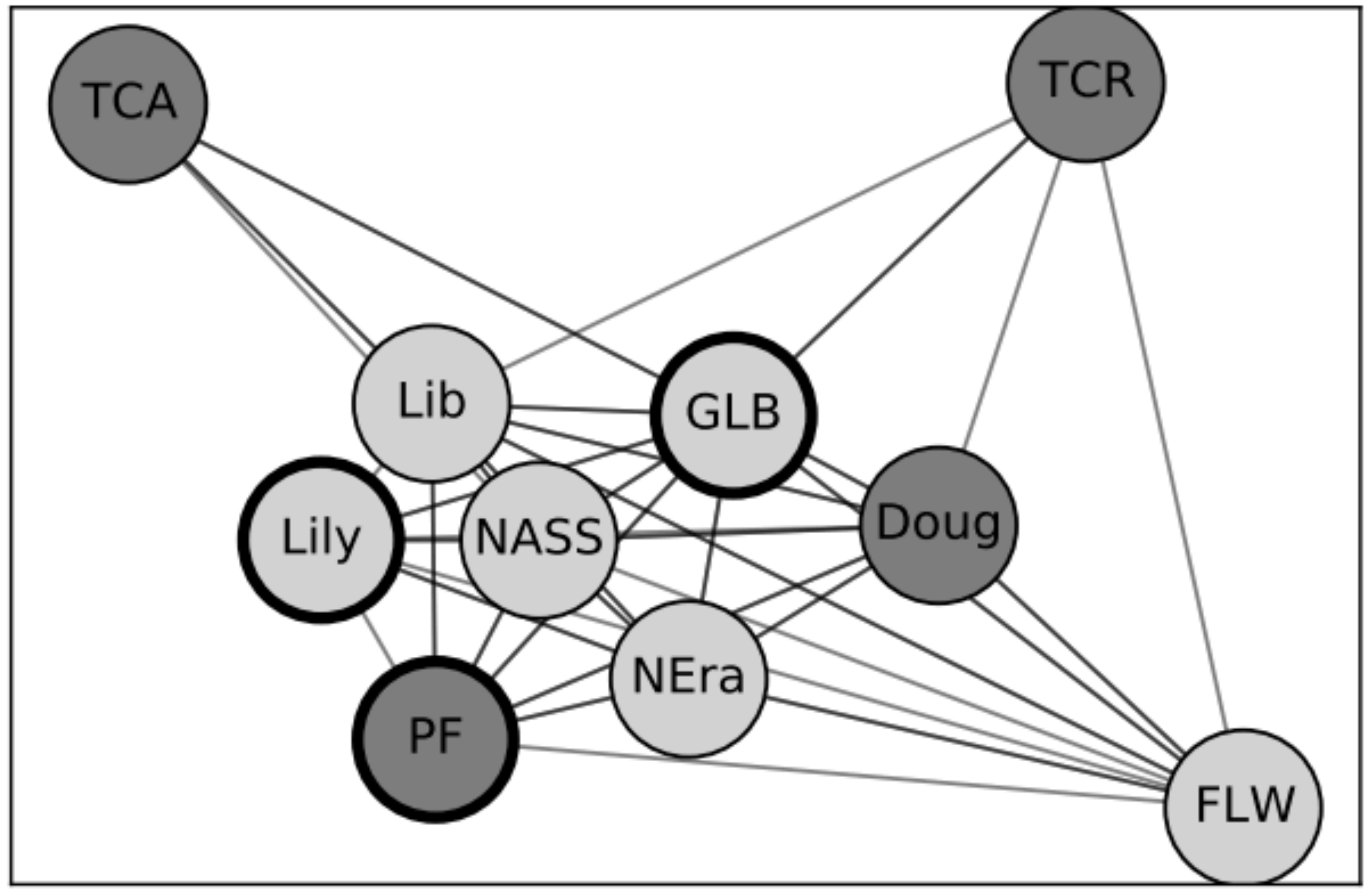
Change and Variation

- Since language is situational, one can learn embeddings that depend on time, geography or other social contexts



- William L. Hamilton, 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 (Volume 1: Long Papers)*, pages 1489–1501, Berlin, Germany. Association for Computational Linguistics.





Soni, Sandeep, Lauren Klein, and Jacob Eisenstein. "Correcting whitespace errors in digitized historical texts." *Proceedings of the 3rd Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*. 2019.

Soni, Sandeep, Lauren F. Klein, and Jacob Eisenstein. "Abolitionist Networks: Modeling Language Change in Nineteenth-Century Activist Newspapers." *Journal of Cultural Analytics* 6.1 (2021).

In class

- Word2Vec demo