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WORDS IN SPACE

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It's Trump's platform, with a dose of DeSantis

Sophia Cai

Illustration: Shoshana Gordon / Axios

Donald Trump used to trash Ron DeSantis. Now, he copies him.

Trump gradually has taken a few pages from DeSantis' playbook on issues that resonate with the far right.

- Last year he revealed an education plan with a proposal for a "Parental Bill of Rights." It calls for more federal influence in how public schools are run, and for cutting funds to schools that teach "gender ideology."
- Months earlier, DeSantis had signed a "Parental Rights in Education" bill with provisions that banned talk about gender and sexuality in
schools.
- Today, "defund schools" is one of Trump's go-to phrases when he talks about his plans for a second term, an Axios analysis found.

via Axios

SOME PROPERTIES WE MIGHT WANT FROM A MEASURE OF SIMILARITY

- Consider two documents, **a** and **b**...
  - Perfect/maximum similarity should occur when comparing **a** to **a**.
  - Symmetry: document **a** is always as close to **b** as **b** is to **a**.
  - If **a** and **b** share no words, similarity should be at a minimum.
  - As **a** and **b** share more words, then similarly should increase.

ENTER: THE DOT PRODUCT

- Recall: cat, dog, fish.
  - The document “cat dog” can be represented as (1, 1, 0).
  - The document “dog fish” can be represented as (0, 1, 1).
- The dot product of two vectors: $a \cdot b = a^T b = a_1 b_1 + a_2 b_2 + \ldots + a_n b_n$
  - $\text{sim}(d_1, d_2) = 1 \cdot 0 + 1 \cdot 1 + 0 \cdot 1 = 1$

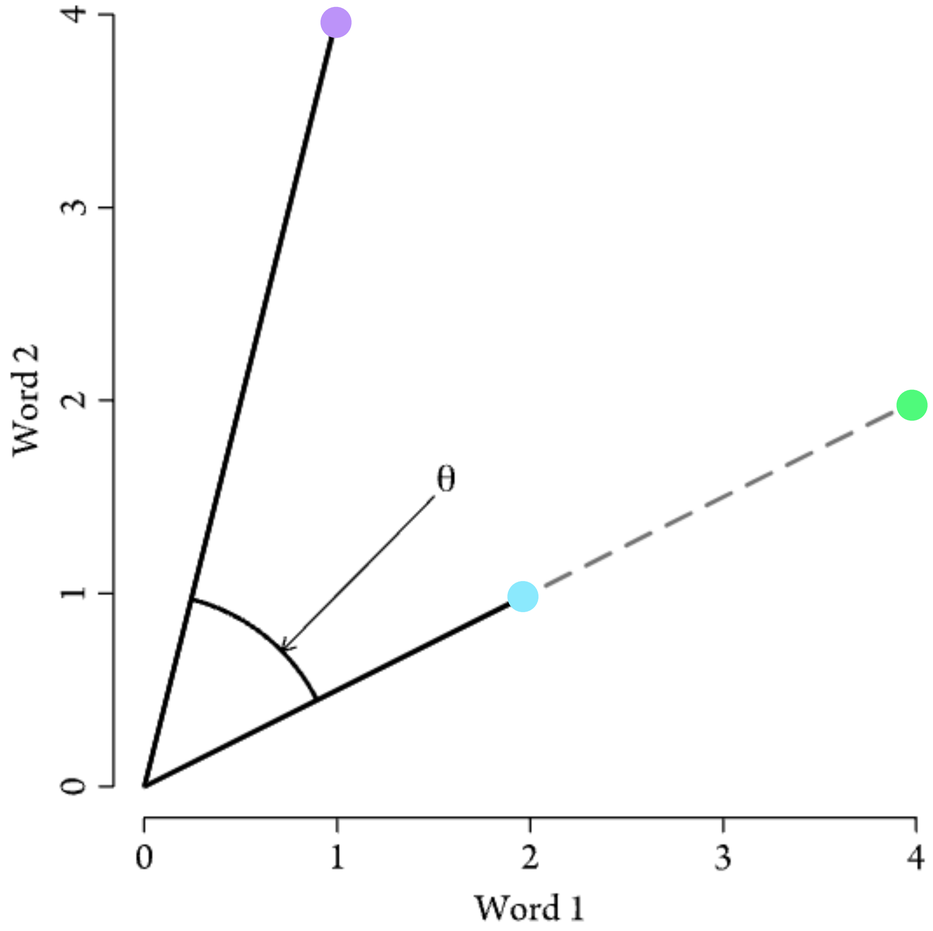
	“by”	“man”	“upon”	Vector	Word count
Hamilton	859	102	374	(859,102,374)	1335
Jay	82	0	1	(82,0,1)	83
Madison	474	17	7	(474,17,7)	498
???	15	2	0	(15,2,0)	17

APPLYING THE DOT PRODUCT

- $W_H \cdot W_? = (859,102,374) \cdot (15,2,0) = 859 \cdot 15 + 102 \cdot 2 + 374 \cdot 0 = 13089$
- $W_M \cdot W_? = (474,17,7) \cdot (15,2,0) = 7144$
- Normalizing vectors:
  - $\|W_H\| = \sqrt{W_H \cdot W_H} = \sqrt{859^2 + 102^2 + 374^2} = 942.42$
  - $\|W_M\| = 474.36$

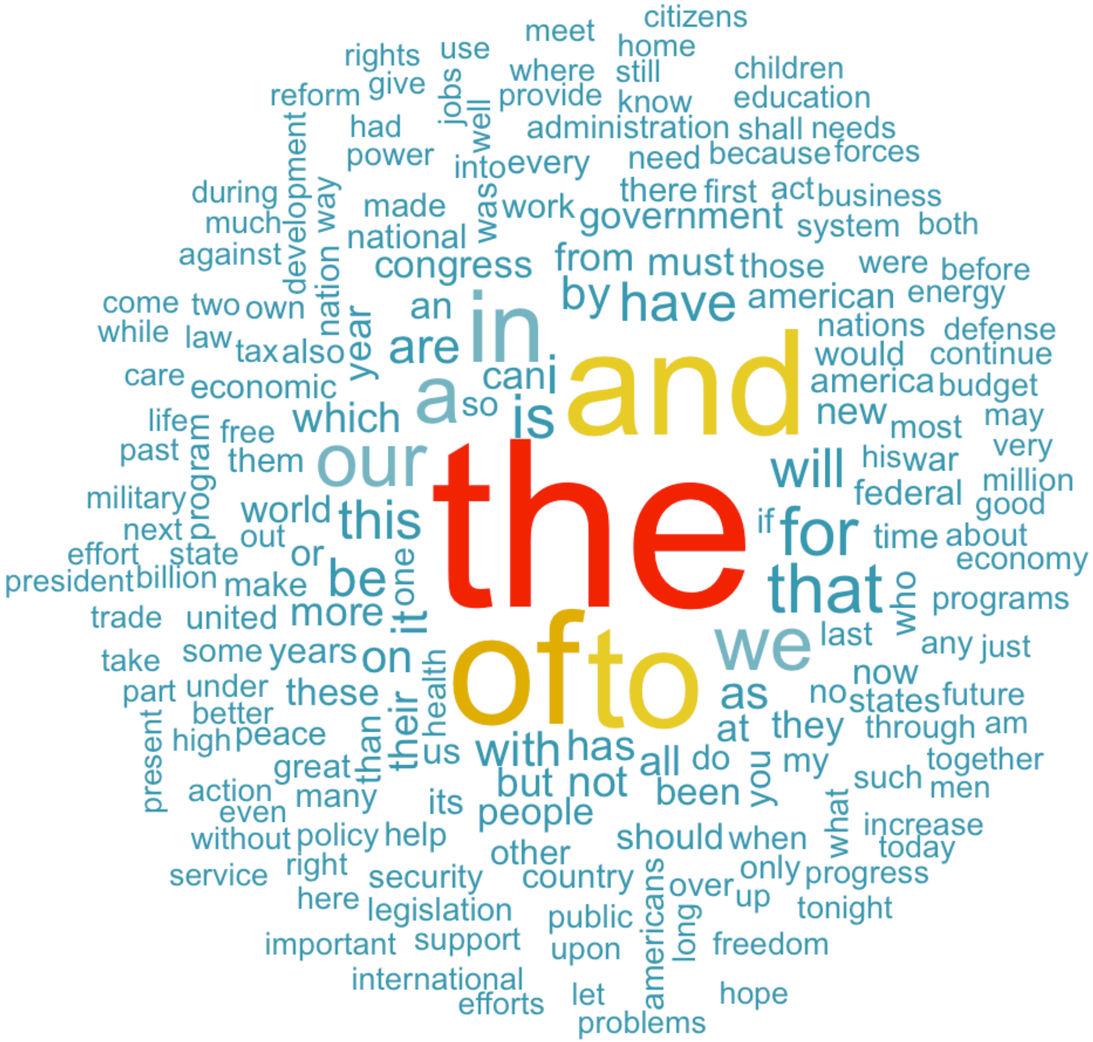
COSINE SIMILARITY

- cosine similarity$(a, b) = \cos\,\theta = \frac{a}{\|a\|} \cdot \frac{b}{\|b\|}$
  - $cs(W_H, W_?) = \frac{W_H \cdot W_?}{\|W_H\| \cdot \|W_?\|} =$
    - $\frac{(859{,}102{,}374) \cdot (15{,}2{,}0)}{\|(859{,}102{,}374)\|\|(15{,}2{,}0)\|} = 0.918$
  - $cs(W_M, W_?) = 0.995$



WORDS IN SPACE

Early State of the Union Addresses



Late State of the Union Addresses

WEIGHTING

- Tf-idf (term frequency inverse document frequency) weighting:

$$W_{ij}^{tf-idf} = \underbrace{\frac{W_{ij}}{W_i}}_{\text{tf}} \times \overbrace{\log\left(\frac{N}{n_j}\right)}^{\text{idf}}$$

  - The word “jobs” appears 612 times in the later SOTUs and 0 times in the early SOTUs. To determine tf-idf for “jobs” in the late period, we…
    - $W_{\text{jobs}}^{tf-idf} = \frac{612}{762087} \times \log\left(\frac{2}{1}\right) = 0.000803 \times 0.693 = 0.000557$

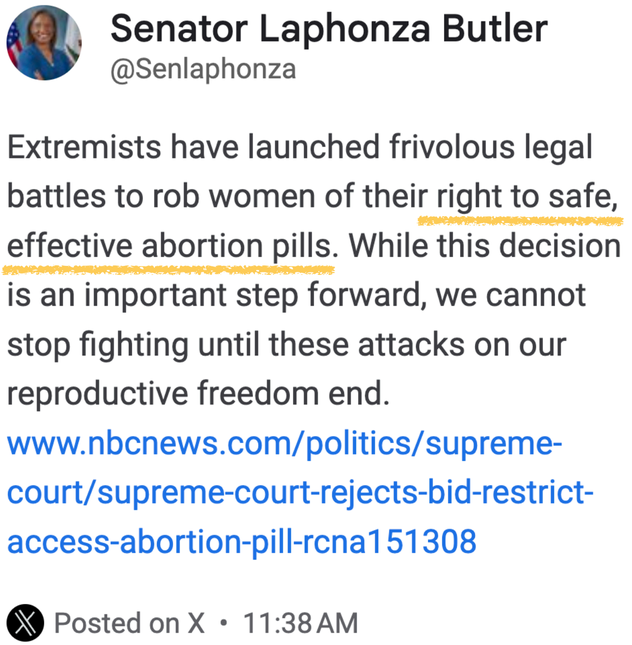
WORDS IN SPACE

Early State of the Union Addresses

Late State of the Union Addresses

WHERE NAIVE WORD SIMILARITY FAILS...

- “The president spoke tonight” and “Biden delivered the State of the Union Address” have low similarity.

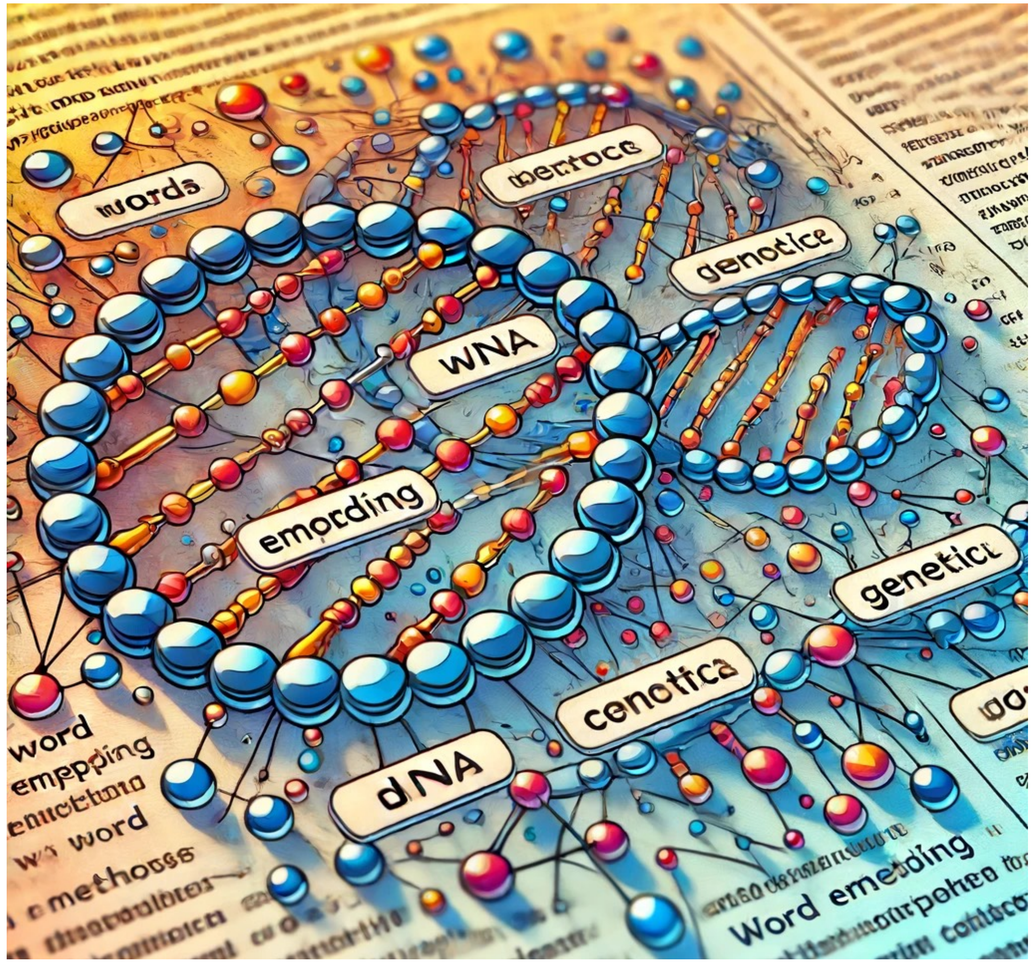


WORD EMEBDDINGS

- Up to this point, we have treated words as **sparse vectors**: cat = (1, 0, 0).
- Now, we will think of words as **dense vectors**:
  - cat = (0.9, 0.1), dog = (0.8, 0.2), fish = (0.1, 0.9).
    - $\text{cs(cat,dog)} = \frac{0.9 \times 0.8 + 0.1 \times 0.2}{\sqrt{0.9^2 + 0.1^2} \times \sqrt{0.8^2 + 0.2^2}} = 0.99$
    - $\text{cs(cat,fish)} = \frac{0.9 \times 0.1 + 0.1 \times 0.9}{\sqrt{0.9^2 + 0.1^2} \times \sqrt{0.1^2 + 0.9^2}} = 0.22$

KEY INSIGHT OF WORD EMBEDDING METHODS

- We use a large corpus (e.g., wikipedia) to learn which words are similar.
  - The distributional hypothesis: “you shall know a word by the company it keeps” (Firth 1957).
- We use those embeddings from our source corpus to learn about our target corpus (**transfer learning**).
- Huge advantage: totally unsupervised, just add text!



via DALL-E

ADVANTAGES OF WORD EMBEDDINGS

- Encoding similarity.

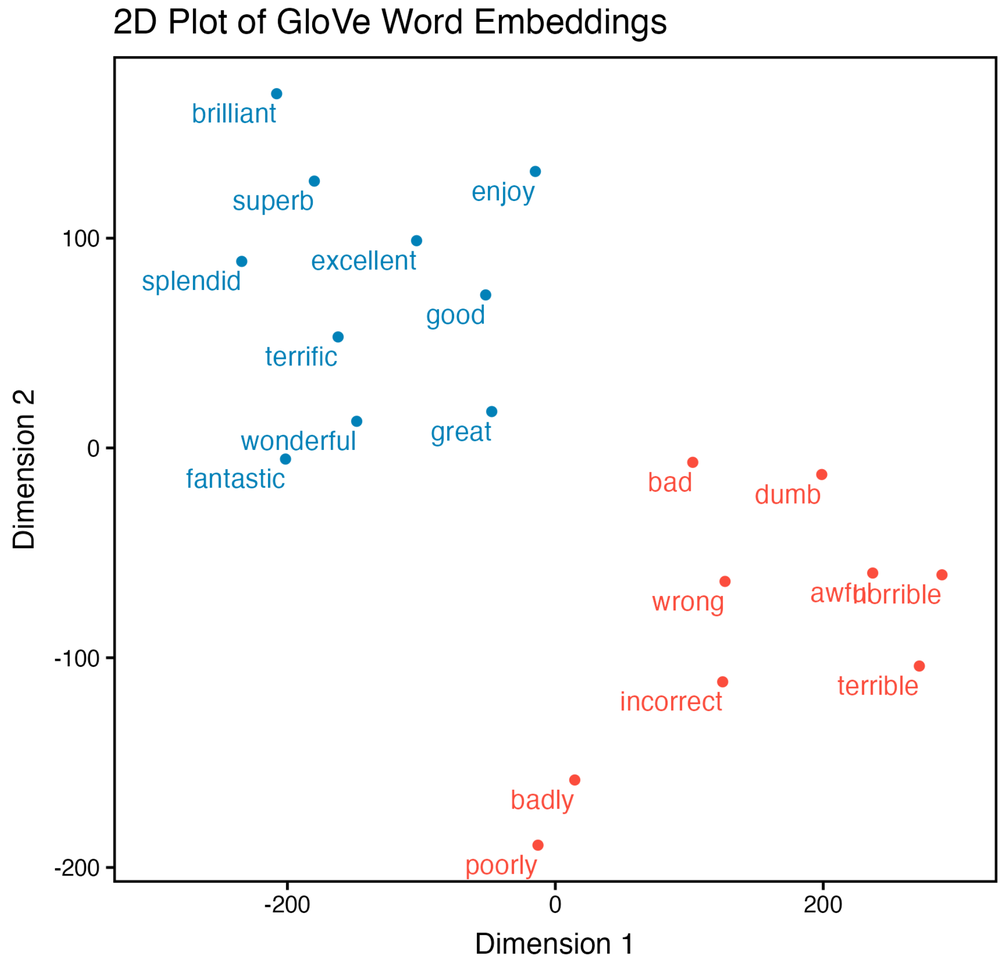
good = (-0.136, -0.116,...,0.246)

wonderful = (0.051,-0.349,...,0.095)

cos(good, wonderful) = 0.61

ADVANTAGES OF WORD EMBEDDINGS

- Encoding similarity.
- Automatic generalization.



ADVANTAGES OF WORD EMBEDDINGS

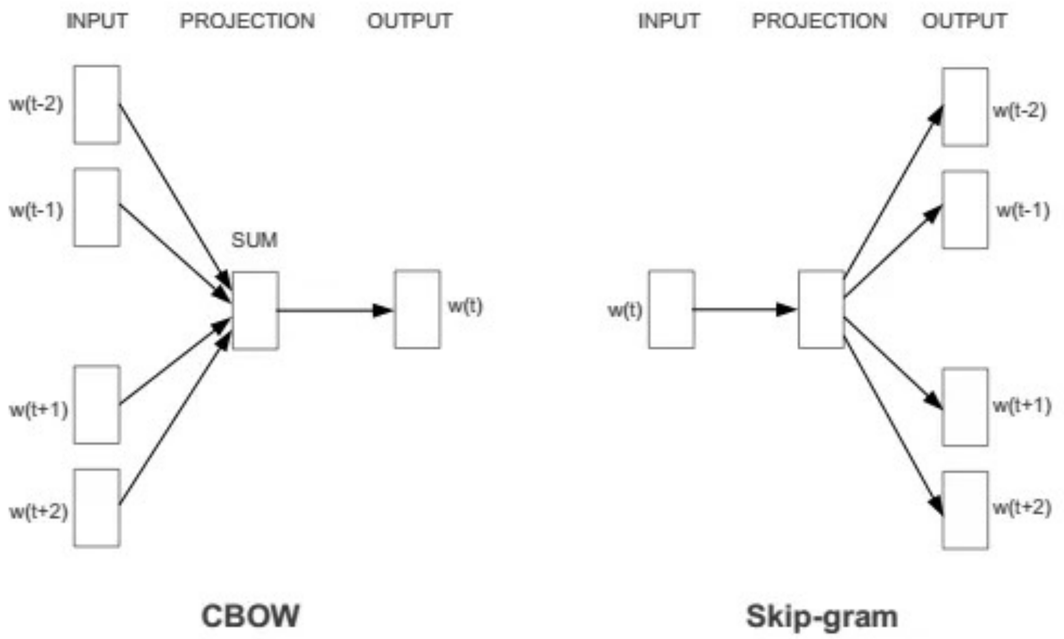
- Encoding similarity.
- Automatic generalization.
- Measuring meaning.

- Rep. Mike Thompson (D-CA): ”Make no mistake, **women's access to reproductive care** remains at risk.”
- Rep. Mark Green (R-TN): "We must continue to fight against **mail-order abortion pills** and fight for **the lives of the unborn**."

via Jamie Dupree

SELF SUPERVISION

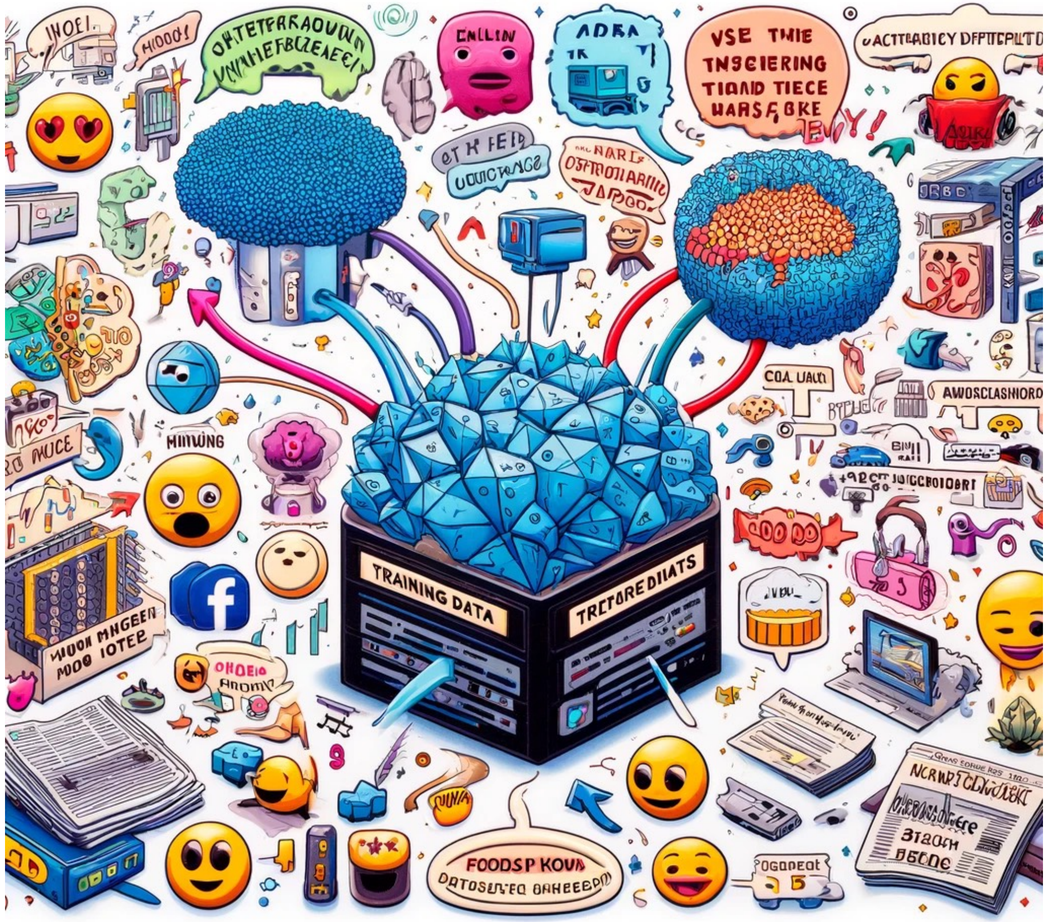
- Self-supervision: labels are provided by the data.
  - An example: “Oranges are the color _____.”
  - Orange: 60%, red: 30%, president: 0.00000000000001%.



via becominghuman.ai

WHAT YOU NEED TO DECIDE AS THE RESEARCHER

- The training data.



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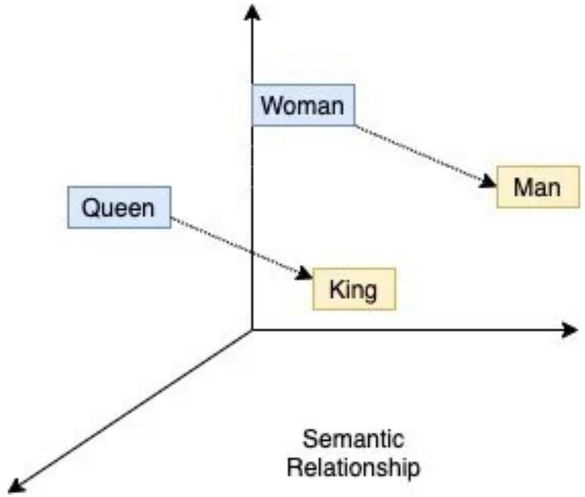
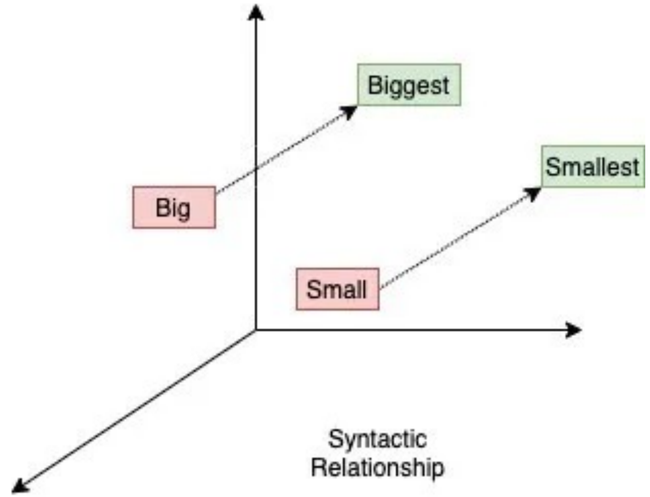
WHAT YOU NEED TO DECIDE AS THE RESEARCHER

- The training data.
- The context window.

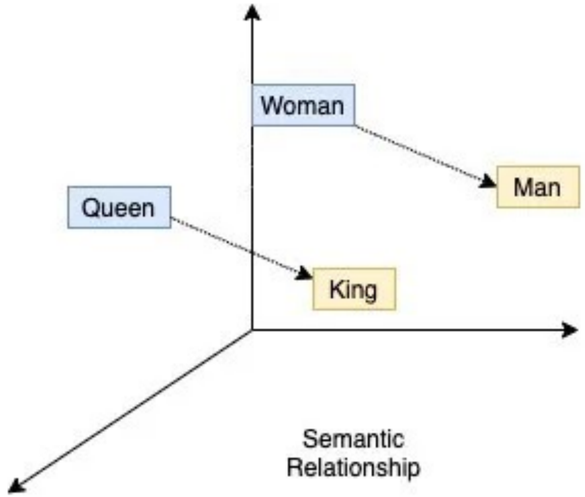


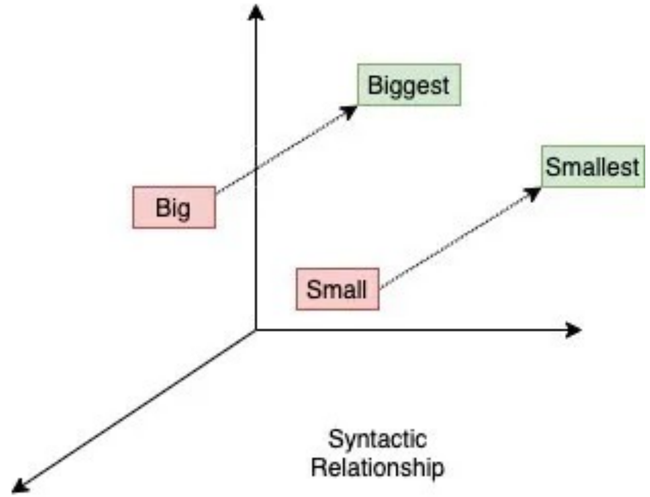


via becominghuman.ai

WHAT YOU NEED TO DECIDE AS THE RESEARCHER

- The training data.
- The context window.
- The embedding dimensions.





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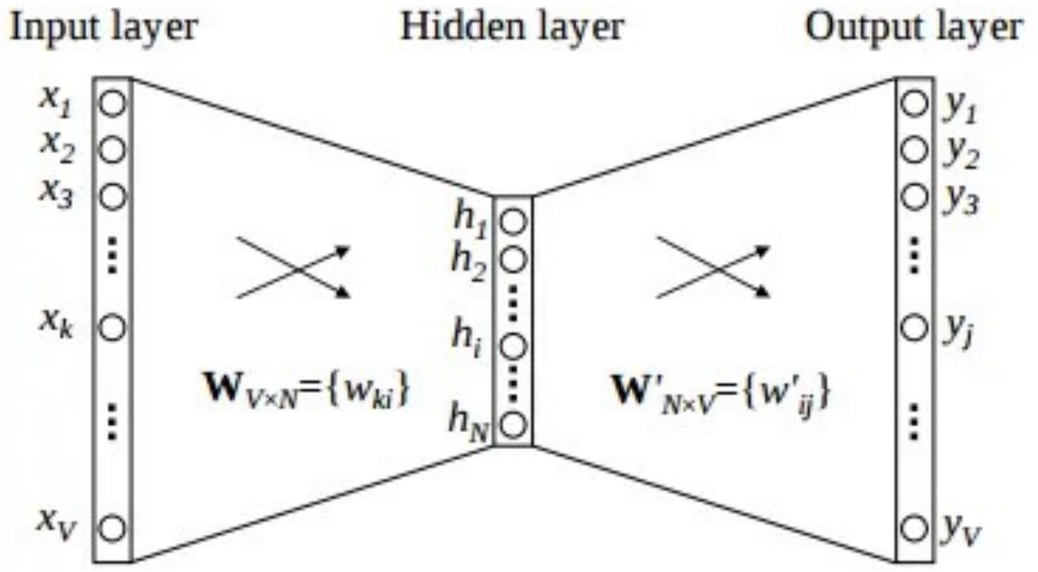
WHAT YOU NEED TO DECIDE AS THE RESEARCHER

- The training data.
- The context window.
- The embedding dimensions.
- The algorithm.



word2vec model architecture

via becominghuman.ai

THE WORD2VEC CBOW MODEL

- CBOW: continuous bag of words.
  - Consider the sentence: “the quick brown fox ___ over the lazy dog.”

$$\text{argmax}_{\mu_{jumps}} = \frac{\exp(\mu_{jumps} \cdot \bar{v})}{\Sigma_j \exp(\mu_j \cdot \bar{v})}$$

  - Where $\bar{v}$ is the average embedding vector of all context words.

THE GLOVE MODEL

- Tries to account for word co-occurrence across the corpus.
- Minimize $J = \sum_{i,j=1}^{V} f(X_{ij})\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$
  - Where $w_i^T \tilde{w}_j$ is the dot product of the target word and a context word.
  - Where $b_i + \tilde{b}_j$ are bias terms that help with model fitting.
  - And $\log X_{ij}$ is the log of the co-occurrence counts for the context and target.

WORDS AS THE OBJECT OF STUDY

- Research question: do Republicans and Democrats mean something different when they say “immigration.”
  - Hypothesis: Republicans use words about enforcement and crime; Democrats use words about reform and humanitarianism.

TABLE 4. Top 10 Nearest Neighbors for the Target Term “Immigration”

Democrats	enact, overhauling, reform, legislation, enacting, overhaul, reforming, revamp, entitlement, bipartisan
Republicans	enforce, laws, enact, enacting, legislate, legislations, enforcing, regularize, immigration, legislation

TABLE 5. Subset of Top Nearest Contexts For The Target Term “Immigration”

Democrats

this congress to take on comprehensive `immigration` reform and fix our broken immigration

should get to work on comprehensive `immigration` reform the immigration system we have

Republicans

administration wants to ignore our nation’s `immigration` laws and immigration process the problem

broken is the enforcement of our `immigration` laws and we have seen that

Rodriguez, Spirling and Stewart (2023)

FROM WORDS TO DOCUMENTS

- Word embedding models output a matrix where each row is a word and the columns account for (unknown) attributes.
- One way to embed documents: average all of the word vectors.
- Determine document similarity through cosine similarity of document averages.

Fig. 4 Nearest neighbors of the LIWC positive emotions dictionary

Garten et al. (2018)

EVEN MORE CONTEXT

- word2vec and GloVe are not context aware.
  - e.g., only one embedding for “bat,” but are we talking about baseball or flying mammals?
- Models like BERT and GPT account for this context, but complicated and costly.

via DALL-E