

Acknowledgement of country

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- @safetydave
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Background on embeddings

Embeddings

aka semantic space, latent space, vector, etc

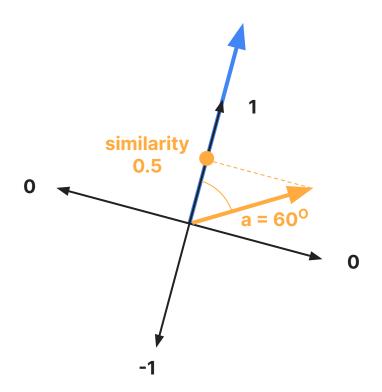
A list (vector) of numbers [0.5, 0.77, 0.03, ...]

Similar things are "close" together



dimension 0

Measuring similarity with cosine





Cosine similarity puns are sticky

Making embeddings

Input data	Train ML model	→ Use model
Any modality	Learn similarities in the data, with some measure of loss	Convert new inputs to embeddings, and back again
Text documents	Predict words based on surrounding words Word2Vec (CBOW/skip-gram)	"Cat" → [0.5, 0.77,] [0.5, 0.8,] → "Cat", "Dog

Embeddings in Thoughtworks ANZ projects

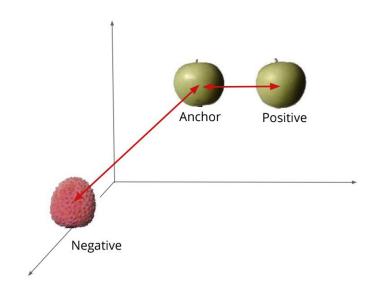
This time with images & contrastive learning/triplet loss

Prompt

Al found similar styles...







"RoomNet" spike

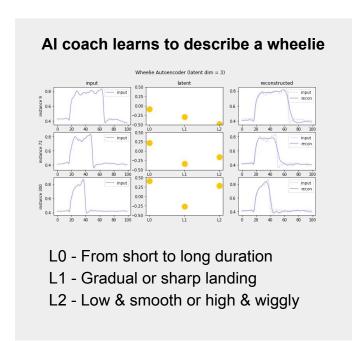
"ProduceNet" representation learning

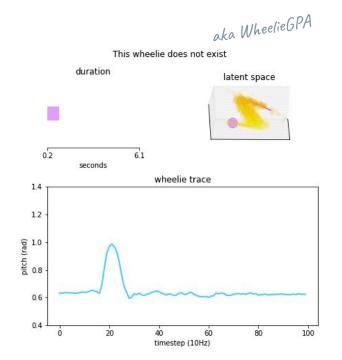
Embeddings in personal projects

This time with time series accelerometer data & autoencoders



The Lockdown Wheelie Project

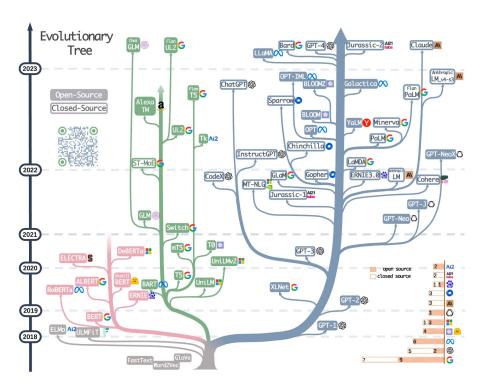




Making embeddings

Input data	Train ML model	→ Use model
Text documents	Predict words based on surrounding words	"Cat" → [0.5, 0.77,]
	Word2Vec (CBOW/skip-gram)	[0.5, 0.8,] → "Cat", "Dog", .
Collection of images with manual or	Ensure similar inputs are closer than dissimilar	△ → [0.5, 0.77,]
self-generated labels	Contrastive Learning (Triplet Loss)	[0.5, 0.8,] → 📤, 👛
Time series data	Output reproduces input via bottleneck	→ [0.5, 0.77,]
	Autoencoder (weighted loss)	[0.5, 0.8,] → ,

Embeddings in LLMs

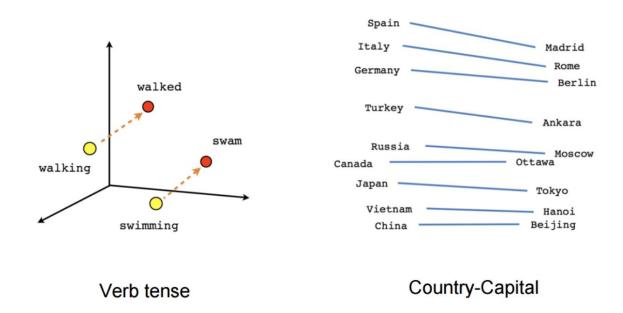


https://github.com/Mooler0410/LLMsPracticalGuide

```
curl https://api.openai.com/v1/embeddings \
  -H "Content-Type: application/json" \
  -H "Authorization: Bearer $OPENAI_API_KEY" \
  -d '{
    "input": "Your text string goes here",
    "model": "text-embedding-ada-002"
    }'
```

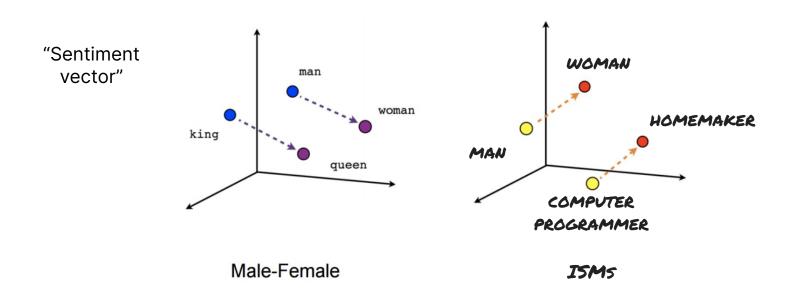
Semantic algebra with embeddings

Kinda handy, like we might do with spatial vectors



But may come with bias and harmful results

Motivating careful curation of training data or de-biasing treatment



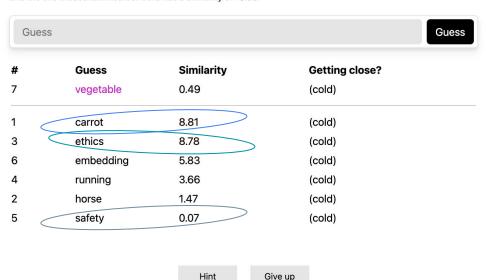
Someone made a game of hide and seek from embeddings...

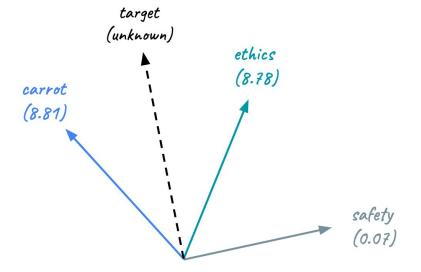
Semantle - a game of semantic hide and seek

Semantle

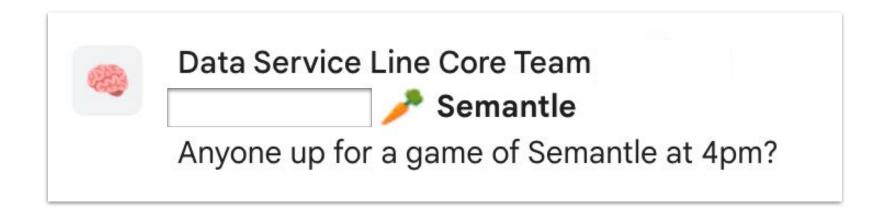


Today is puzzle number **494**.The nearest word has a similarity of **83.89**, the tenth-nearest has a similarity of 45.49 and the one thousandth nearest word has a similarity of 19.85.





Any given Friday



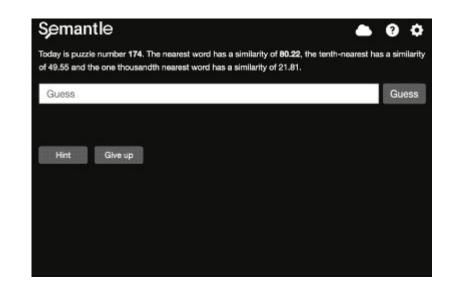
... and you'll never guess what I did next

(In the world before ChatGPT)

Automated and augmented semantle solvers

Personal project aims

- Fu Play around and find out
- Get a better feeling for how embeddings capture semantics
- Find solutions automatically with different approaches - but also...
- Explore how people and machines work together on problems

















https://safetydave.net/sketching-semantle-solvers/ https://safetvdave.net/second-semantle-solver/ https://safetvdave.net/synthesising-semantle-solvers/ https://safetydave.net/smarter-semantle-solvers/

Let's play live!

Oh I'm asking for trouble

This browser (screen shared)

- ✓ Setup:
 - Go to https://semantle.com
 - Select play with friends
 - Get game code and share

- Watch the demo:
 - Make your own guesses if you like

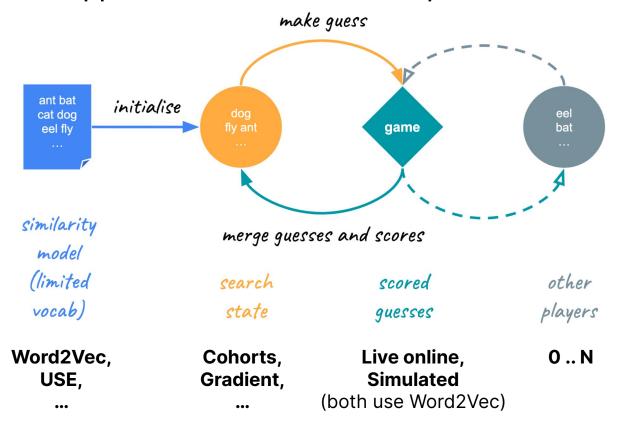
Solver browser (playing same game)

- Setup:
 - Run notebook, which loads https://semantle.com
 with webdriver
 - Manually select play with friends
 - Manually enter game code

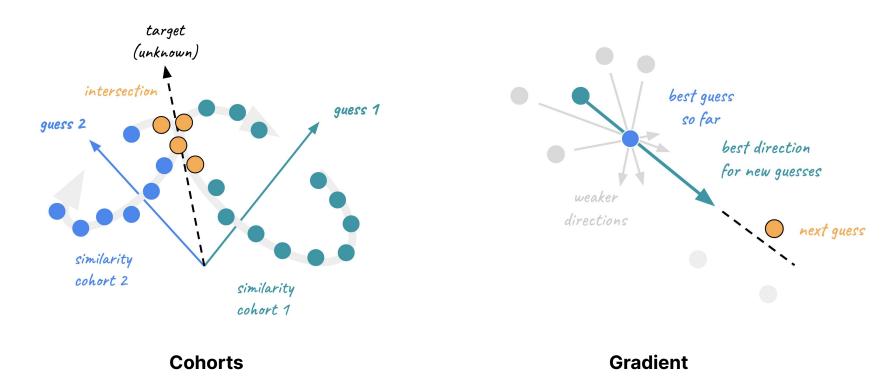
Start the demo:

 Run the solver method which will make guesses based on the game state

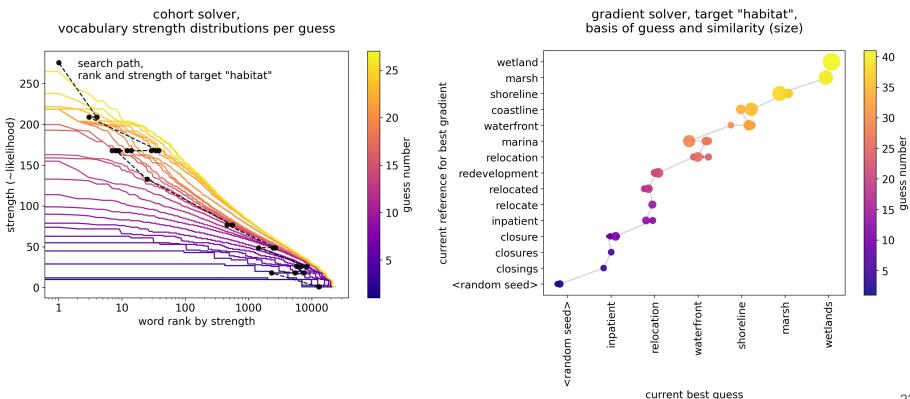
Simplified RL approach with modular components



Two semantic search strategies - conceptual



Two semantic search strategies - visualised



What about ChatGPT?

Obviously, we must ask ChatGPT to play

Just prompting for now

You are playing a game called semantle, where you must discover a hidden word by making guesses. For each guess you will get a score out of 100 that measures how close the guess is to the hidden word, based on word2ec cosine similarity. What is your first guess?

Intro game

My first guess in the game Semantle would depend on the context and any hints or clues provided. Without any specific information, I will make a random guess. Let's go with the word "sunshine."

No context,

The score for "sunshine" is 6.74

random guess

Based on the score of 6.74 for the word "sunshine," it seems that the hidden word is not closely related to "sunshine." To make a more informed guess, I would need additional information or context about the hidden word. Could you provide any hints or clues to narrow down the possibilities?

Moar hints pls!

Ok. I will make guesses too, and give you the result in the format "guess: score". After each of my guesses, you should make another guess

I'll play too

Sure, I'm ready to continue the game. Please provide your first guess, and I'll give you the result in the format "guess: score." After that, I'll make my next guess based on the information provided. Let's proceed!

civilization: 20.01

Helpful clue

§ Yo

Your guess: civilization

Score: 20.01

Based on the given score, it appears that the hidden word is somewhat related to "civilization." Here's my guess:

My guess: history

Semantically

similar guess

ChatGPT finds semantle hard too

Anyone who's played can relate to this



Thank you for the score. Based on the low score for "Duration," it seems that it is not close to the hidden word.

Gets stuck in local maxima

Since this is a word-guessing game and the scores provided have not indicated a close match yet, it is challenging to make an accurate guess without additional information or context.

Vents about Semantle (don't anthropomorphise though)

Could you please provide any hints or clues related to the hidden word? It would greatly help in making a more informed guess.

What can we learn from playing semantic hide and seek?

Team heuristics /



Things we learned

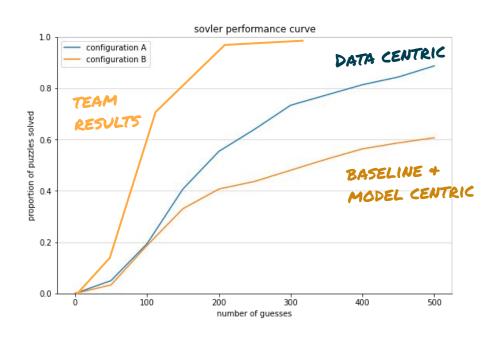
- Play on a Friday afternoon with the Data & Al team 🍹
- Start with "carrot" (no empirical basis for effectiveness)
- It's usually not a complicated word
- Helpful search strategies:
 - Diverse styles 🤿
 - Antonyms may be similar, not just synonyms
 - Try different verb conjugations, etc 🔀
 - Extrapolate a sentiment vector from ~1,000 word to ~100 word (typically this is only rationalised post-hoc)
 - Hints are OK after 300 guesses □

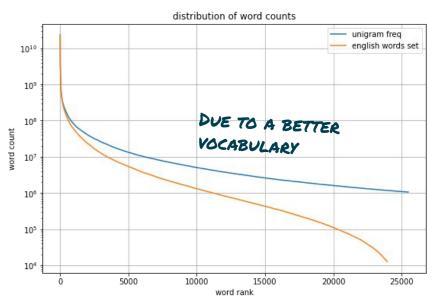
Robustness to varying semantics

	People semantics	Word2Vec similarity (same as Semantle)	USE similarity
People search	Somewhat inscrutable		
	Somewhere from 13 to 307 guesses		
Cohort search		Arbitrarily good performance (cheat)	Significantly degraded performance
Gradient search		Almost as good as human performance	Minimal performance degradation

Data-centric improvement efforts

Beat model-centric





Human and machine learn from each other

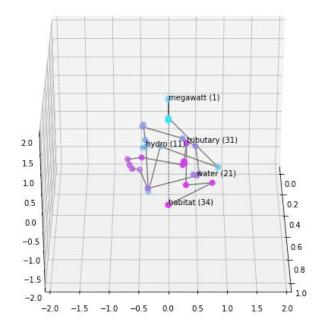
When playing together

One can unstick the other

The high-dimensional semantic search space is highly non-linear (it's hard to find the secret word unless you're already close, and you can get stuck on local maxima)

This is also true in designing products and services with many degrees of freedom - think software!

Social machines aid knowledge management

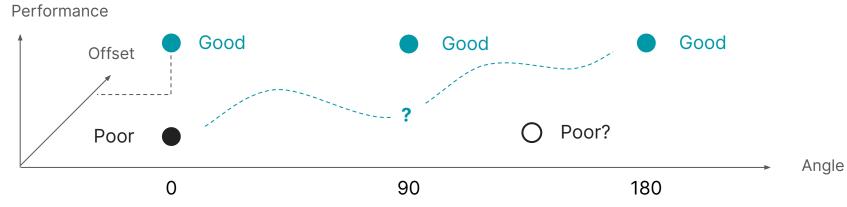


For unsmooth design spaces





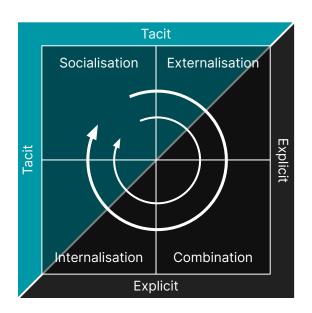




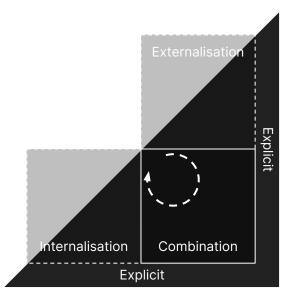
Social machines aid knowledge management

Nonaka-Takeuchi or SECI model

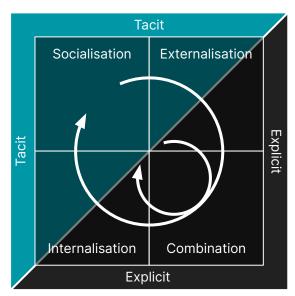
Human-driven



Naive exclusive automation



Social machines augment



Thanks!

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