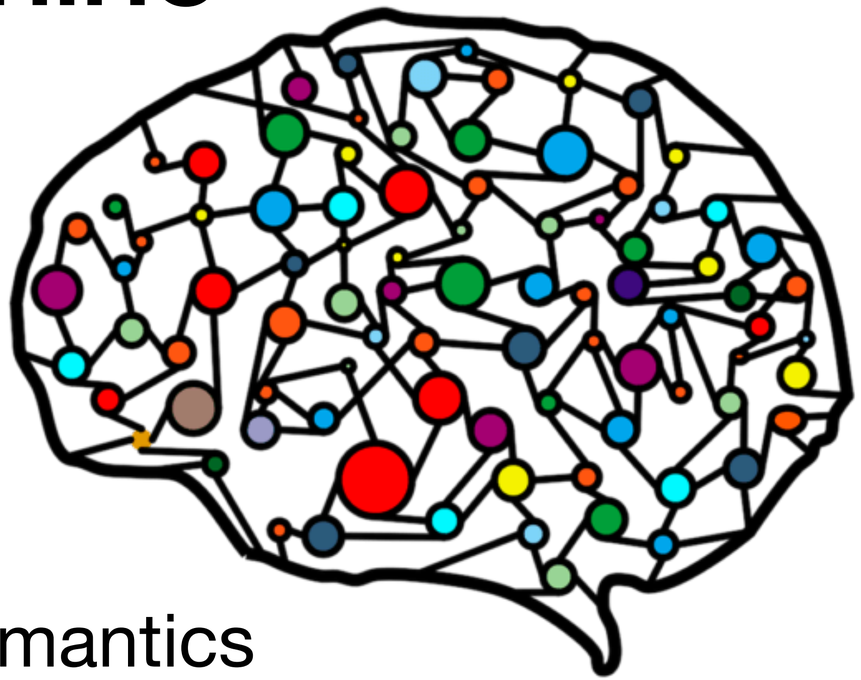
General Principles of Human and Machine Learning



Lecture 11: Language and Semantics

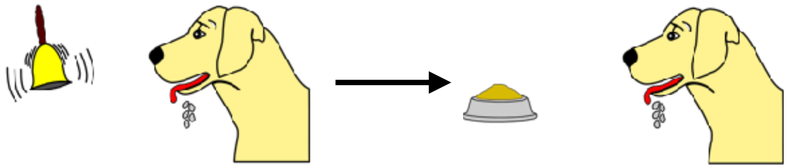
Dr. Charley Wu

https://hmc-lab.com/GPHML.html

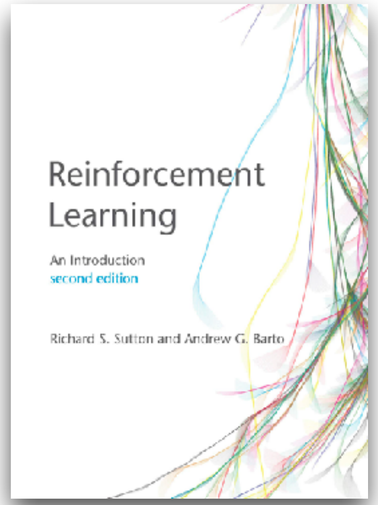
The story so far…

Learning to behave

Pavlovian (classical) conditioning

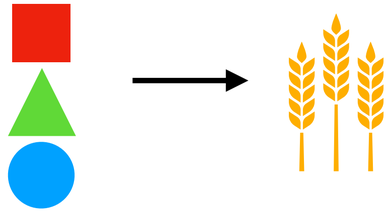


Learn which environmental cues *predict* reward

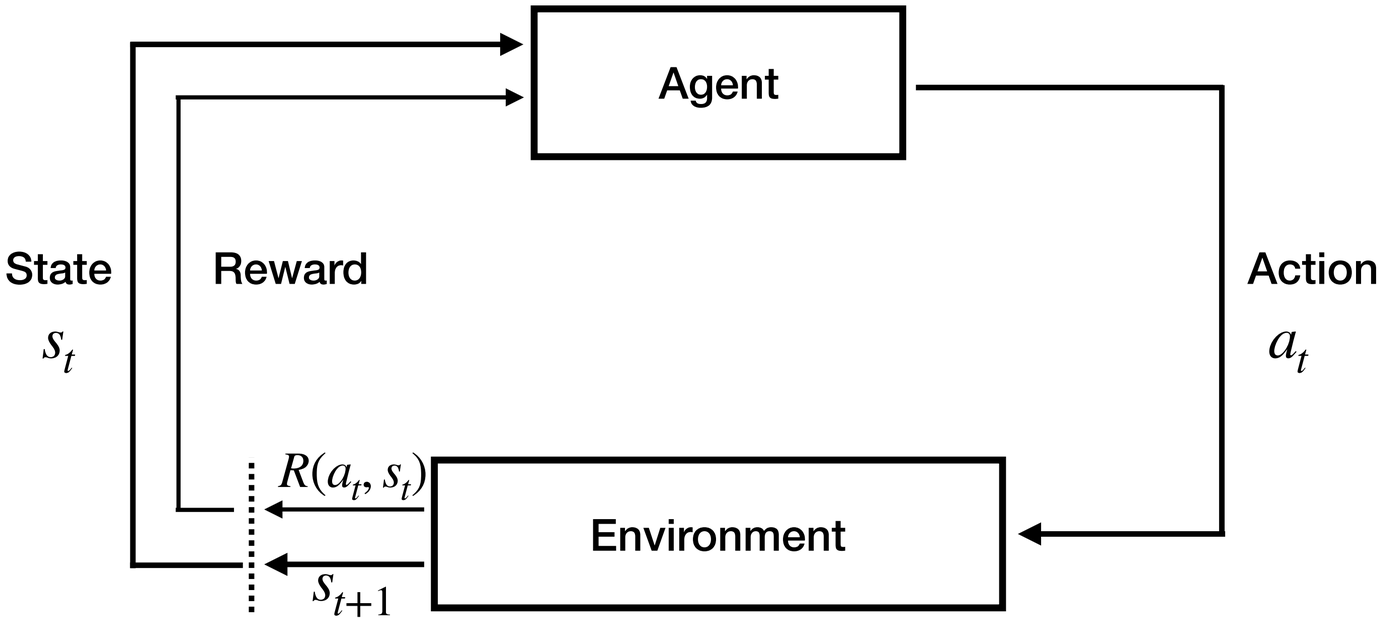


Reinforcement Learning

Operant (instrumental) conditioning

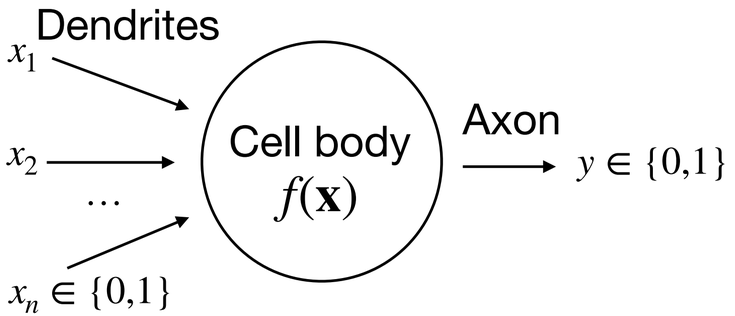


Learn which actions *predict* reward



Symbolic vs. Subsymbolic AI

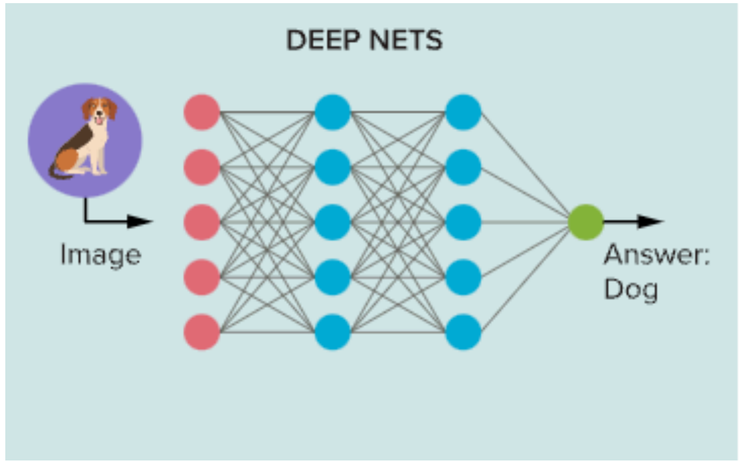
Subsymbolic AI



McCulloch & Pitts (1943)

Symbolic vs. Subsymbolic AI

Subsymbolic AI



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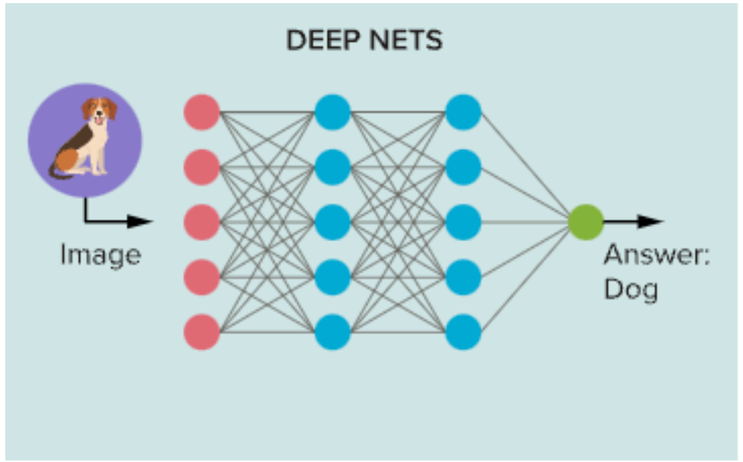
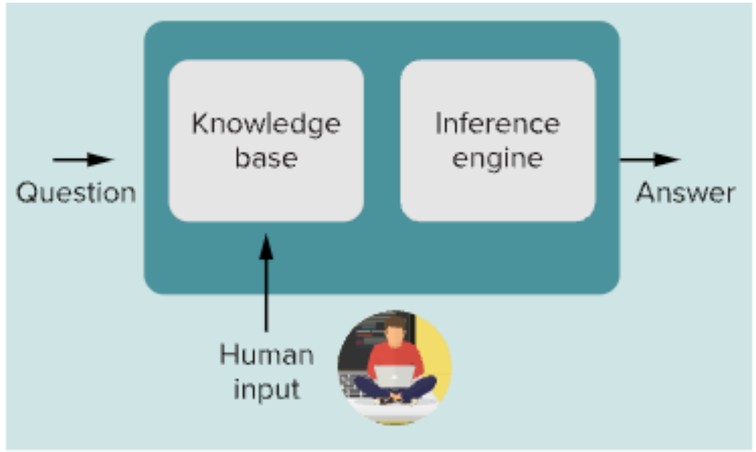


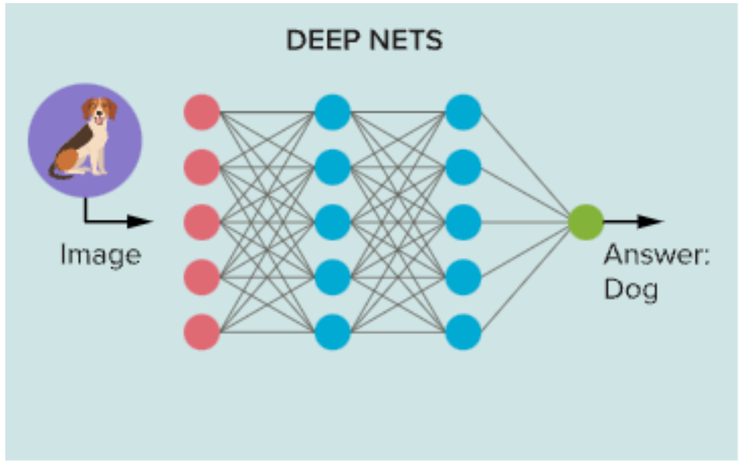
*Gradient descent is analogous to the delta-rule

Symbolic vs. Subsymbolic AI

Symbolic AI



Subsymbolic AI



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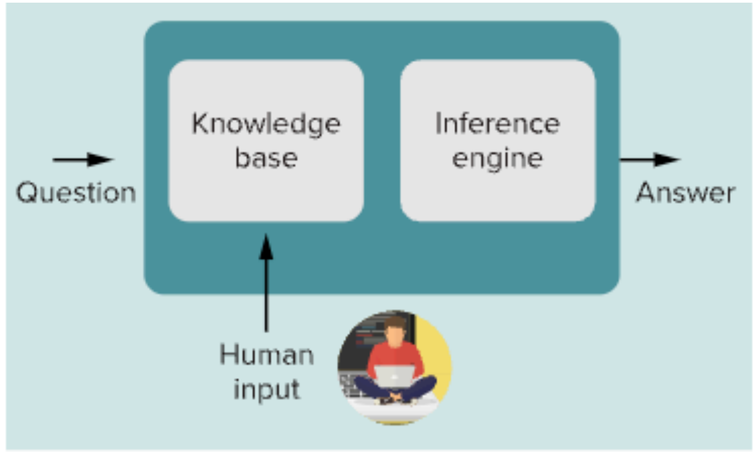
Symbolic vs. Subsymbolic AI

Physical symbol system hypothesis: manipulating **symbols** and **relations**

Symbolic AI



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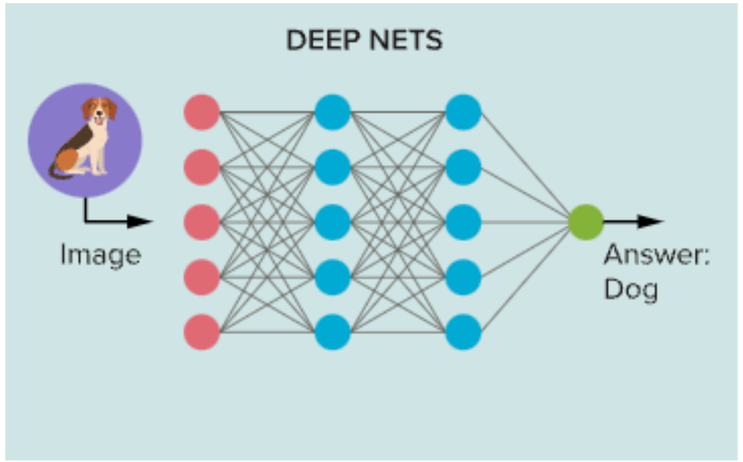

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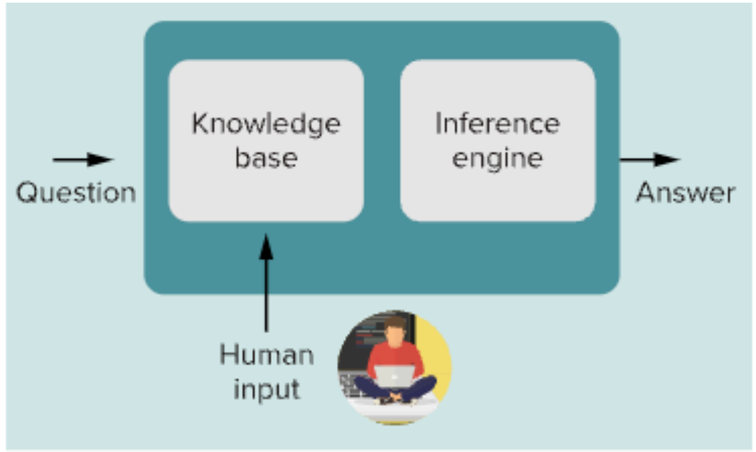

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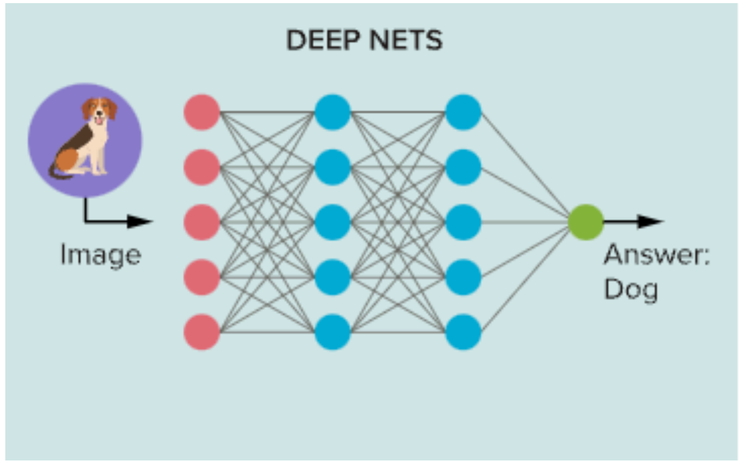

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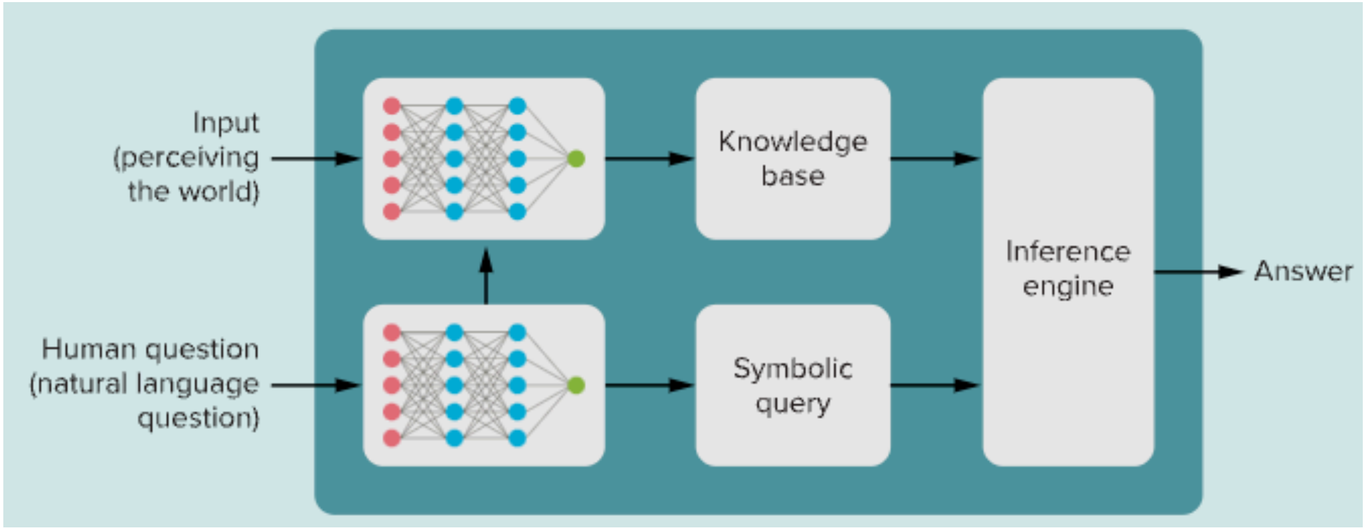
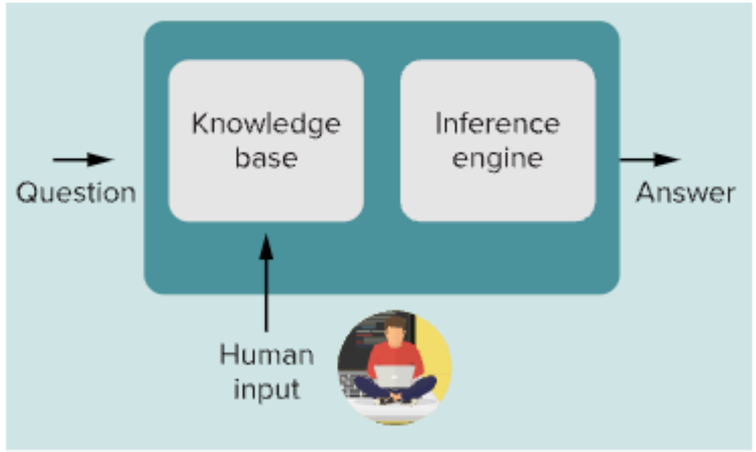
Hybrid systems



Symbolic vs. Subsymbolic AI

Physical symbol system hypothesis: manipulating **symbols** and **relations**

Symbolic AI



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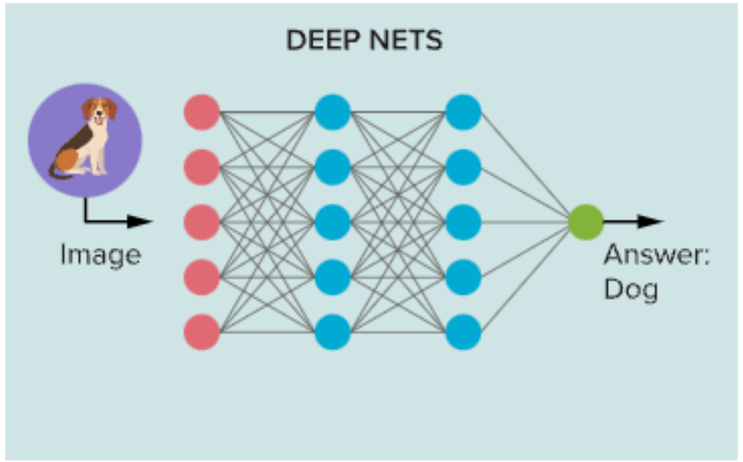

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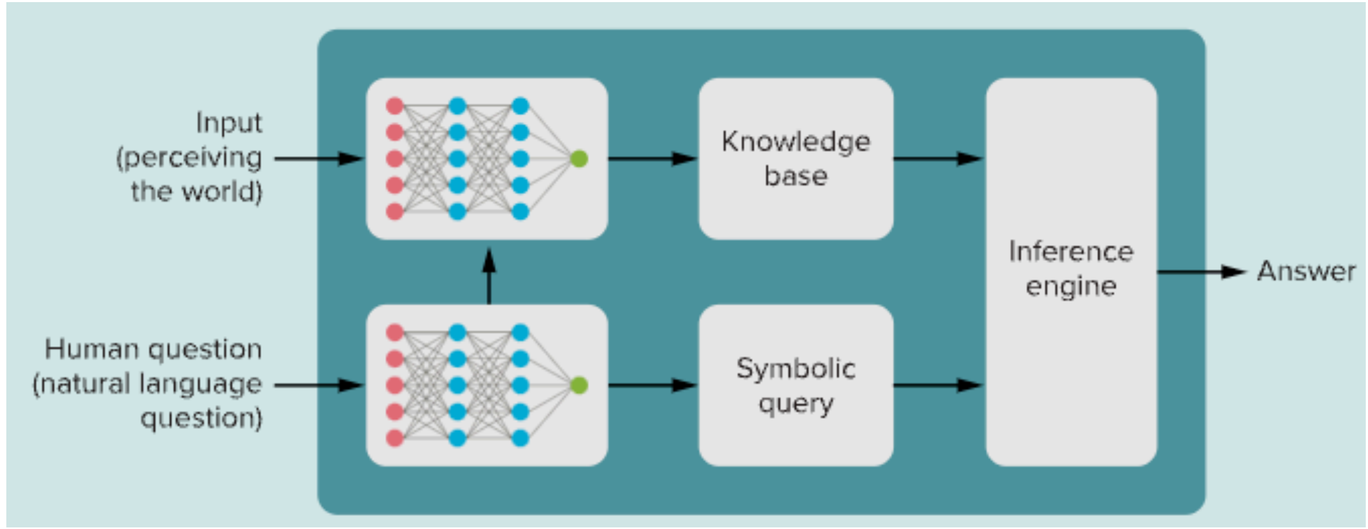
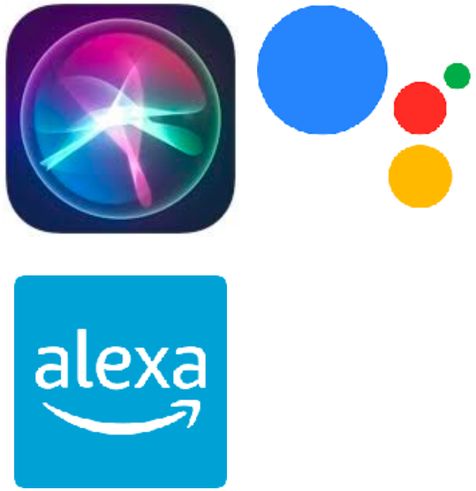
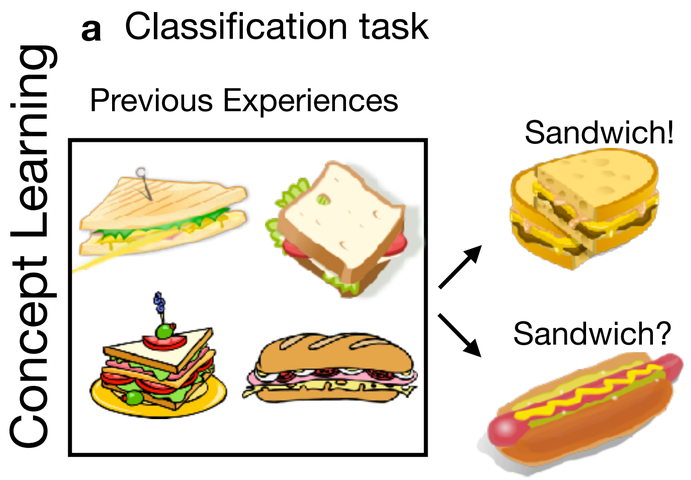
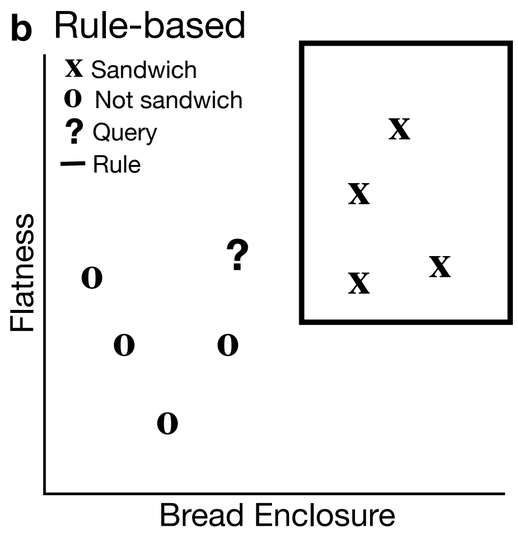


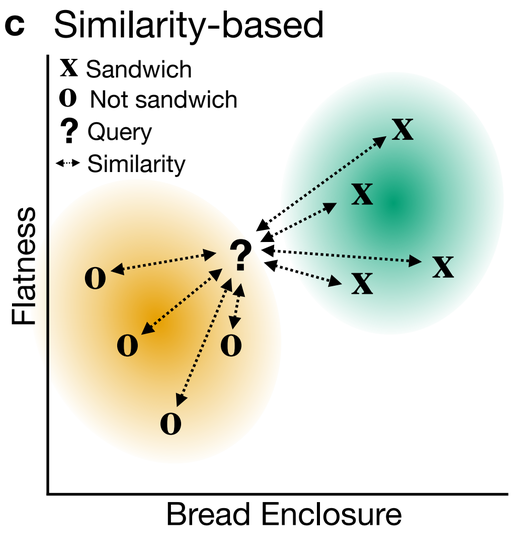


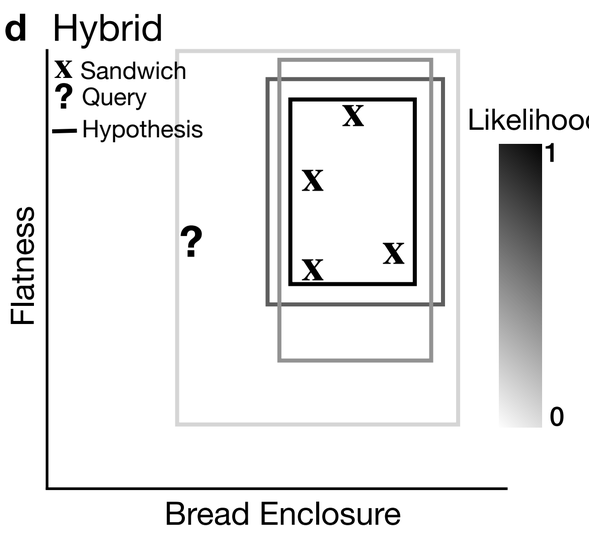
Learning concepts and functions

Concept Learning

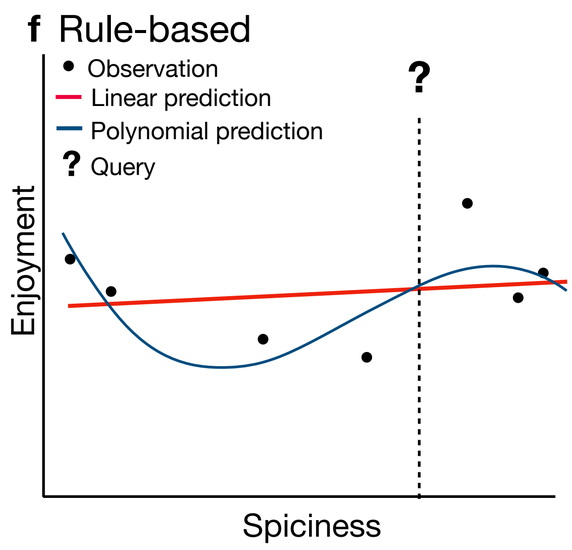


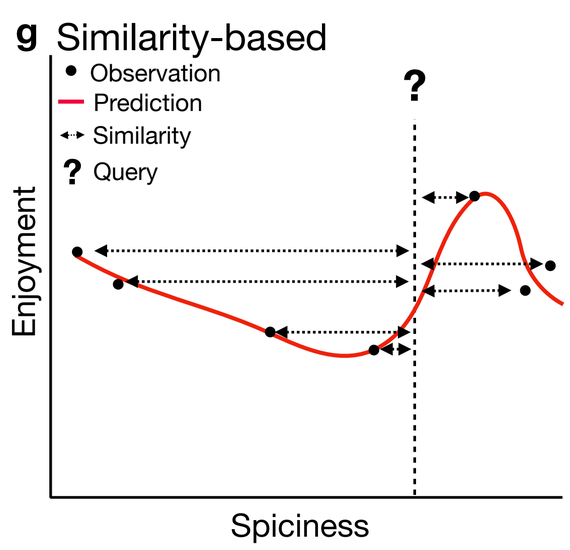


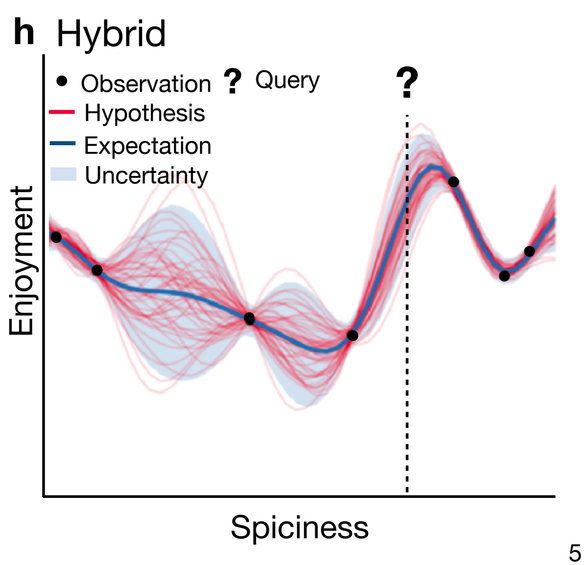




Function Learning







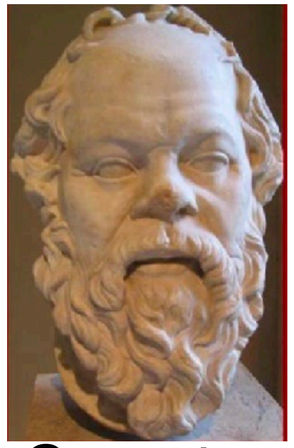
What is still missing?

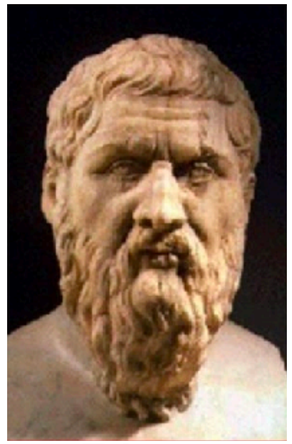
What is still missing?

Today's agenda

- Plato's problem and the Poverty of the Stimulus argument (Chomsky, 1986)
- Latent Semantic Analysis (Landauer & Dumais , 1997)
- Word2vec (Mikolov et al,. 2013)
- RNN and LSTM language models
- LLMs

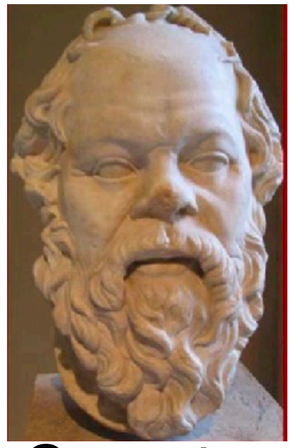
Meno’s Paradox


Socrates


Plato

And how will you enquire, Socrates, into that which you do not know? What will you put forth as the subject of enquiry? And if you find what you want, how will you ever know that this is the thing which you did not know? **“Meno” - Plato**

Meno’s Paradox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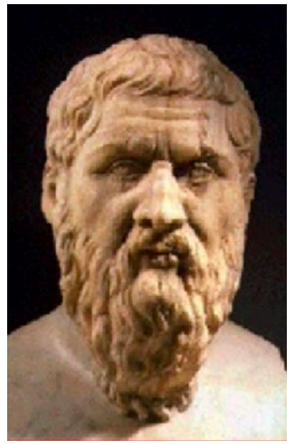
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How can we learn what we don’t already know? How can we acquire new concepts?

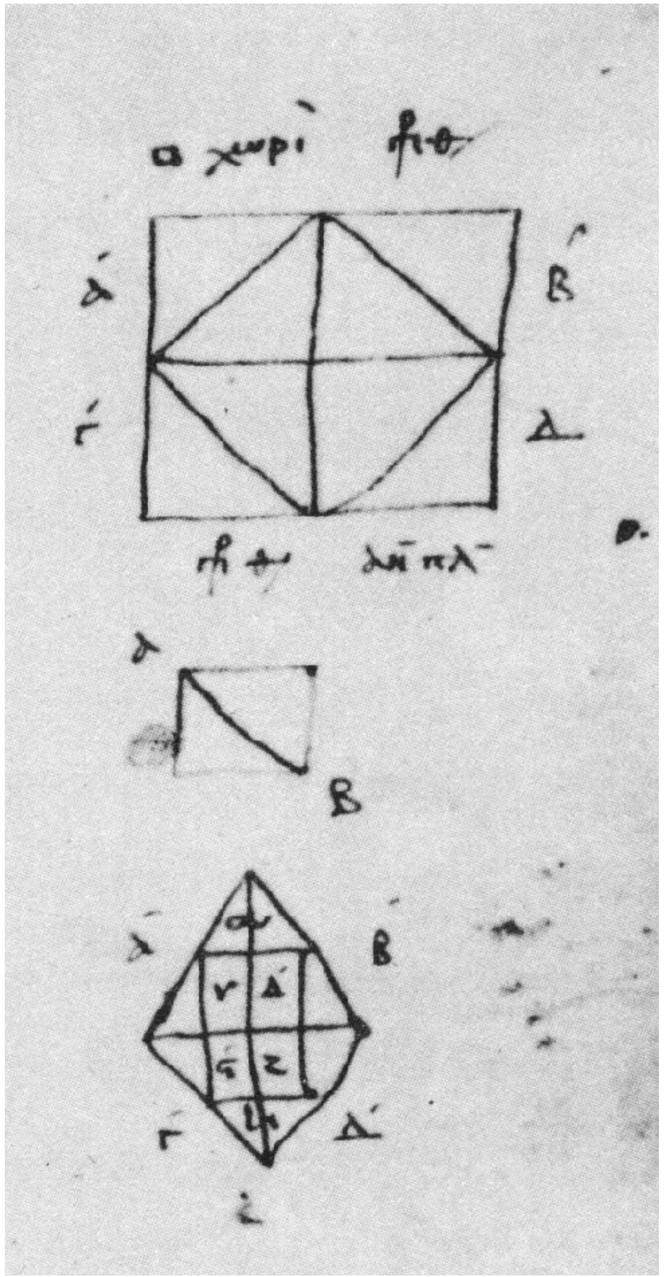
Is (some) knowledge innate?

Plato's theory of *anamnesis*

- knowledge is in the soul from eternity
- the soul is immortal and repeatedly incarnated
- each time knowledge is forgotten in the trauma of birth
- what one perceives to be learning, then, is the recovery of what one has forgotten

Demonstrated by having a slave boy intuitively solving geometry problems he was not instructed in

- (just goes to show what kinds of theories you need to develop to explain learning without an account of generalization!)



Chomsky: Universal Grammar (UG)

- **Plato's problem** (Chomsky, 1986): "How comes it that human beings, whose contacts with the world are brief and personal and limited, are nevertheless able to know as much as they do know?"
  - Language acquisition in children suggests they "attain infinitely more than they experience"
- **Poverty of the stimulus**: it seems like there is a disparity between the amount of input (experience) and the output (acquired language)
  - Thus, there is a missing factor and that factor is Universal Grammar (UG): "*the system of categories, mechanisms, and constraints that shared by all human languages and considered to be innate*"
- Output (language ability) > input (experience)
- Therefore: language = input + UG

Criticisms of Universal Grammar

- Universality of grammatical structure across languages is overstated
  - Pirahã language lacks recursion, embedded clauses, quantifiers, and color terms (Everett, 2005), which are commonly taken to be universals
- *Similarity-based generalization* explains how children generalize beyond observed evidence
  - Learning probabilistic patterns rather than hard and fast rules (Distributional hypothesis; McDonald & Ramscar, 2001)
- Even without negative examples (explicit instruction of what is ungrammatical), *prediction-error learning* based on failure of expectations serves as a form of implicit feedback (Ramscar & Yarlett, 2007)
- Evolutionary argument
  - Convergence across languages is not due to some innate universal structure in our brains, but due to general processes/constraints of human cognition (Tomasello, 2008)

Landauer & Dumais (1997)

Solving Plato's Problem with Latent Semantic Analysis (LSA)

- **Latent semantic analysis (LSA)**
  - Describe the *similarity* between words based on the similarity of contexts in which they occur
- One of the first computational approaches to solving Plato's problem
  - Focusing on semantic learning (i.e., the meaning of words) rather than grammar learning (the relational structure or syntax between words)
  - Specifically modeling "induction" (reasoning beyond the available evidence) in semantics

A Text sample (context)

Word/	1	.	.	.	.	.	.	.	.	.	.	.	.	.	30,000
1	x	x	x	x	x	x	.	.	.	x	x	x	x	x	x
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x	x
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x	x
60,000	x	x	x	x	x	x	.	.	.	x	x	x	x	x	x

B Factor (dimension)

Word/	1	.	.	.	300
1	y	.	.	.	y
.	y	.	.	.	y
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	y	.	.	.	y
60,000	y	.	.	.	y

C Factor (dimension)

Sample/	1	.	.	.	300
1	z	.	.	.	z
.	.	.	.	.	z
.	z	.	.	.	z
.	z	.	.	.	z
30,000	z	.	.	.	z

LSA algorithm

- Simple idea: *Represent the meaning of words based on the company they keep*
- **Input**: a matrix (A) containing counts of which words occur in which contexts (i.e., texts)
- **Process**: matrix factorization using singular value decomposition (SVD; see next slide)
- **Outputs**:
  - Word vectors (B) and Context vectors (C)
  - Both are mapped to the same high-dimensional latent space (300 dims)
  - The distance between word vectors captures similarity, which can be used to generalize

A

Word/	Text sample (context)															30,000
1	x	x	x	x	x	x	.	.	.	x	x	x	x	x		x
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x		x
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.		.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.		.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.		.
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x		x
60,000	x	x	x	x	x	x	.	.	.	x	x	x	x	x		x

B

Word/	Factor (dimension)															300
1	y	.	.	.												y
.	y	.	.	.												y
.	.	.	.	.												.
.	.	.	.	.												.
.	.	.	.	.												.
.	y	.	.	.												y
60,000	y	.	.	.												y

C

Sample/	Factor (dimension)															300
1	z	.	.	.												z
.	.	.	.	.												z
.	z	.	.	.												z
.	z	.	.	.												z
30,000	z	.	.	.												z

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A — Text sample (context)

Word/	1	.	.	.	.	.	.	.	.	.	.	.	.	30,000
1	x	x	x	x	x	x	.	.	.	x	x	x	x	x
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	x	x	x	x	x	x	.	.	.	x	x	x	x	x
60,000	x	x	x	x	x	x	.	.	.	x	x	x	x	x

B — Factor (dimension)

Word/	1	.	.	.	300
1	y	.	.	.	y
.	y	.	.	.	y
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	y	.	.	.	y
60,000	y	.	.	.	y

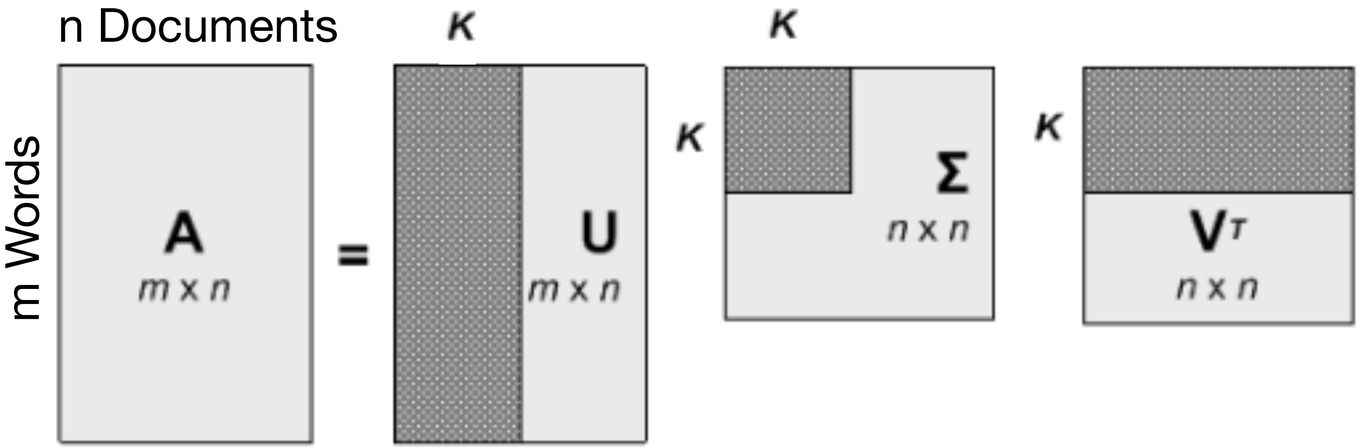
C — Factor (dimension)

Sample/	1	.	.	.	300
1	z	.	.	.	z
.	.	.	.	.	z
.	z	.	.	.	z
.	z	.	.	.	z
30,000	z	.	.	.	z

Singular Value Decomposition (SVD)

- SVD is a generalization of *eigendecomposition* (square matrix only) to any rectangular matrix
  - break down the description of $\mathbf{A}$ into a numer of components (i.e., basis functions) based on the outer product of $\mathbf{U}$ and $\mathbf{V}^T$
  - Components are weighted by the values in $\mathbf{\Sigma}$, which is a diagonal matrix (0s except for the diagonal)
- No unique solution, but usually computed through iterative methods finding progressively better solutions until convergence
- Using only the top K components, we get an efficient approximation

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$$



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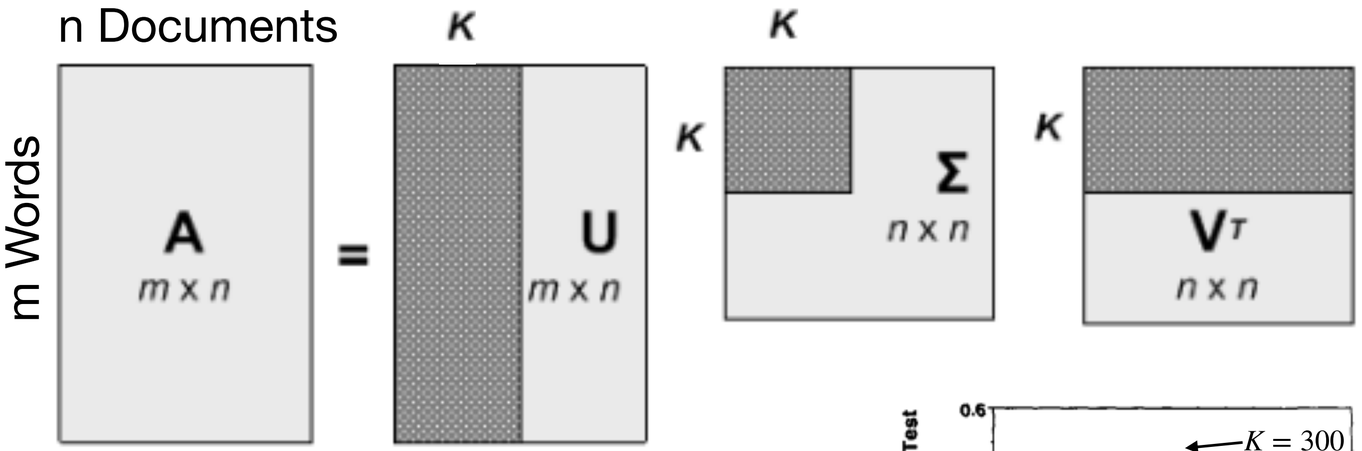

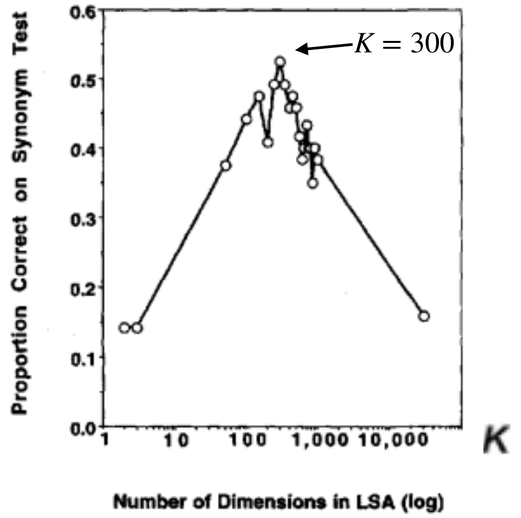

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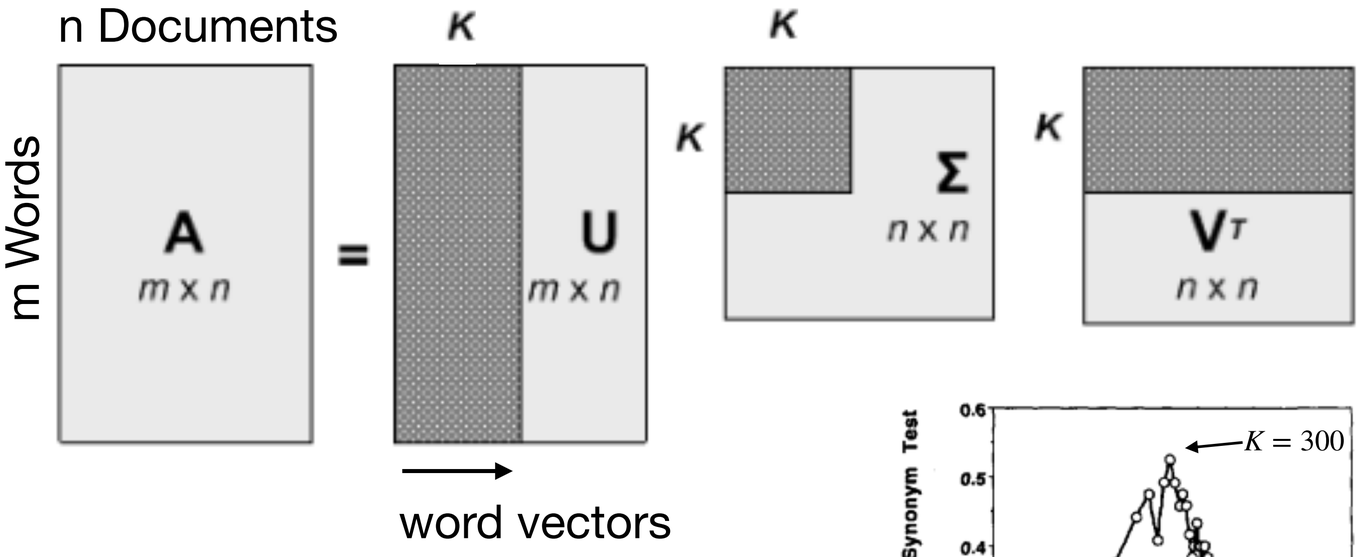
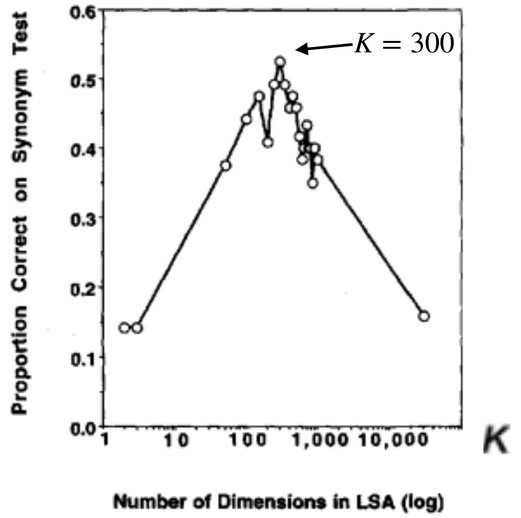
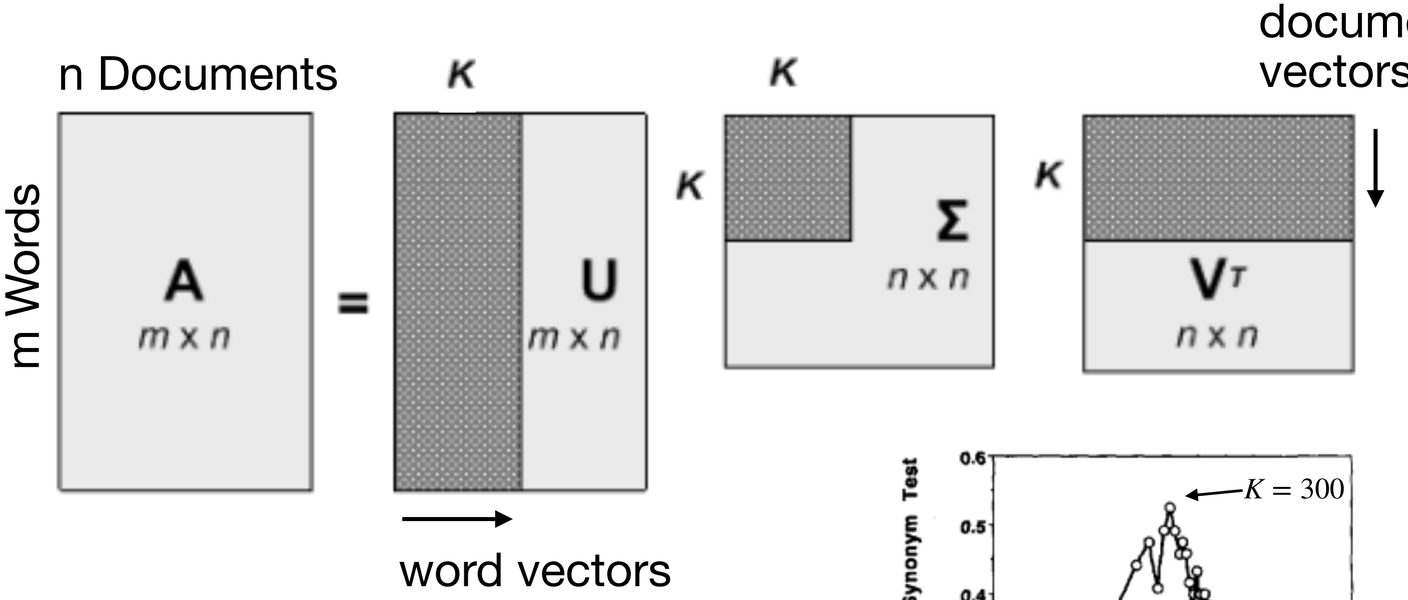


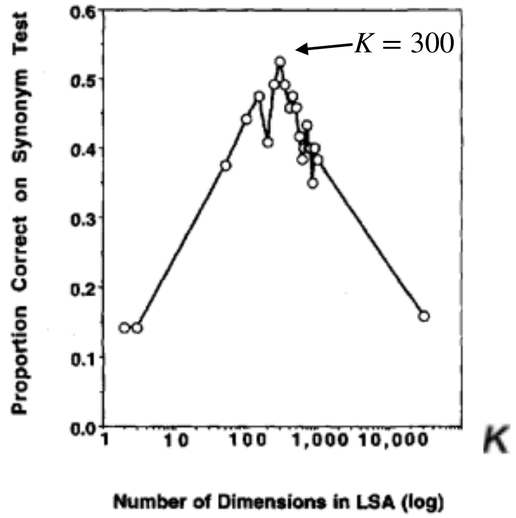


Singular Value Decomposition (SVD)

- SVD is a generalization of *eigendecomposition* (square matrix only) to any rectangular matrix
  - break down the description of $\mathbf{A}$ into a numer of components (i.e., basis functions) based on the outer product of $\mathbf{U}$ and $\mathbf{V}^\mathsf{T}$
  - Components are weighted by the values in $\mathbf{\Sigma}$, which is a diagonal matrix (0s except for the diagonal)
- No unique solution, but usually computed through iterative methods finding progressively better solutions until convergence
- Using only the top K components, we get an efficient approximation

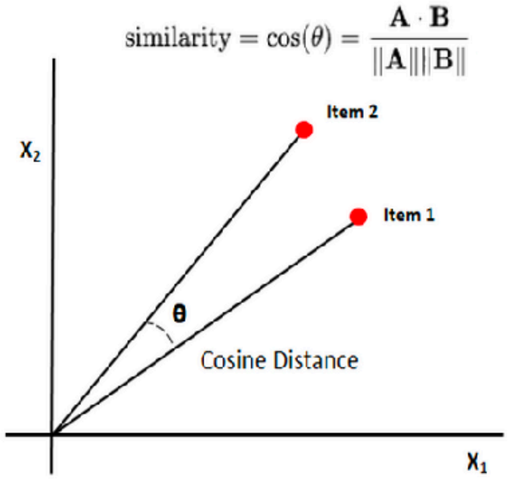
$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\mathsf{T}$$





Using word vectors to model semantic learning

- Local context of words predict long-range generalization by using the Cosine similarity between word vectors
- Synonym test: predicting which words are synonyms based on cosine distance performed as well as foreign students testing at US colleges
- Mode performance (y-axis) improves with more text (x-axis) and more training samples with the stem word (shapes)
  - Predicted learning rates comparable to late elementary/high school children (10-15 words per day)



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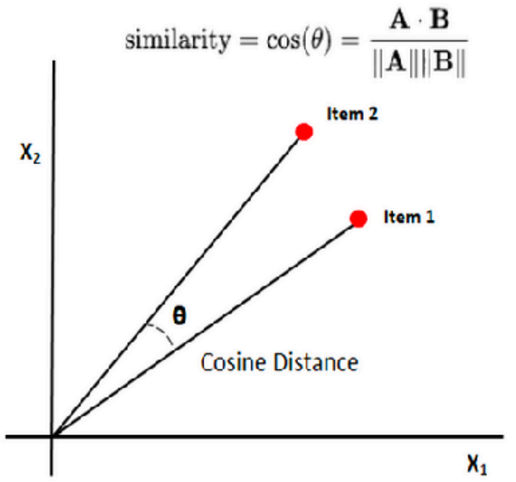

Stem: levied

Choices: (a) imposed

(b) believed

(c) requested

(d) correlated

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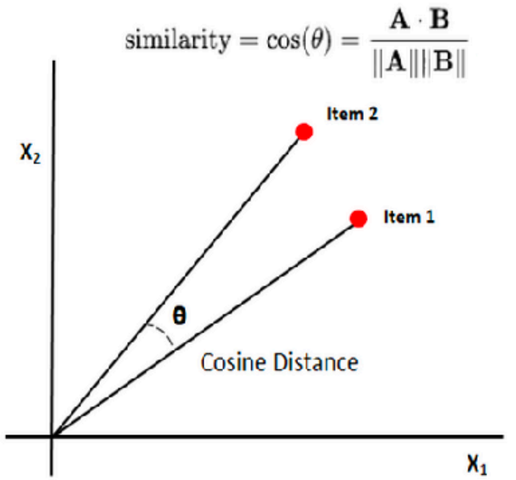

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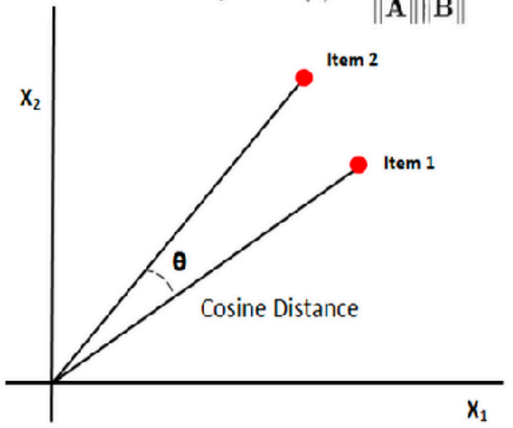

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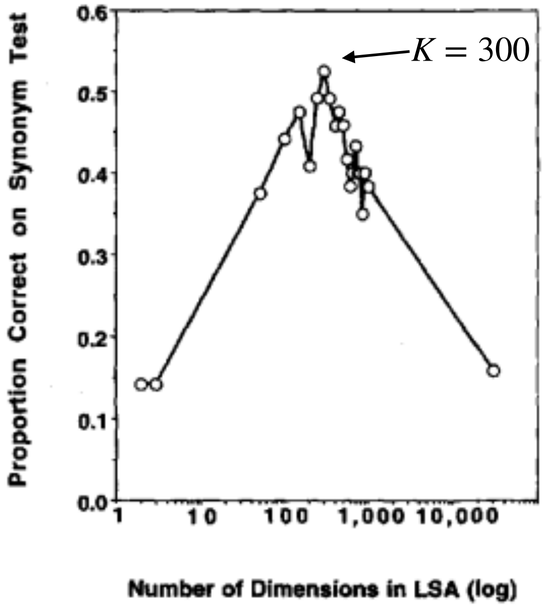

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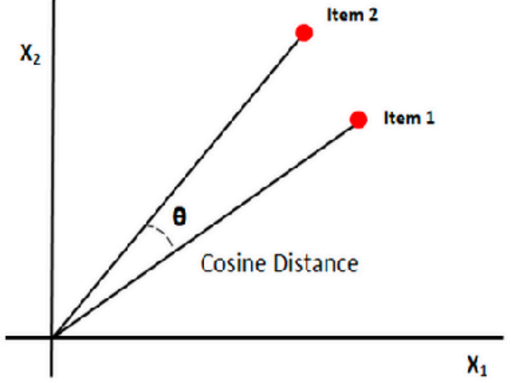

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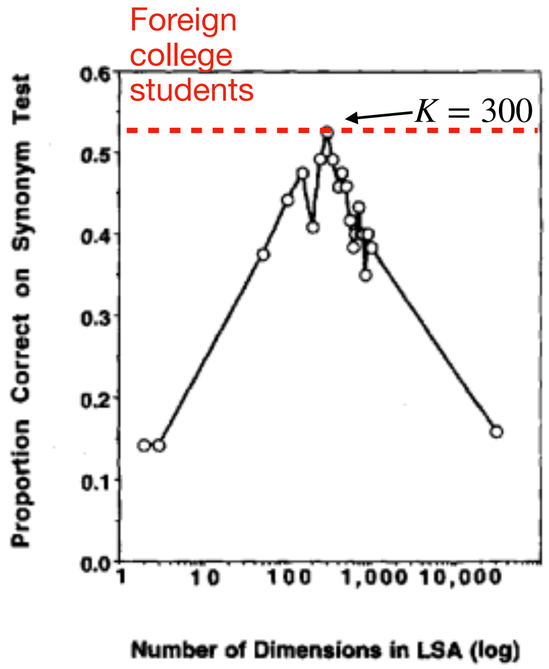

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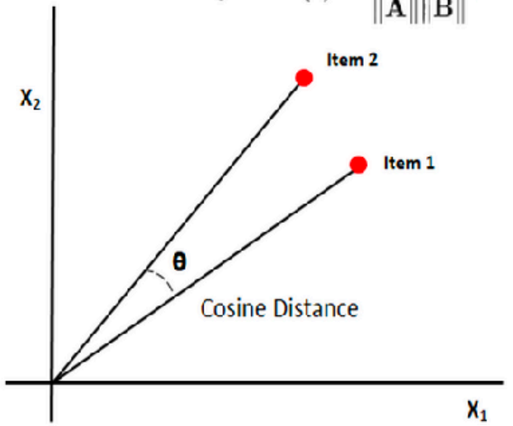

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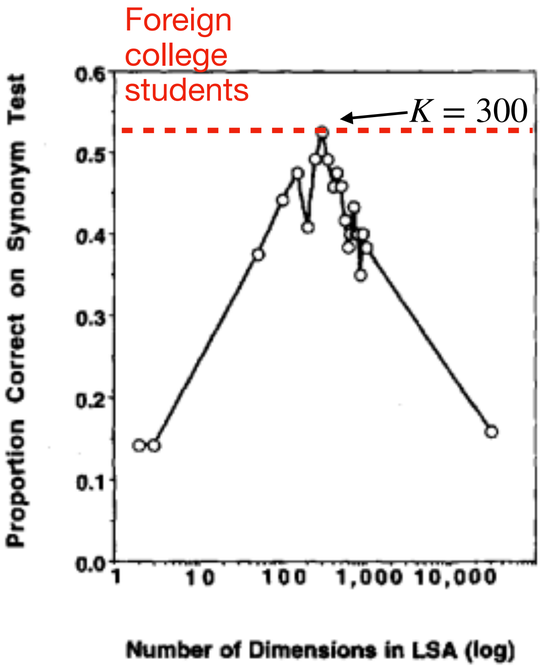
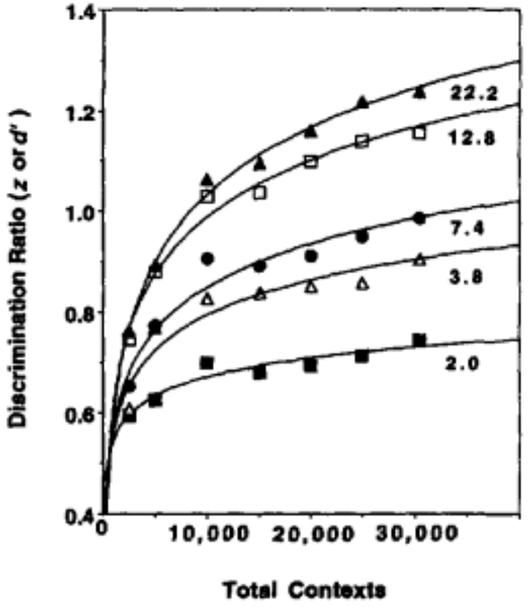
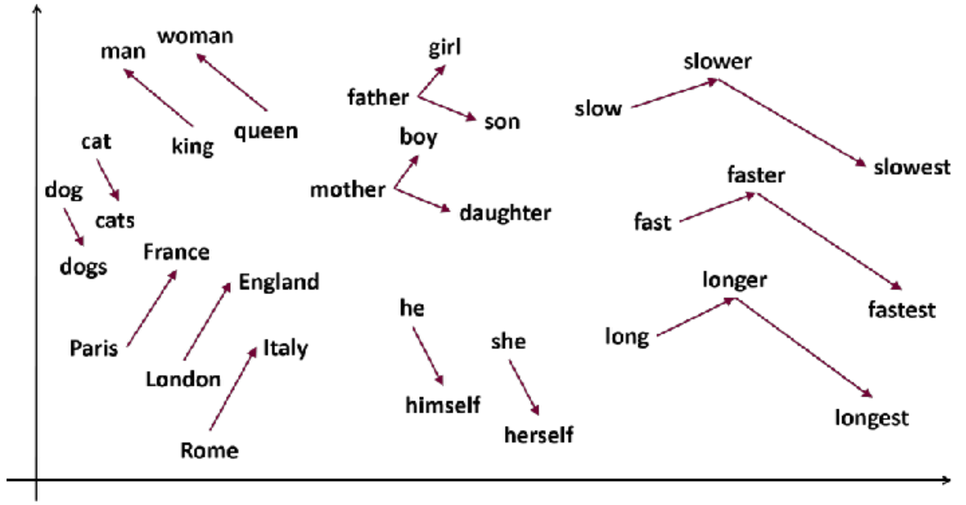


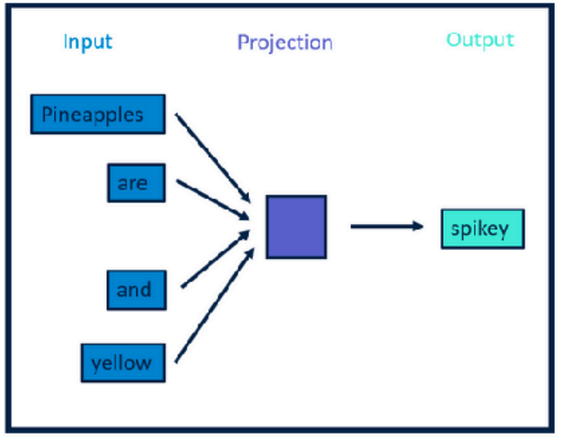


numbers indicate number of training samples with the stem word

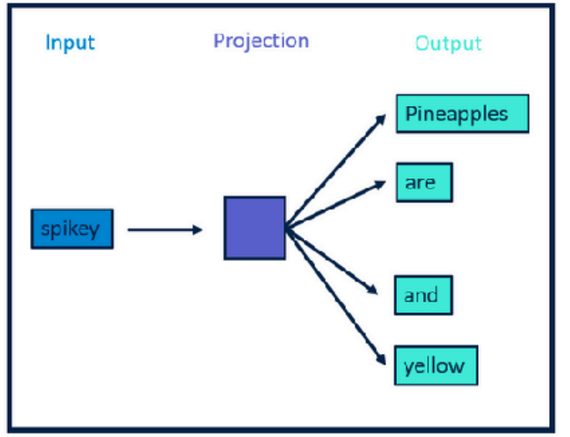
Word2Vec

- Using neural networks to learn word vectors at scale (Mikolov et al., 2013)
- Two training methods that are inversely related to each other
  - **Cumulative bag of words** (CBOW): predicting the target word based on the context (neighboring words)
  - **Skip-gram**: predicting the context based on the target word
  - Iteratively move a context window through training text, and update network weights to minimize prediction loss
- Same basic principle as LSA (local context), but richer geometric interpretations of word vectors based on the need to predict words

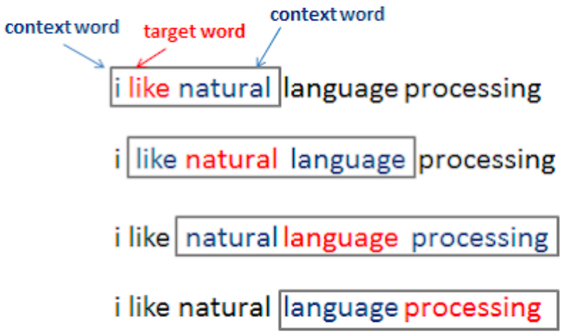




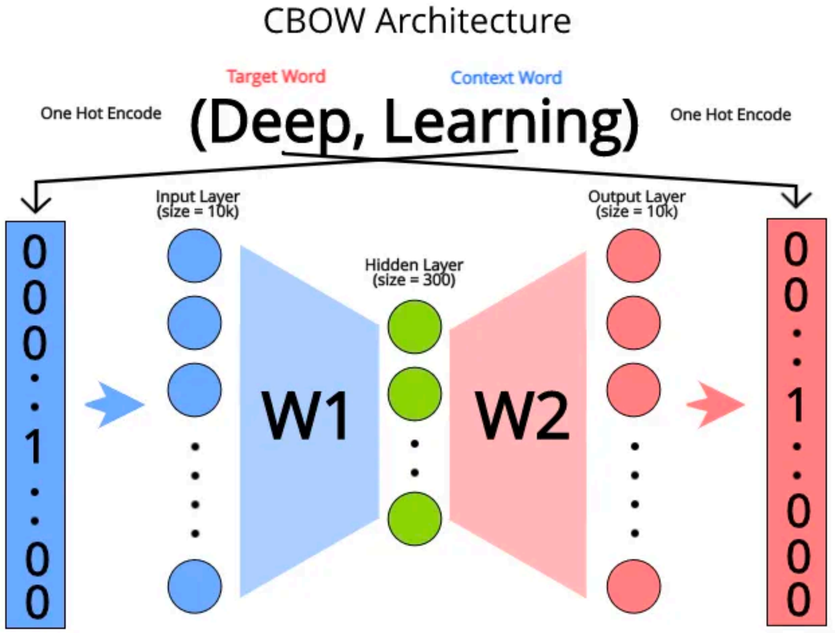
CBOW

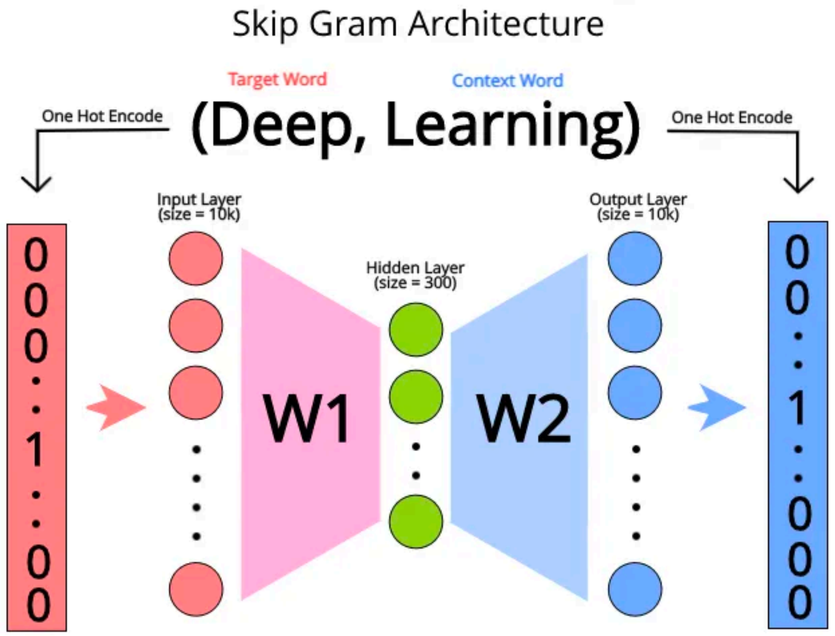


Skip-gram

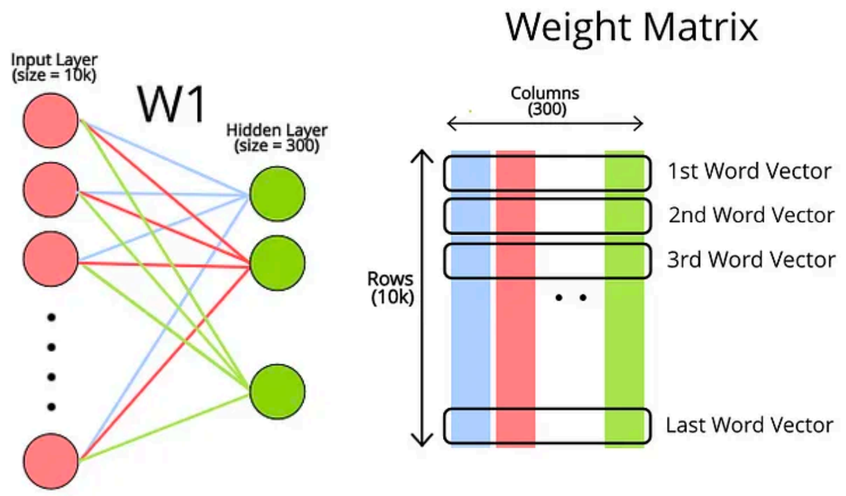


Word2vec architecture





- One hot encoding of words
- Word vectors are extracted from the weight matrix of the encoder

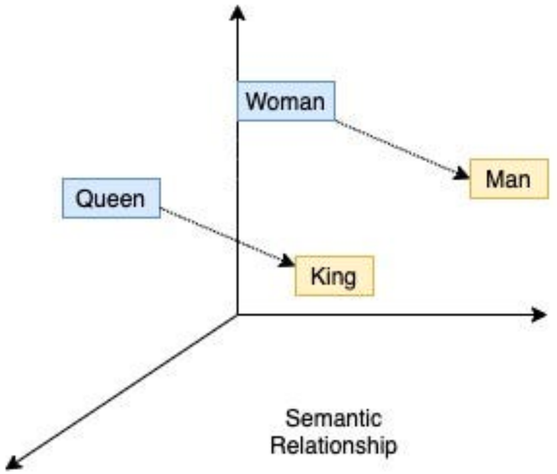


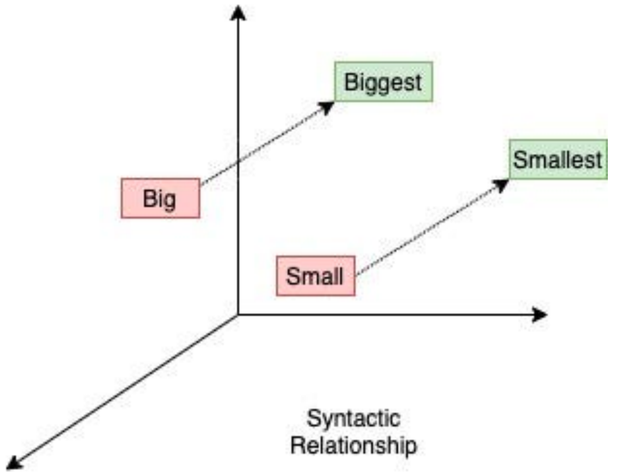
Word2vec results

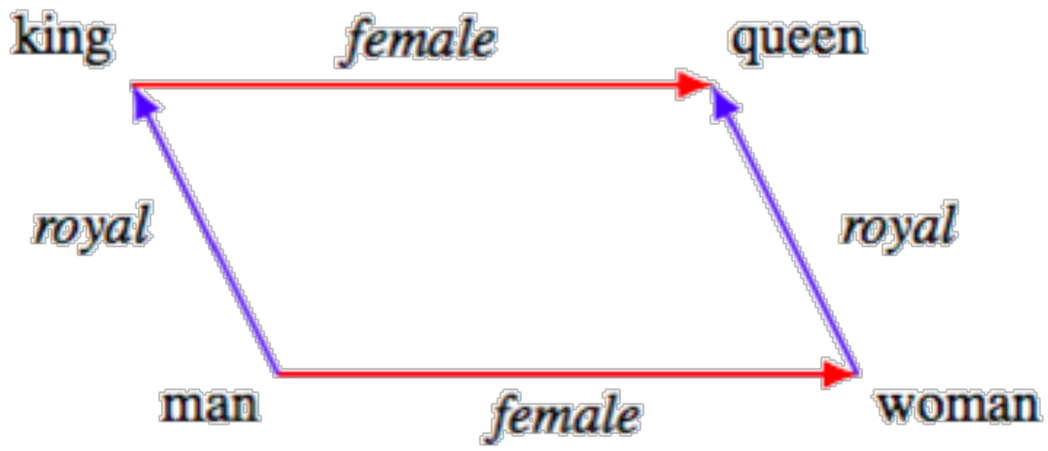
- Both semantic and syntactic relationships
- Similar relationships exist on the same hyperplane
- Reasoning about analogies can be done through addition and subtraction

$$\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{woman}} \approx \overrightarrow{\text{queen}}$$

- Try out a demo here: https://rare-technologies.com/word2vec-tutorial/#bonus_app







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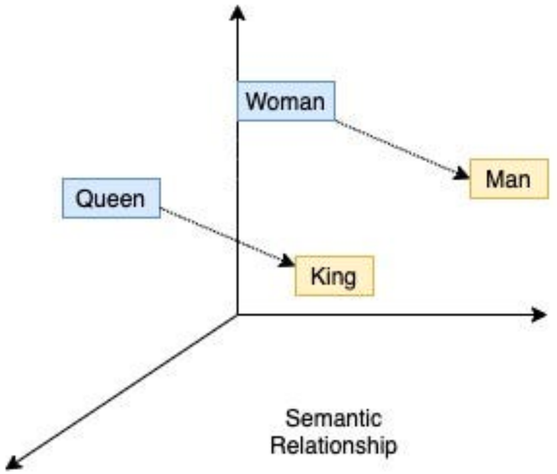
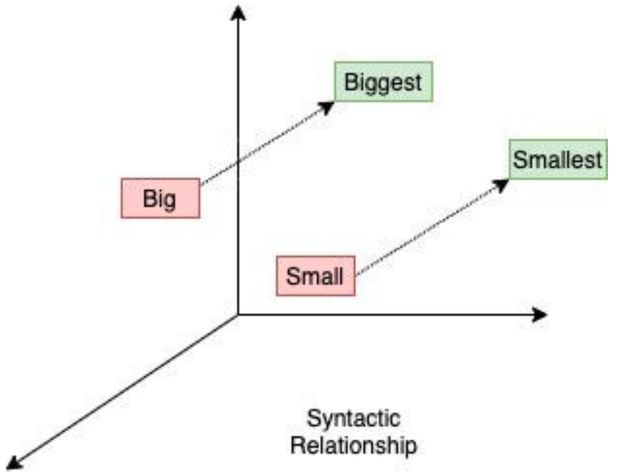
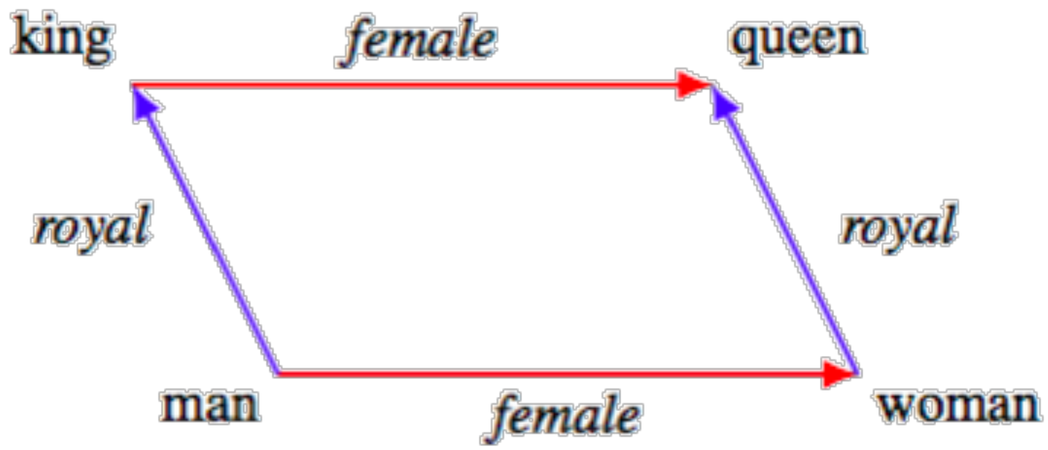
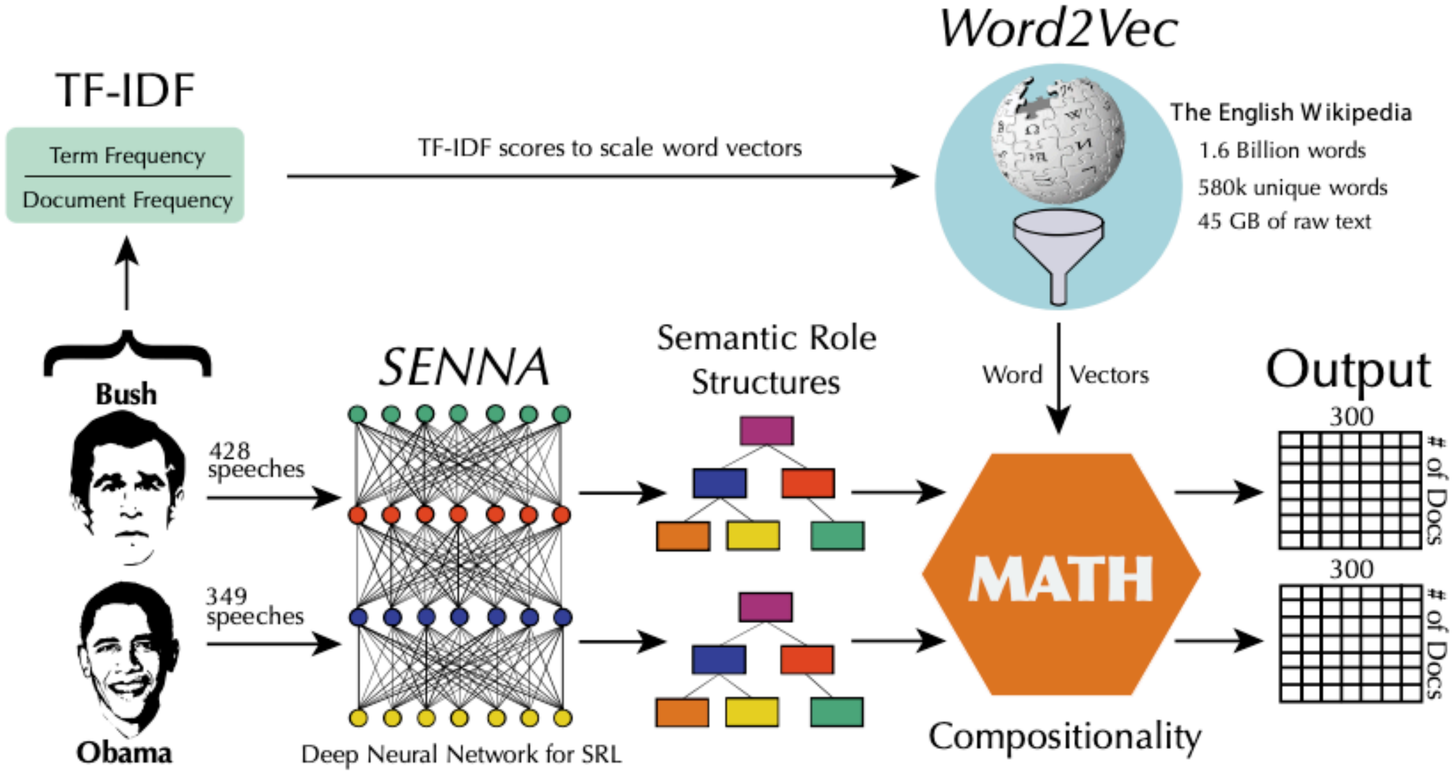






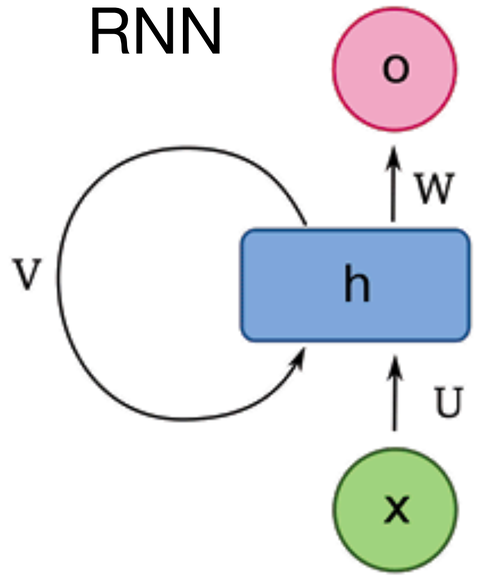
Word2vec advantages and applications

- Scalable and cheap to train
  - entire English Wikipedia took 48 hrs on my laptop when I was a masters student in 2014
- Geometric properties provide a host of applications
  - text classification
  - sentiment analysis
  - topic modeling



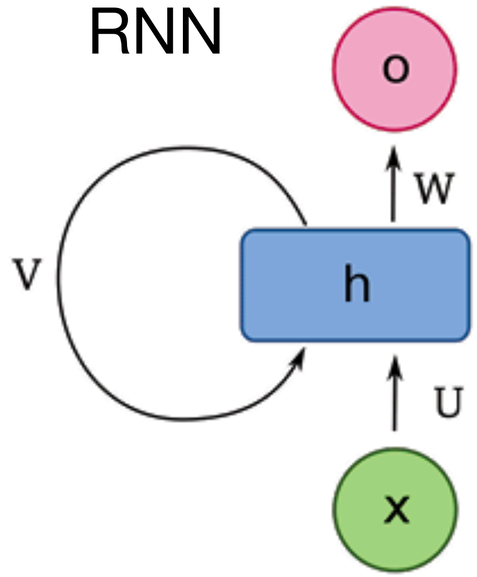
Wu, Skowron, & Petta (2014); my first poster presentation!

RNNs for generating language



RNNs for generating language

- Recursive Neural Networks (RNNs)
  - RNNs map input x to some hidden state h, which is used to predict the output o
  - at each timestep, h_T is a function of x_t and previous hidden state h_{t-1}
  - hidden states are passed forward in time to provide a dynamically changing context for interpreting the input



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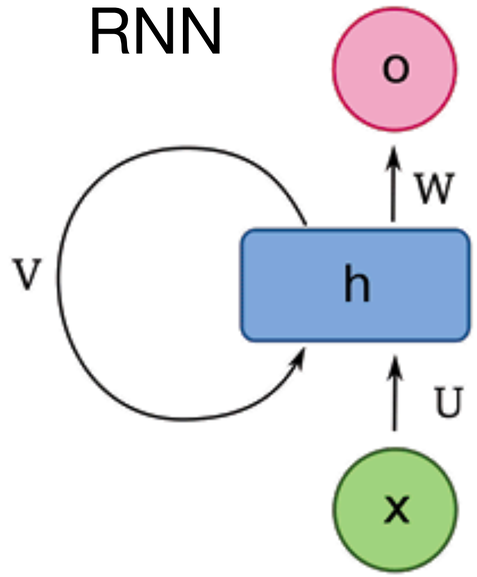

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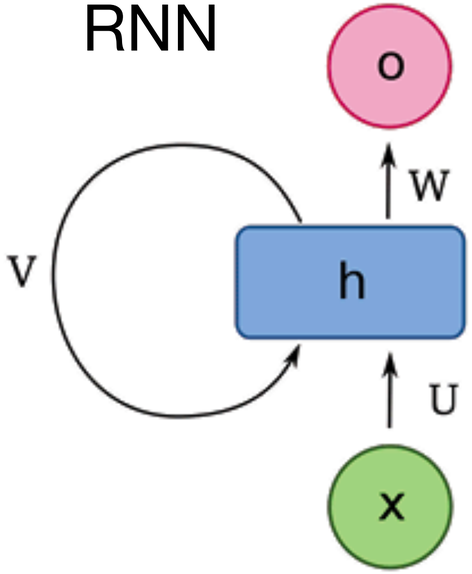
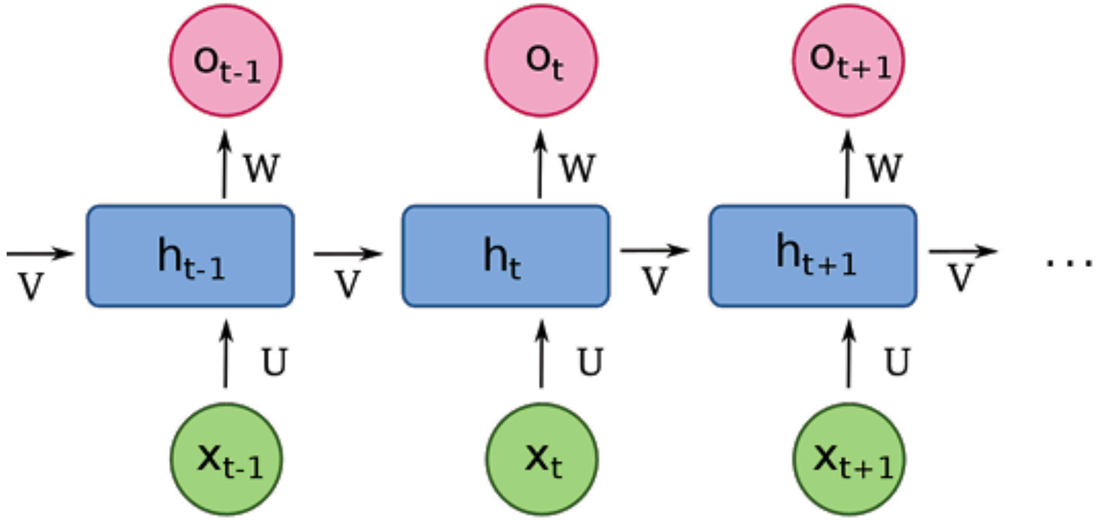


Unfolded



Long short-term memory (LSTMs)

- LSTMs (Hochreiter & Schmidhuber, 1995) add additional modules that learn when to store long-term memories and when to forget
- Key difference from RNNS: has both shorterm and longterm hidden states
  - **Input** gate: selects which new information (filter) gets stored in longterm memory (after multiplying with **tanh activation**)
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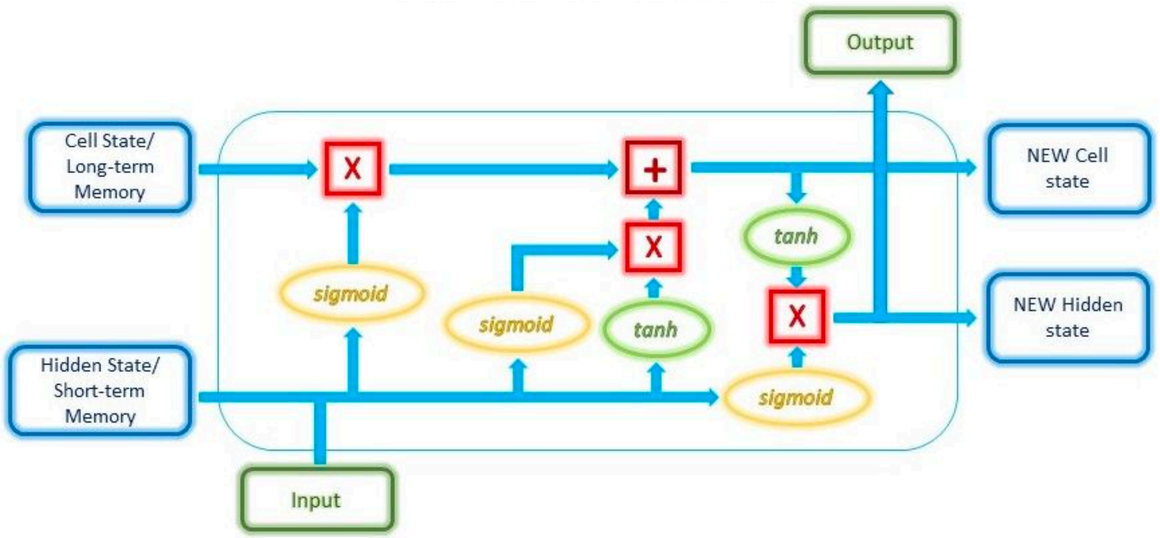
LSTM

Gabriel Loye (2019)



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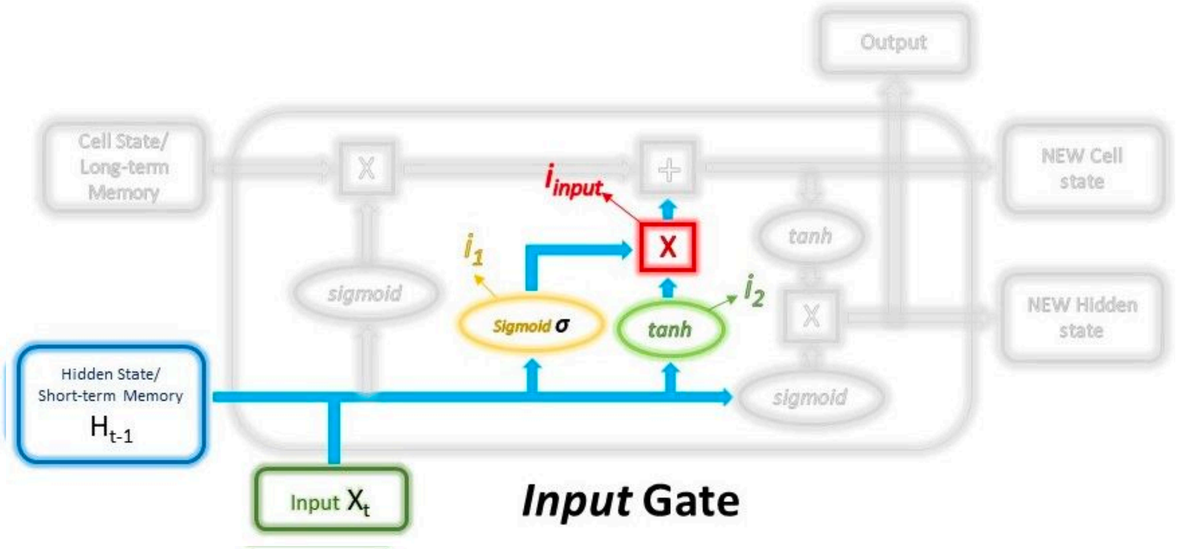

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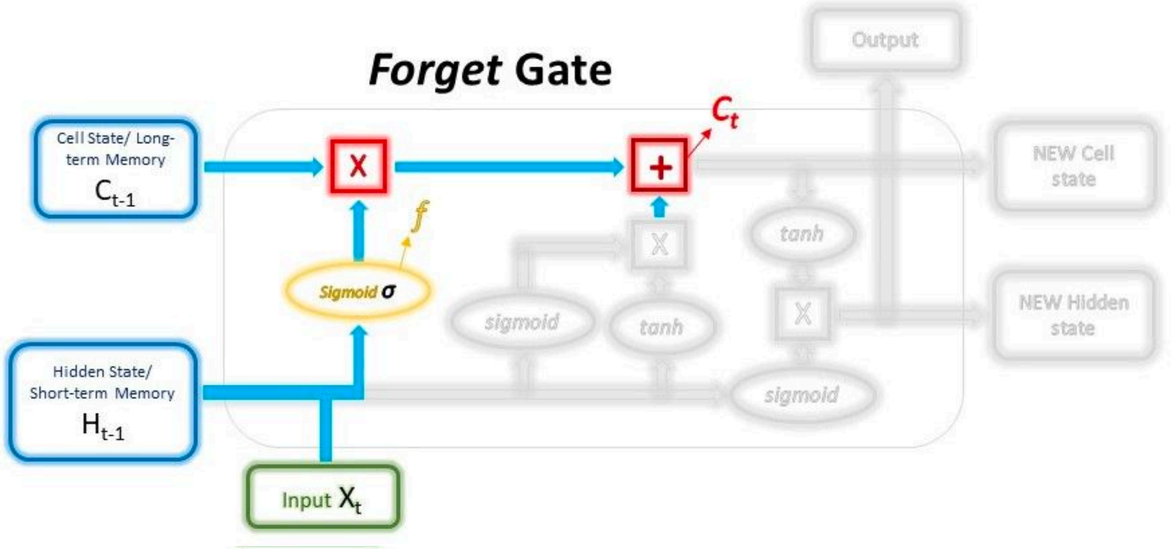

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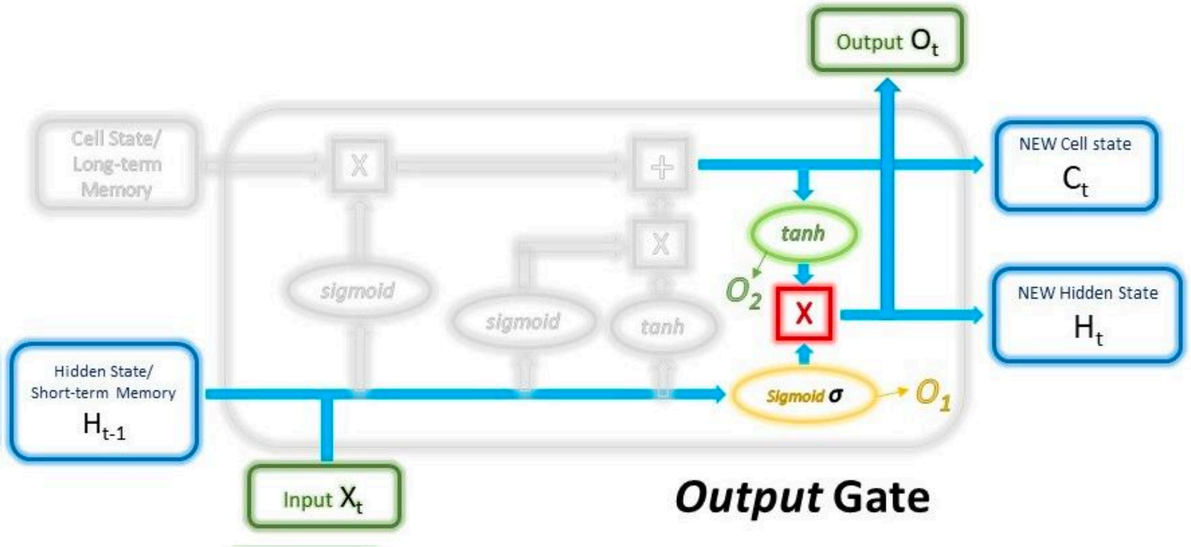
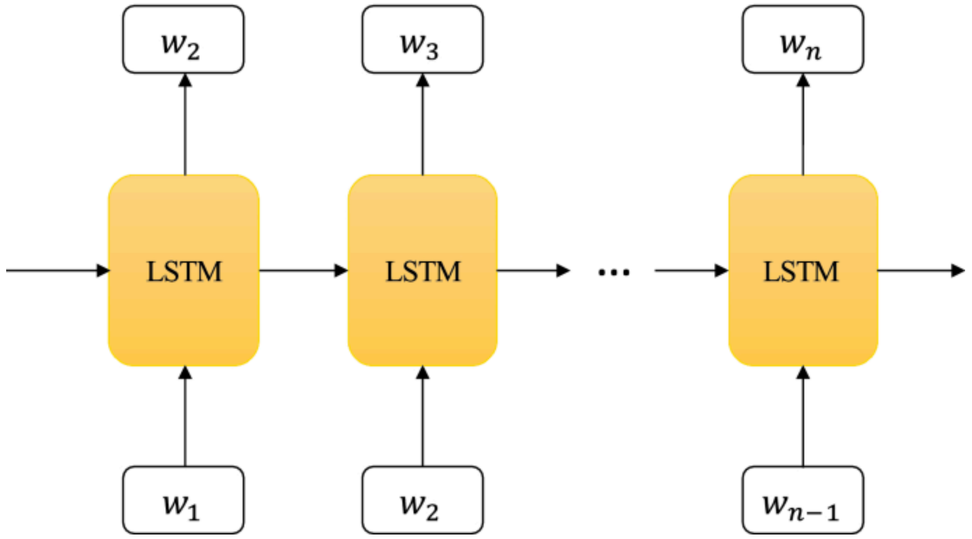


LSTM language models

- Generative model of language viewed as a sequence generation problem
  - *predict the next word based on the previous word*, with the hidden states carried over for the entire string
  - Use gradient descent with backpropogation through time to minimize prediction error
- Vanishing gradient issue with RNNs is (mostly) avoided, since gates control the flow of information
- Not only represents text, but can generate new text that is (mostly) coherent



Demo

Shakespeare Text Generation (RNN)

Write like Shakespeare. Generate a text using Recurrent Neural Network (RNN)

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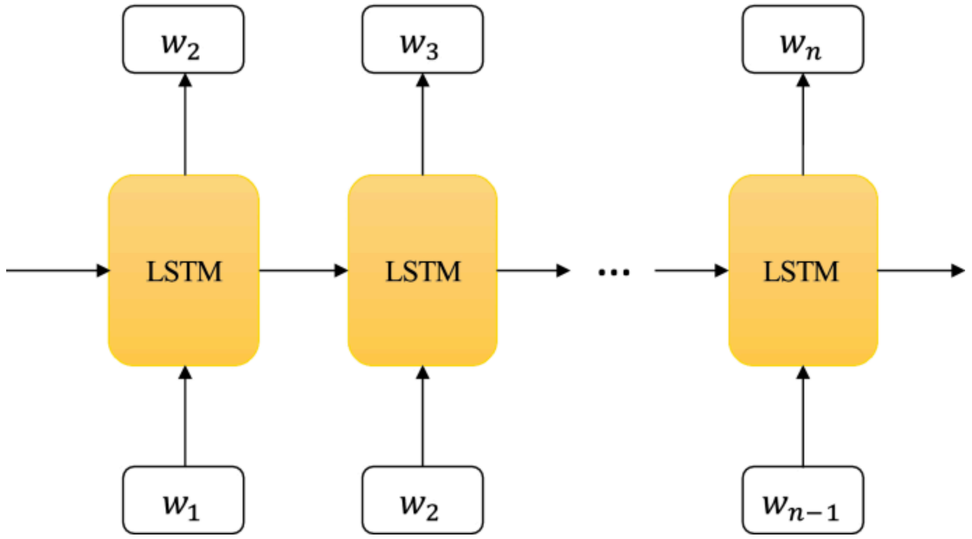

Demo

```
def build_model(vocab_size, embedding_dim, rnn_units, batch_size):
    model = tf.keras.models.Sequential()

    model.add(tf.keras.layers.Embedding(
      input_dim=vocab_size,
      output_dim=embedding_din,
      batch_input_shape=[batch_size, None]
    ))

    model.add(tf.keras.layers.LSTM(
      units=rnn_units,
      return_sequences=True,
      stateful=True,
      recurrent_initializer=tf.keras.initializers.GlorotNormal()
    ))

    model.add(tf.keras.layers.Dense(vocab_size))

    return model
```

Shakespeare Text Generation (RNN)

Write like Shakespeare. Generate a text using Recurrent Neural Network (RNN)

Interim summary

- Plato's problem and poverty of the stimulus argument led people like Chomsky to believe that language learning is underdetermined (not enough data)
- LSA showed how *local contexts* (which words occur in which texts) can enable generalization by learning latent word embeddings
- Word2vec provides a neural-network implementation based on *predicting neighboring words* within a moving context window, where word vectors have interesting geometric properties for AI applications
- RNNs and LSTMs use supervised learning to *predict which word occurs next* in a sequence, providing a method for generating text
  - LSTMS use a series of gates and dual hidden states (short vs. longterm) to avoid the vanishing gradient problem and capture long-term dependencies

5 min break

Large Language Models

can chatgpt

- can chatgpt **access the internet**
- can chatgpt **write code**
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Large Language Models

Last real scientific paper from OpenAI in 2020

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Generate bullet points that should be on a "introduction to large language models" slide for graduate students in cognitive science, neuroscience, psychology, and machine learning

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- **Definition**: Large language models are advanced artificial intelligence systems designed to process and generate human-like language.
- **Key Components:** These models typically consist of deep neural networks with millions or even billions of parameters, allowing them to learn and capture complex patterns in language data.
- **Training Process**: Large language models are trained on massive amounts of text data from various sources, such as books, articles, and websites, using unsupervised learning techniques.
- **Natural Language Understanding**: They excel at tasks like language understanding, text generation, sentiment analysis, language translation, summarization, and question answering.

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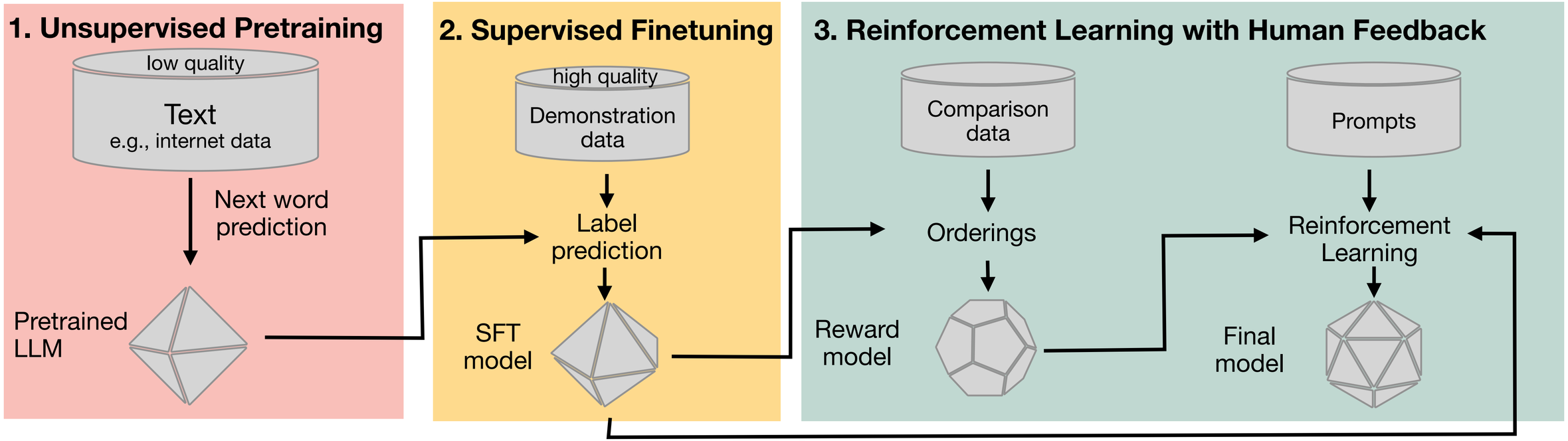
But really, what are LLMs?

- Self-attention mechanism used in massively hierarchical architecture of transformers networks
- Context window prediction (similar to word2vec)
- Various forms of training
  - Unsupervised text prediction
  - Supervised training on labeled data
  - Reinforcement learning from human feedback (RLHF)
- The future of AI

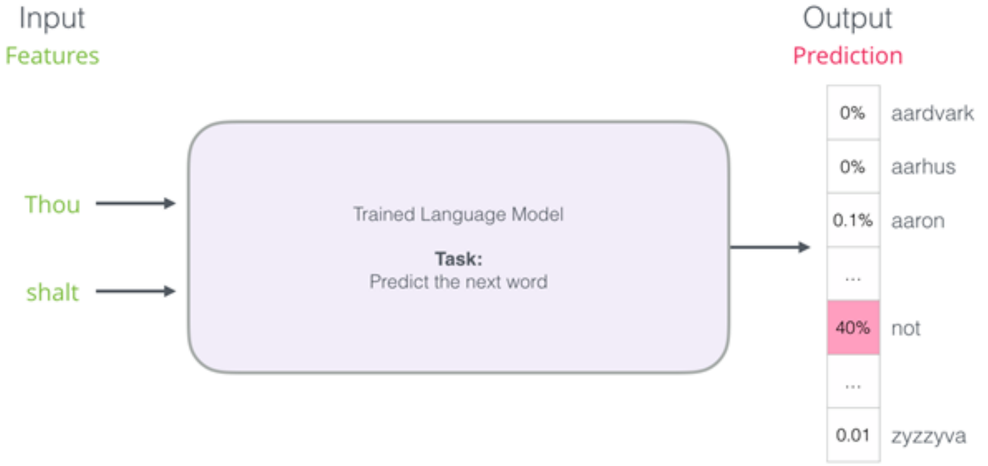
How do LLMs learn

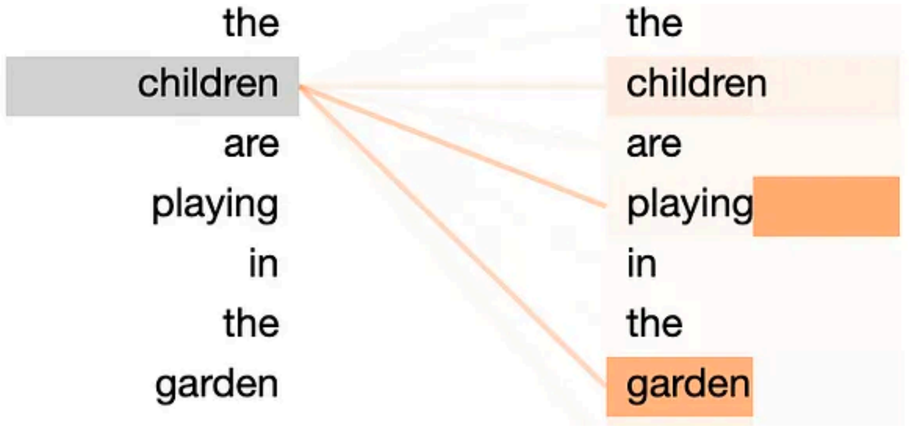
- Combination of multiple Machine Learning techniques
  1. ***Unsupervised*** pre-training: predict the next word in a sentence
  2. ***Supervised*** fine-tuning: predict hand-curated labels
  3. ***Reinforcement learning*** with human feedback: adapt policy based on human raters

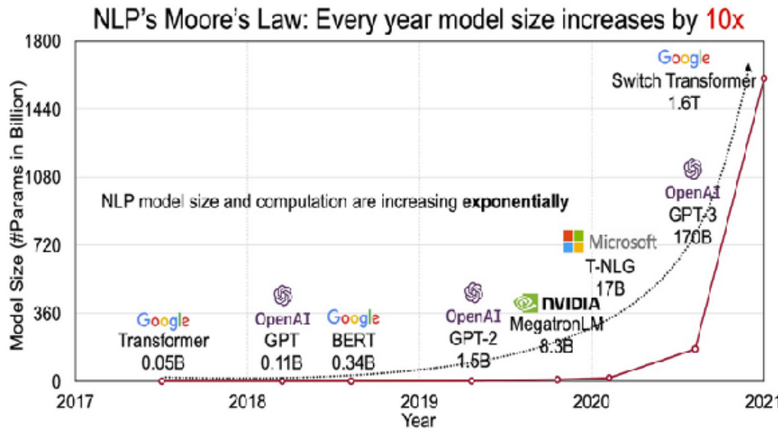


1. Unsupervised pre-training

- Next word prediction, with error used to update weights
- Key concepts:
  - **Attention Mechanism** provides contextual guidance, by focusing on relevant parts of input for better output
    - e.g., “children” is associated with the activity “playing” and the location of the activity “garden”
    - Each word is processed with contextual guidance
  - **Transformer Networks**
    - Deep learning architecture, using attention mechanism to encode and decode text
    - LLMs are many transformer networks, stacked hierarchically







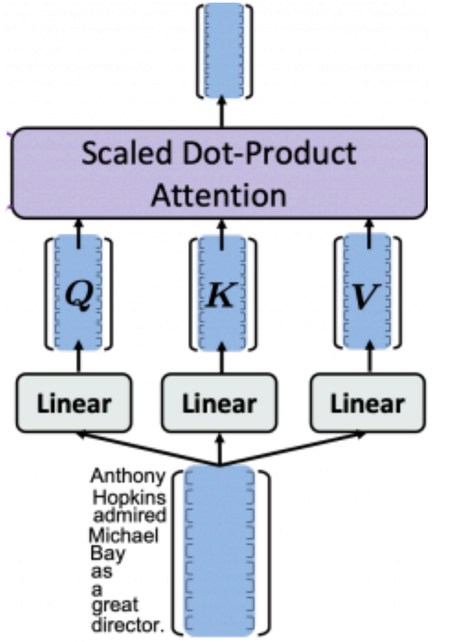
Vaswani et al., (2017)

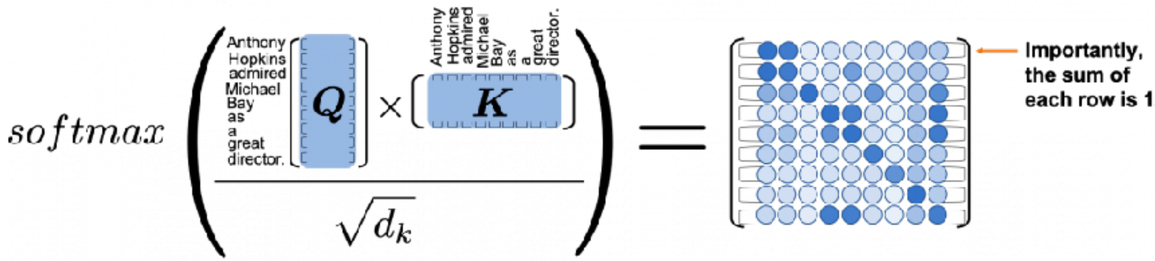
Self-Attention

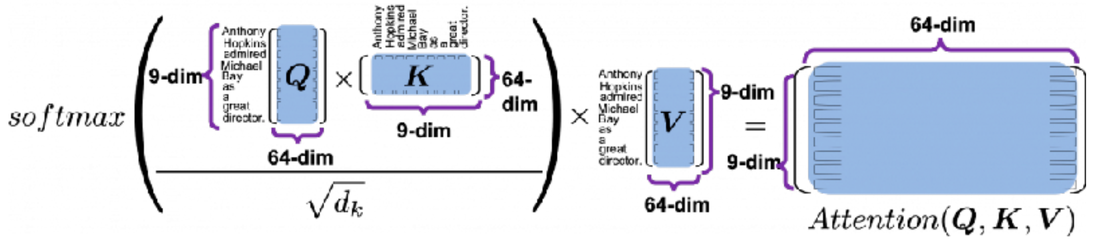
- Self-attention captures relationships between different words/tokens in a sequence

- Each input is mapped to $\boldsymbol{Q}$uery, $\boldsymbol{K}$ey, and $\boldsymbol{V}$alue representations through fully connected **Linear** ANNs
  - Analogous to information retrieval (e.g., searching for videos on youtube): the search engine maps **query** (text in search bar) to **keys** (video title/description) associated with each candidate, and then presents us with a set of matches (**values**)
- $QK^\top$ produces a *score*, which is then put through a softmax to weight the relative importance of each word for each other word (scaled by dimensionality $\sqrt{d_k}$)
- This is then multipled against $\boldsymbol{V}$alue representations to generate a contextualized representation of the text

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V^\top$$

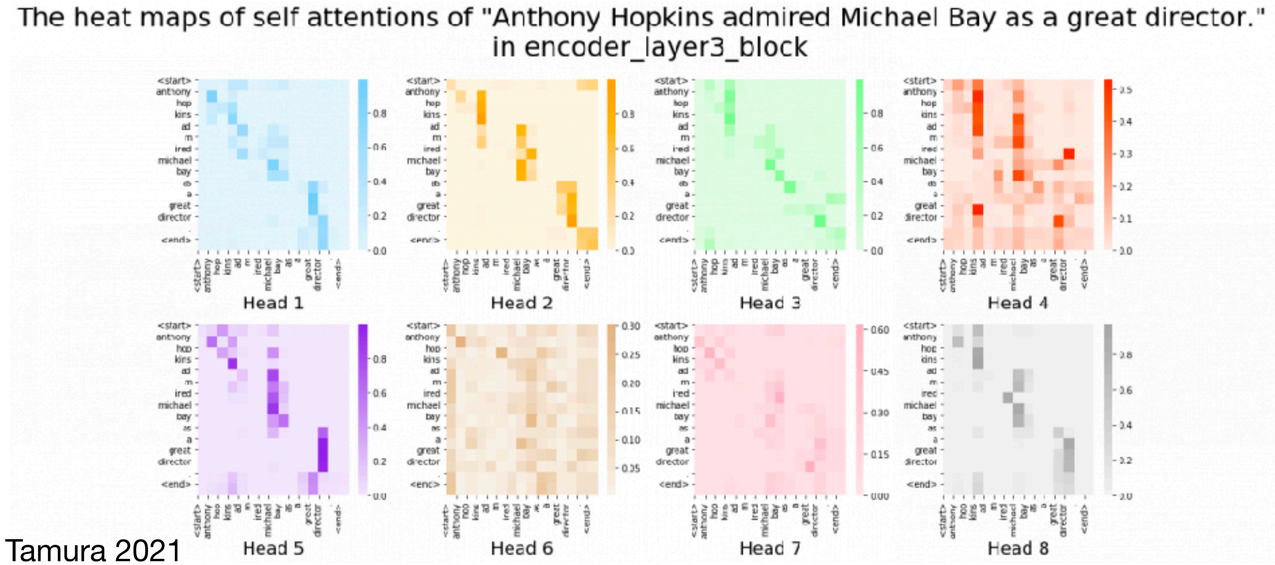


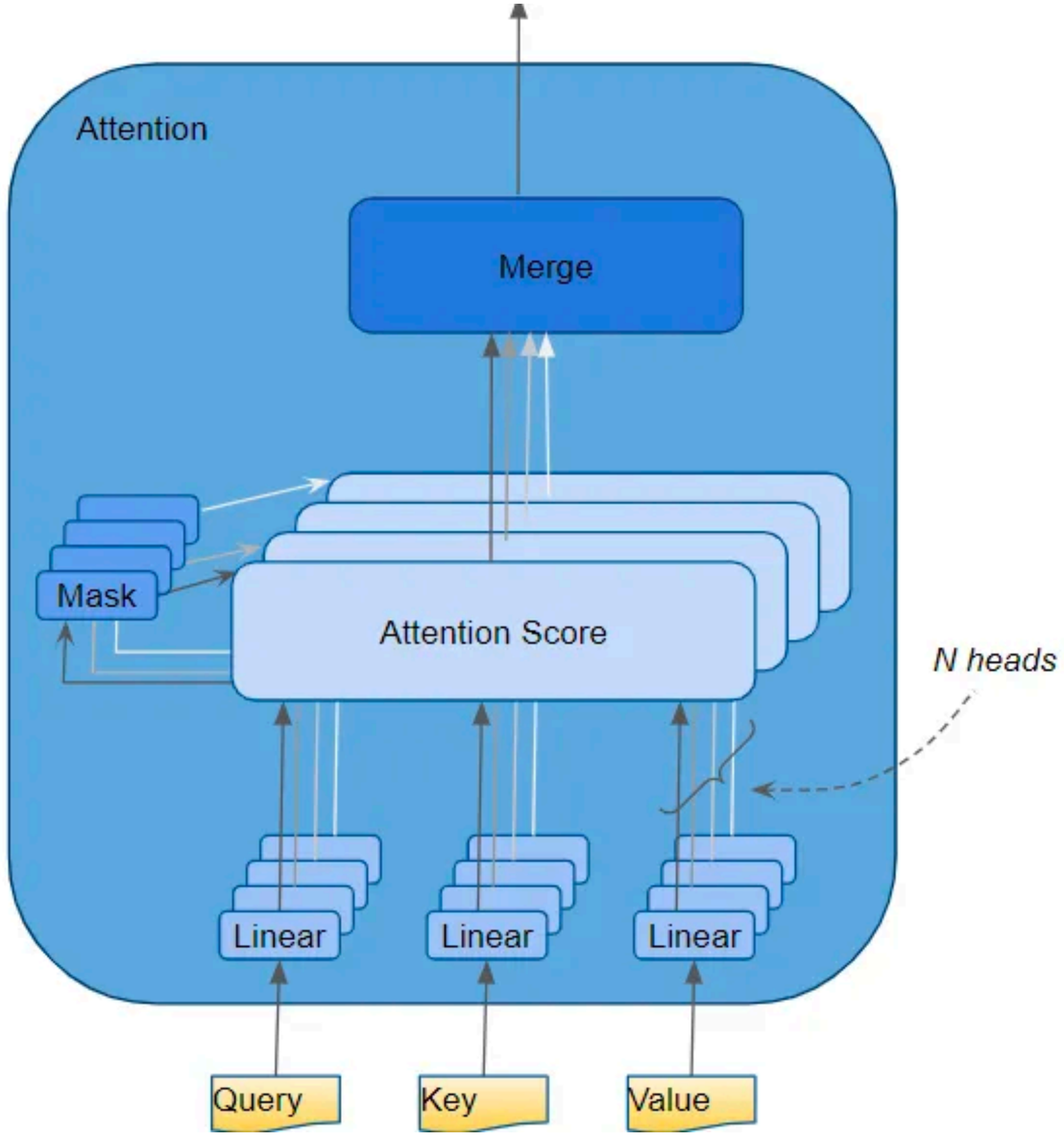




Multi-head attention

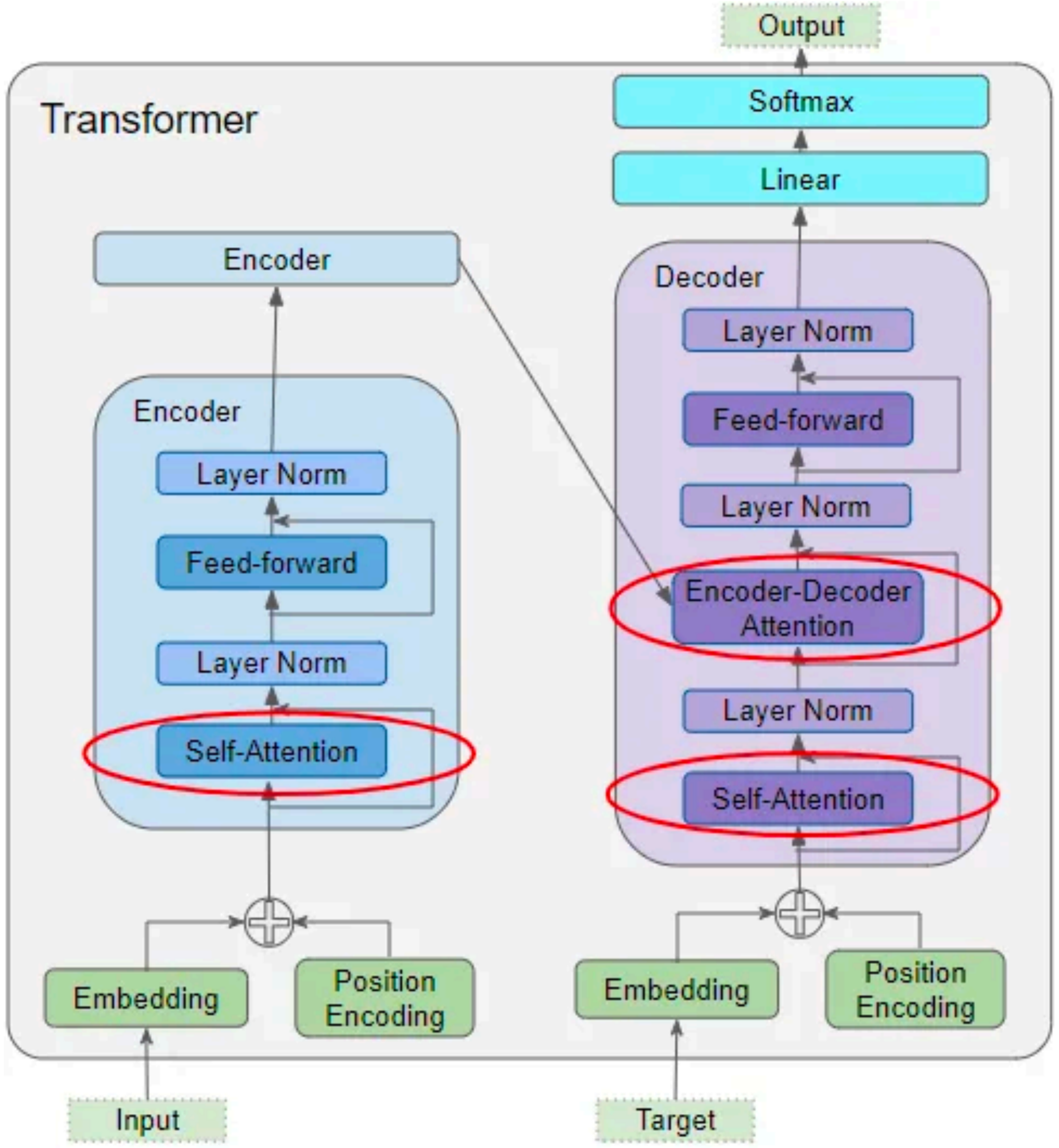
- Attention mechanism can be repeated across N attention heads in parallel
- Each head has different linear mappings (Q,K,Vs), each computing attention (on different types of relationships)
- Outputs of each head are merged together





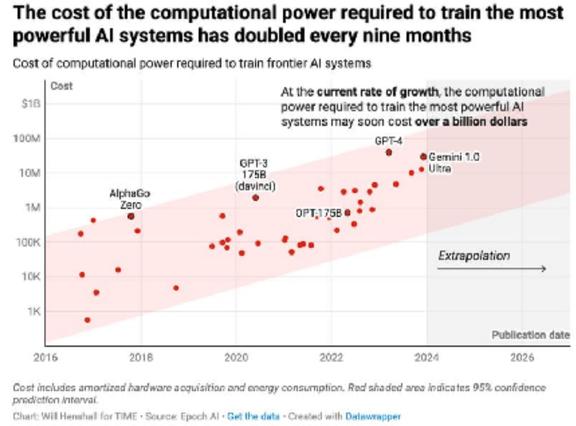
Transformers

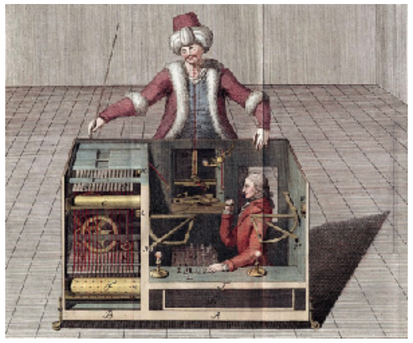
- Encoder-decoder architecture
  - Encoder represents the input
  - Decoder takes the target and the encoded representation to predict the output
- Attention is used in 3 places
  - the input
  - the target
  - the relationship between target and input

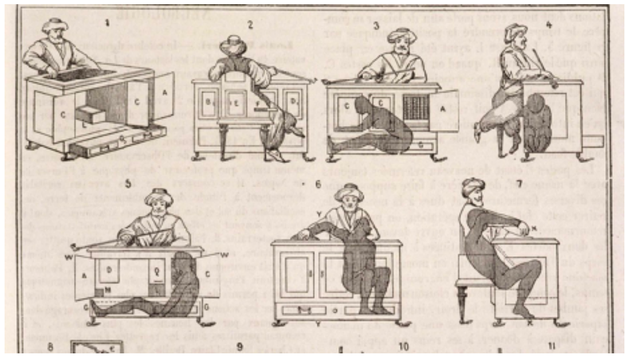


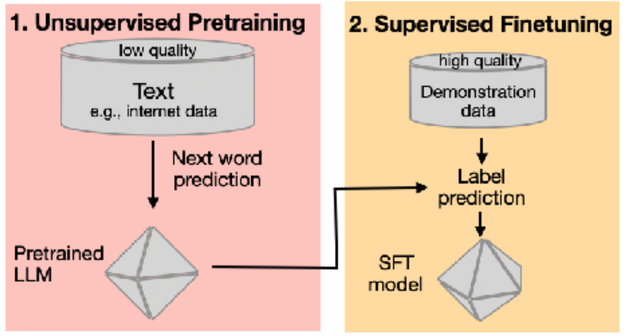
2. Supervised fine-tuning (SFT)

- **Unsupervised pre-training** uses cheap data, but is computationally demanding
  - Training ChatGPT3 ~ yearly energy consumption of 1,000 US households
- **Supervised fine-tuning** uses expensive data from human labels, but is computationally cheap, since dataset is smaller
  - Labeled data comes an army of Amazon Mechanical Turk workers
  - Provides demonstrations of desired outputs

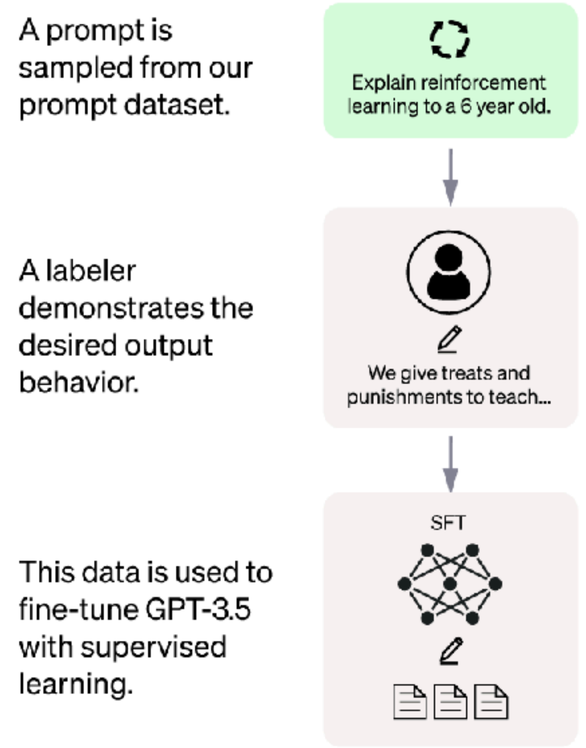






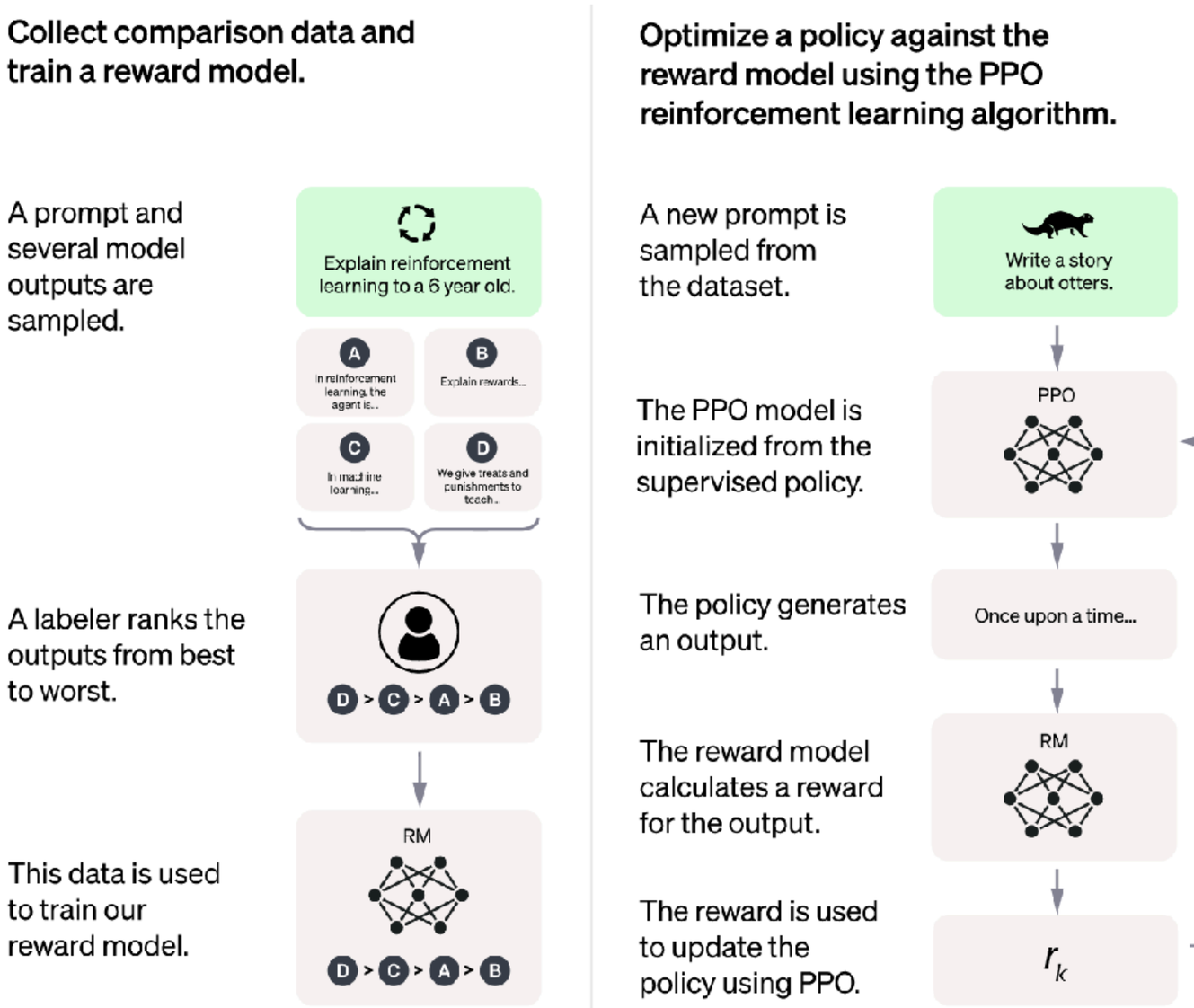


Collect demonstration data and train a supervised policy.



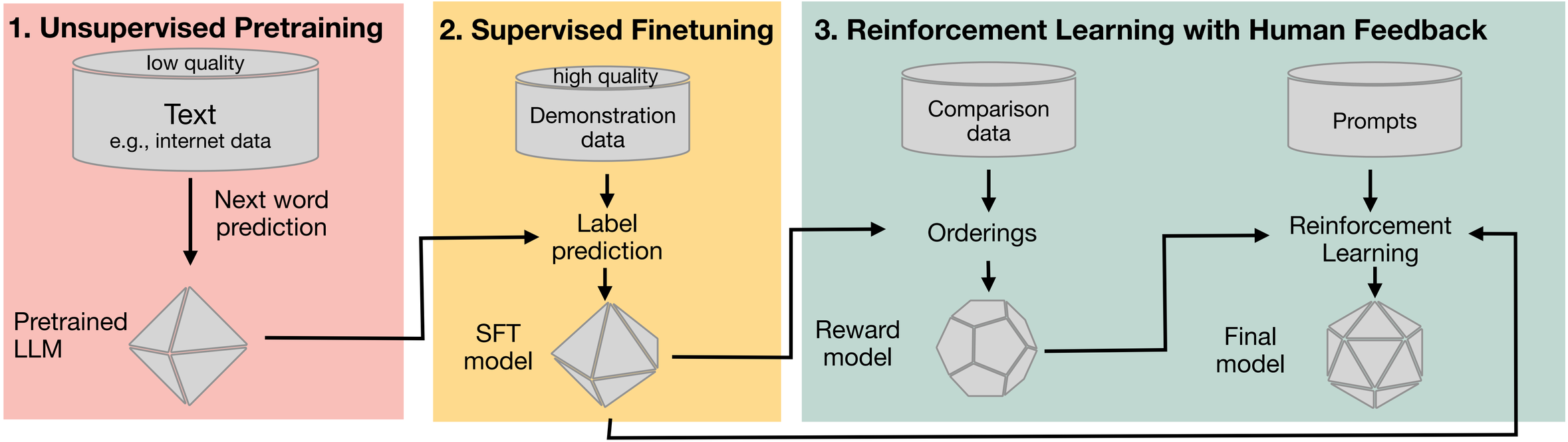
3. Reinforcement learning with human feedback (RLHF)

- Labeled outputs only go so far
  - Too many possible prompts and situations
- RL is well-equipped to generalizing in novel settings
  - [AlphaGo] more unique board states than atoms in the known universe!
- RL training not only instructs which outputs are correct, but teaches more general patterns via reward representations and behavioral policies
  - Comparison data used to train **reward model** (which outputs are better)
  - Prompt data used to **train policy** (how to select an output to generate)



LLM Overview

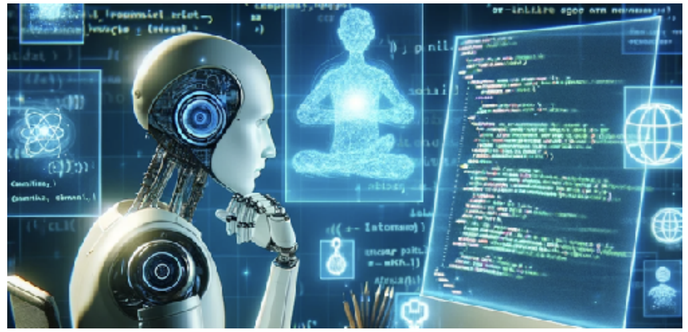
- Massive scale of next word prediction
- Sequentially refined via human data, to produce desired outputs



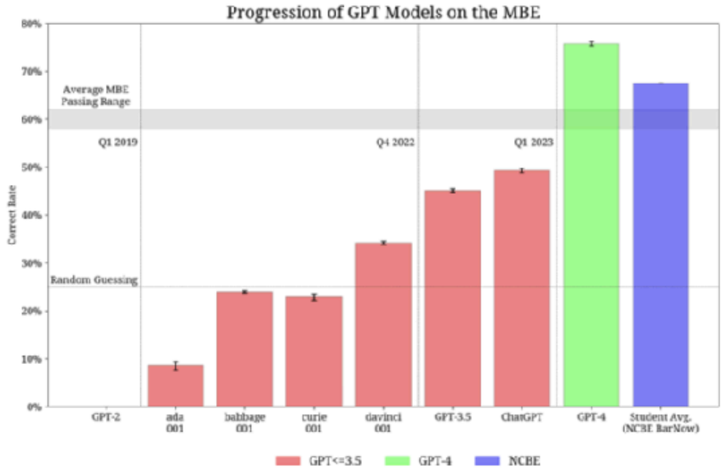
LLM capabilities

Good

Writing and coding tasks



Passing the Bar exam



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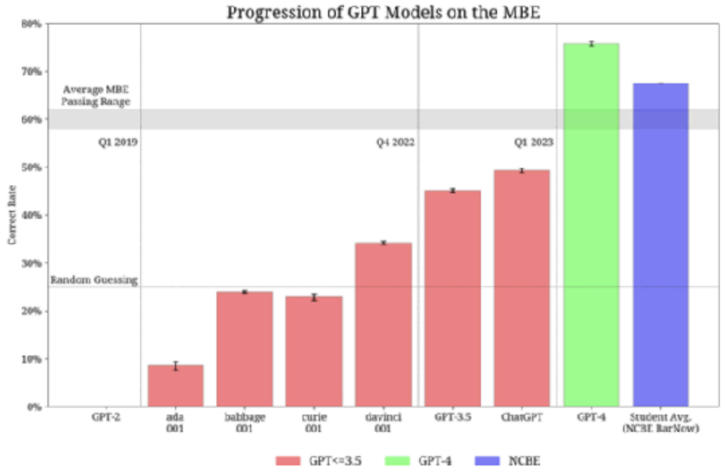

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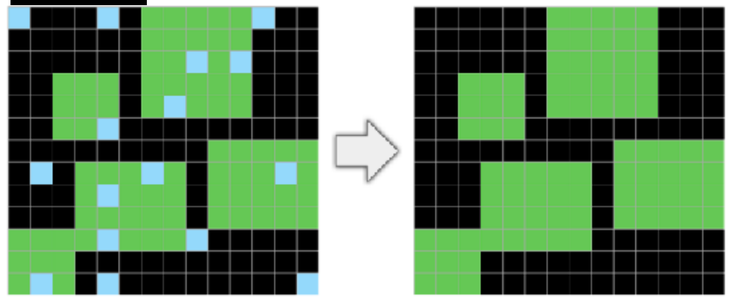
ARC PRIZE

AGI progress has stalled. New ideas are needed. Chollet (2019)



OpenToM Benchmark (Xu et al., 2024)

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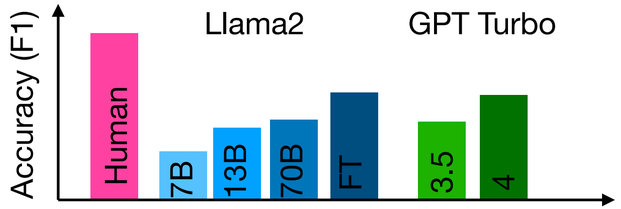

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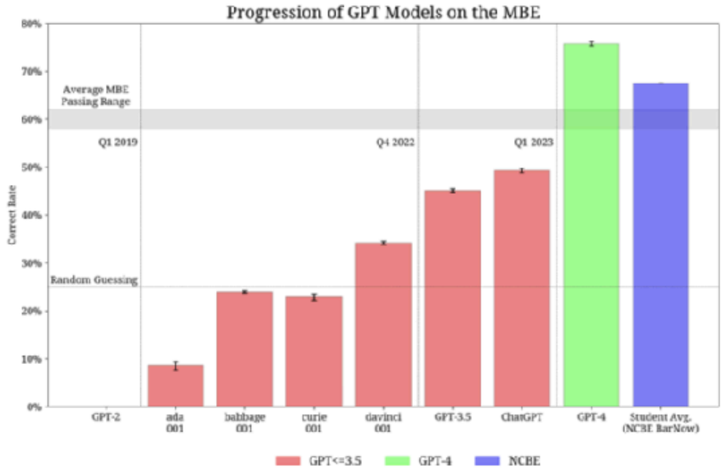

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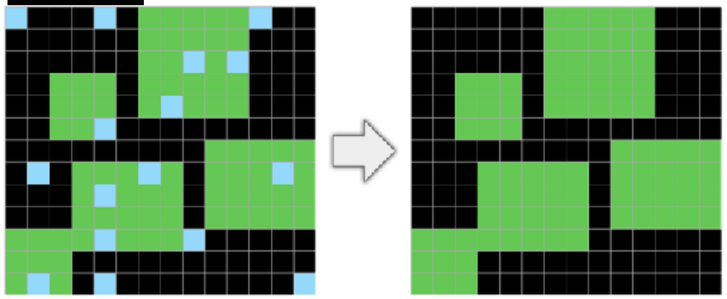

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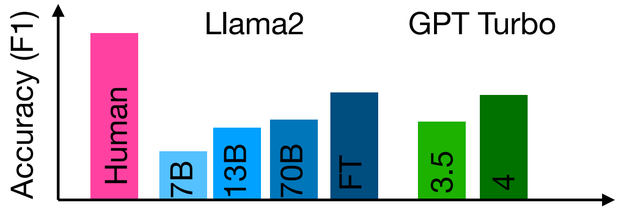

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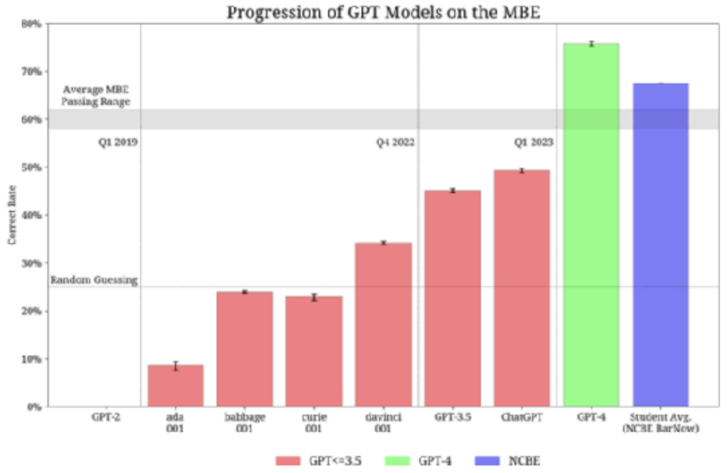

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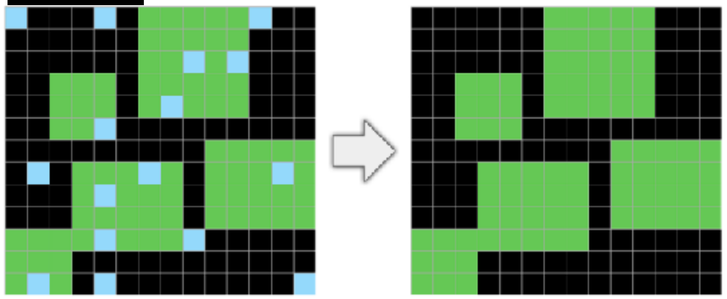

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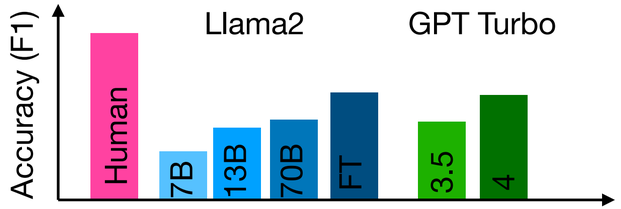

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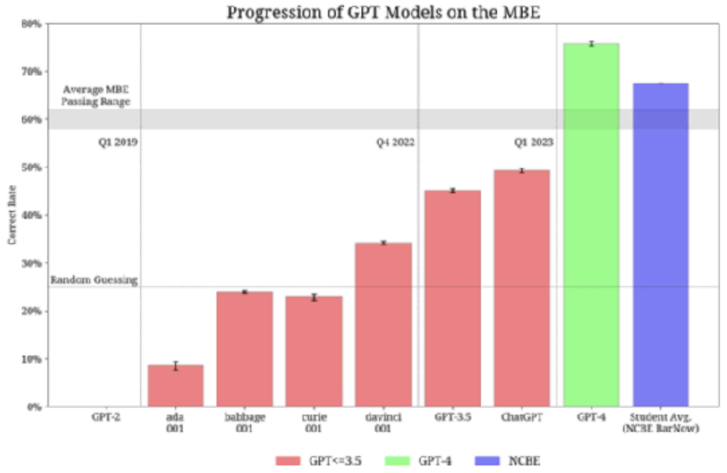

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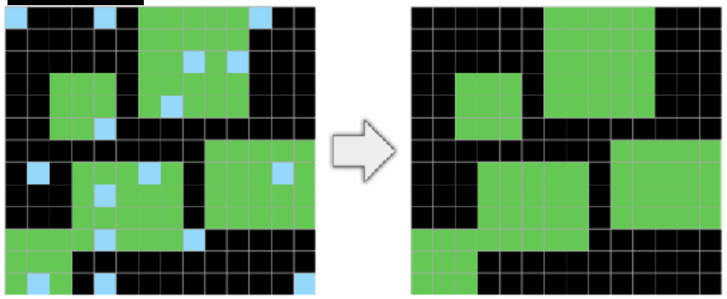

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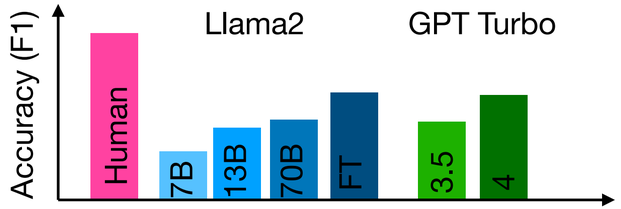

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Please.

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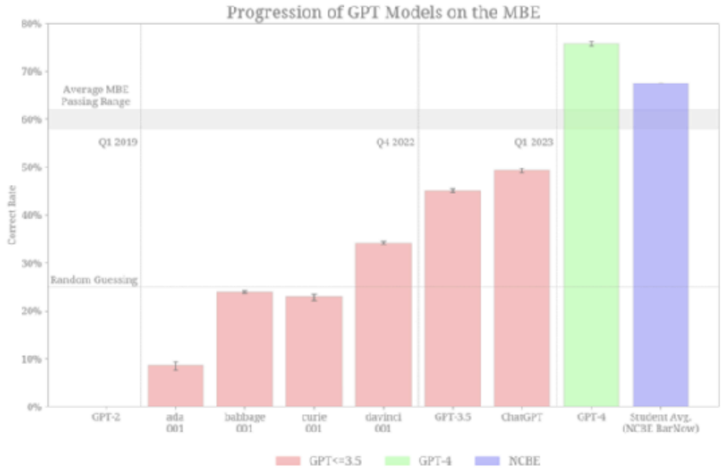

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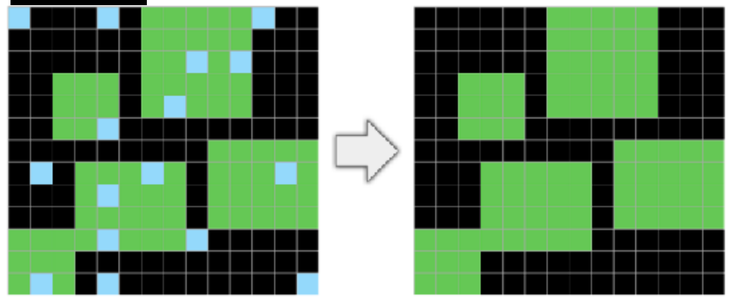

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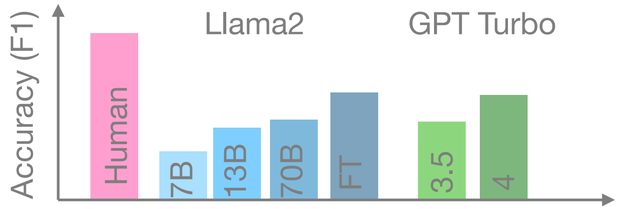

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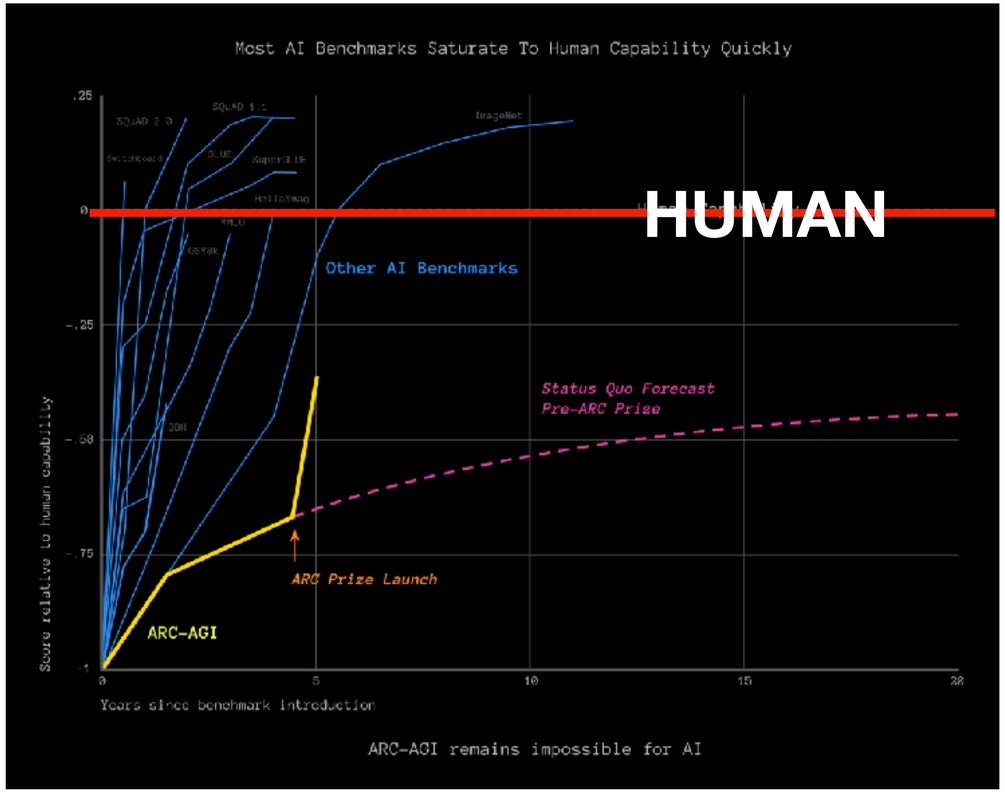
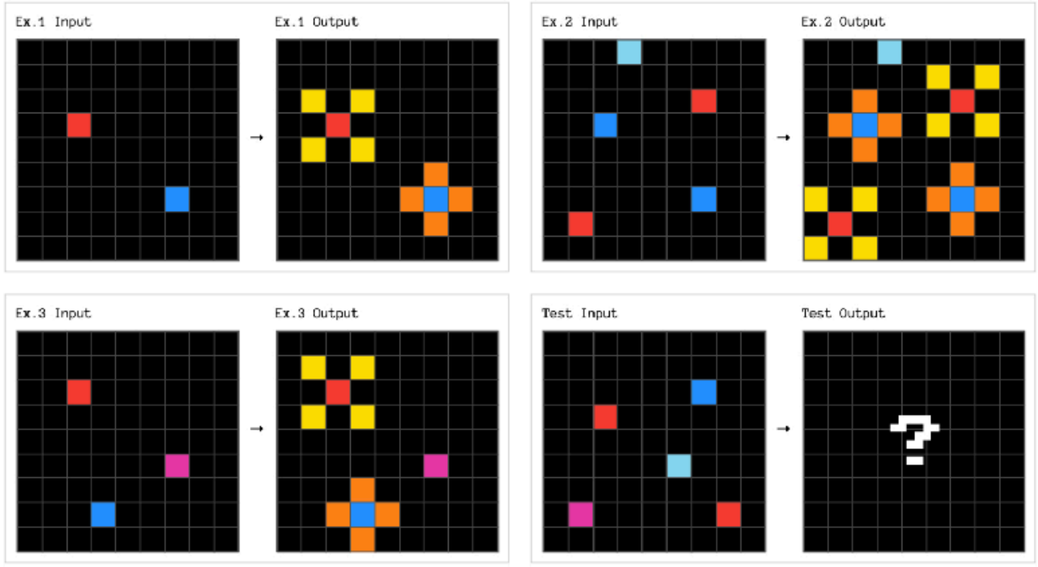
- $1+ million public competition, evaluated on a ***private*** dataset
  - 2024 winner: 53% performance; **grand prize still unclaimed**
  - You could probably get 100% (arcprize.org/)





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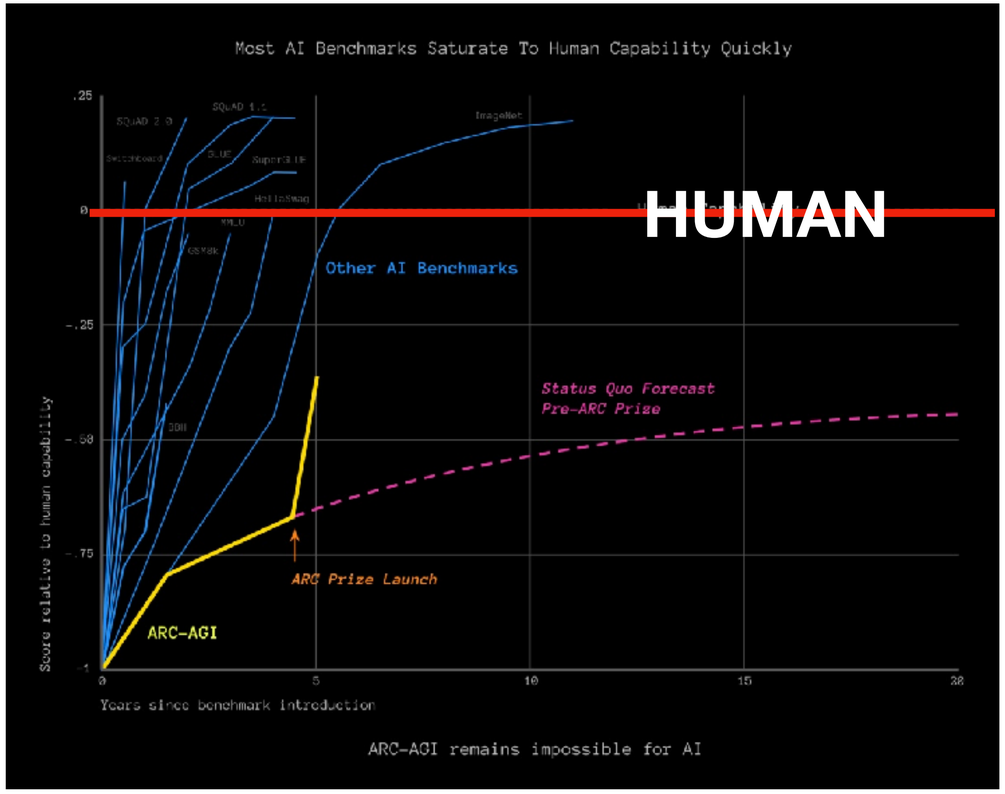
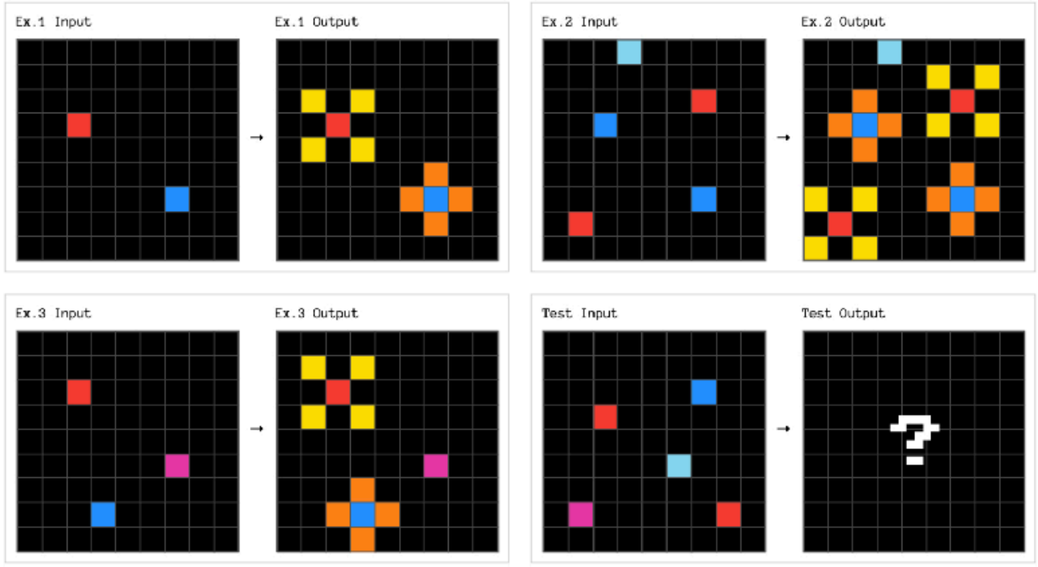
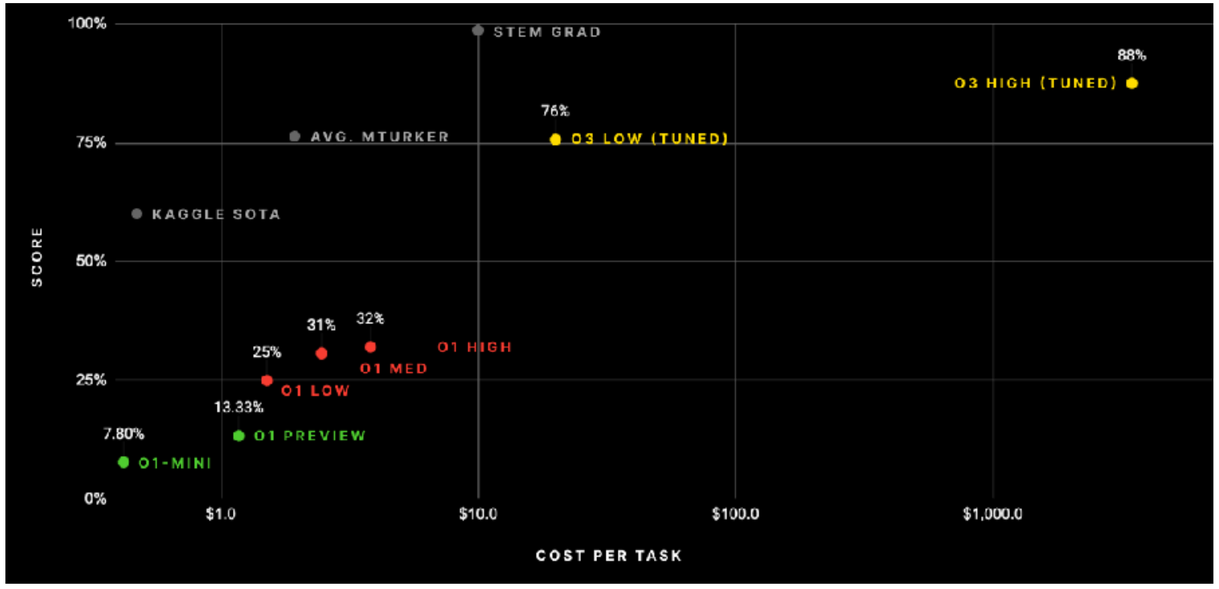


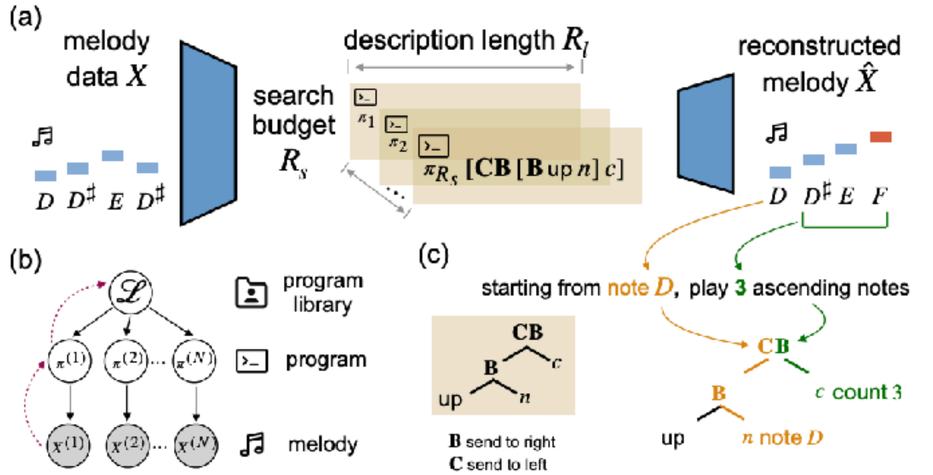


- **Public/semi-private** dataset evaluation results (exposed to commercial APIs and may have data leakage)

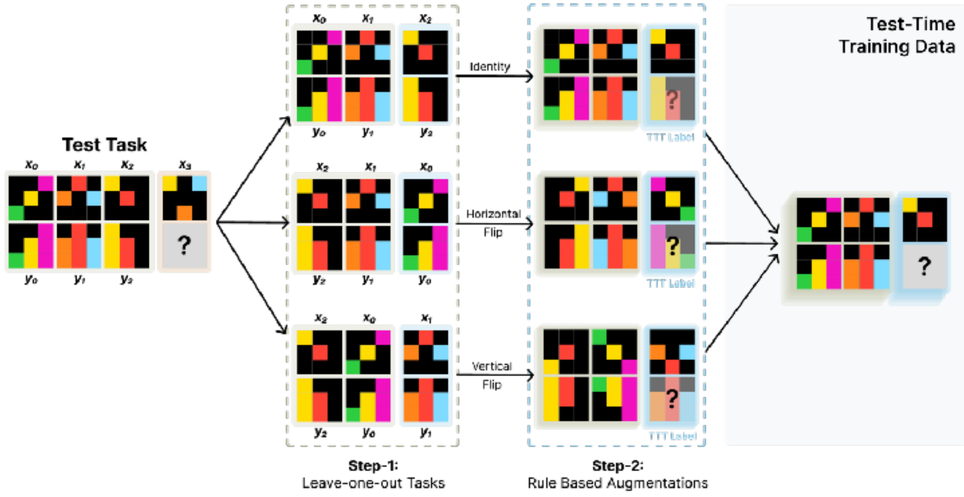


Towards AGI in 2025

- Two main ingredients are responsible for these latest improvements in the ARC challenge (Chollet et al., 2025)
  - **Deep learning-guided program synthesis**
    - Learn compositional and domain-general task-solving programs, rather than brute-force search
    - Programs are functions mapping inputs to outputs; but combinatorial explosion of potential functions makes search difficult
  - **Test-time training**
    - Models are typically trained on a large dataset, and then weights are frozen on the test set
    - Test-time training allows for the weights to change to adapt to the specific context of the task at test-time



Zhou, Nagy & Wu (2024)

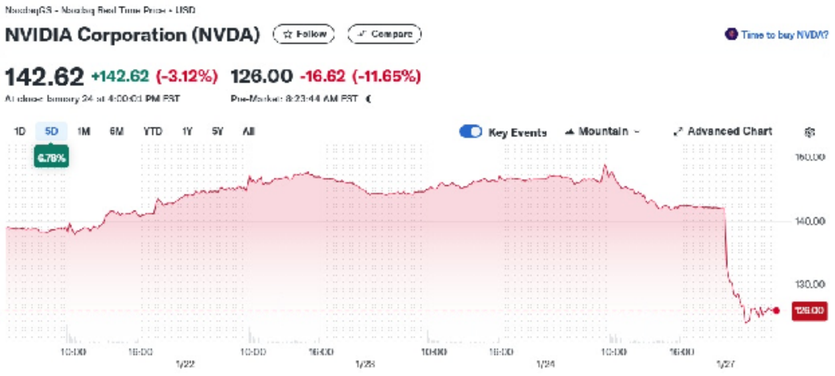


Akyürek et al., (2024)

Breaking news

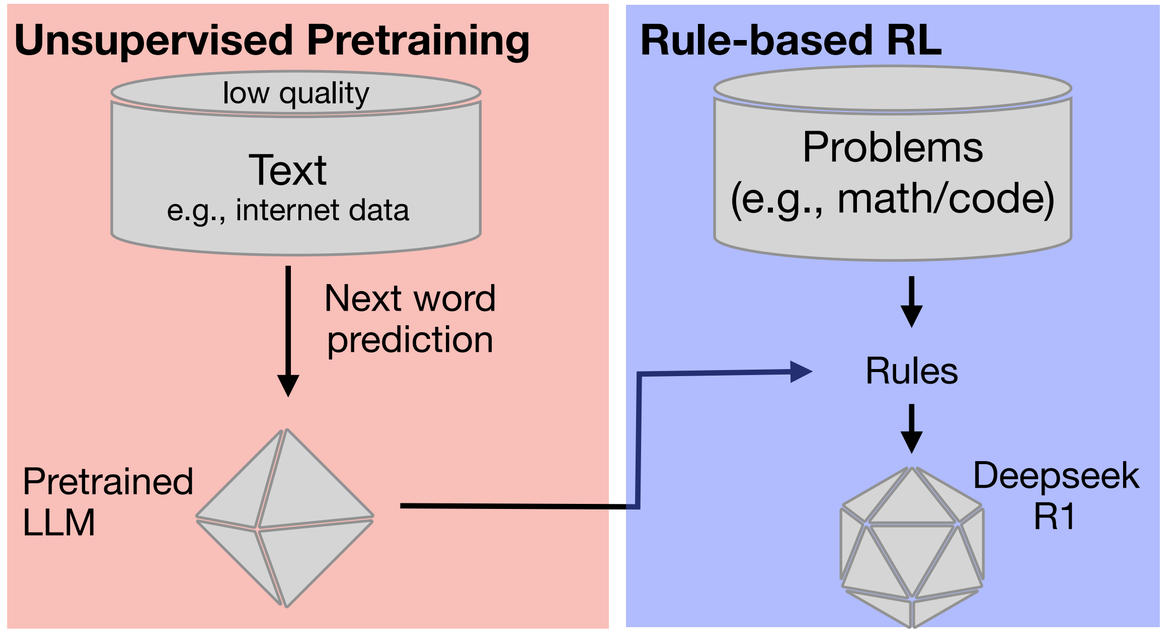
deepseek

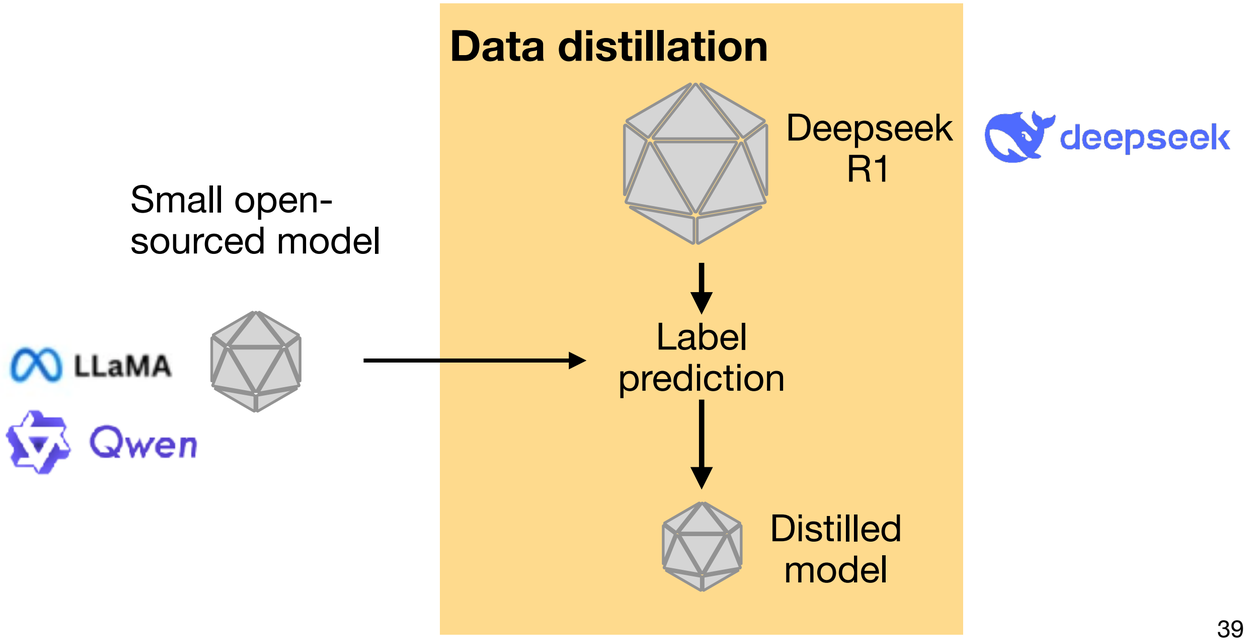
- New open-sourced model at orders of magnitude less cost
  - for training
  - and for inference
- Yesterday, tech stocks crashed, particularly NVIDIA



DeepSeek R1

- **Rule-based RL**
  - Skip SFT and RLHF
  - Do direct RL on the pretrained model to learn **rules**
    - Math/coding problems allow you to directly evaluate the correctness of answers
    - Sample a bunch of outputs and assign rewards, then learn the general rule
- **Data distillation to train smaller models**
  - Use a larger model to train a simpler one using SFT
    - Training small open-sourced models using R1 as the SFT data source achieves comparable performance fo GPT-4o



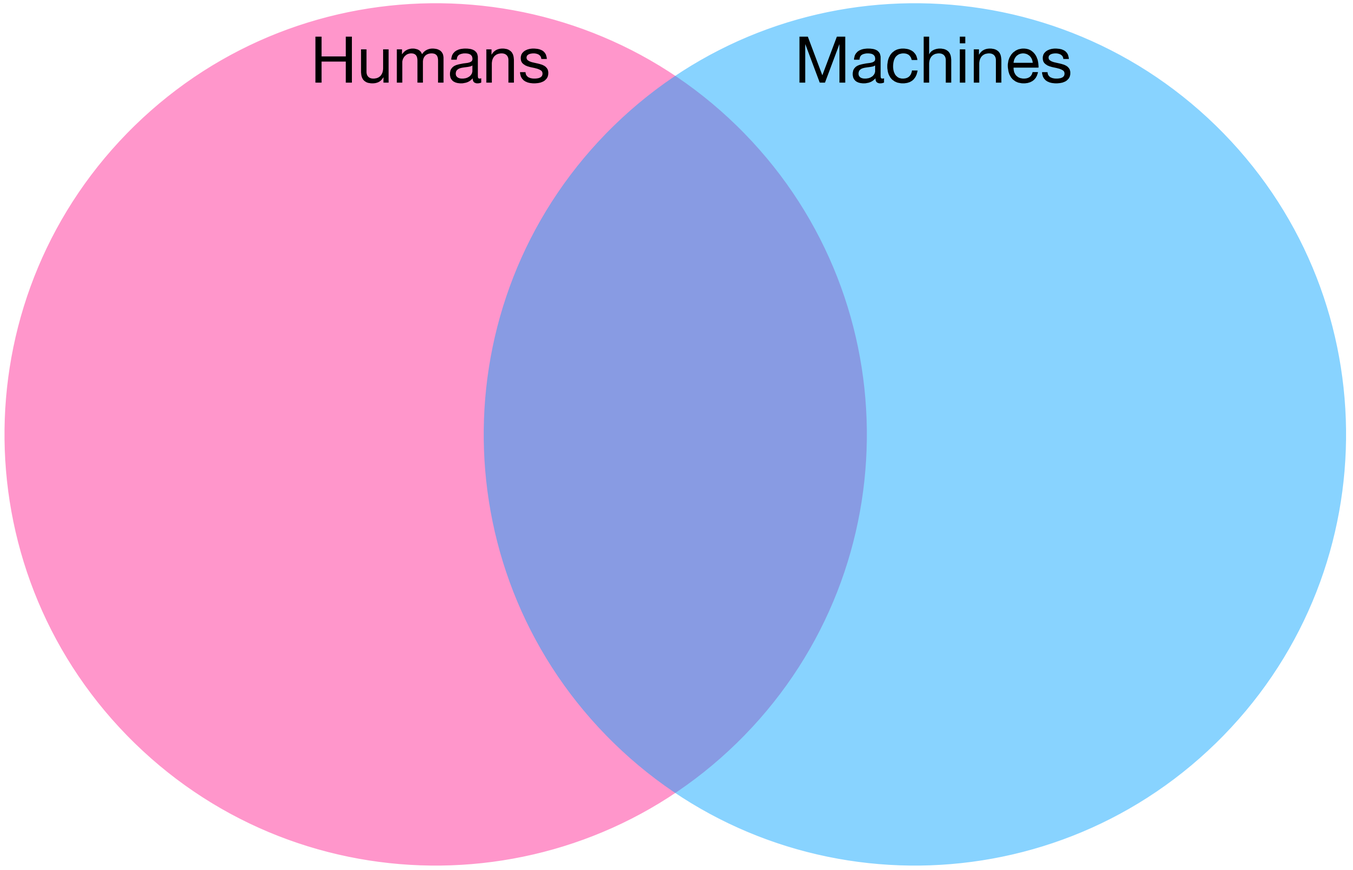


Summary

- Vector space representations of semantics (word embeddings) are a powerful tool for modeling language, where (cosine) *similarity* between vectors provides a means for *generalization*
- Semantic representations are (usually) learned via *predicting* which words come next and/or supervised labels provided by human trainers
- Attention provides a powerful mechanism to contextualize semantic representations, using transformation of Query, Key, and Value matrices to encode *relational structure*
- Adding RLHF and massively more parameters by hierarchically stacking transformer networks plays a large role in how we got chatGPT
  - But new methods from DeepSeek (rule-based RL and data distillation) are massively changing the playing field, with better performance at a fraction of the training costs
- Although some shared principles (e.g., similarity, prediction, relational structure), the learning mechanisms and scale of training data is quite distinct from human learning
  - LLMs haven't solved the poverty of the stimulus problem, since they have a glut of experience; ARC performance orders of magnitude more costly
  - Still an open question humans obtain "infinitely more than we experience"

Next week

General Principles + Exam Prep



- For **next week's tutorial,** please prepare 2-3 candidate exam questions:
  - Short answer question format
  - You are incentivized to bring plausible questions that would be sufficiently challenging, thought provoking, and feasible
  - Good questions will be included on the exam