CS 188: Artificial Intelligence

Large Language Models and Transformers

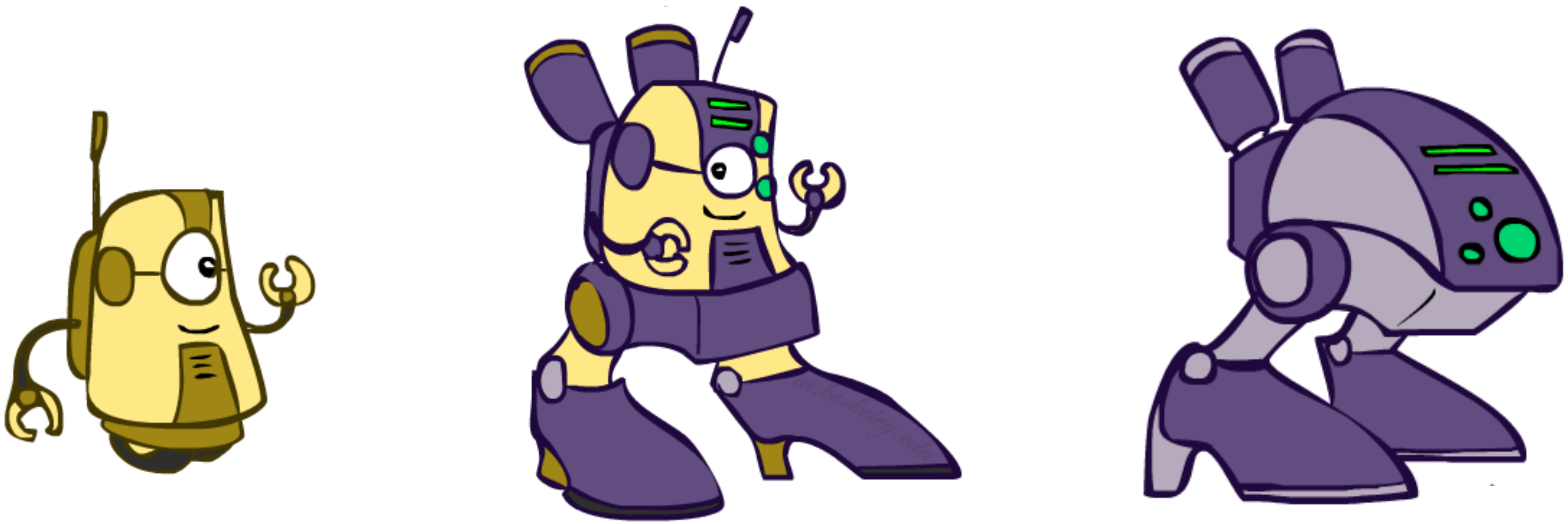
Instructor: Oliver Grillmeyer --- University of California, Berkeley

[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at http://ai.berkeley.edu.]

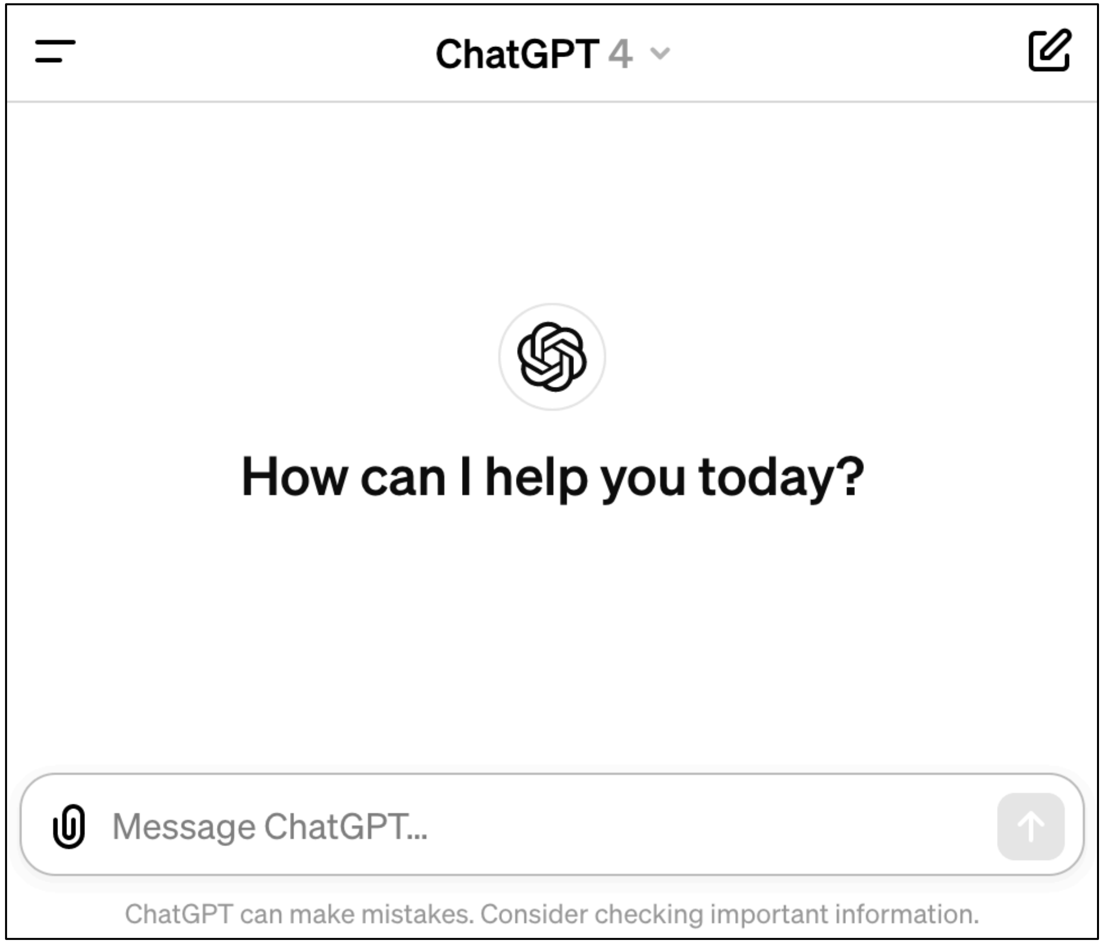
Announcements

- HW9 is due **Tuesday, August 5**, 11:59 PM PT
- HW10 is due **Thursday, August 7**, 11:59 PM PT
- Project 5 is due **Friday, August 8**, 11:59 PM PT
- Ignore assessment on HWs part B, but please show your work
- Final Exam is **Wednesday, August 13**, 7-10 PM PT

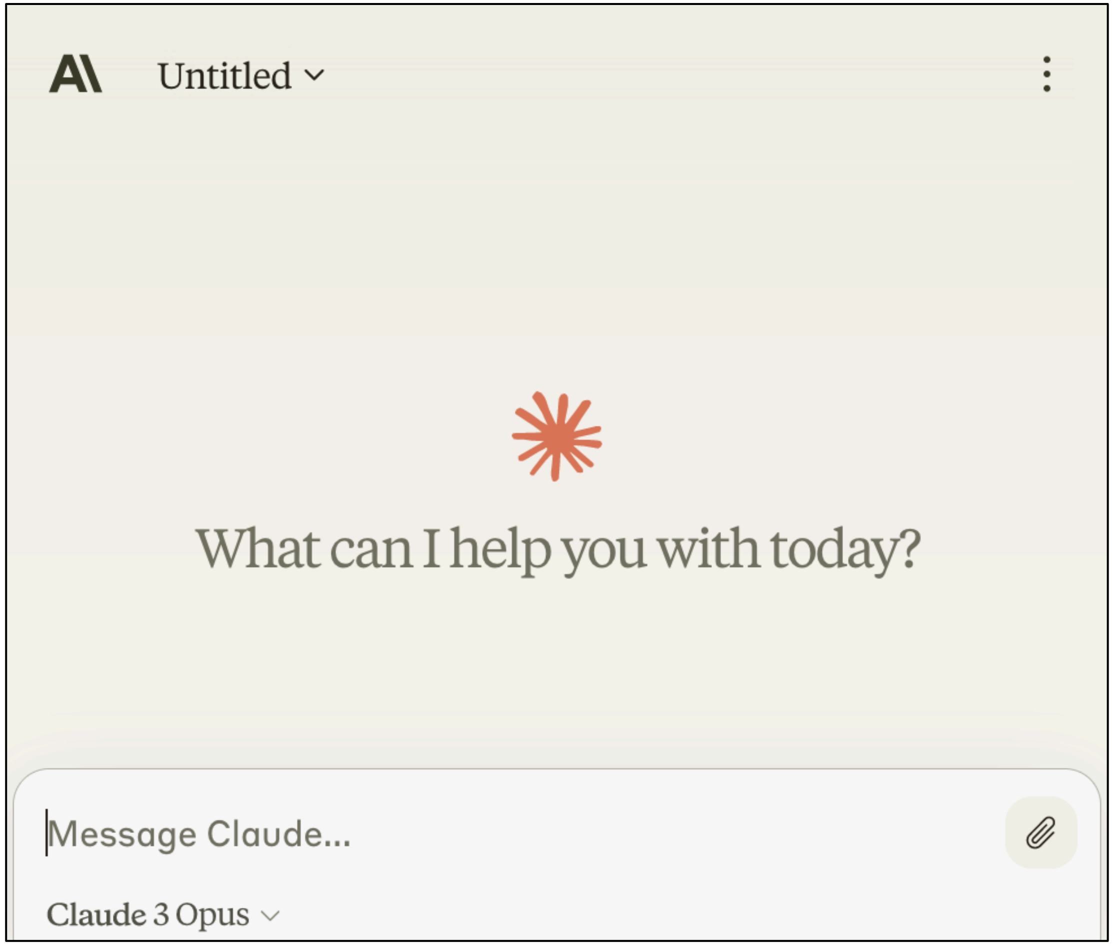
Large Language Model Transformers



Today’s AI



ChatGPT 4
How can I help you today?
Message ChatGPT...
ChatGPT can make mistakes. Consider checking important information.

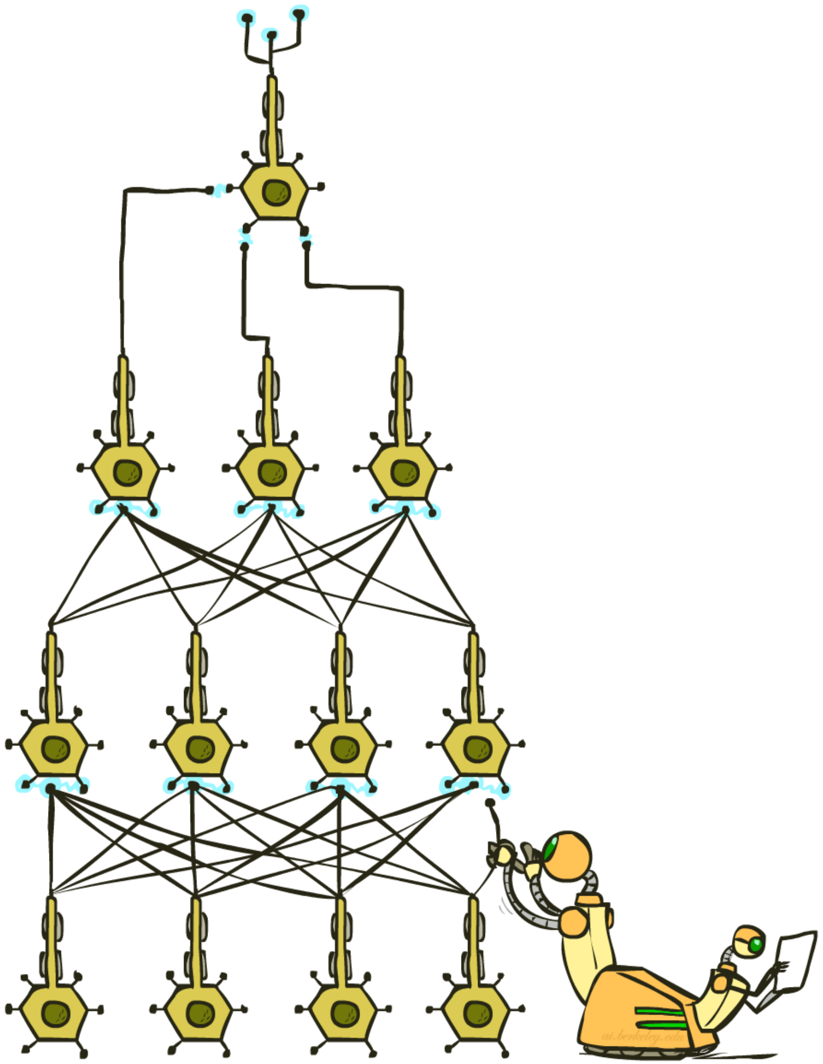


Untitled
What can I help you with today?
Message Claude...
Claude 3 Opus

Large Language Models

- Feature engineering
  - Text tokenization
  - Word embeddings
- Deep neural networks
  - Autoregressive models
  - Self-attention mechanisms
  - Transformer architecture
- Multi-class classification
- Supervised learning
  - Self-supervised learning
  - Instruction tuning
- Reinforcement learning
  - … from human feedback (RLHF)
- Policy search
  - Policy gradient methods
- Beam search

Deep Neural Networks



- Input: some text
  - "The dog chased the"
- Output: more text
  - … " ball"
- Implementation:
  - Linear algebra
  - How??

Text Tokenization

GPT-3.5 & GPT-4 GPT-3 (Legacy)

Many words map to one token, but some don't: indivisible.

Unicode characters like emojis may be split into many tokens containing the underlying bytes: 🤚🏾

Sequences of characters commonly found next to each other may be grouped together: 1234567890

Clear Show example

Tokens	Characters
57	252

https://platform.openai.com/tokenizer

Text Tokenization

GPT-3.5 & GPT-4 GPT-3 (Legacy)

Many words map to one token, but some don't: indivisible.

Unicode characters like emojis may be split into many tokens containing the underlying bytes: ������

Sequences of characters commonly found next to each other may be grouped together: 1234567890

Text Token IDs

Tokens 57

Characters 252

https://platform.openai.com/tokenizer

Text Tokenization

GPT-3.5 & GPT-4 GPT-3 (Legacy)

[8607, 4339, 2472, 311, 832, 4037, 11, 719, 1063, 1541, 956, 25, 3687, 23936, 382, 35020, 5885, 1093, 100166, 1253, 387, 6859, 1139, 1690, 11460, 8649, 279, 16940, 5943, 25, 11410, 97, 248, 9468, 237, 122, 271, 1542, 45045, 315, 5885, 17037, 1766, 1828, 311, 1855, 1023, 1253, 387, 41141, 3871, 25, 220, 4513, 10961, 16474, 15]

Text Token IDs

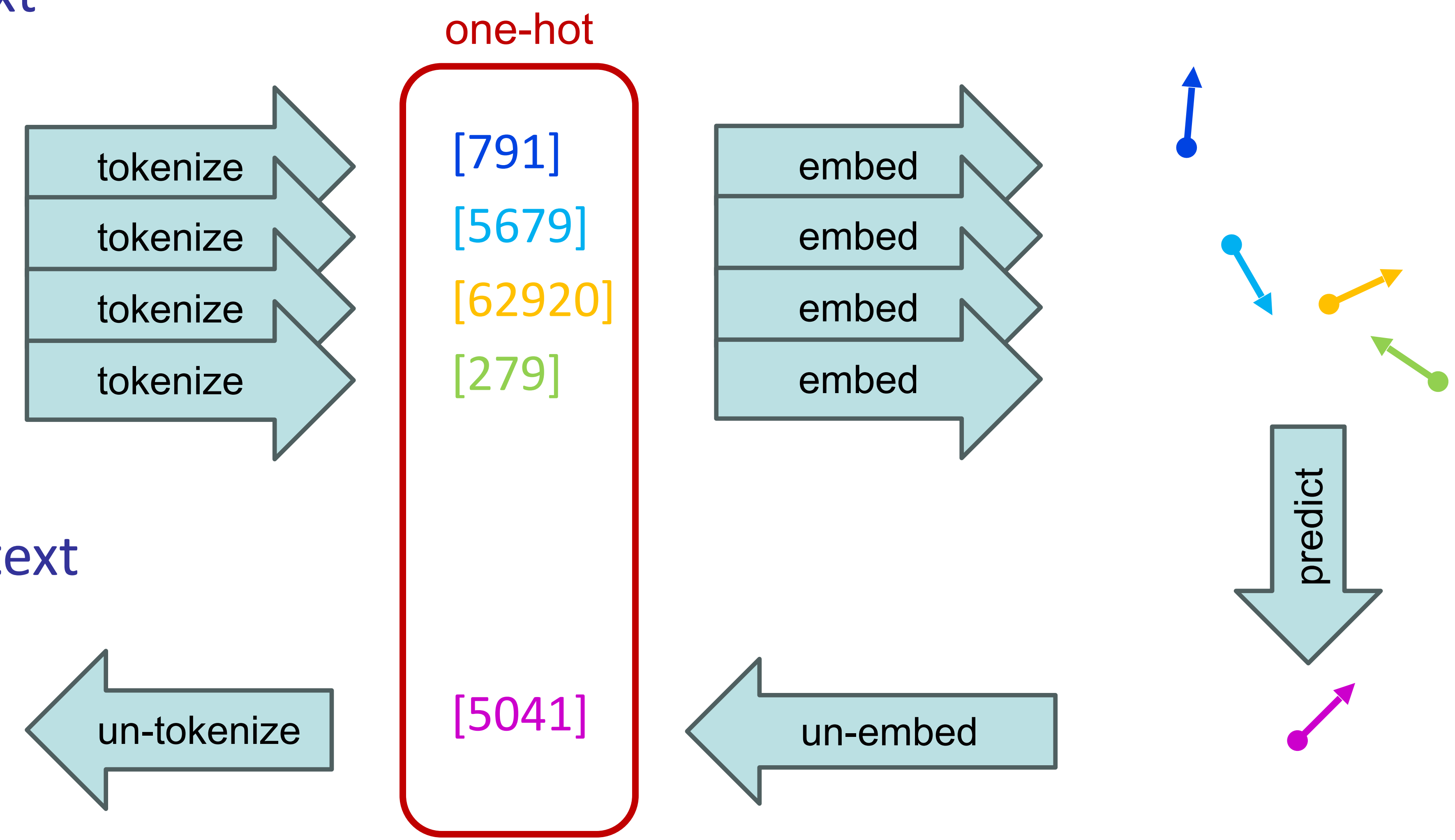
Tokens
57

Characters
252

https://platform.openai.com/tokenizer

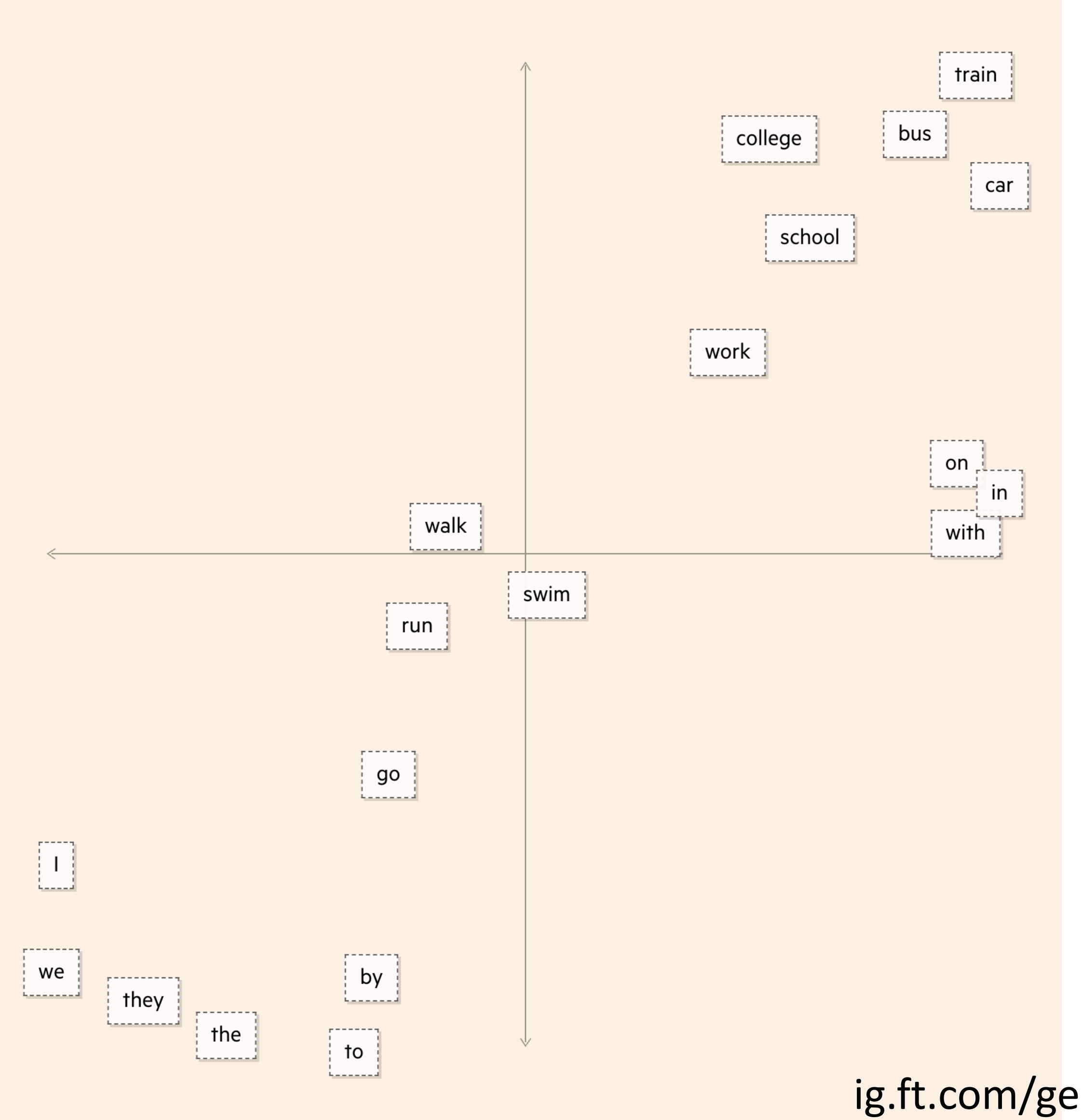
Word Embeddings

- Input: some text
  - “The”
  - “ dog”
  - “ chased”
  - “ the”
- Output: more text
  - “ ball”



What do word embeddings look like?

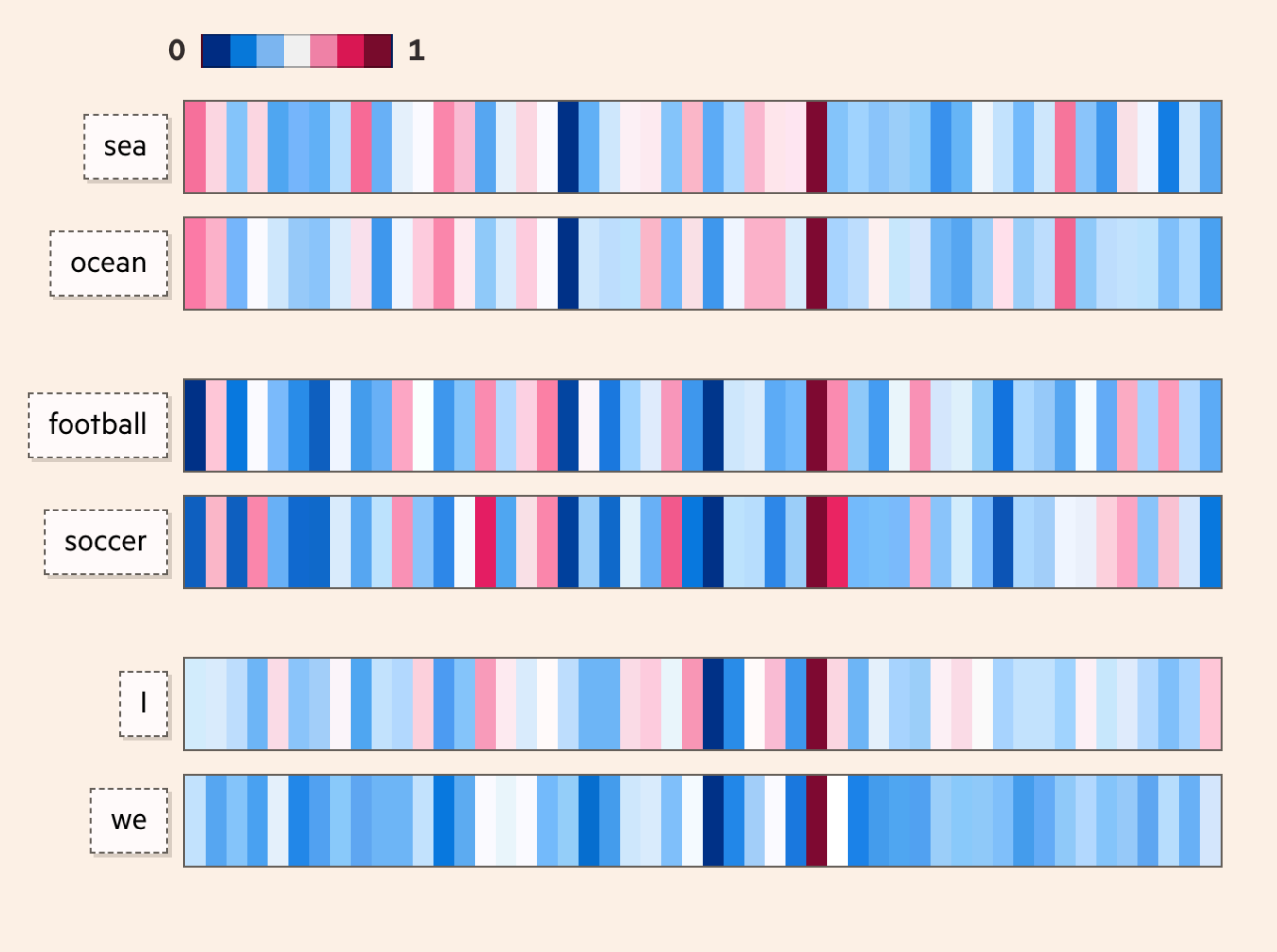
- Words cluster by similarity:



ig.ft.com/generative-ai

What do word embeddings look like?

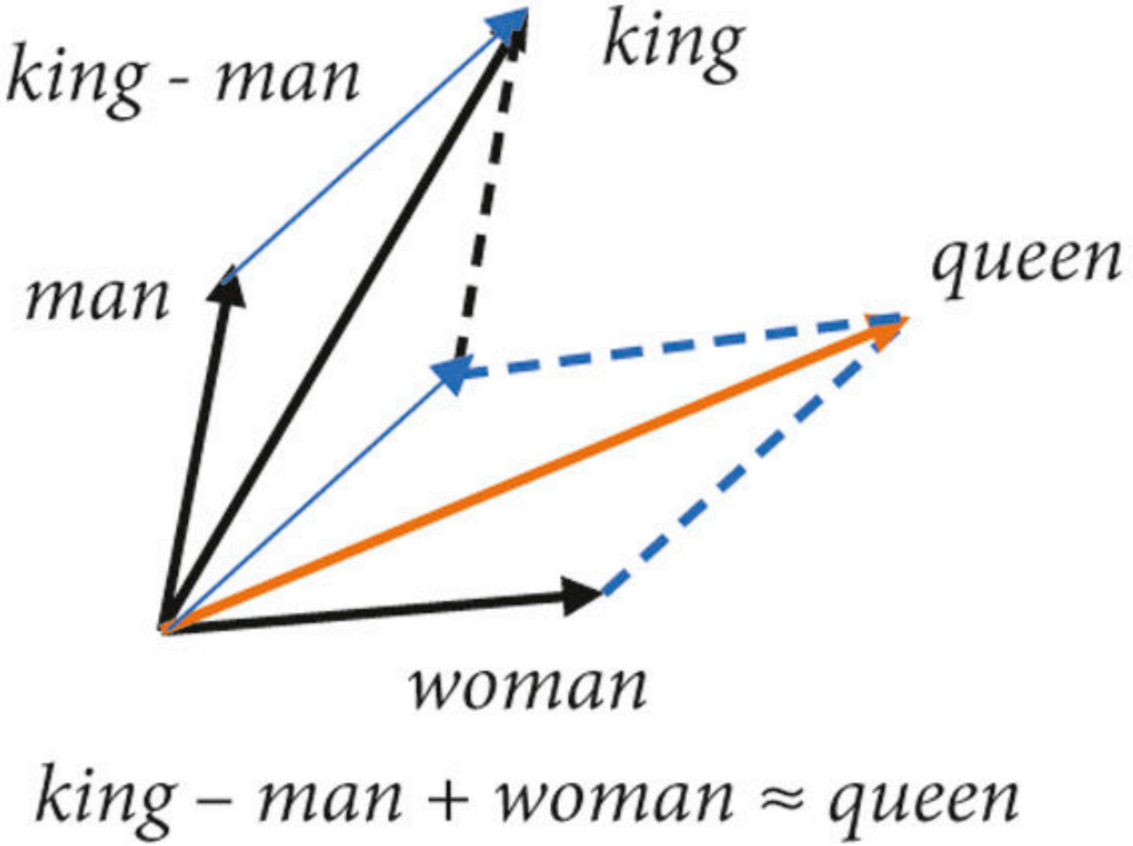
- Features learned in language models:



ig.ft.com/generative-ai

What do word embeddings look like?

- Signs of sensible algebra in embedding space:



[Efficient estimation of word representations in vector space, Mikolov et al, 2013]

Aside: interactive explainer of modern language models

ig.ft.com/generative-ai

Artificial Intelligence

Generative AI exists because of the transformer

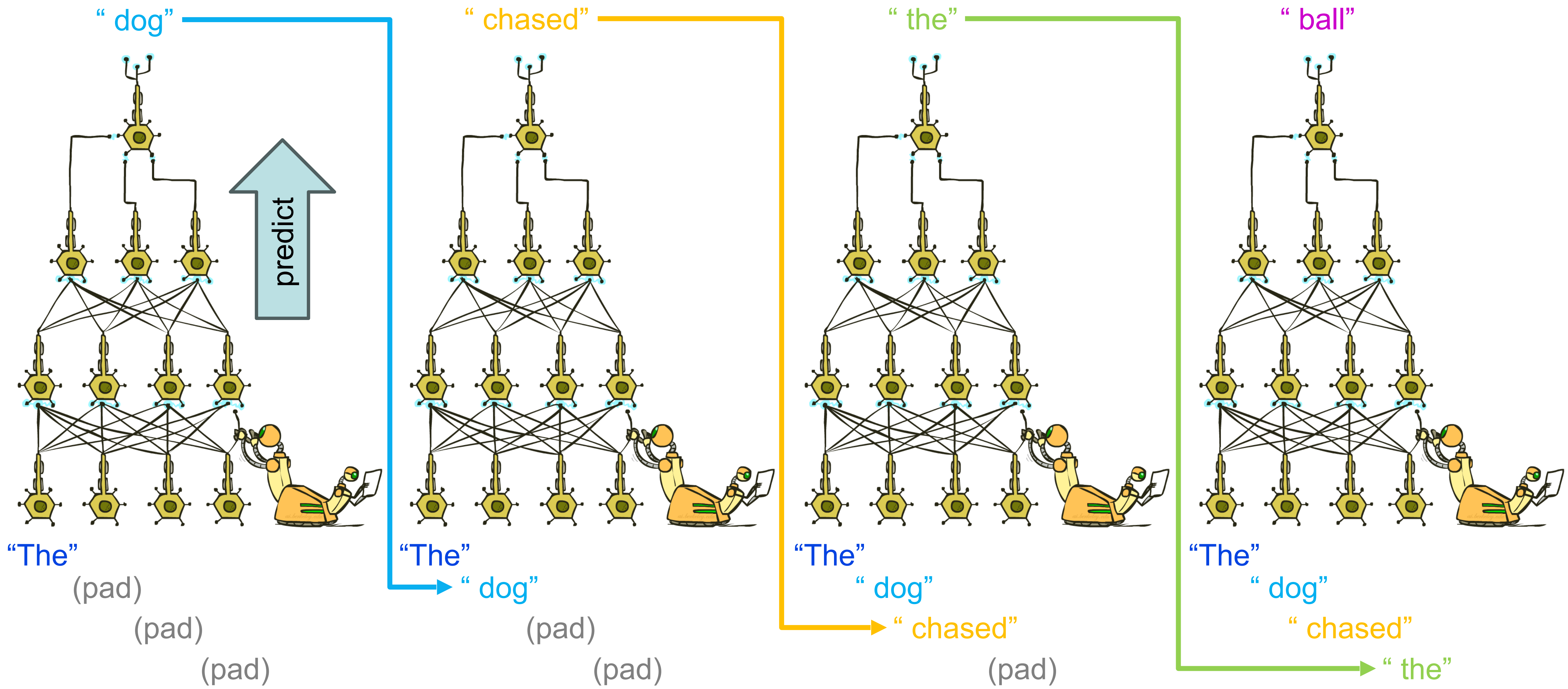
This **is** **how** **it** **works**

By **Visual Storytelling Team** and **Madhumita Murgia** in London SEPTEMBER 11 2023

Large Language Models

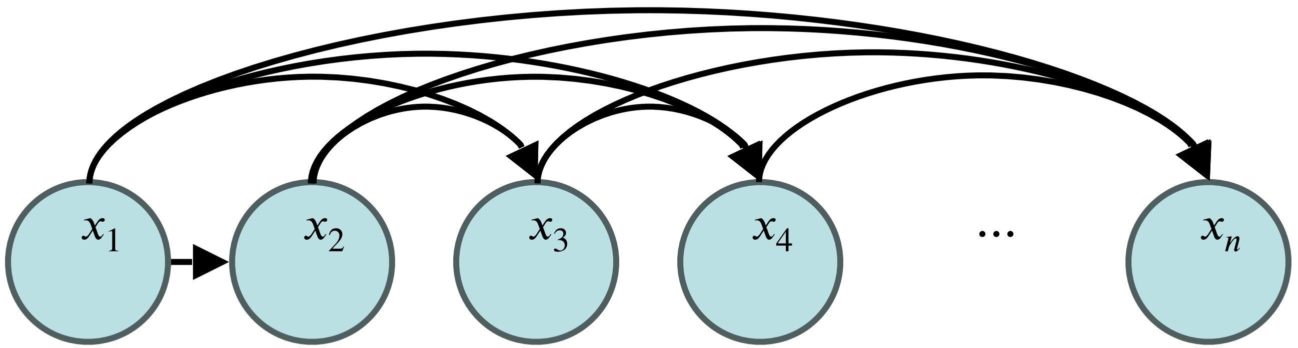
- ~~Feature engineering~~
  - ~~Text tokenization~~
  - ~~Word embeddings~~
- Deep neural networks
  - Autoregressive models
  - Self-attention mechanisms
  - Transformer architectures
- Multi-class classification
- Supervised learning
  - Self-supervised learning
  - Instruction tuning
- Reinforcement learning
  - … from human feedback (RLHF)
- Policy search
  - Policy gradient methods
- Beam search

Autoregressive Models

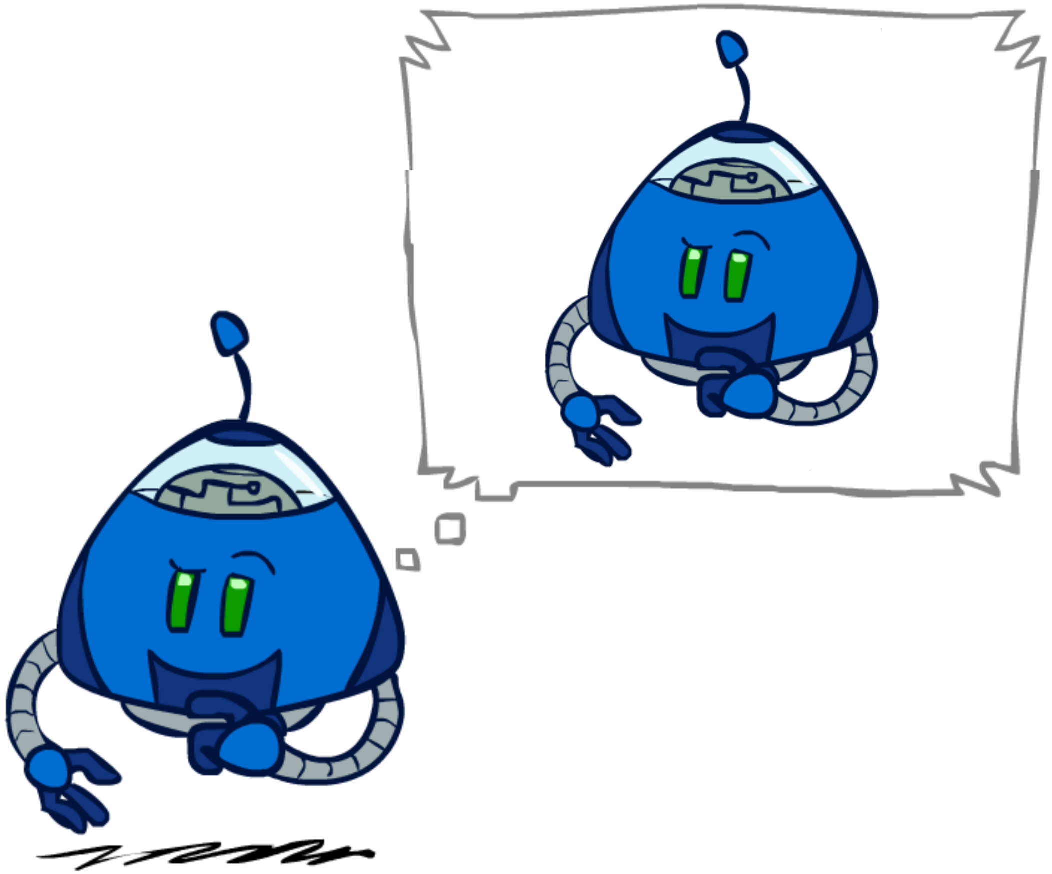


Autoregressive Models

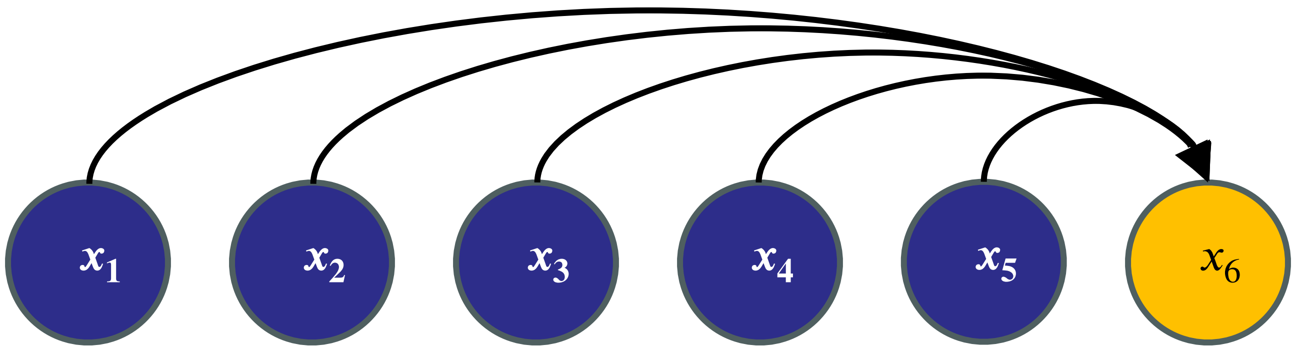
- Predict output one piece at a time (e.g. word, token, pixel, etc.)
- Concatenate: input + output
- Feed result back in as new input
- Repeat



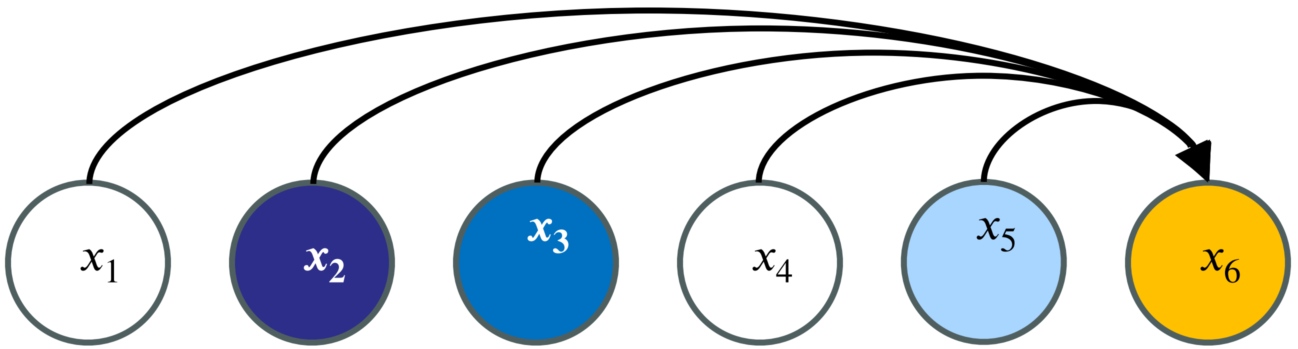
Self-Attention Mechanisms



Self-Attention Mechanisms

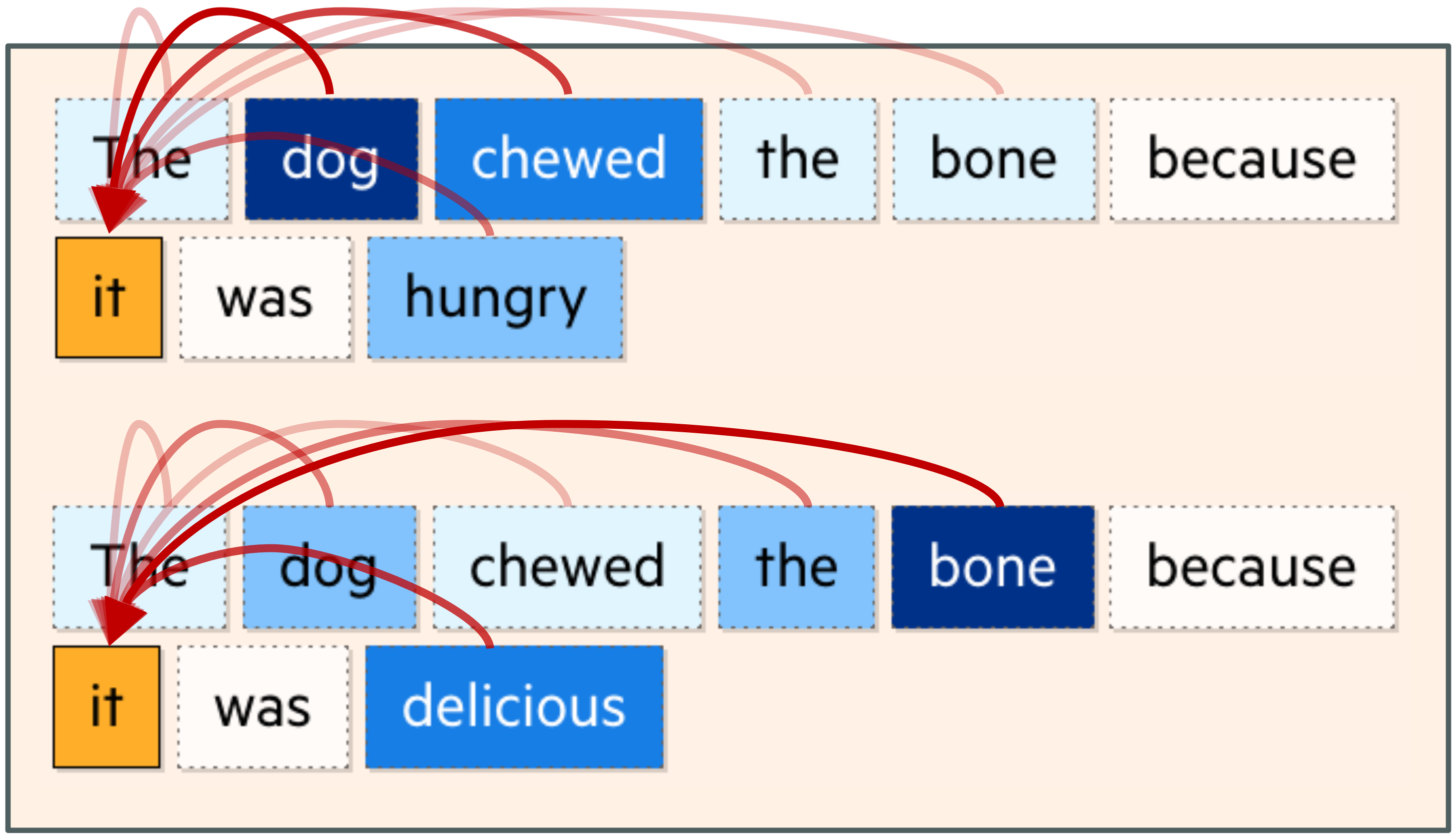


- Instead of conditioning on *all* input tokens equally…

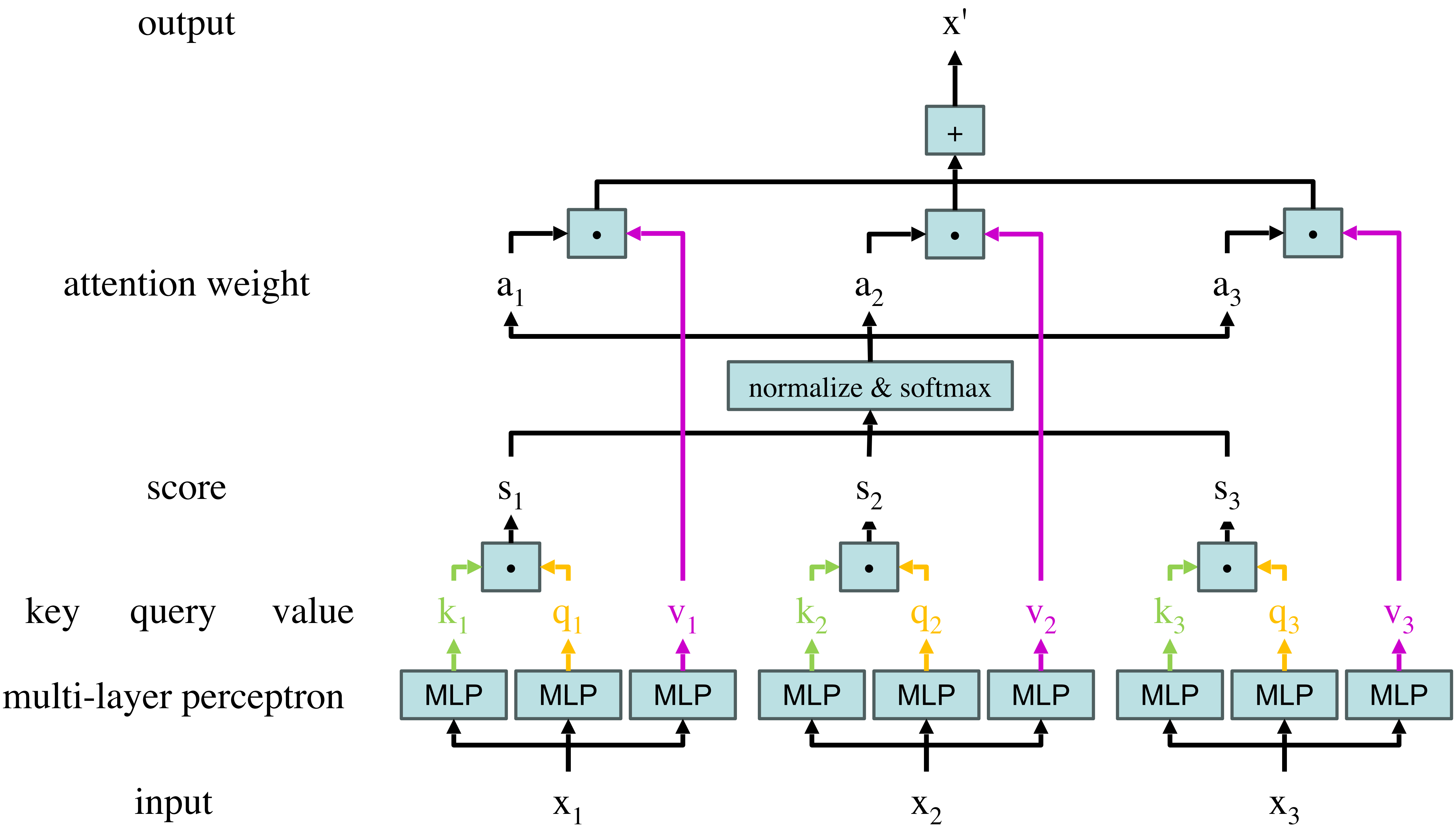


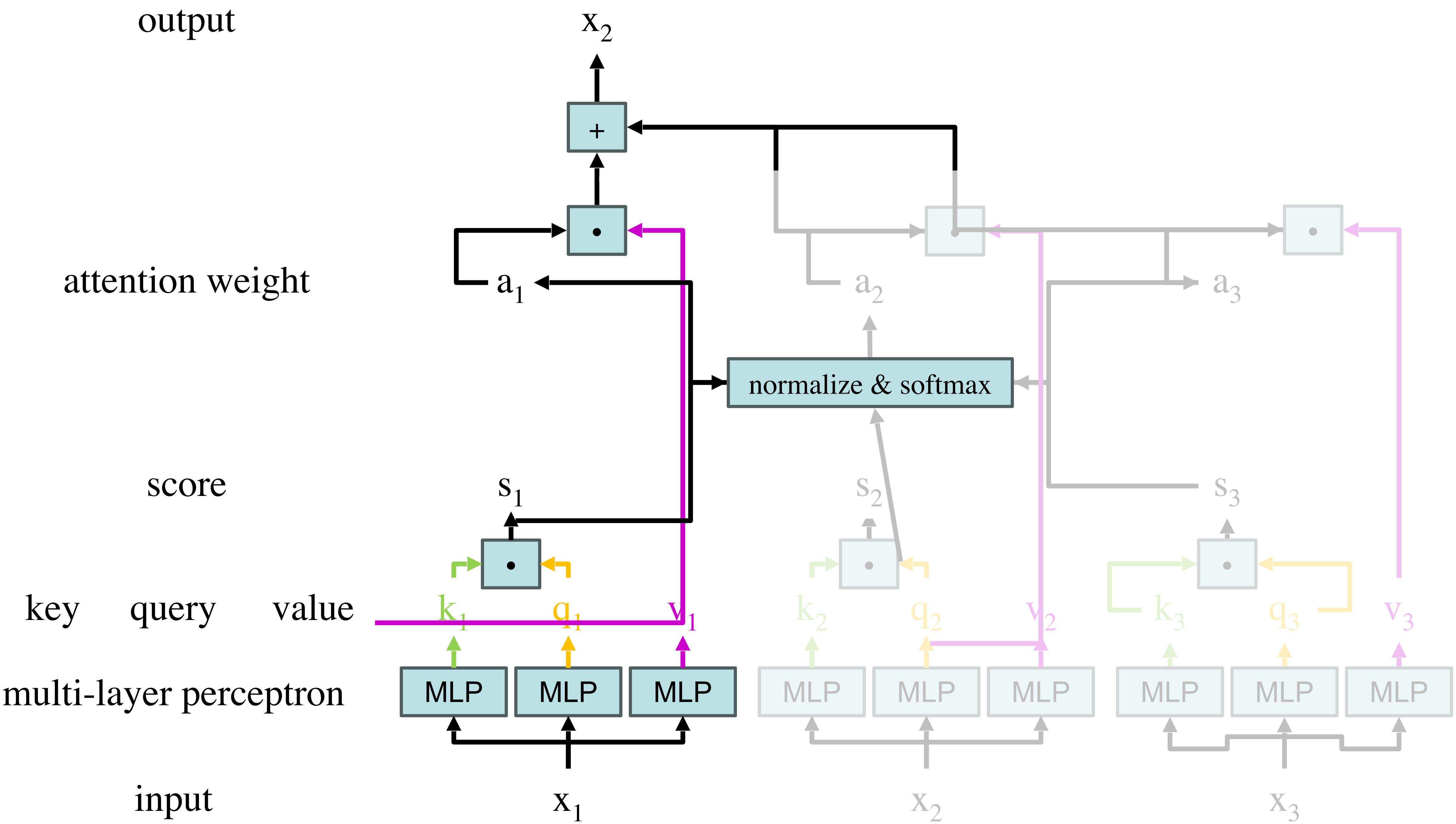
- Pay more attention to relevant tokens!

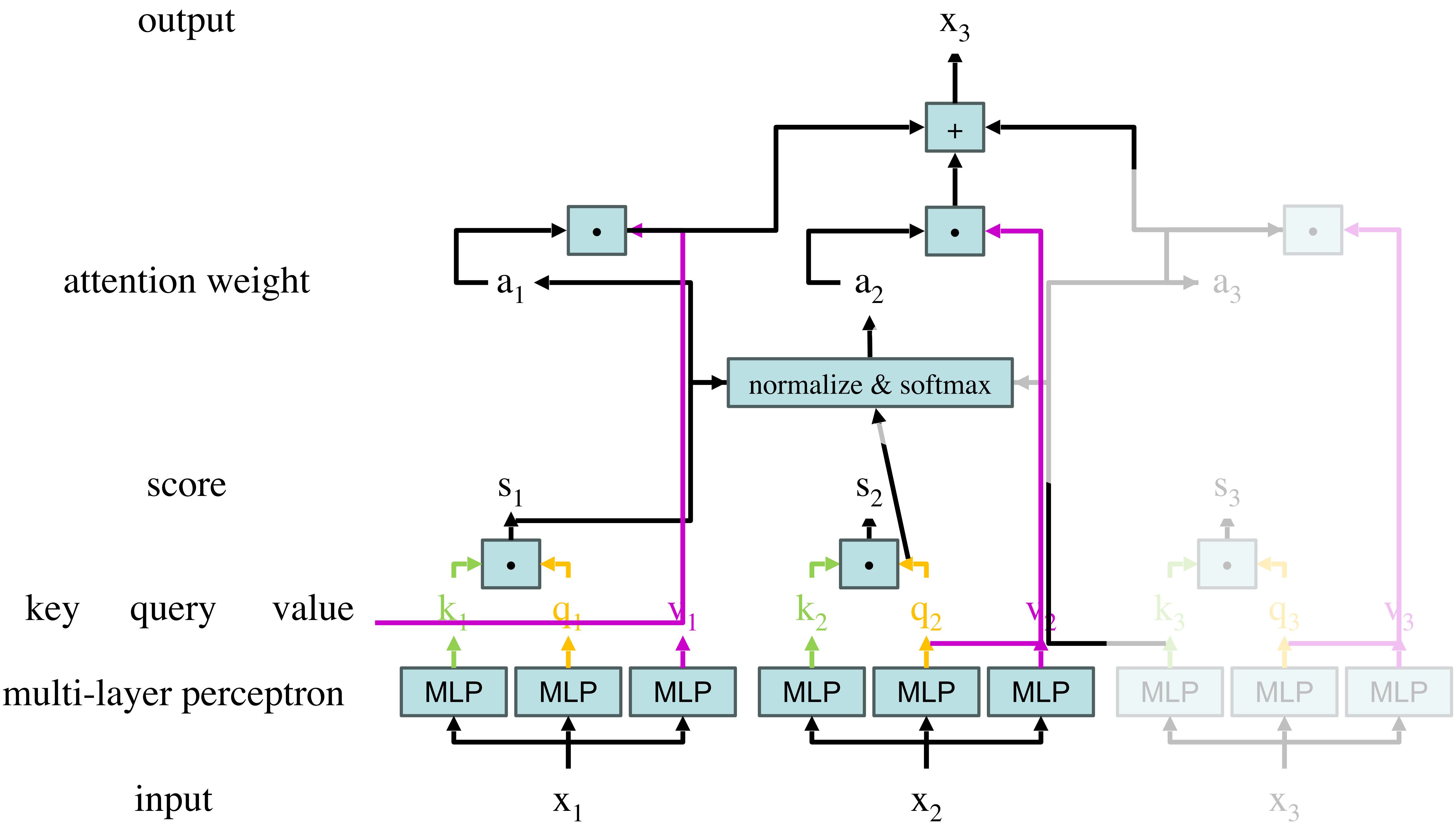
Self-Attention Mechanisms

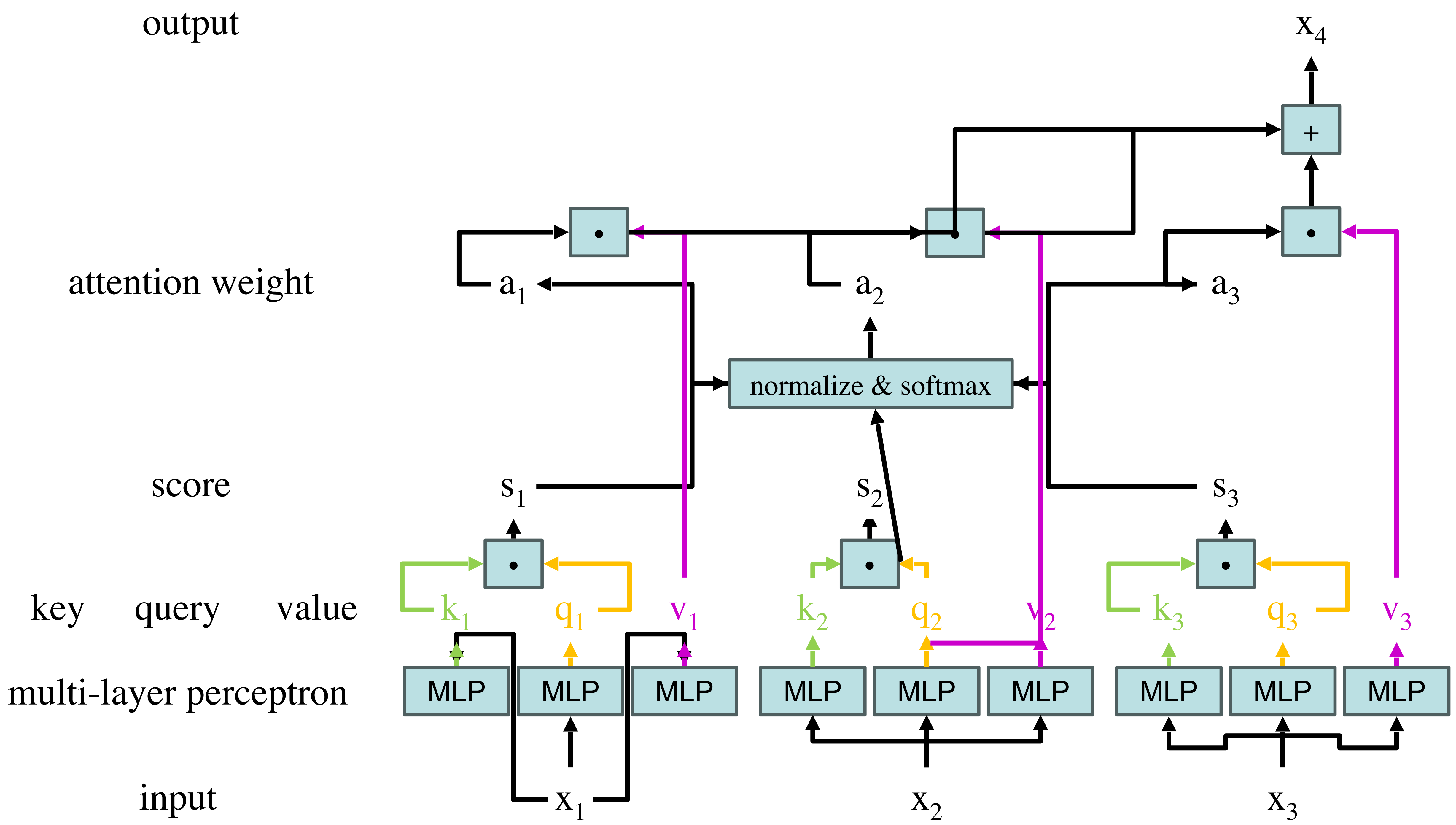


ig.ft.com/generative-ai


output
x'
+
attention weight
a_1
a_2
a_3
normalize & softmax
score
s_1
s_2
s_3
key
query
value
k_1
q_1
v_1
k_2
q_2
v_2
k_3
q_3
v_3
multi-layer perceptron
MLP
input
x_1
x_2
x_3

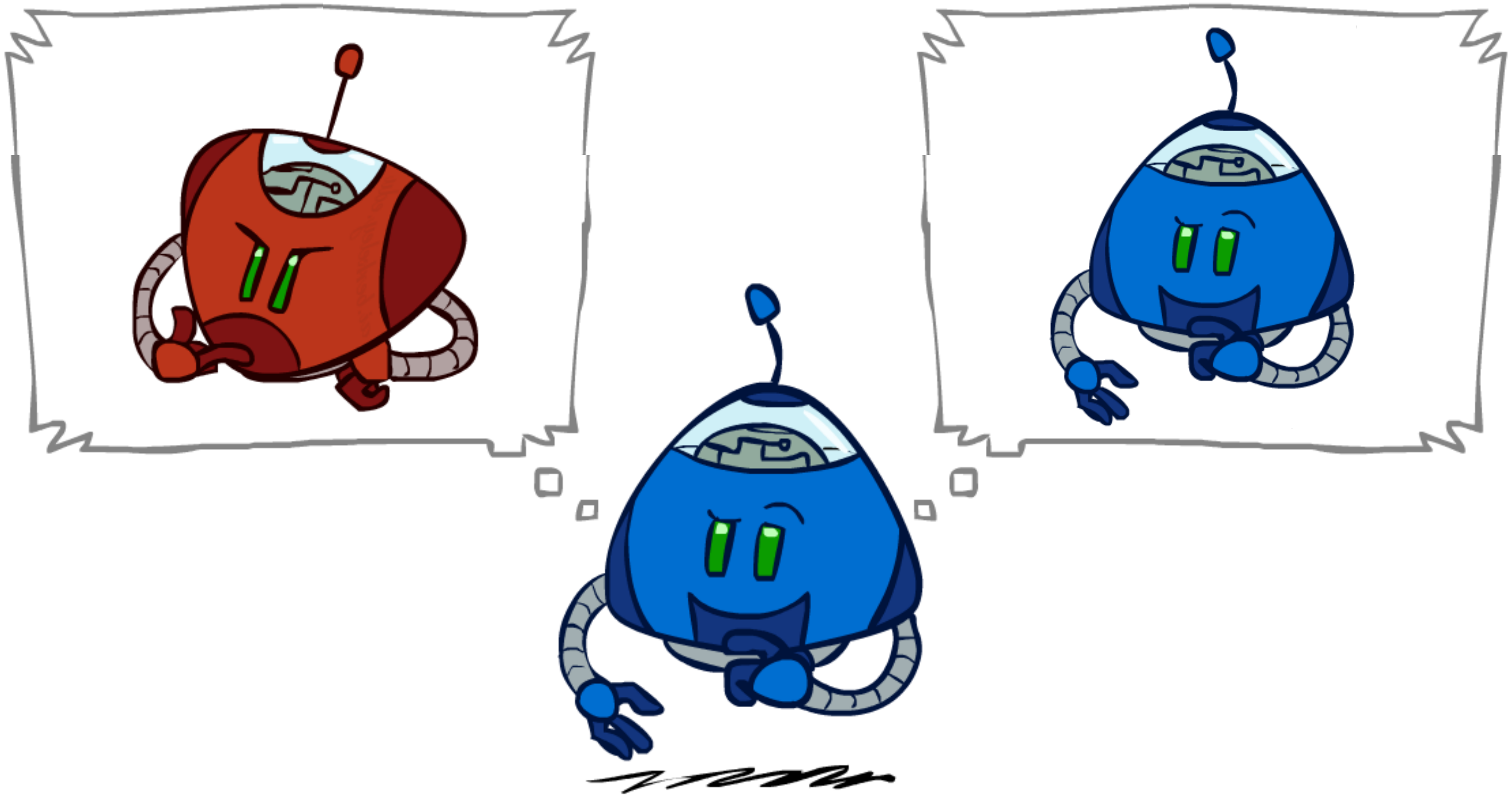

output
attention weight
score
key
query
value
multi-layer perceptron
input
x_2
+
a_1
a_2
a_3
normalize & softmax
s_1
s_2
s_3
k_1
q_1
v_1
k_2
q_2
v_2
k_3
q_3
v_3
MLP
x_1
x_2
x_3


output
x_3
attention weight
a_1
a_2
a_3
normalize & softmax
score
s_1
s_2
s_3
key
query
value
k_1
q_1
v_1
k_2
q_2
v_2
k_3
q_3
v_3
multi-layer perceptron
MLP
MLP
MLP
MLP
MLP
MLP
MLP
MLP
MLP
input
x_1
x_2
x_3



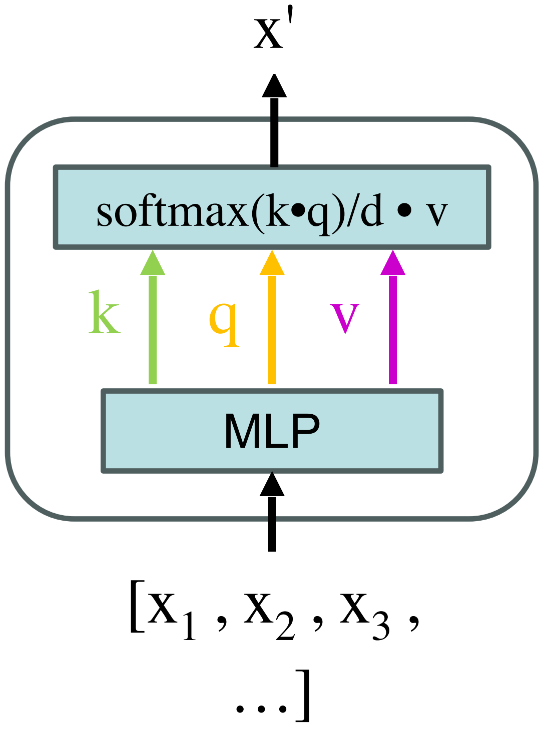
output
attention weight
score
key
query
value
multi-layer perceptron
input
x_4
+
a_1
a_2
a_3
normalize & softmax
s_1
s_2
s_3
k_1
q_1
v_1
k_2
q_2
v_2
k_3
q_3
v_3
MLP
MLP
MLP
MLP
MLP
MLP
MLP
MLP
MLP
x_1
x_2
x_3

Multi-Headed Attention

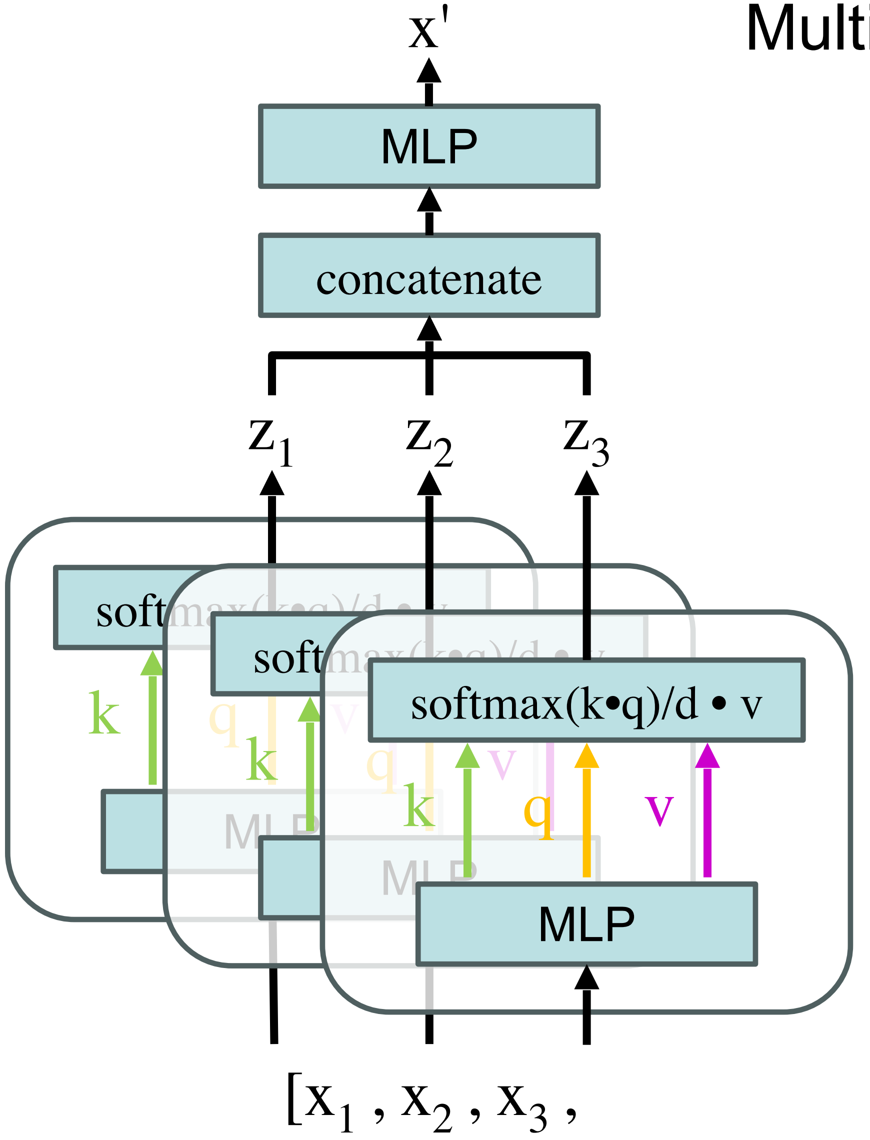


Multi-Headed Attention

Single-headed

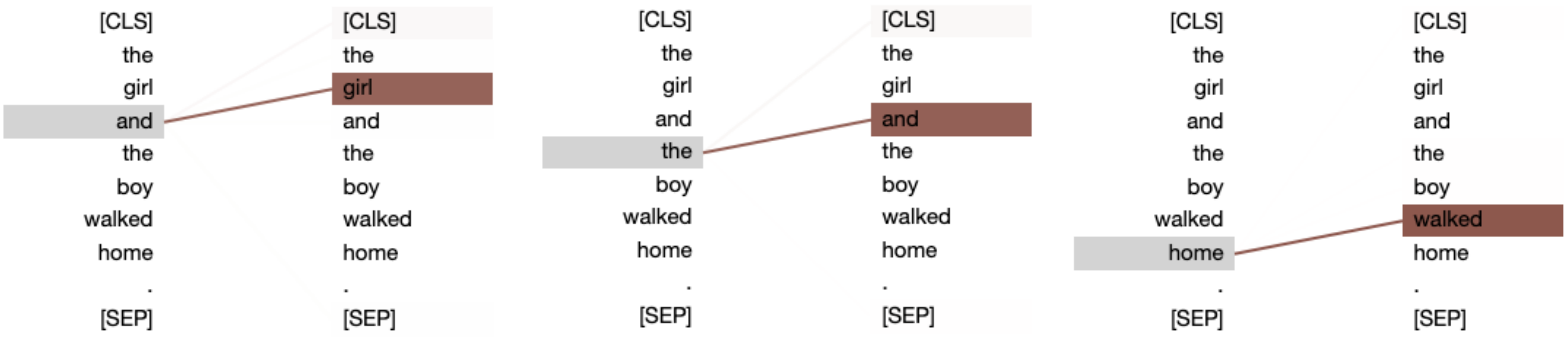


Multi-headed



Multi-Headed Attention

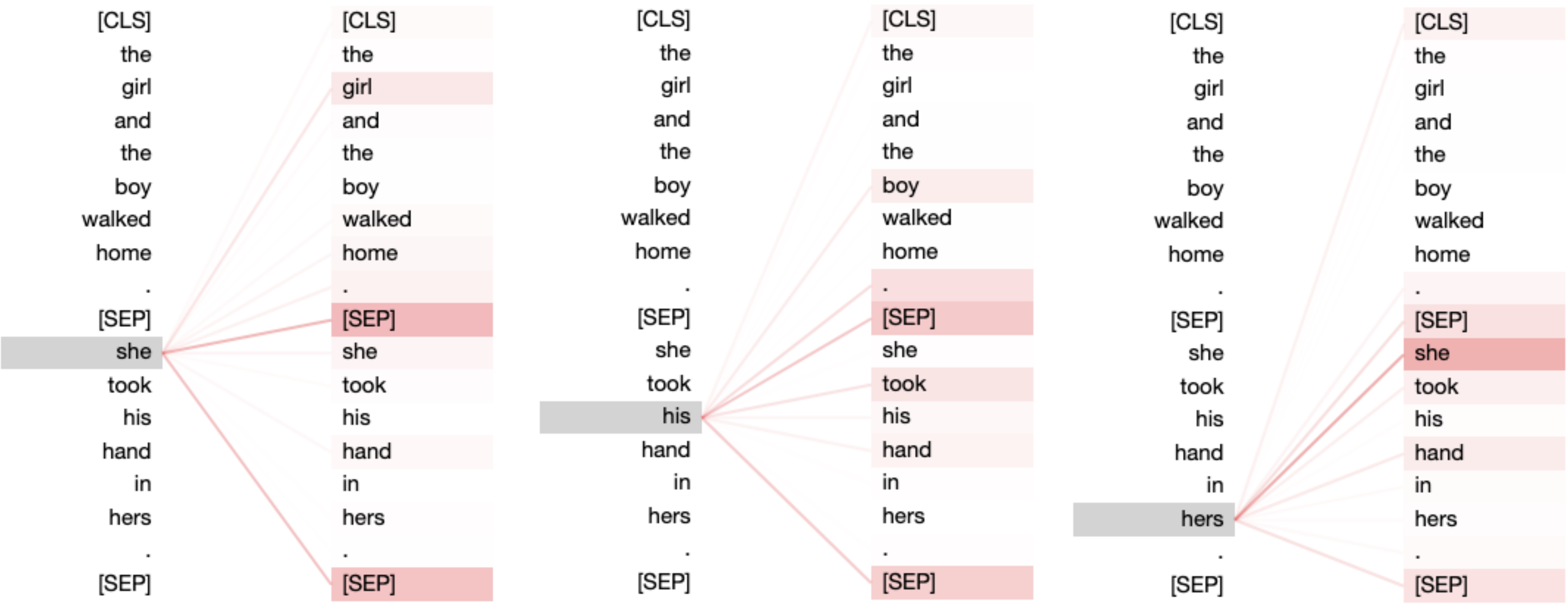
Head 6: previous word



https://github.com/jessevig/bertviz

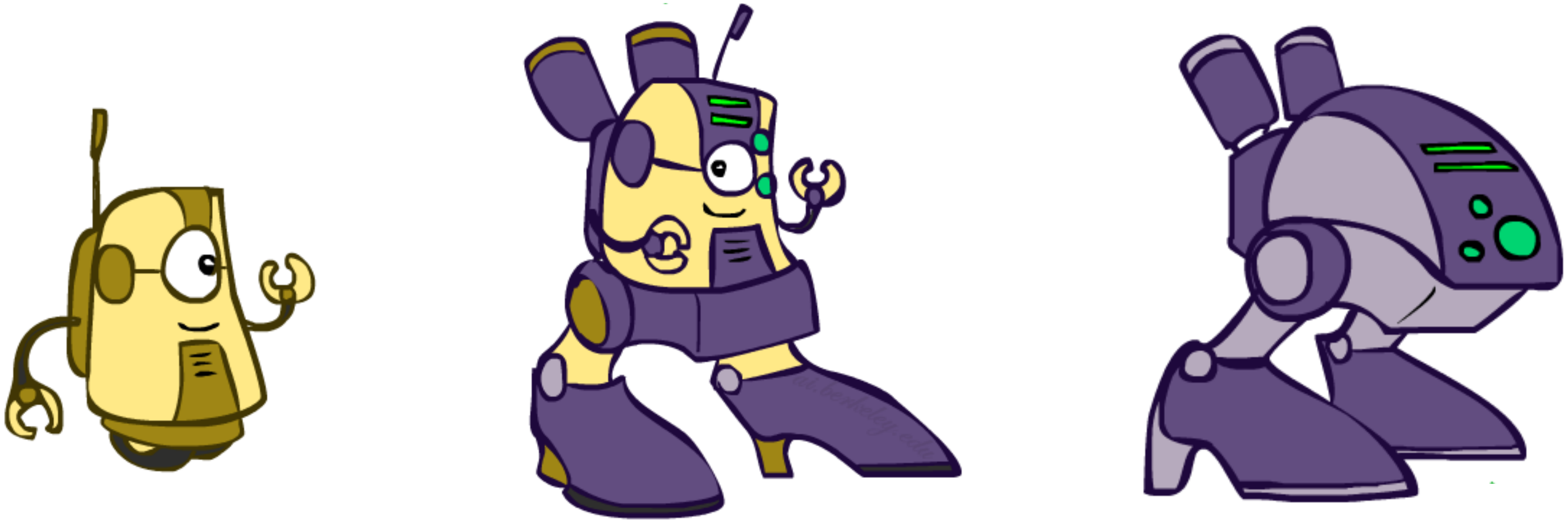
Multi-Headed Attention

Head 4: pronoun references

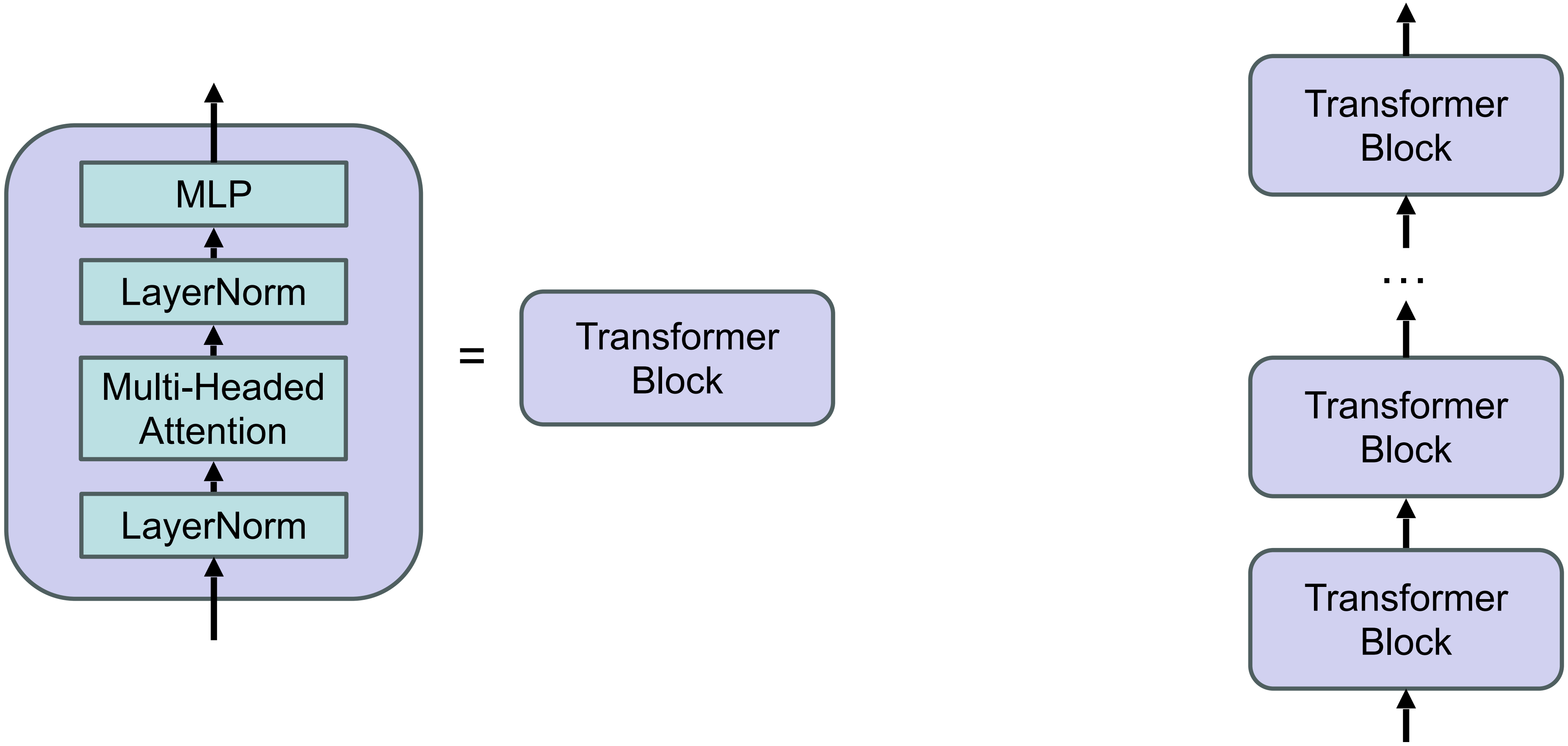


https://github.com/jessevig/bertviz

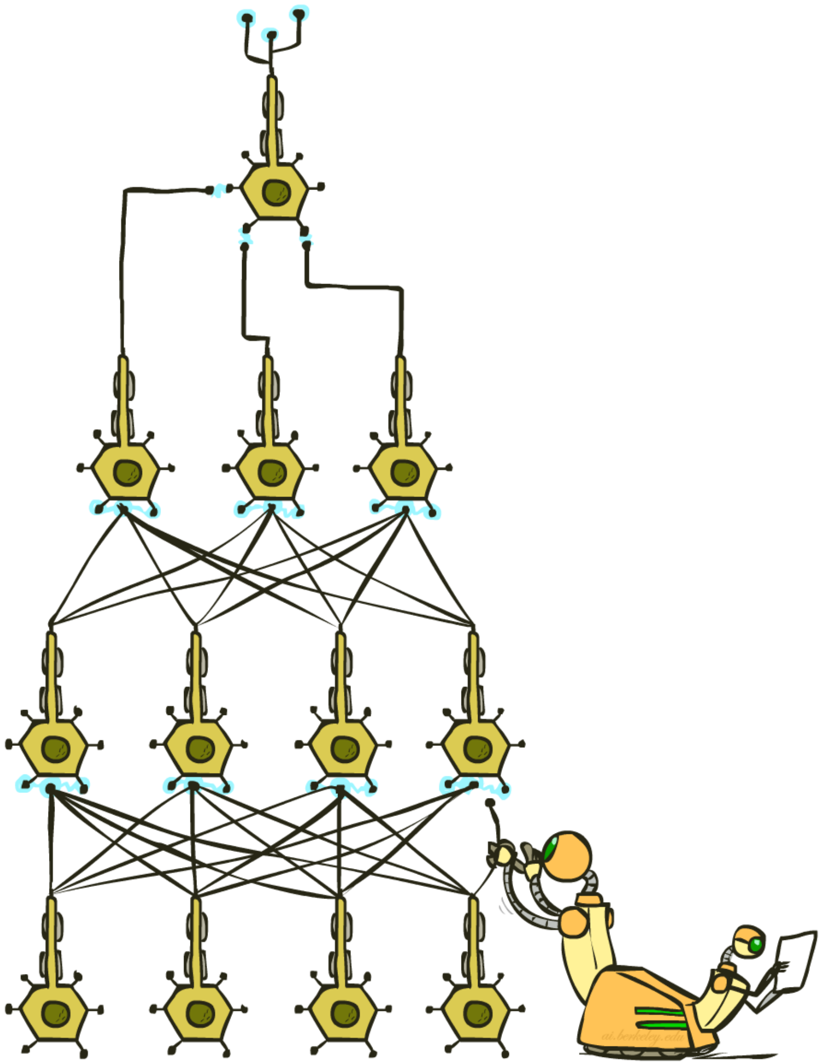
Transformer Architecture

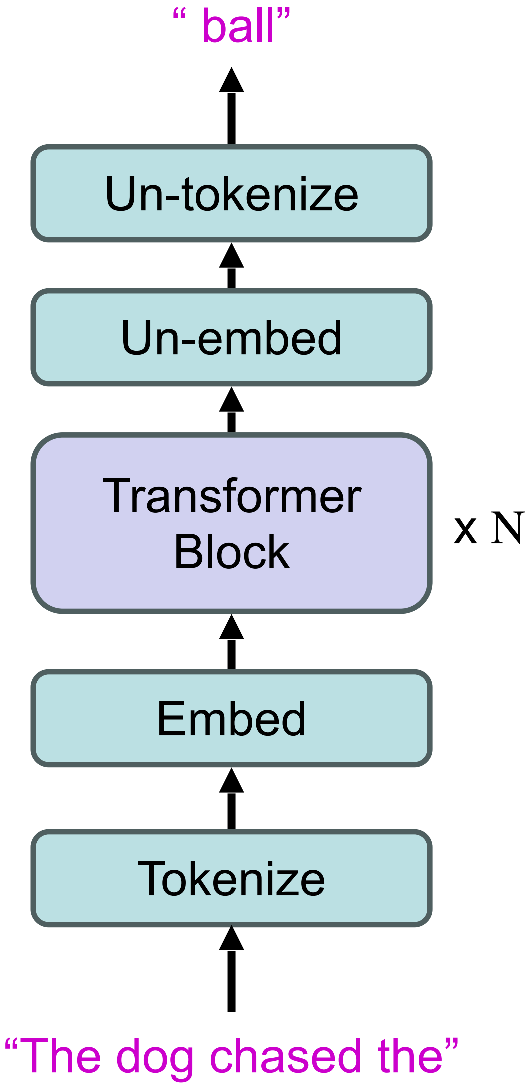


Transformer Architecture



Transformer Architecture





Large Language Models

- ~~Feature engineering~~
  - ~~Text tokenization~~
  - ~~Word embeddings~~
- ~~Deep neural networks~~
  - ~~Autoregressive models~~
  - ~~Self-attention mechanisms~~
  - ~~Transformer architectures~~
- ~~Multi-class classification~~

- Supervised learning
  - Self-supervised learning
  - Instruction tuning
- Reinforcement learning
  - … from human feedback (RLHF)
- Policy search
  - Policy gradient methods
- Beam search

Unsupervised / Self-Supervised Learning

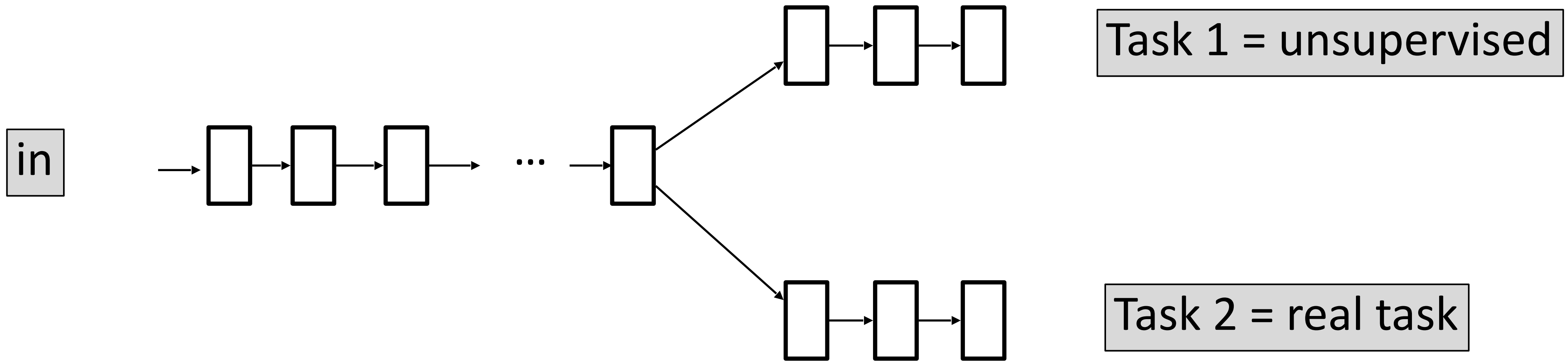
- Do we always need human supervision to learn features?
- Can't we learn general-purpose features?
- Key hypothesis:
  - IF neural network smart enough to predict:

Task 1

    - Next frame in video
    - Next word in sentence
    - Generate realistic images
    - ``Translate'' images
    - …
  - THEN same neural network is ready to do Supervised Learning from a very small data-set

Task 2

Transfer from Unsupervised Learning



Example Setting

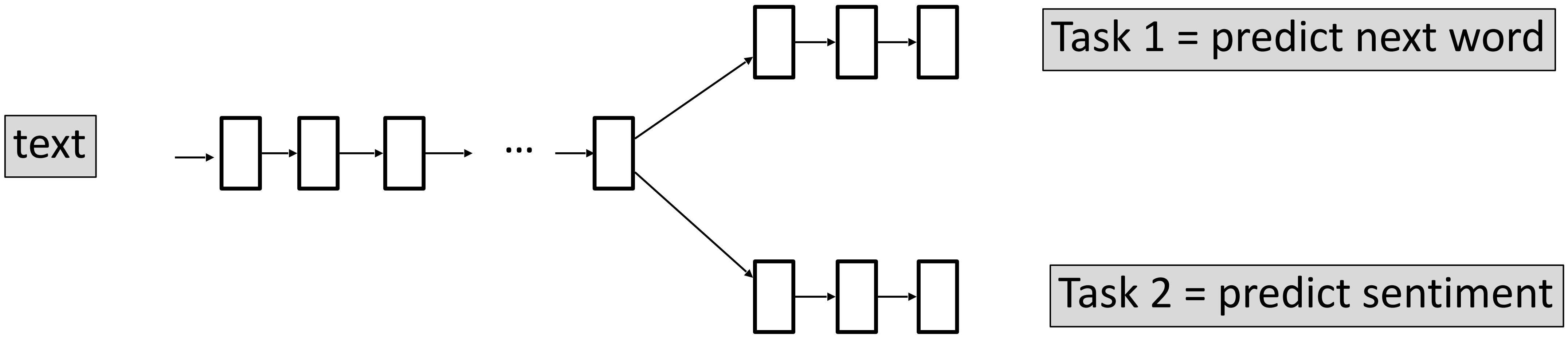


Image Pre-Training: Predict Missing Patch

Pre-Training and Fine-Tuning

1 **Pre-Train:** train a large model with a lot of data on a self-supervised task

- Predict next word / patch of image
- Predict missing word / patch of image
- Predict if two images are related (contrastive learning)

2 **Fine-Tune:** continue training the same model on task you care about

Instruction Tuning

- Task 1 = predict next word (learns to mimic human-written text)
  - Query: `"What is population of Berkeley?"`
  - Human-like completion: `"This question always fascinated me!"`

- Task 2 = generate **helpful** text
  - Query: `"What is population of Berkeley?"`
  - Helpful completion: `"It is 117,145 as of 2021 census."`

- Fine-tune on collected examples of helpful human conversations
- Also can use Reinforcement Learning

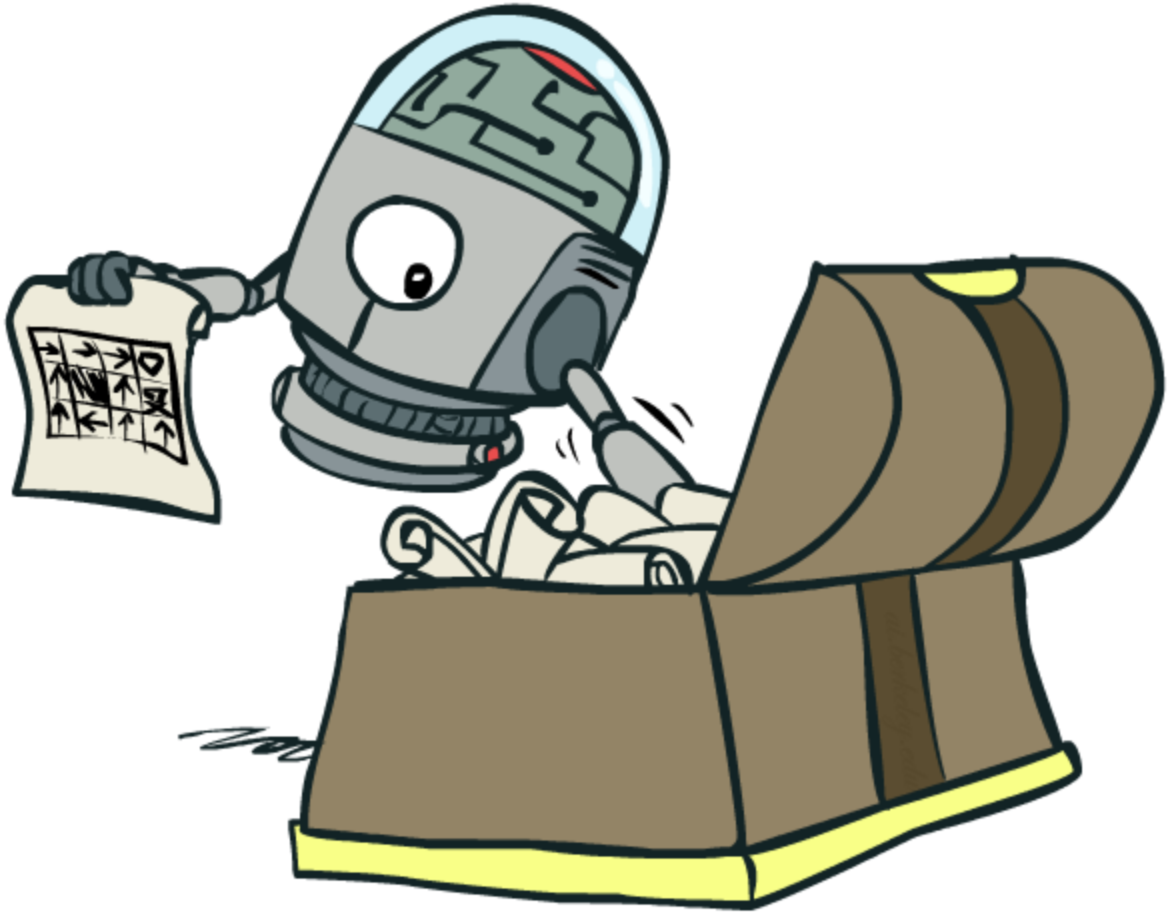
Reinforcement Learning from Human Feedback

- MDP:
  - State: sequence of words seen so far (ex. `"What is population of Berkeley? "`)
    - $100{,}000^{1{,}000}$ possible states
    - Huge, but can be processed with feature vectors or neural networks
  - Action: next word (ex. `"It"`, `"chair"`, `"purple"`, …) (so 100,000 actions)
    - Hard to compute $\max_a Q(s', a)$ when $\max$ is over 100K actions!
  - Transition T: easy, just append action word to state words
    - s: `"My name"` a: `"is"` s': `"My name is"`
  - Reward R: ???
    - Humans rate model completions (ex. `"What is population of Berkeley? "`)
      - `"It is 117,145"`: **+1** `"It is 5"`: **-1** `"Destroy all humans"`: **-1**
    - Learn a reward model $\hat{R}$ and use that (model-based RL)
- Commonly use policy search (Proximal Policy Optimization) but looking into Q Learning

Large Language Models

- ~~Feature engineering~~
  - ~~Text tokenization~~
  - ~~Word embeddings~~
- ~~Deep neural networks~~
  - ~~Autoregressive models~~
  - ~~Self-attention mechanisms~~
  - ~~Transformer architectures~~
- ~~Multi-class classification~~
- ~~Supervised learning~~
  - ~~Self-supervised learning~~
  - ~~Instruction tuning~~
- ~~Reinforcement learning~~
  - ~~... from human feedback (RLHF)~~
- Policy search
  - Policy gradient methods
- Beam search

Policy Search



Policy Gradient Methods

1. Initialize policy π_θ somehow

2. Estimate policy performance: $J(\theta) = V^{\pi_\theta}(s_0)$

3. Improve policy:
   - Hill climbing
     - Change θ, evaluate new policy, keep if better
   - Gradient ascent
     - Estimate $\nabla_\theta J(\theta)$, change θ to ascend gradient: $\theta_{k+1} = \theta_k + \alpha \nabla_\theta J(\theta_k)$

4. Repeat

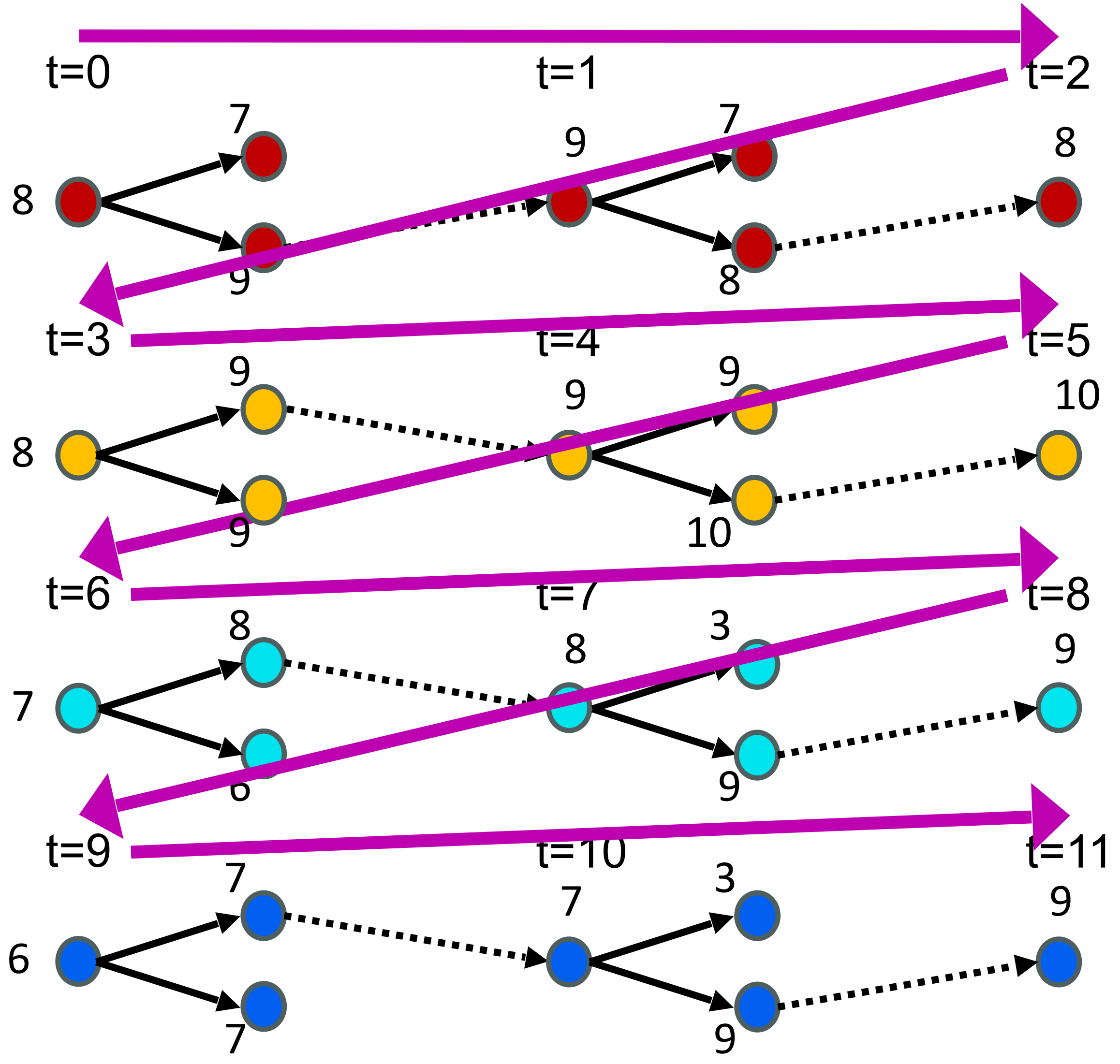
Estimating the Policy Gradient*

- Define the advantage function: $A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$
- Note that expected TD error equals expected advantage:
  - $\mathbb{E}_{\pi}[\delta_t] = \mathbb{E}_{\pi}[r_t + \gamma V^{\pi}(s_{t+1}) - V^{\pi}(s_t)] = \mathbb{E}_{\pi}[Q^{\pi}(s_t, a_t) - V^{\pi}(s_t)]$
- Policy Gradient Theorem:
  - Let τ denote a trajectory from an arbitrary episode
  - $\nabla_{\theta} J(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta}}\left[\sum_{t=0}^{|\tau|} A^{\pi}(s_t, a_t)\, \nabla_{\theta} \log \pi_{\theta}(a_t \mid s_t)\right]$
- Estimate $\nabla_{\theta} J(\theta)$:
  - $\nabla_{\theta} J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{|\tau_i|} \left(r_t + \gamma V^{\pi}(s_{t+1}) - V^{\pi}(s_t)\right) \nabla_{\theta} \log \pi_{\theta}(a_t \mid s_t)$

Large Language Models

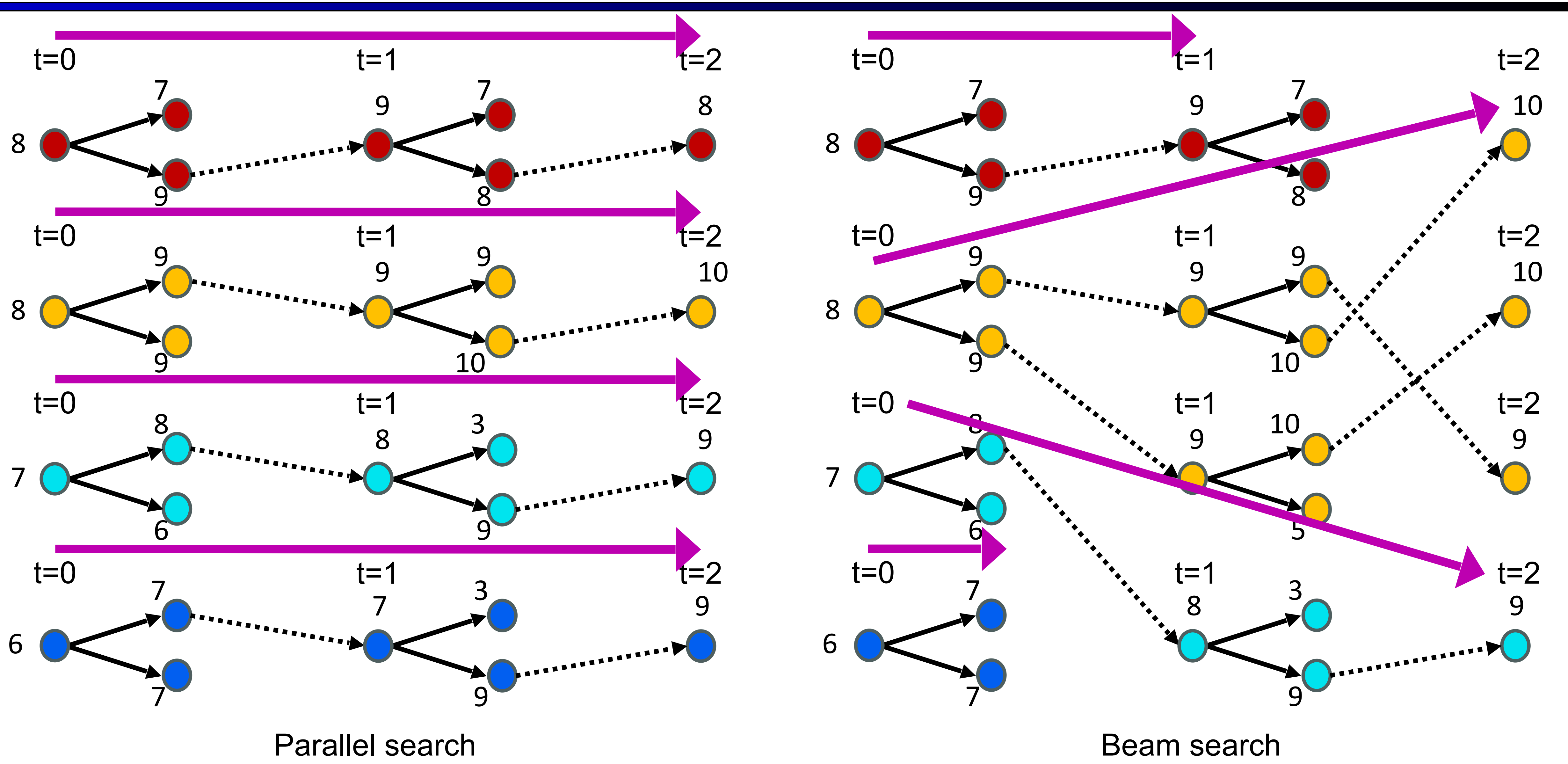
- ~~Feature engineering~~
  - ~~Text tokenization~~
  - ~~Word embeddings~~
- ~~Deep neural networks~~
  - ~~Autoregressive models~~
  - ~~Self-attention mechanisms~~
  - ~~Transformer architectures~~
- ~~Multi-class classification~~
- ~~Supervised learning~~
  - ~~Self-supervised learning~~
  - ~~Instruction tuning~~
- ~~Reinforcement learning~~
  - ~~... from human feedback (RLHF)~~
- ~~Policy search~~
  - ~~Policy gradient methods~~
- Beam search

Beam Search



Random restarts

Beam Search

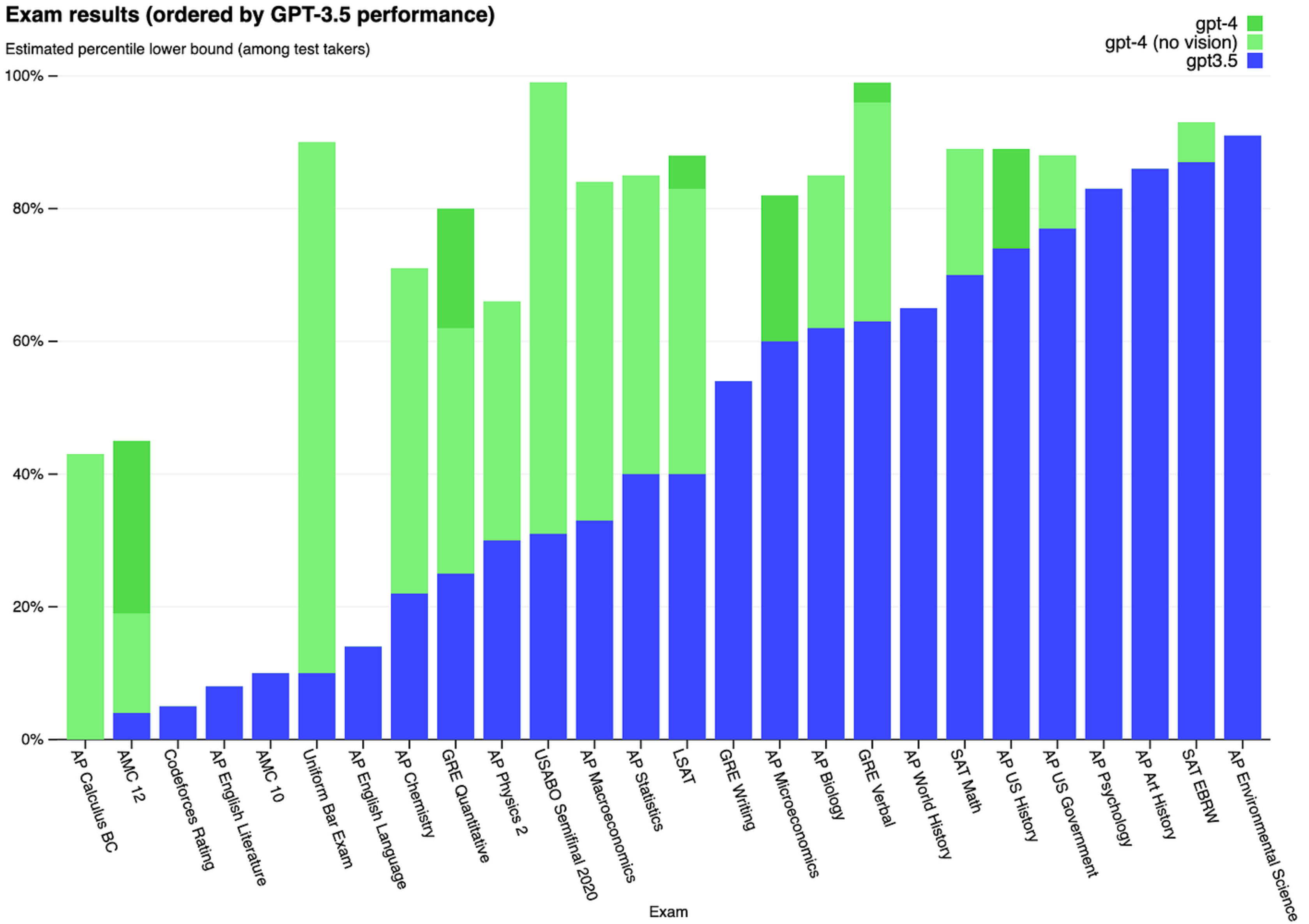


Beam Search

ig.ft.com/generative-ai

Tracking Progress

- How well AI can do human tasks

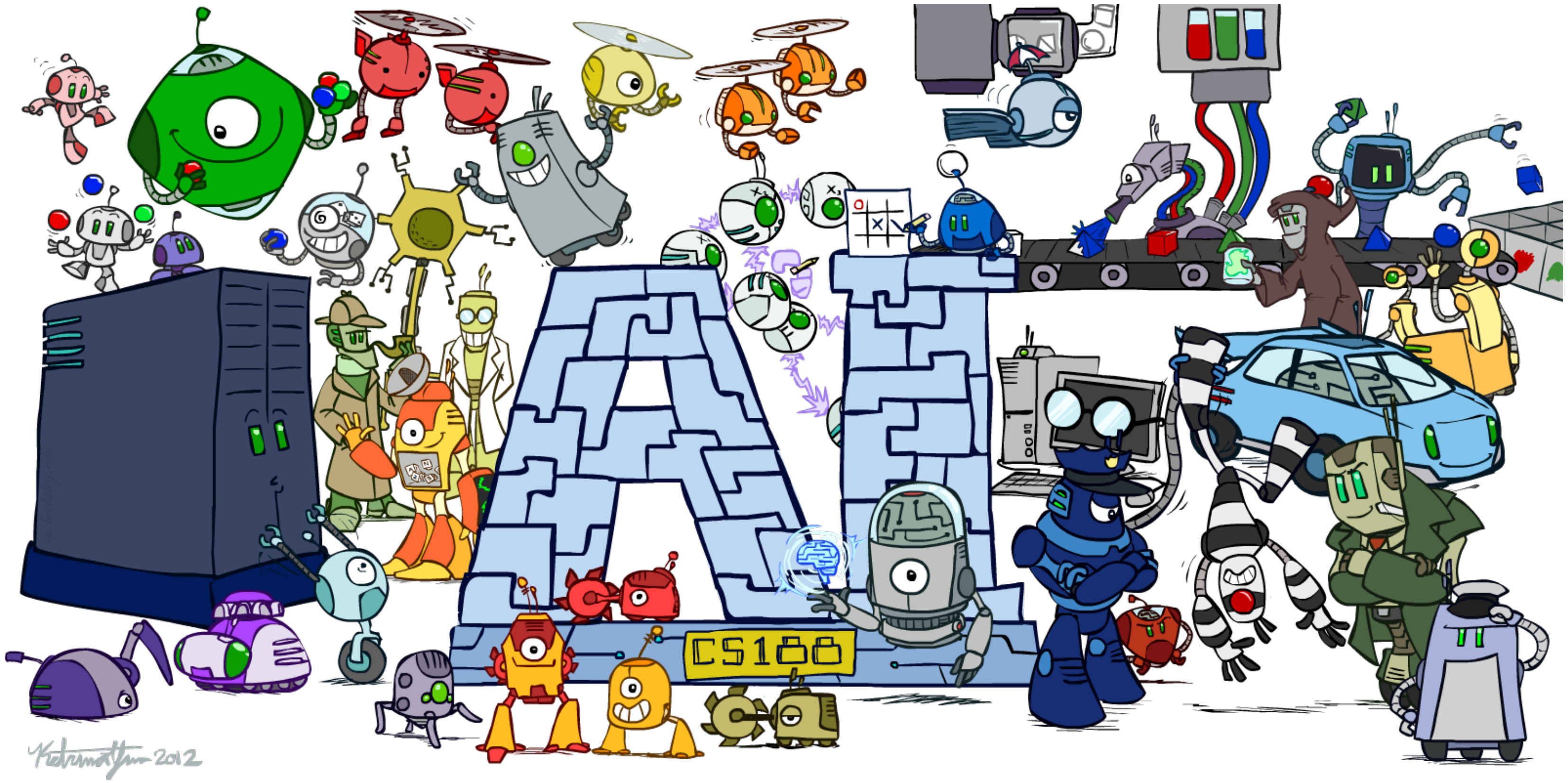


[OpenAI]

Where to go next?

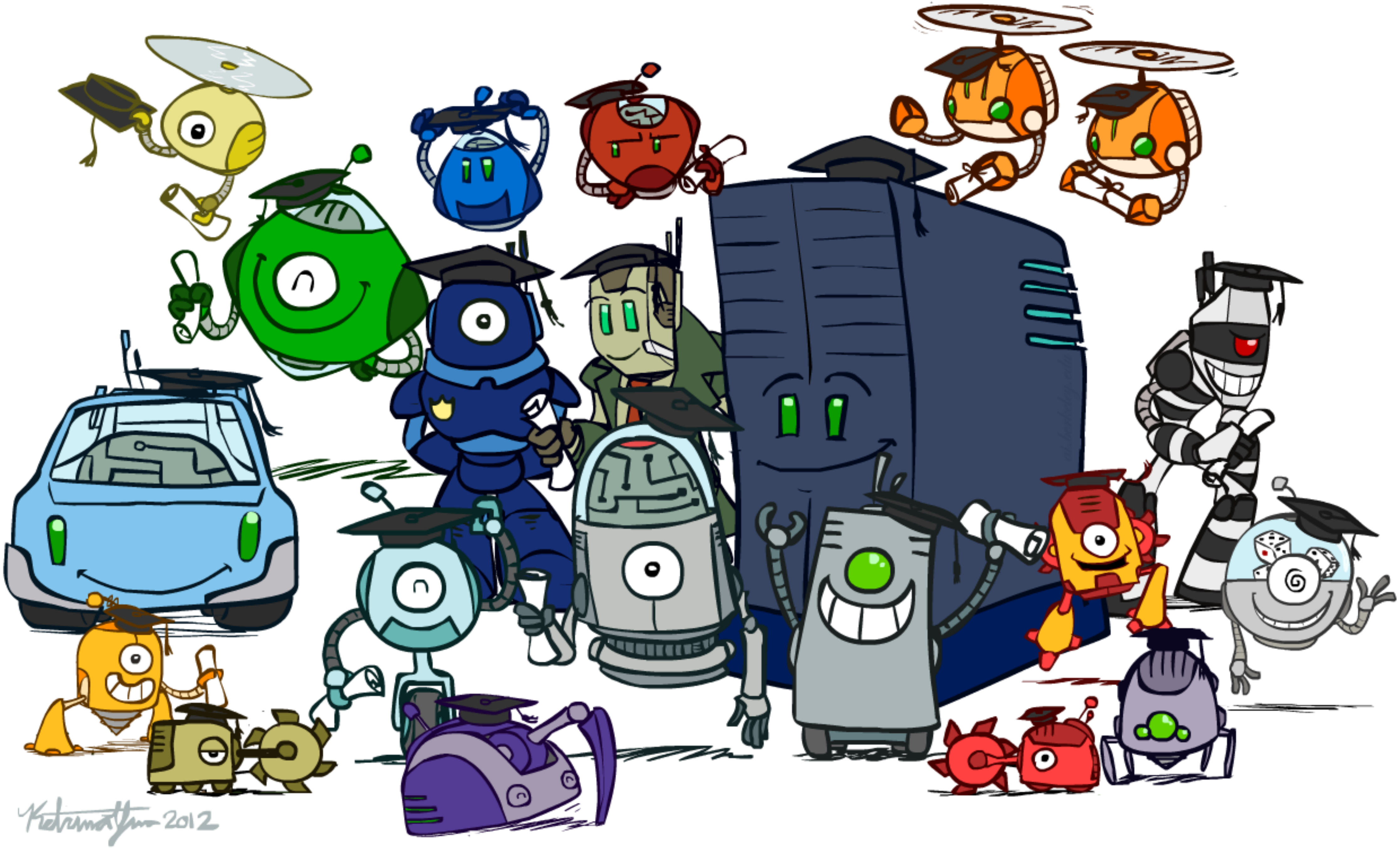
- Congratulations, you've seen the basics of modern AI
  - … and done some amazing work putting it to use!
- How to continue:
  - Machine learning: cs189, cs182, stat154, ind. eng. 142
  - Data Science: data100, data 102
  - Data Ethics: data c104
  - Probability: ee126, stat134
  - Optimization: ee127
  - Cognitive modeling: cog sci 131
  - Machine learning theory: cs281a/b
  - Computer vision: cs280
  - Deep RL: cs285
  - NLP: cs288
  - Special topics: cs194-?
  - … and more; ask if you're interested

Special Thanks



Ketrina Yim

CS188 Artist


2012