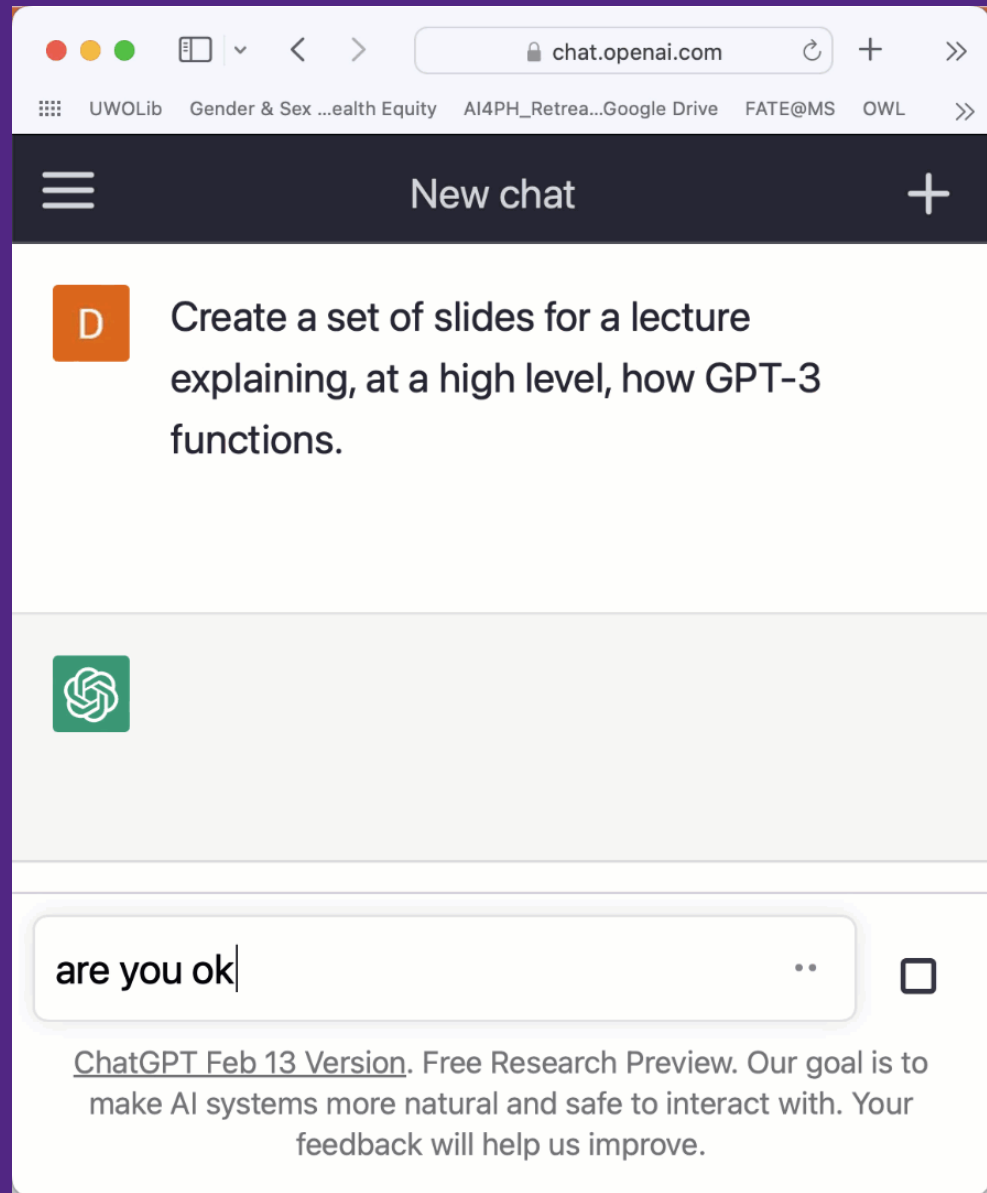


# Neural Network Language Models

CS 4417B

The University of Western Ontario

# GPT-X



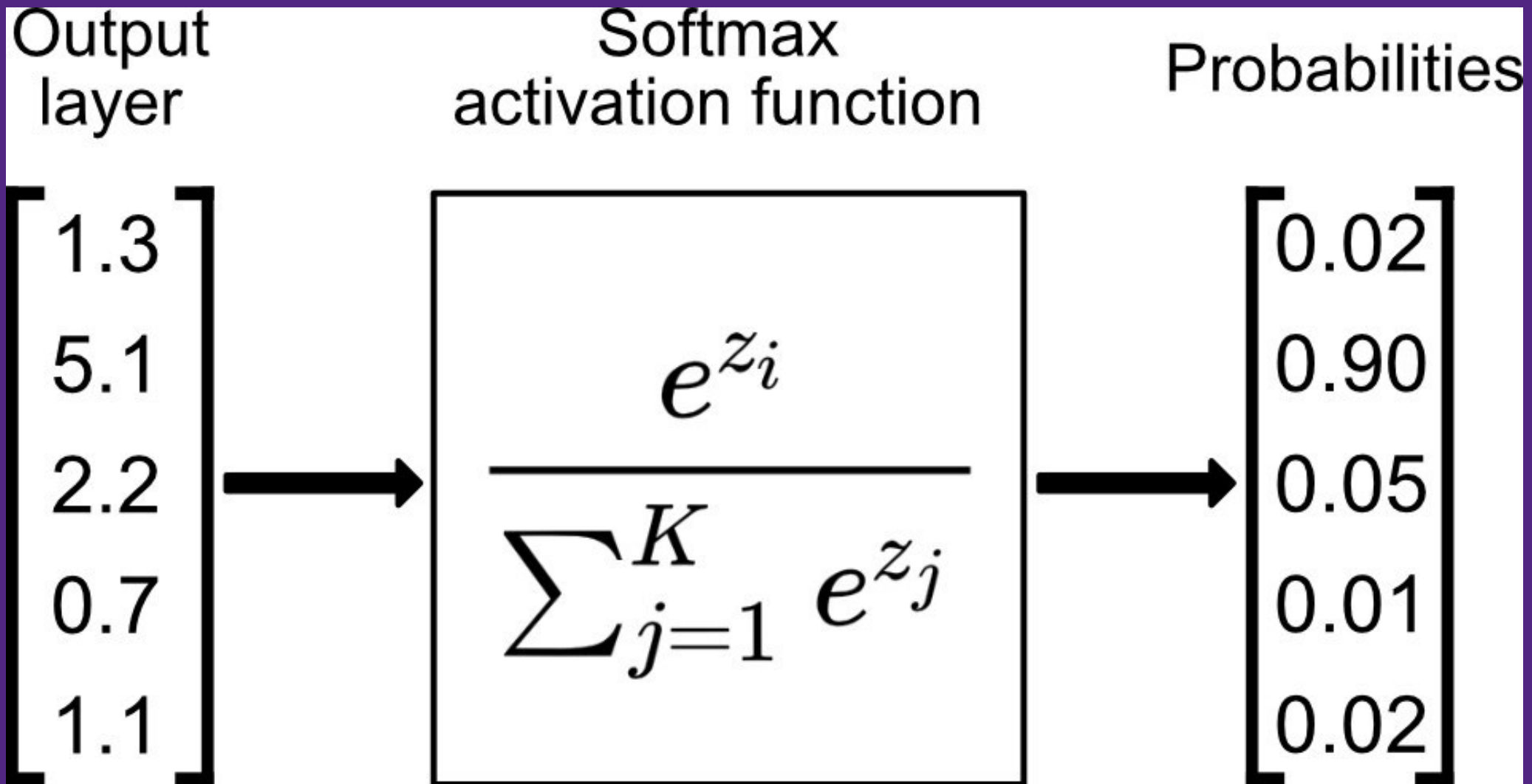
# Neural Network Language Models

- Input: Sequence of words
- Output: Probability over next word
- Instead of storing a number for every  $n$ -gram, distribution is computed using the weights in the network.
- I am just giving a **high level overview** of how things work. Best detailed [NOT REQUIRED WATCHING] video is <https://youtu.be/kCc8FmEb1nY> (Requires neural network background.)

# Ideas in GPT

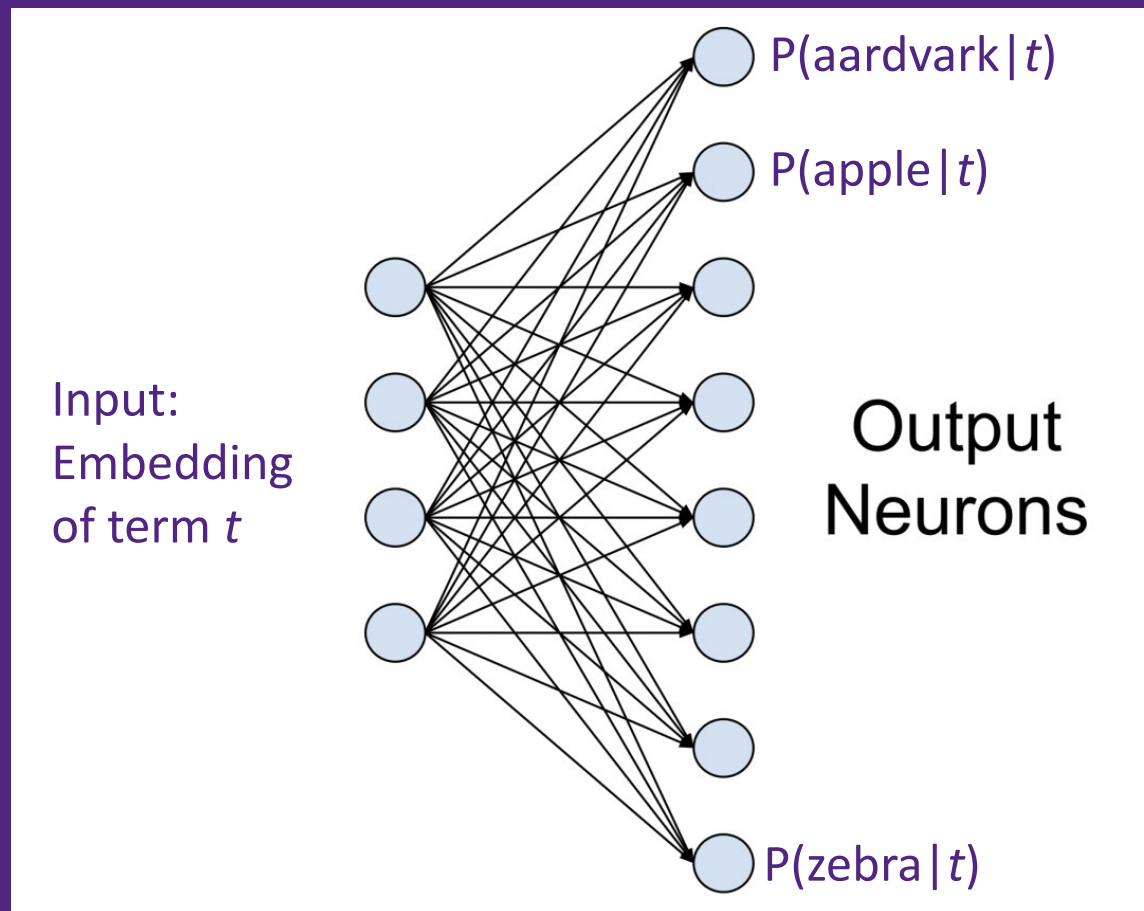
- Softmax output
- Hidden layers
- “Attention” to communicate information from word to word (big deal)
- Word embeddings and position information
- Byte-pair encodings

# Reminder: Softmax



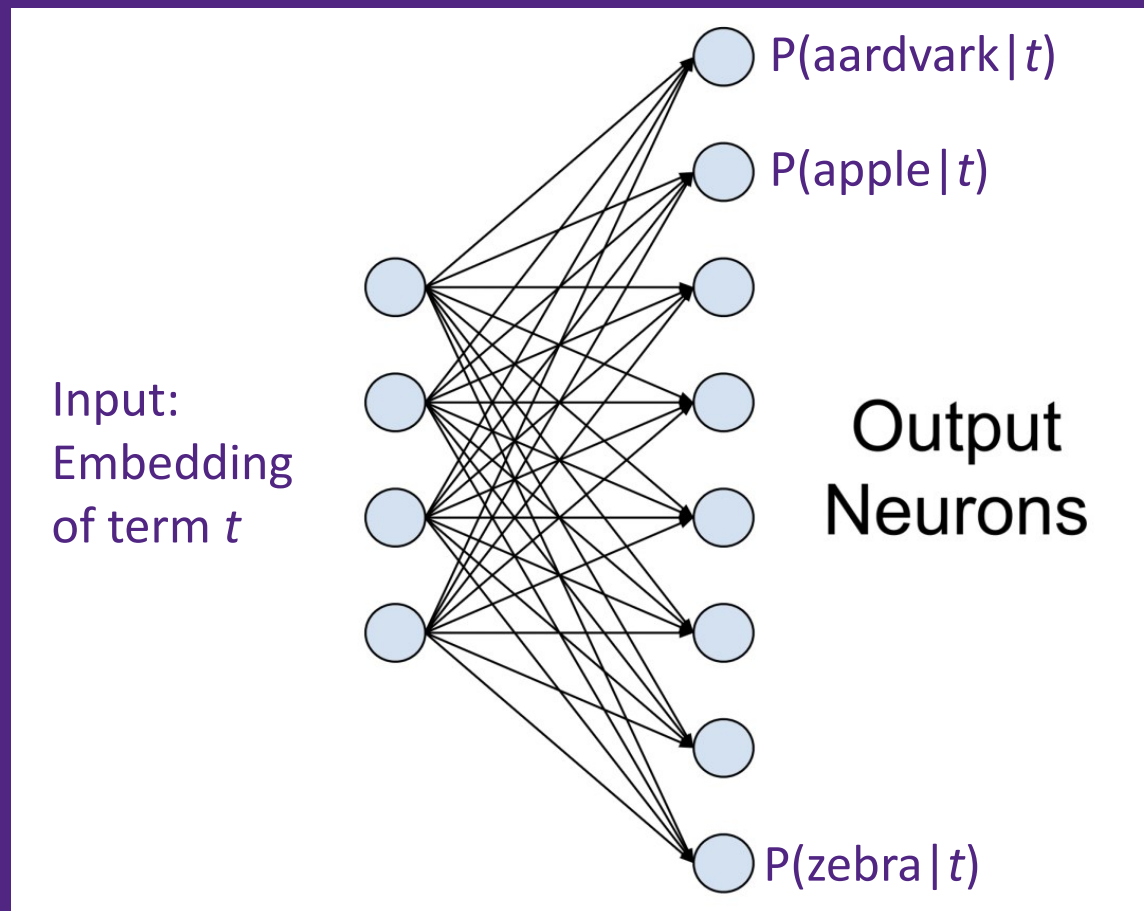
# Output layer

- Produces probability distribution over tokens



# Output layer

- Produces probability distribution over tokens

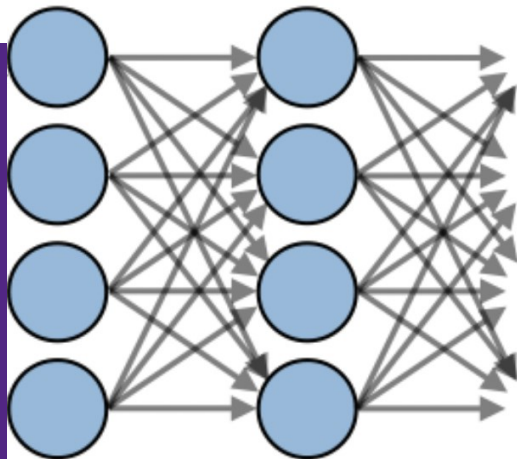


A)  $m^*(m-1)$     B)  $m^*m$     C)  $m^*p$     D)  $p^*(m-1)$

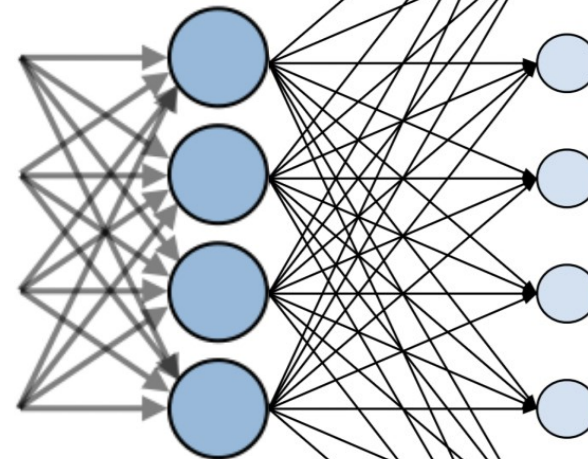
# Output layer after hidden layers

- Produces probability distribution over terms/tokens

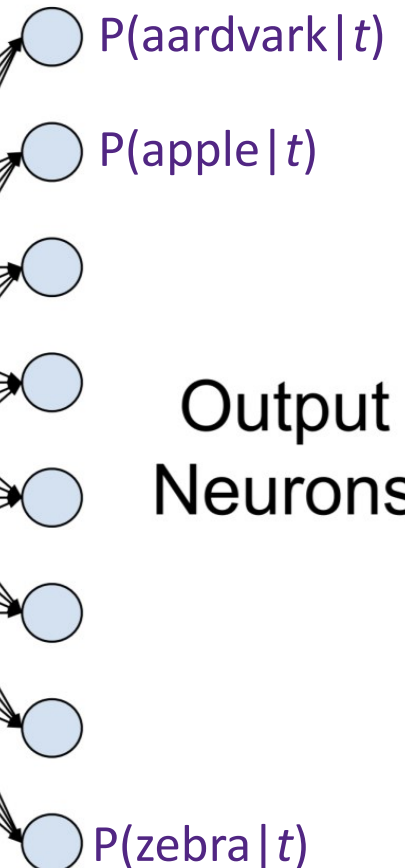
Input:  
Embedding  
of term  $t$



...

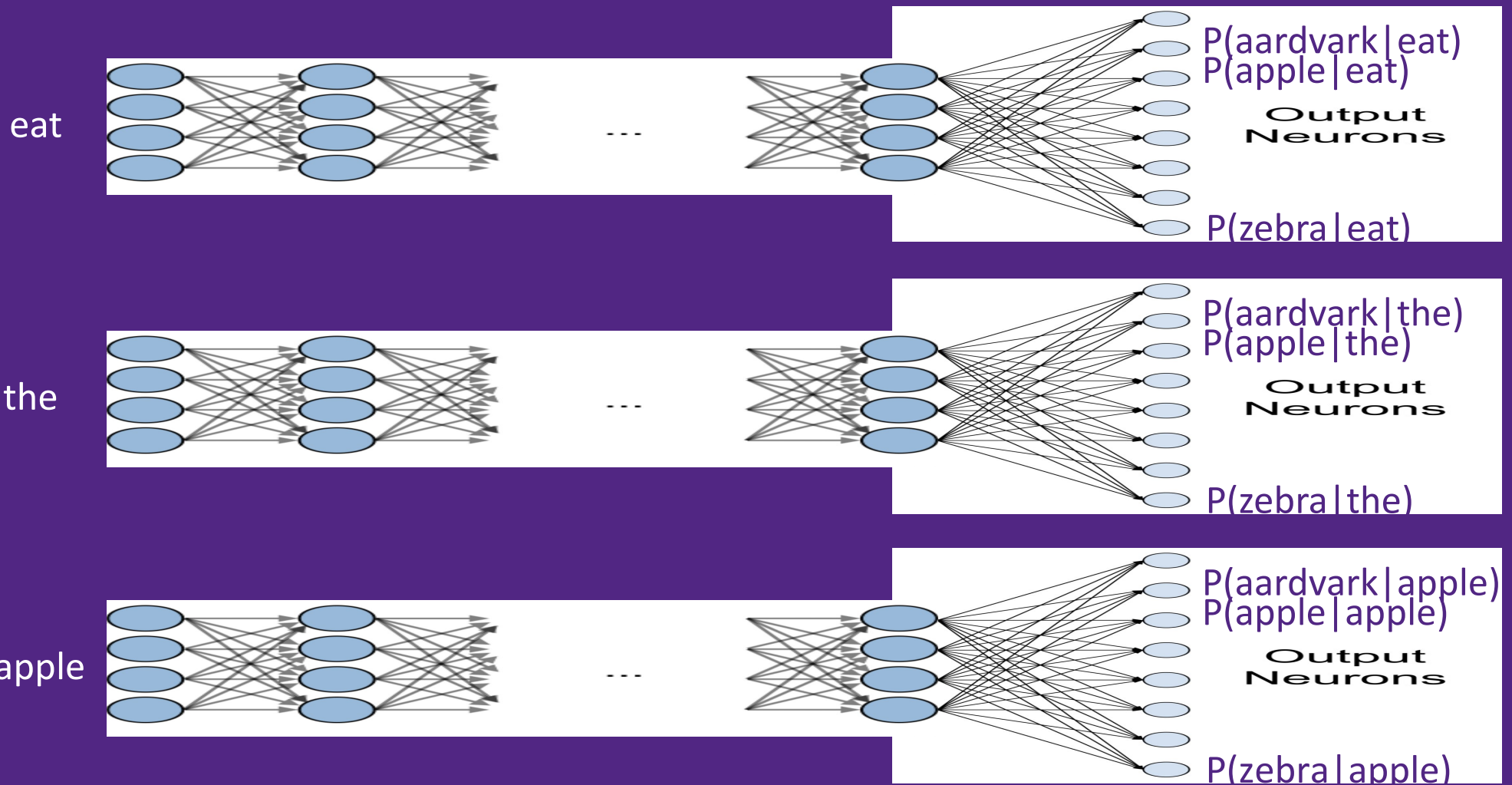


Output  
Neurons

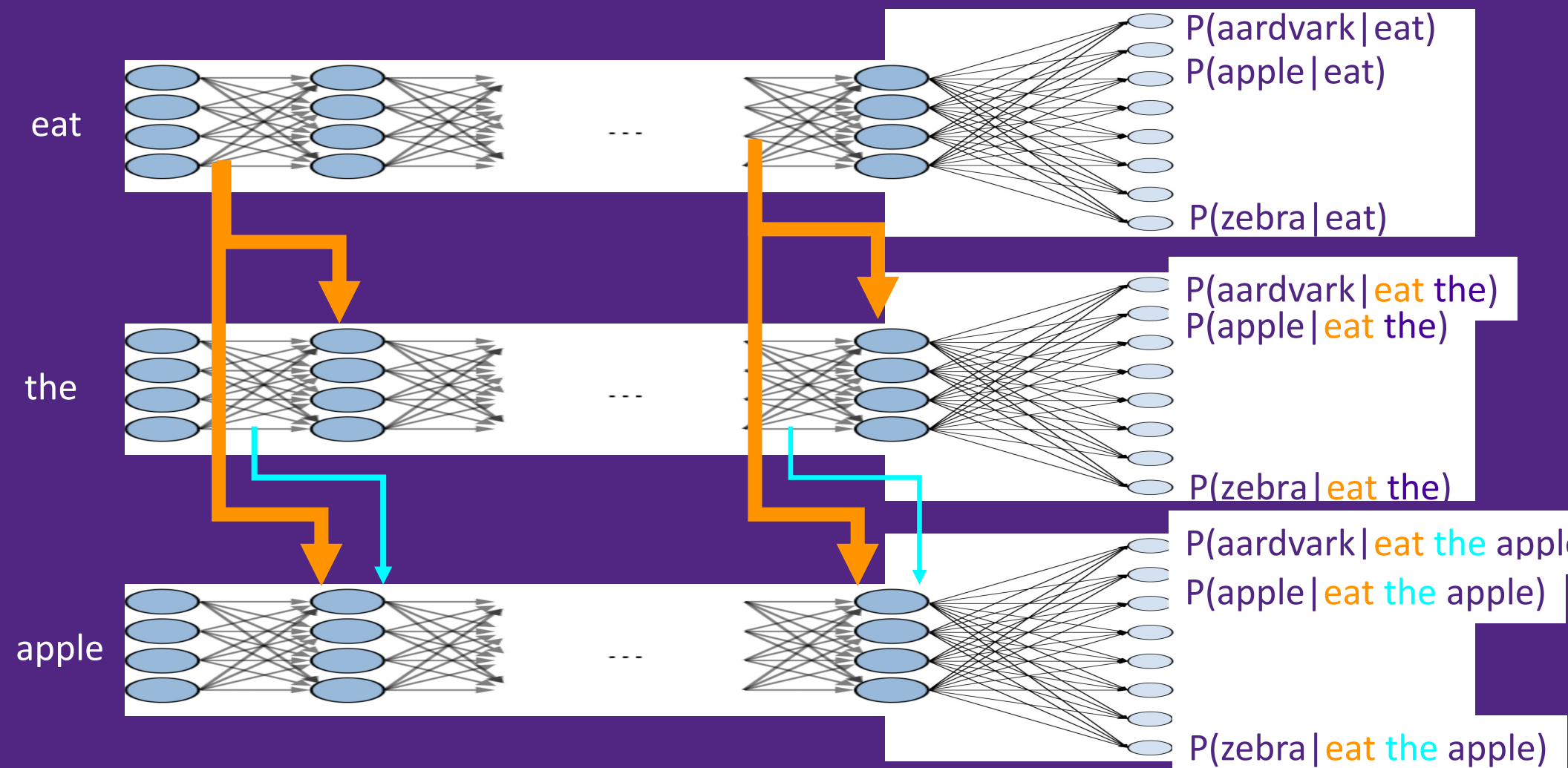




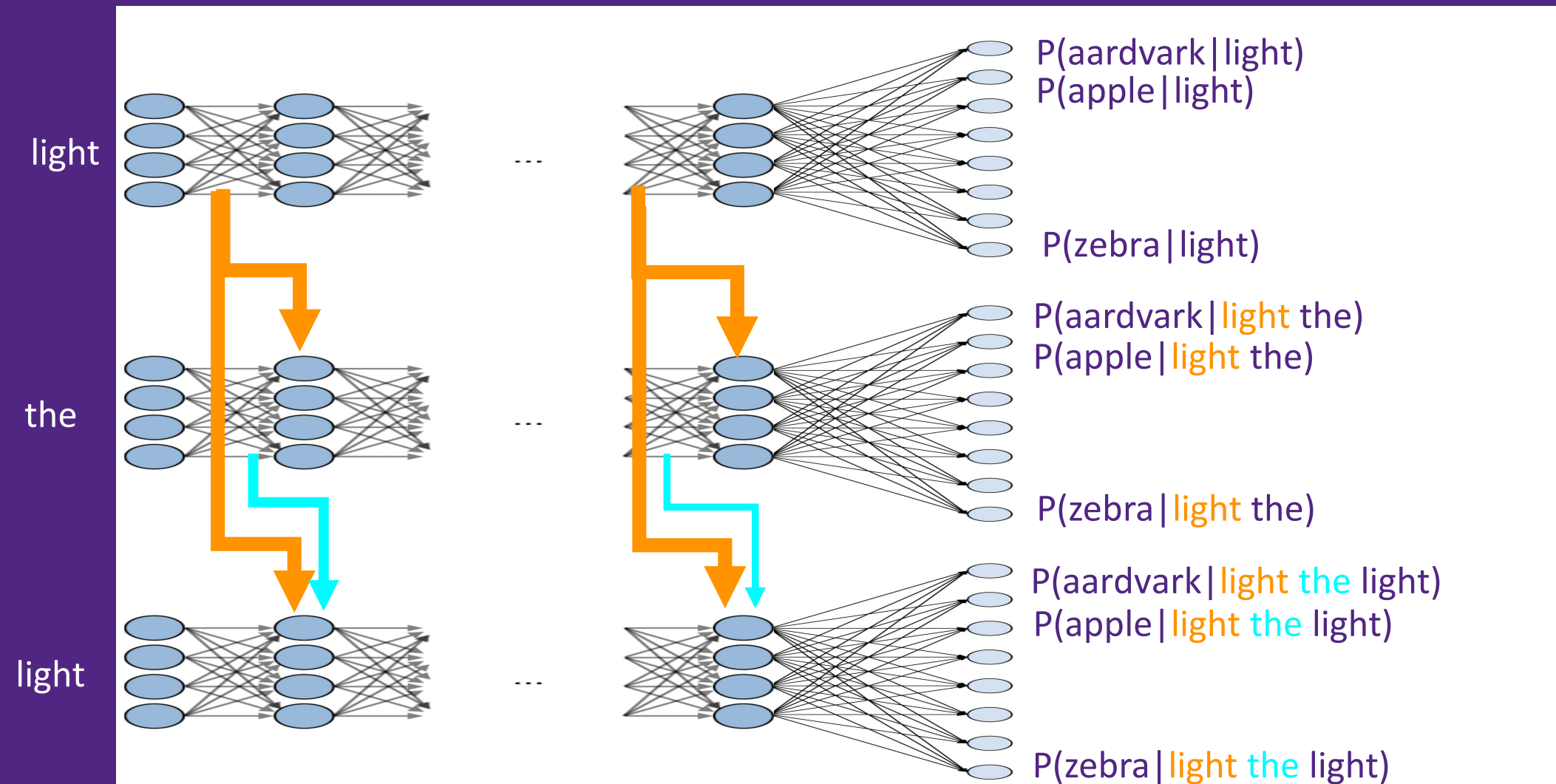
# Simultaneous computations



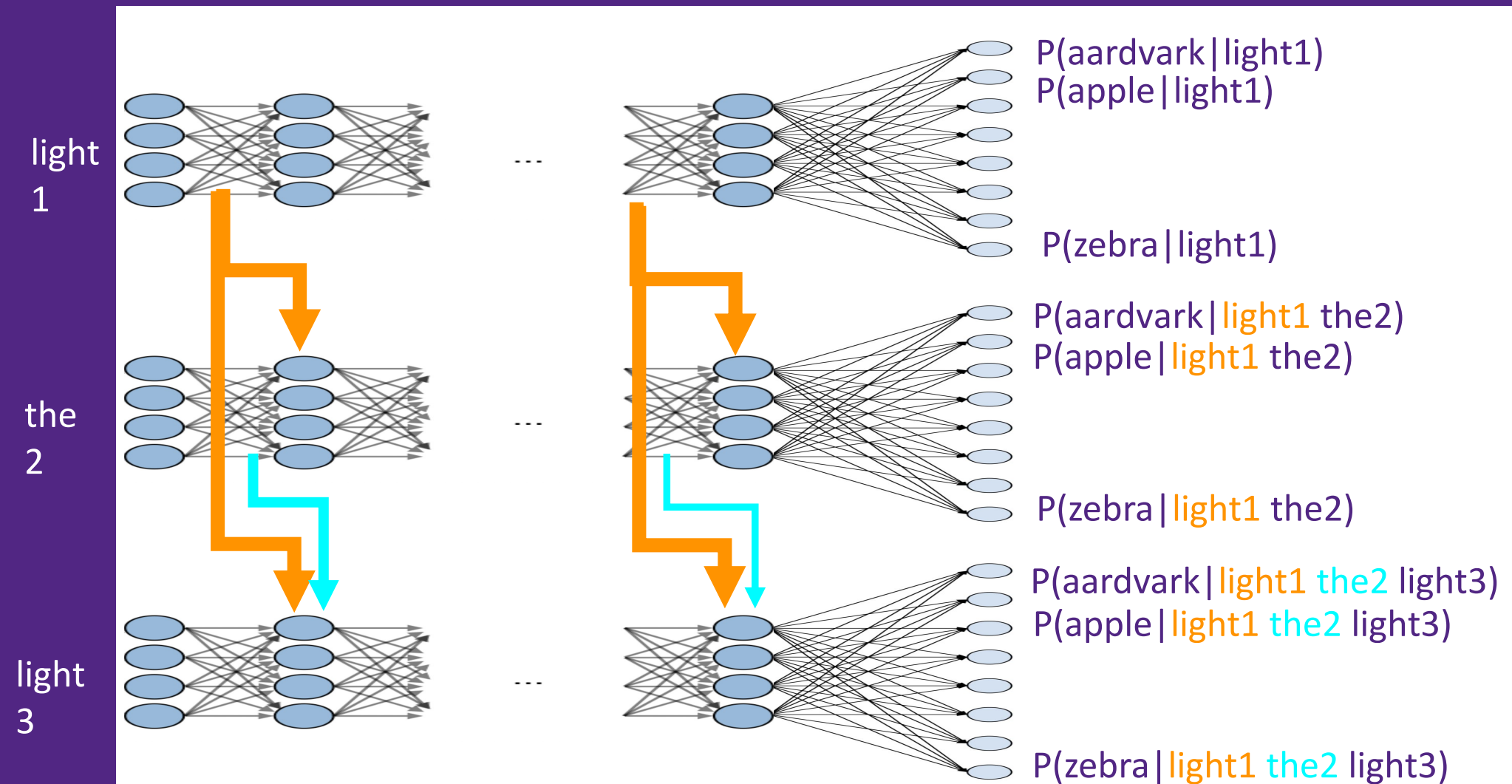
# “Attention”



# Positional Encodings



# Positional Encodings



# Tokenization:

## “Byte-Pair Encoding”

- Issue: “Out-of vocabulary” words
- Idea
  - Fix number of allowed tokens
  - Allocate tokens to frequently occurring sequences of characters
  - Still allow any sequence of characters to be mapped to tokens
- GPT-2: 256 one-byte tokens + 50000 learned tokens + 1 special end-of-sequence token

# Byte pair encoding

- Start with 1 token per byte
- If a pair of bytes occurs frequently, make a new token
  - If “t” “h” occurs a lot, create a new token “t” “h” and a merge rule.
  - If “th” “e” occurs a lot, create a new token “the” and a merge rule.
  - Stop when bored. (For GPT, after 50000 merges.)
- To tokenize a new sentence, apply the rules in order.
- Common sequences will get their own token; uncommon ones won't
- *Any* sequence of bytes is tokenizable
- In GPT, one token is about  $\frac{3}{4}$  of a word, on average.
- <https://platform.openai.com/tokenizer>

# Parameters

- GPT-2
  - Vocabulary size: 50,257
  - Context length 1024
  - $10^{9.18}$  parameters
- GPT-3
  - Vocabulary size: 50,257
  - Context length 2048
  - $10^{11.25}$  parameters

# Parameters

- GPT-2
  - Vocabulary size: 50,257
  - Context length 1024
  - $10^{9.18}$  parameters
  - Count-based:  $\sim 10^{4814}$  parameters
- GPT-3 (English part)
  - Vocabulary size: 50,257
  - Context length 2048
  - $10^{11.25}$  parameters
  - Count-based  $\sim 10^{9628}$  parameters



ChatGPT

### Step 1

#### Collect demonstration data and train a supervised policy.

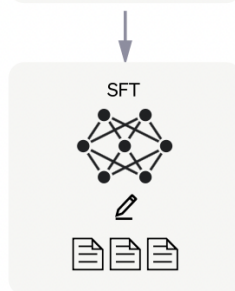
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



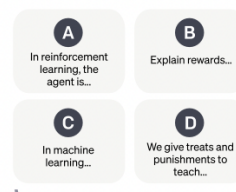
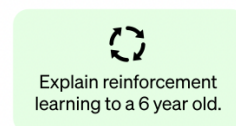
This data is used to fine-tune GPT-3.5 with supervised learning.



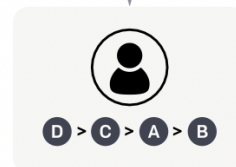
### Step 2

#### Collect comparison data and train a reward model.

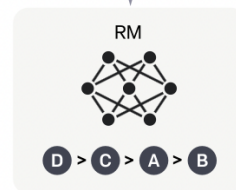
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



### Step 3

#### Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

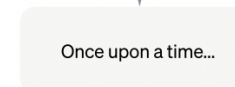
A new prompt is sampled from the dataset.



The PPO model is initialized from the supervised policy.



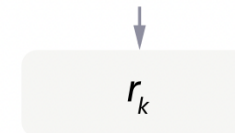
The policy generates an output.



The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.

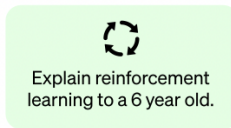


# Fine-tune GPT for prompt/response

Step 1

**Collect demonstration data and train a supervised policy.**

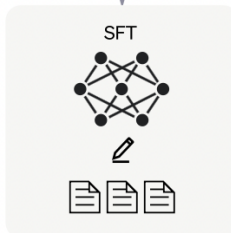
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.

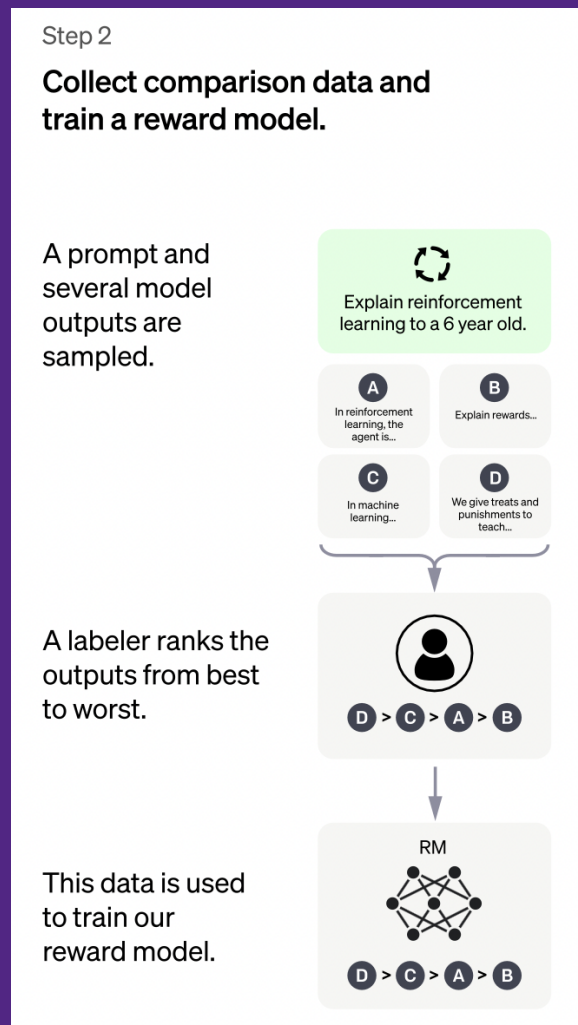


This data is used to fine-tune GPT-3.5 with supervised learning.



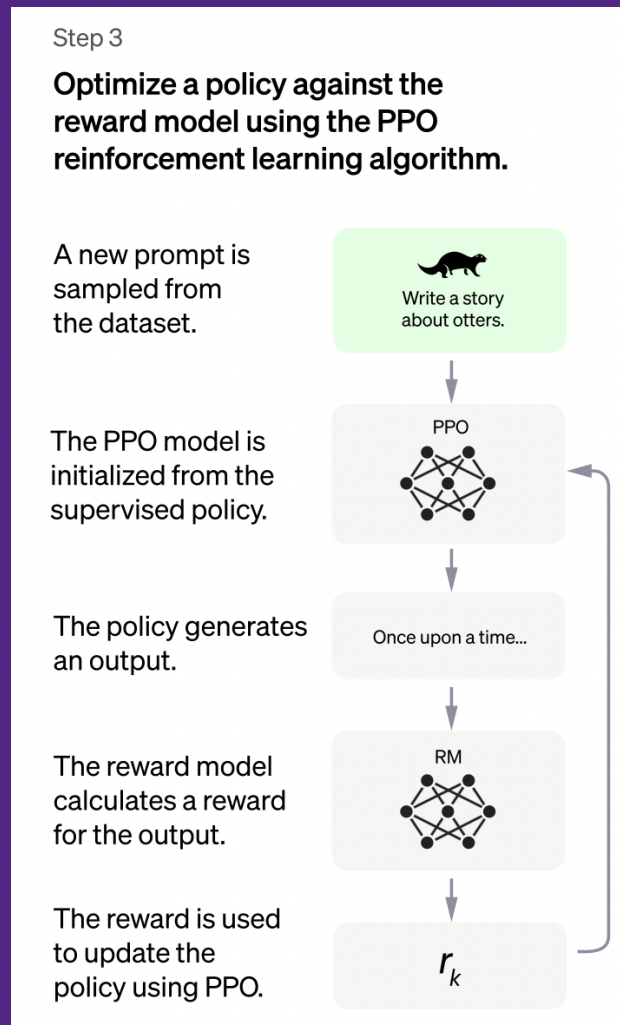
- Use *human-created* pairs of prompts and responses
- Fine-tune the language production model

# Learn a model that can rank responses




- Use human-derived *rankings* of responses
- Training pairs are (model outputs, rankings)
- Learn to predict the ranking of a series of outputs (which is best?)

# Train a more sophisticated babbling model based on the reward model



- Learn how to *produce* good responses by trying to produce high rewards according to the learned reward model
- Human not required at this point.
- <https://arxiv.org/pdf/2203.02155.pdf>

# Concerns about Large Language Models

- On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 
- FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency
- March 2021
- Pages 610–623
- <https://doi.org/10.1145/3442188.3445922>

# Environmental

- Average human is responsible for an estimated 5t *CO*<sub>2</sub>
- Authors trained a Transformer (big) model [136] with neural architecture search and estimated that the training procedure emitted 284t of *CO*<sub>2</sub>.

# Representation

- Pew Internet Research's 2016 survey reveals 67% of Reddit users in the United States are men, and 64% between ages 18 and 29.<sup>13</sup>
- Similarly, recent surveys of Wikipedians find that only 8.8–15% are women or girls [9].
- The training set for GPT-3 was a filtered version of the Common Crawl dataset, developed by training a classifier to pick out those documents most similar to the ones used in GPT-2's training data, i.e. documents linked to from Reddit [25], plus Wikipedia and a collection of books.



# Data changes – what is updated?

- For instance, the Black Lives Matter movement (BLM) influenced Wikipedia article generation and editing such that, as the BLM movement grew, articles covering shootings of Black people increased in coverage and were generated with reduced latency [135].

# Curation, Documentation, Accountability

- “Feeding AI systems on the world’s beauty, ugliness, and cruelty, but expecting it to reflect only the beauty is a fantasy.” [p.1541]
- [15] Ruha Benjamin. 2019. Race After Technology: Abolitionist Tools for the New Jim Code. Polity Press, Cambridge, UK.

# The Stochastic Parrot

- Language models repeat what they are taught, injecting controlled randomness to create new and different text.
- Because LMs produce text that is so convincing, it's important to consider what went into their construction when assessing the credibility of what they produce.



He walked on the moon & walked up Ararat, searching in vain for Noah's Ark.



I am not aware of any astronaut who has walked on the moon and also walked on Mount Ararat searching for Noah's Ark. The only lunar missions were carried out by NASA as part of the Apollo program between 1969 and 1972, and none of the astronauts on those missions were known to have searched for Noah's Ark on Mount Ararat. Mount Ararat is a mountain located in Turkey, near the borders of Armenia and Iran, that is said in some religious texts to be the final resting place of Noah's Ark after the biblical flood. However, there is no scientific evidence to support the existence of a historical ark, or that a flood as described in the Bible ever occurred.

[https://en.wikipedia.org/wiki/James\\_Irwin](https://en.wikipedia.org/wiki/James_Irwin)