



Lecture 1: Introduction and Course Overview

Instructor: Swabha Swayamdipta
USC CSCI 544 Applied NLP
Aug 27, Fall 2024





OpenAI Is Testing an A.I.-Powered Search Engine

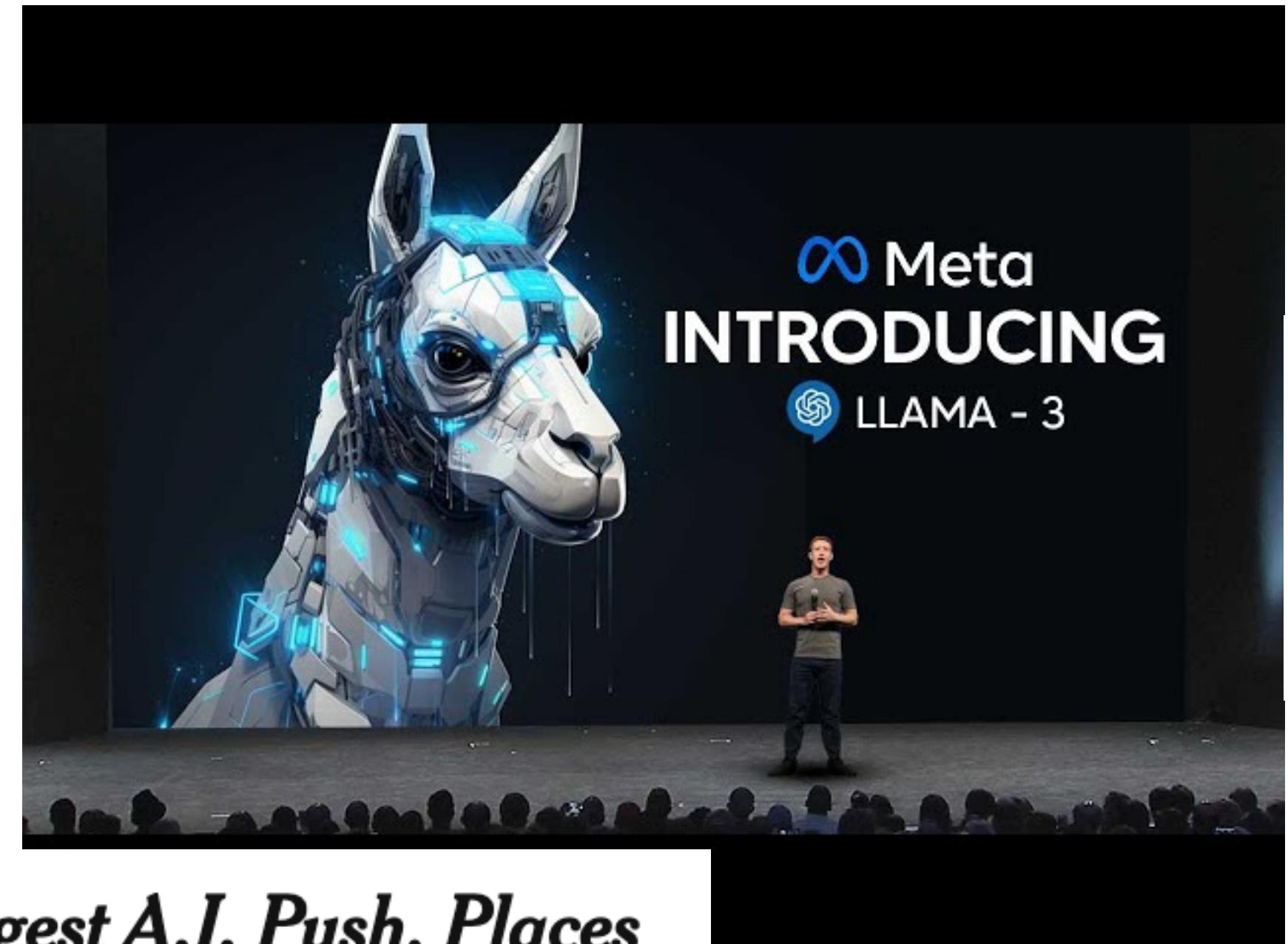
Can You Be Emotionally Reliant on an A.I. Voice? OpenAI Says Yes.

A.I.'s Insatiable Appetite for Energy

Meta, in Its Biggest A.I. Push, Places Smart Assistants Across Its Apps

In Constant Battle With Insurers, Doctors Reach for a Cudgel: A.I.

A.I. Can Write Poetry, but It Struggles With Math



Aided by A.I. Language Models, Google's Robots Are Getting Smart

In Big Election Year, A.I.'s Architects Move Against Its Misuse

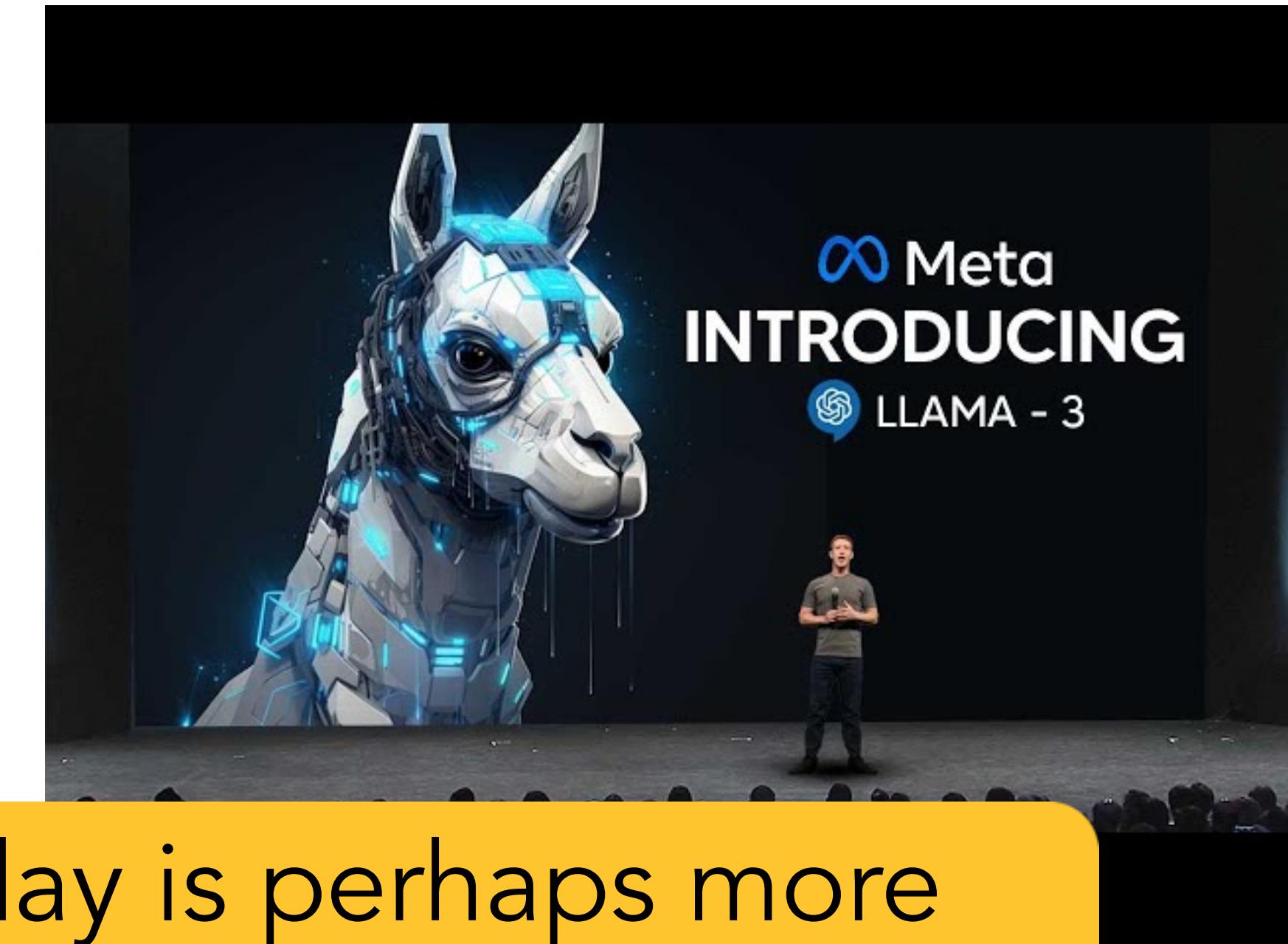
The Chef Is Human. The Reviewer Isn't.



THE SHIFT

Google C.E.O. Sundar Pichai on the A.I. Moment: 'You Will See Us Be Bold'

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OpenAI Is Testing an A.I.-Powered Search Engine

NLP today is perhaps more relevant than it ever has been!

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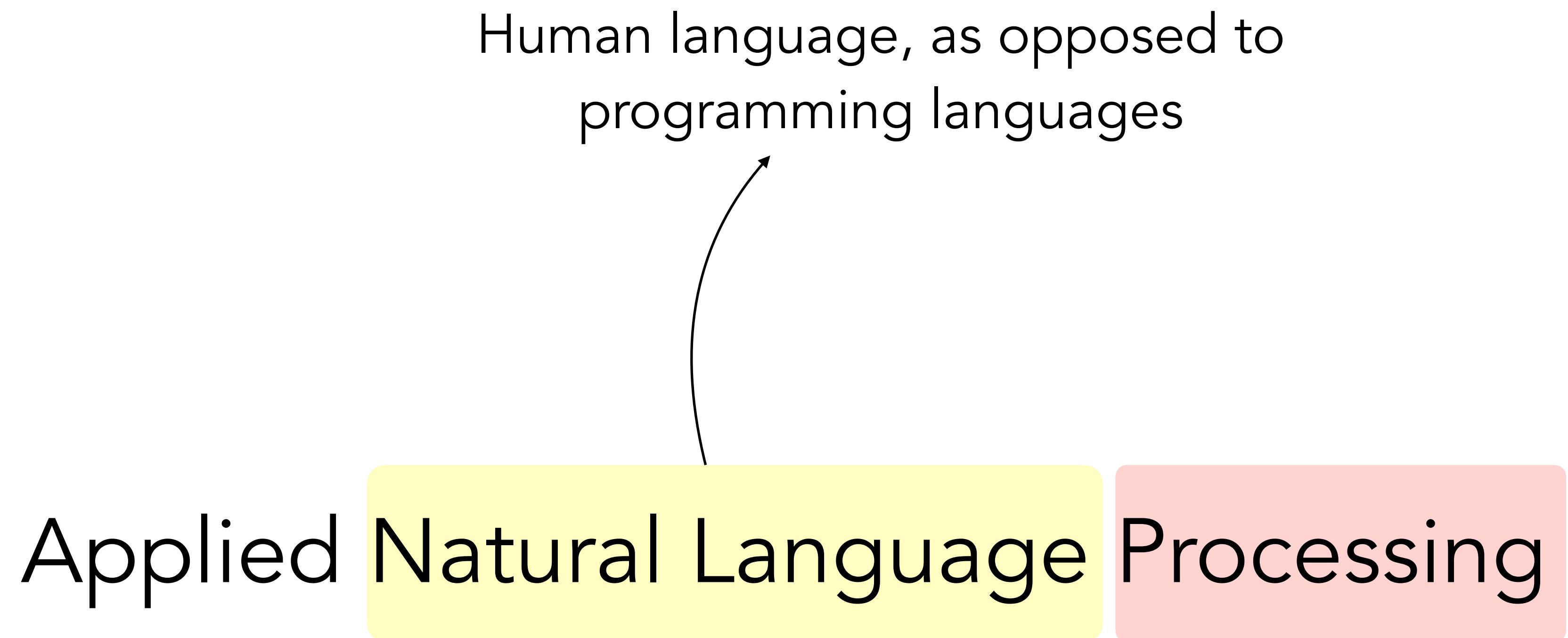
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Applied Natural Language Processing

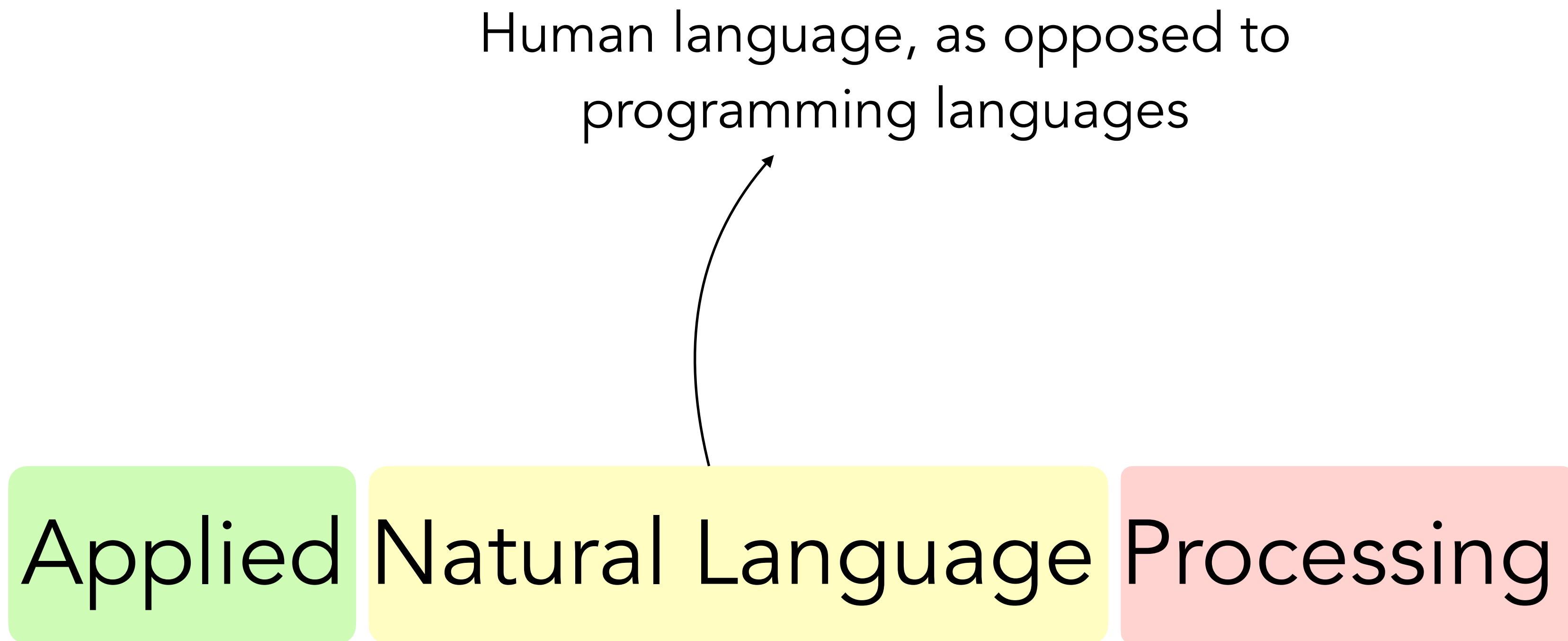
Applied Natural Language Processing

Automatic, as opposed to manual





Automatic, as opposed to manual



Human language, as opposed to
programming languages

As opposed to theoretical, or focused on linguistics

Automatic, as opposed to manual

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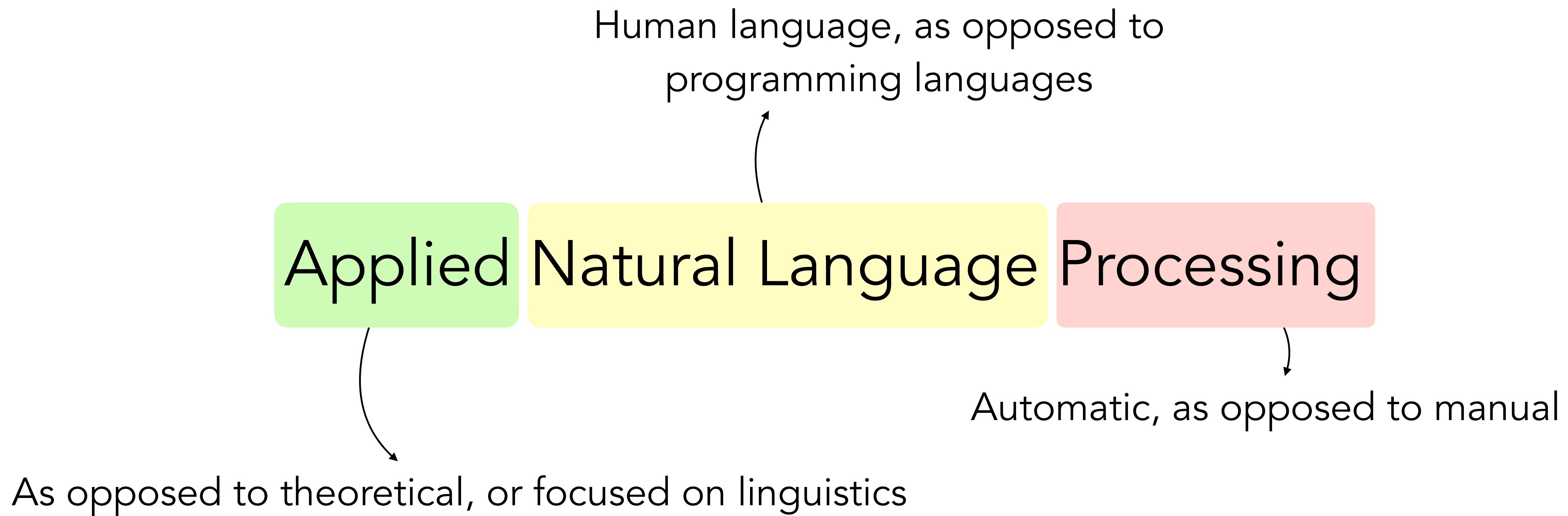
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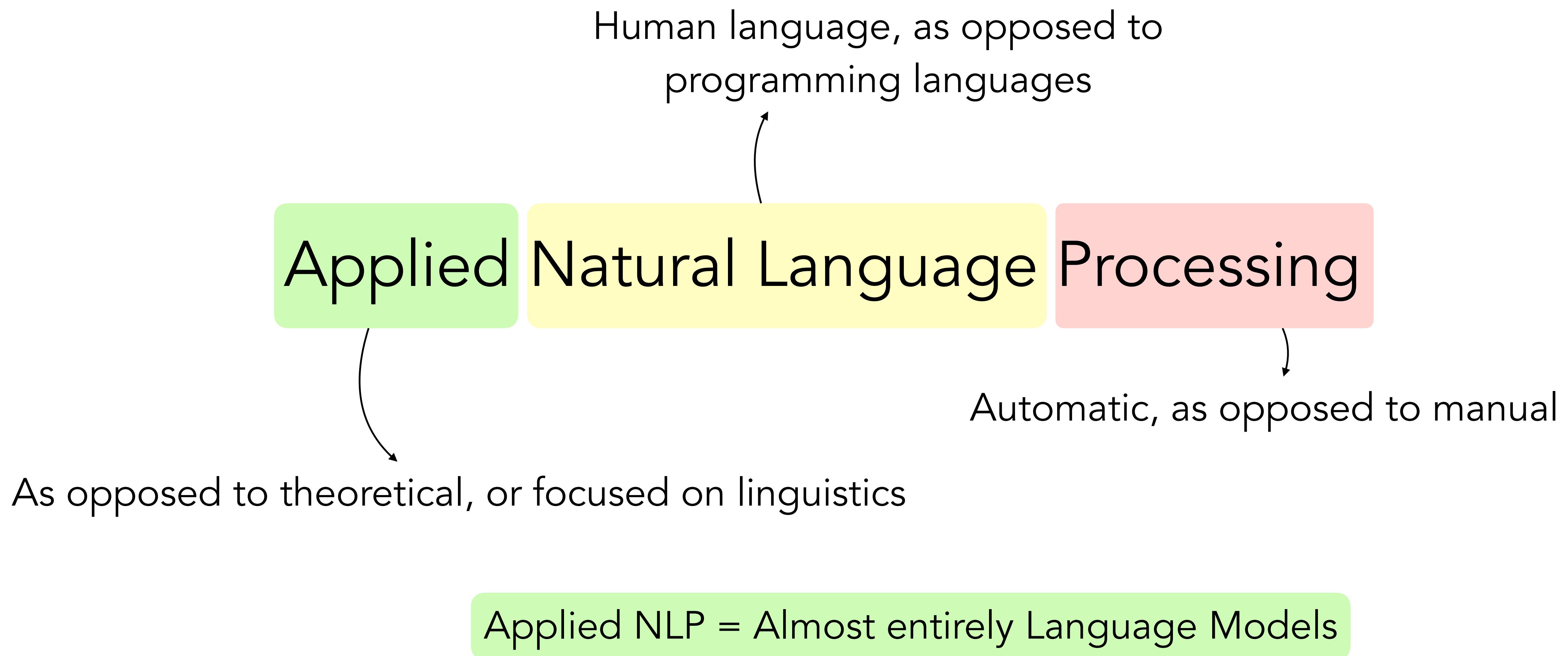
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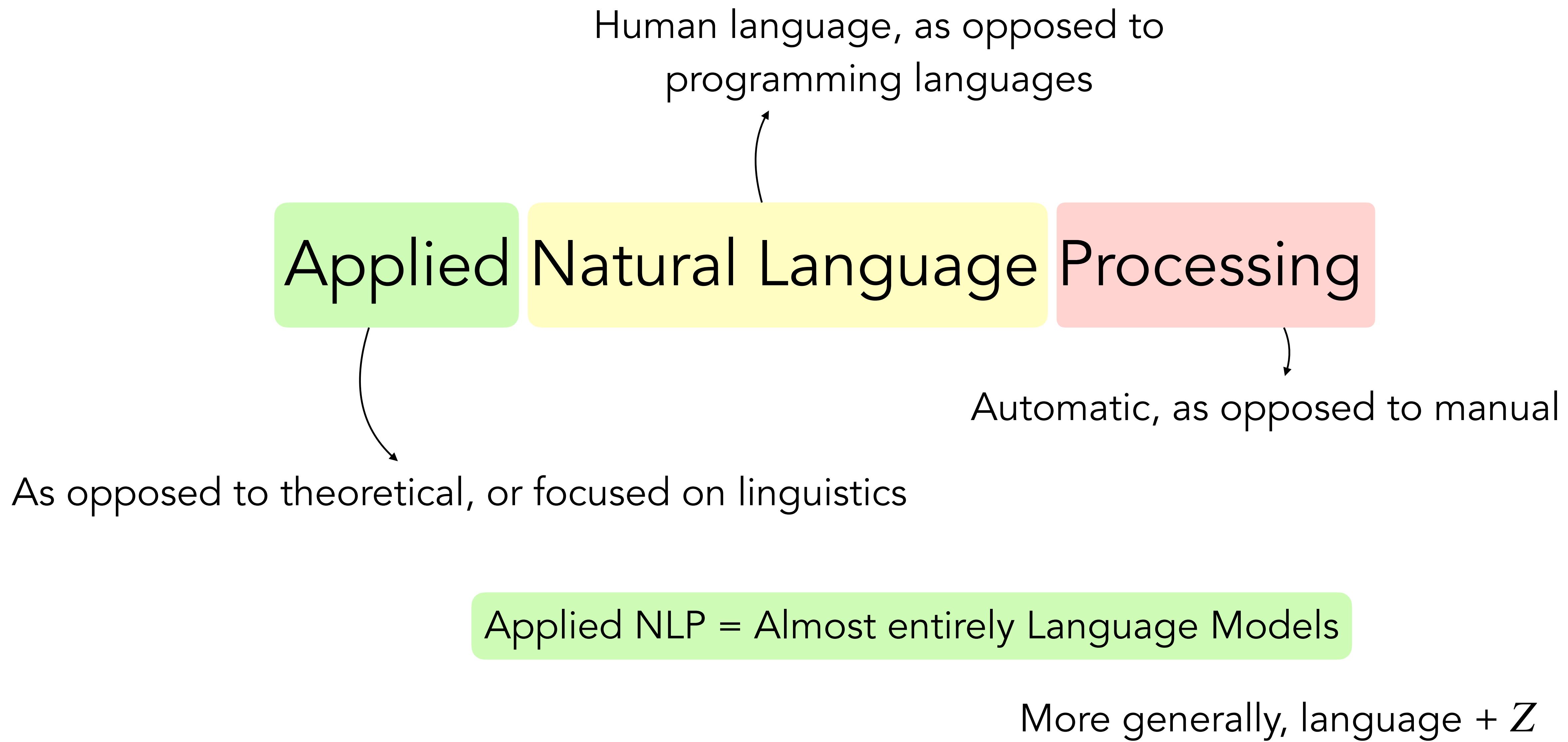
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- Processing: produce outputs (Y) with language or text as input (X)
 - Outputs can be more language / text as well!







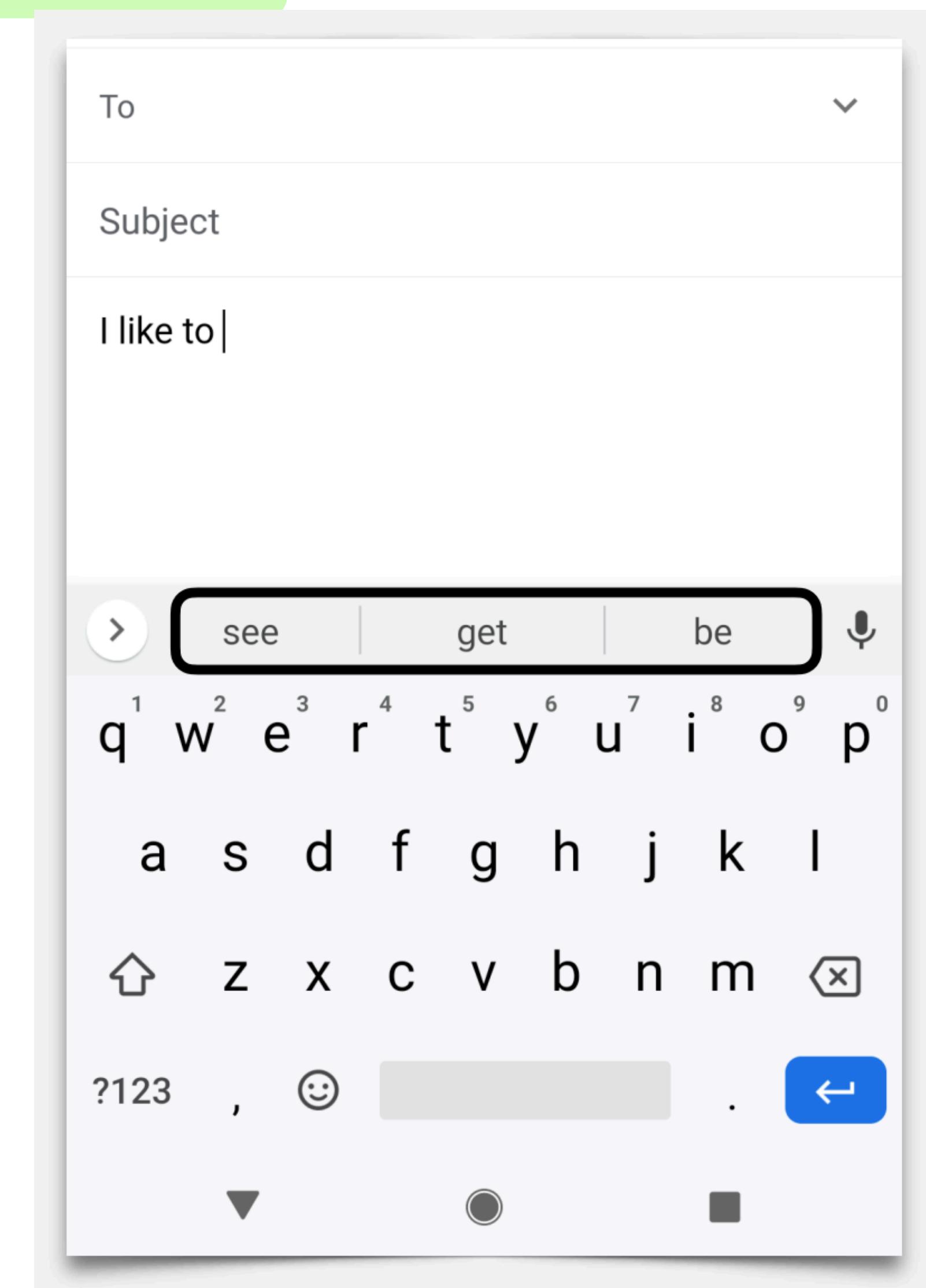
Language Models

Language Models

- Task: Given a sequence of words so far (**the context**), predict what comes next

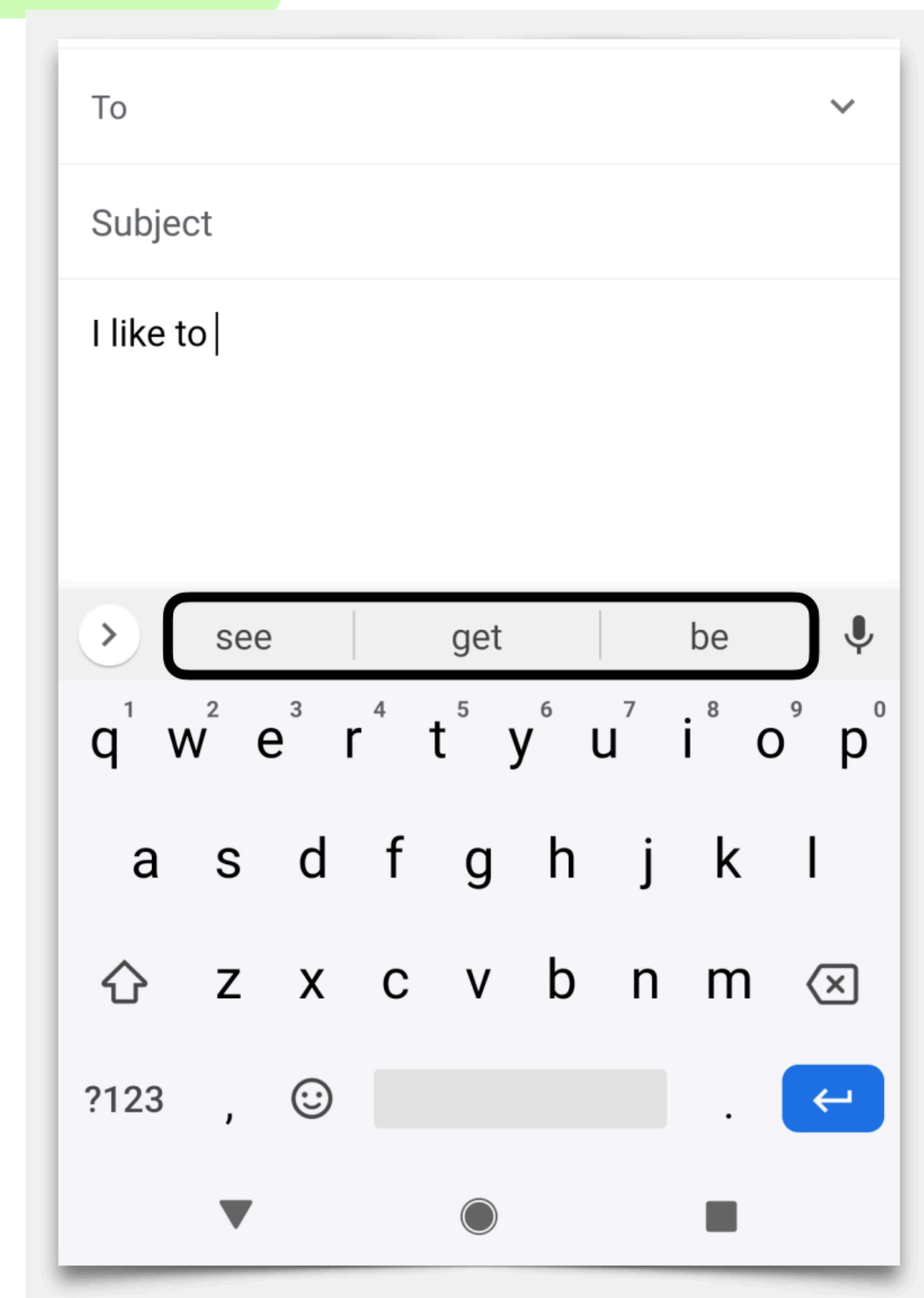
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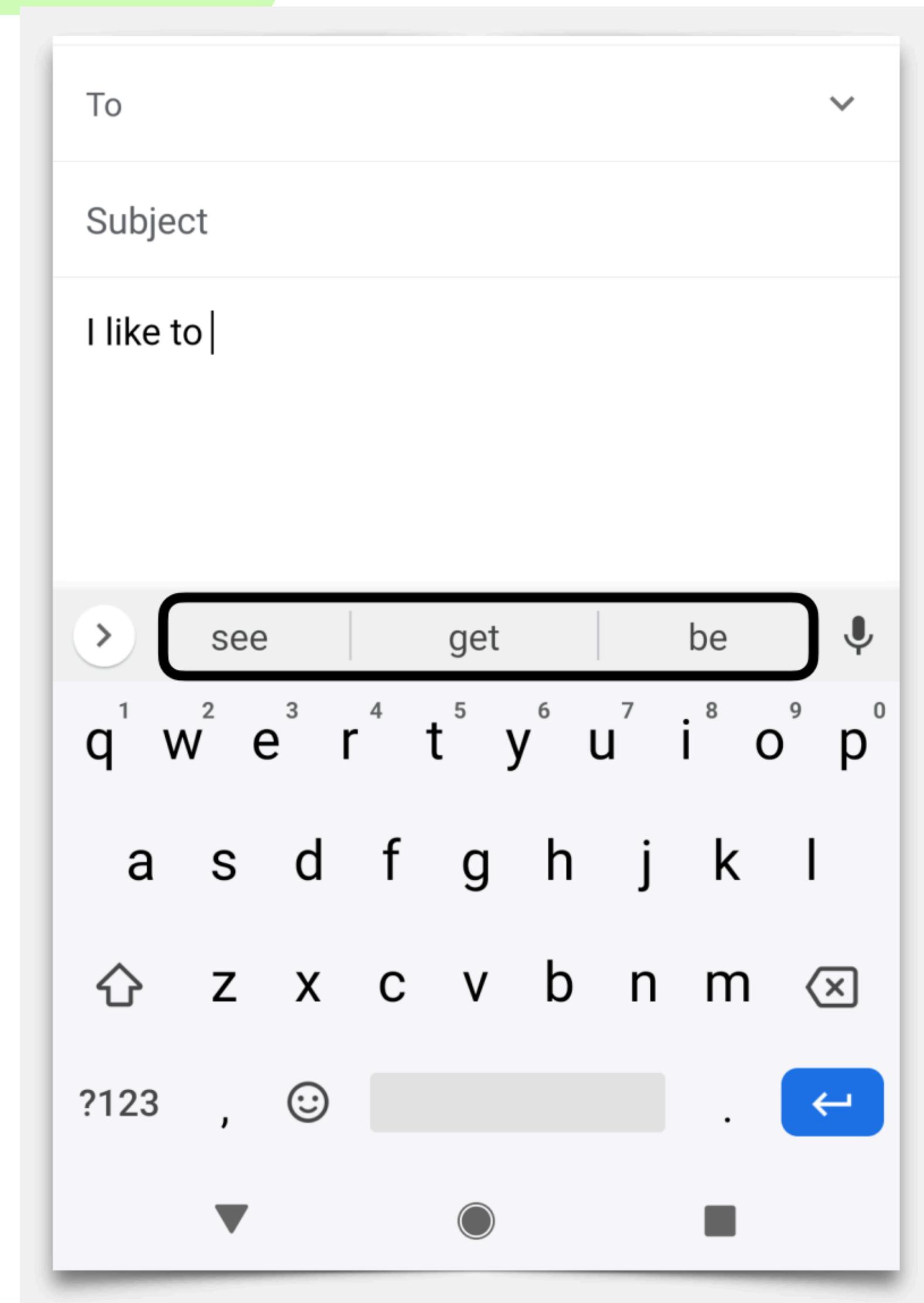
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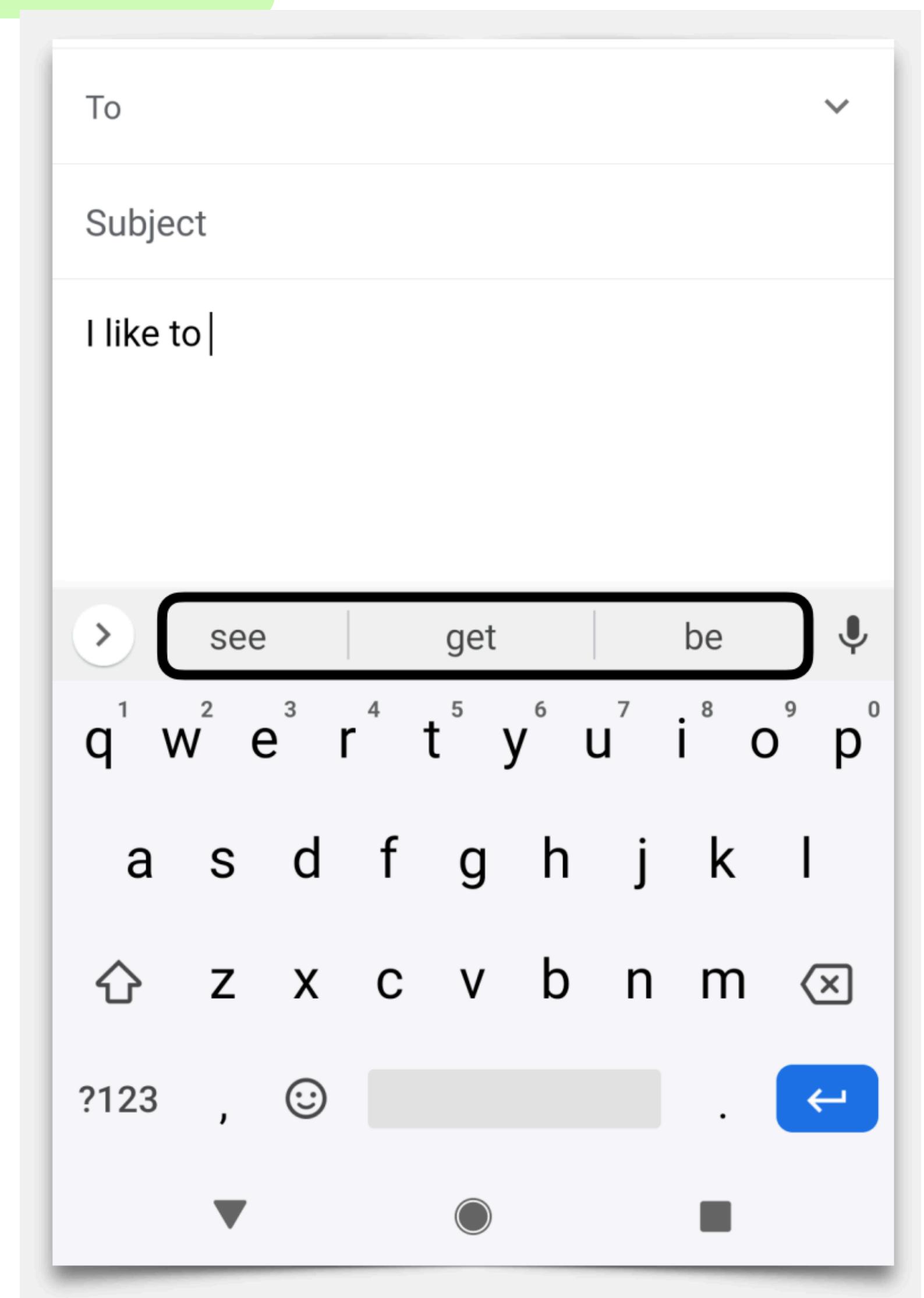
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- Question: what is X and what is Y here?
 - Input X = Language and Output Y = Language



Language Model as Autocomplete

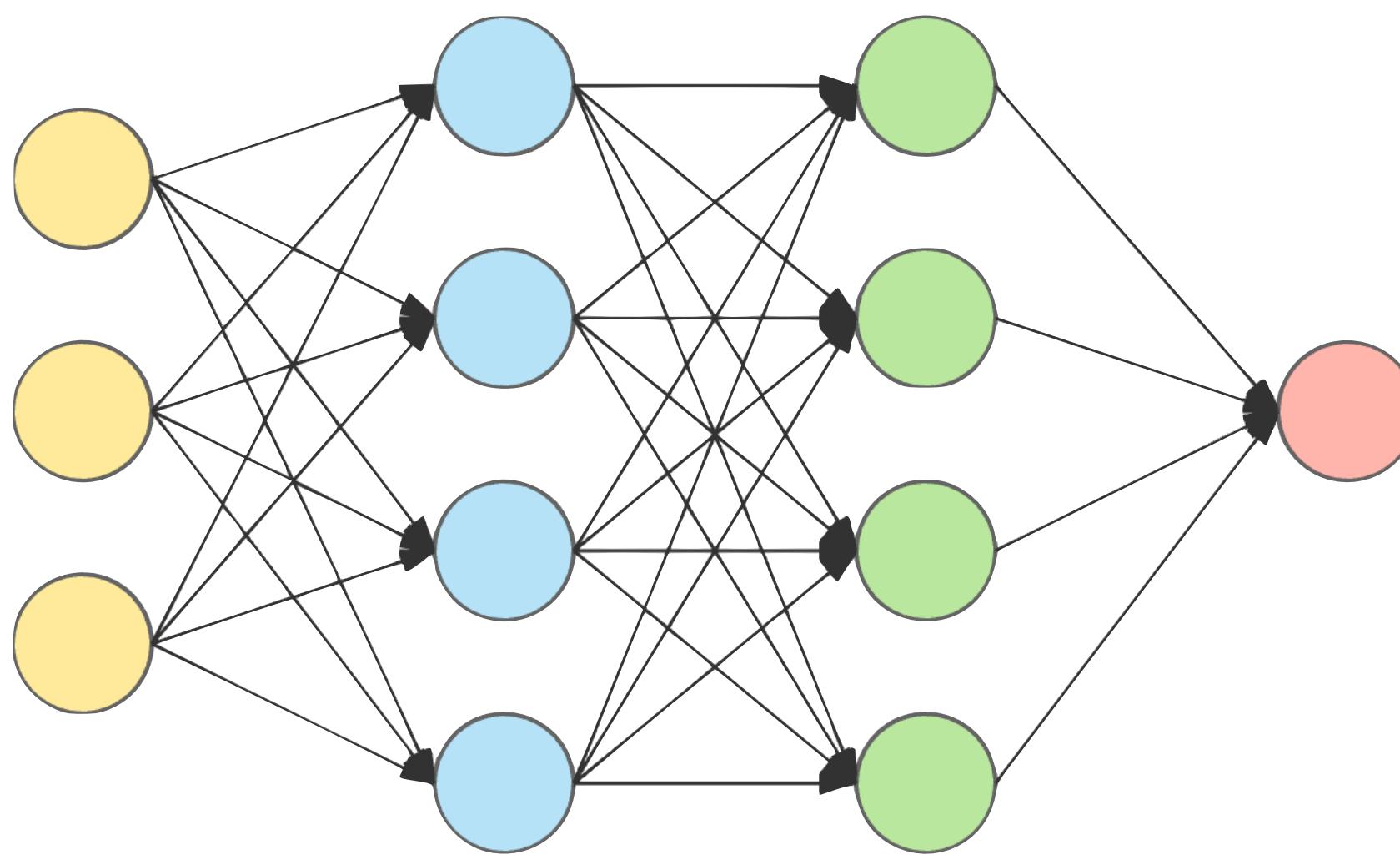
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Dance the...



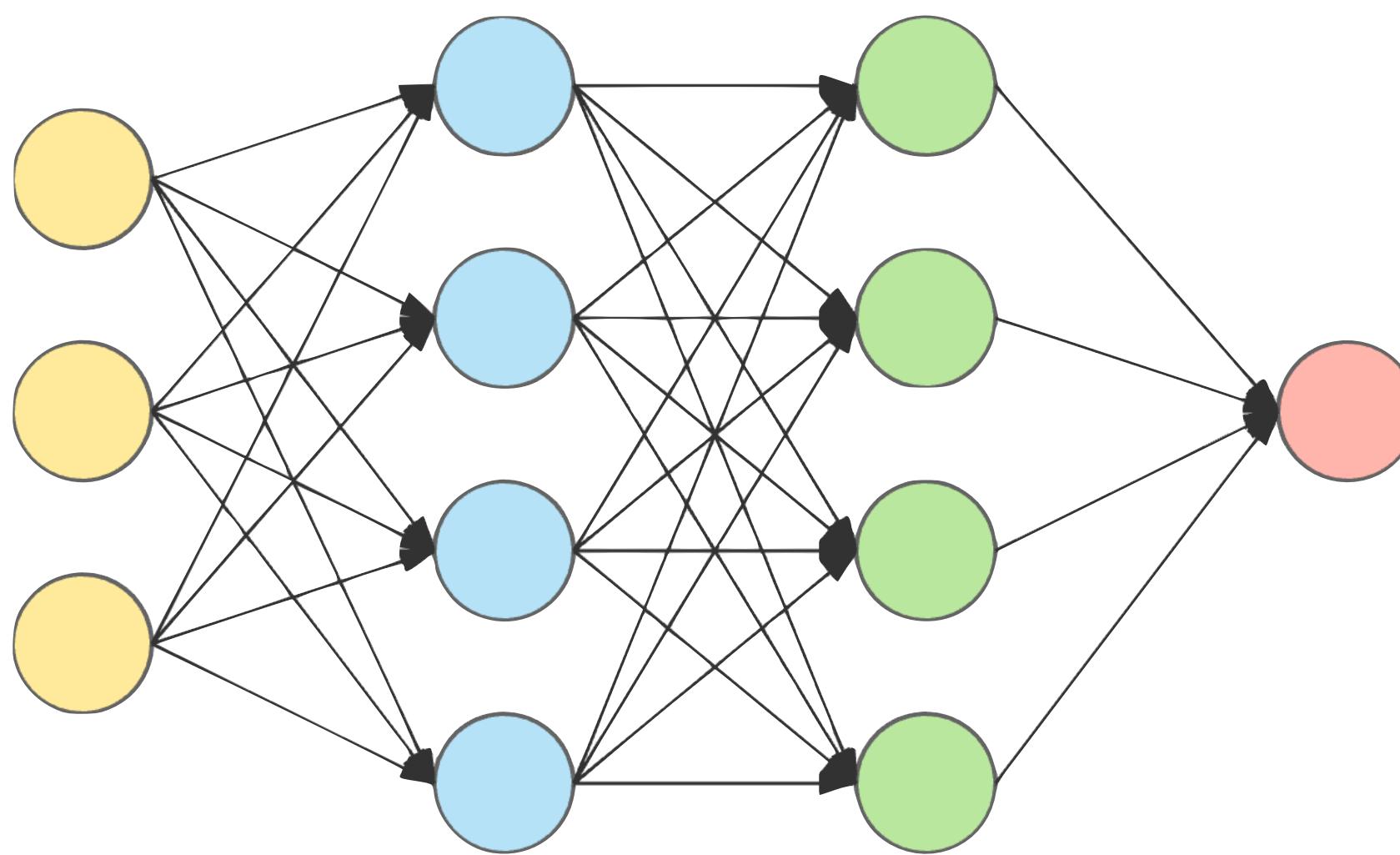
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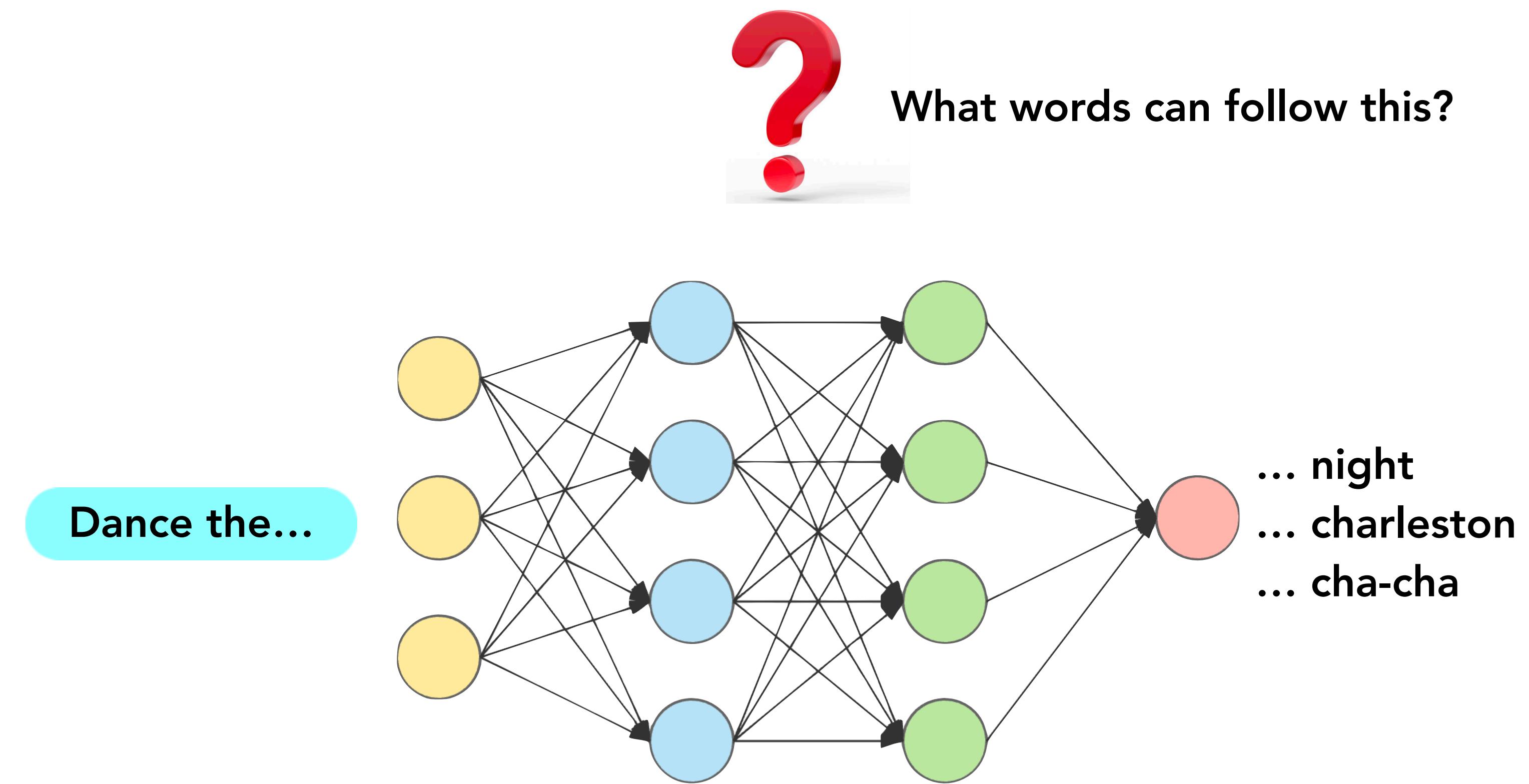


What words can follow this?



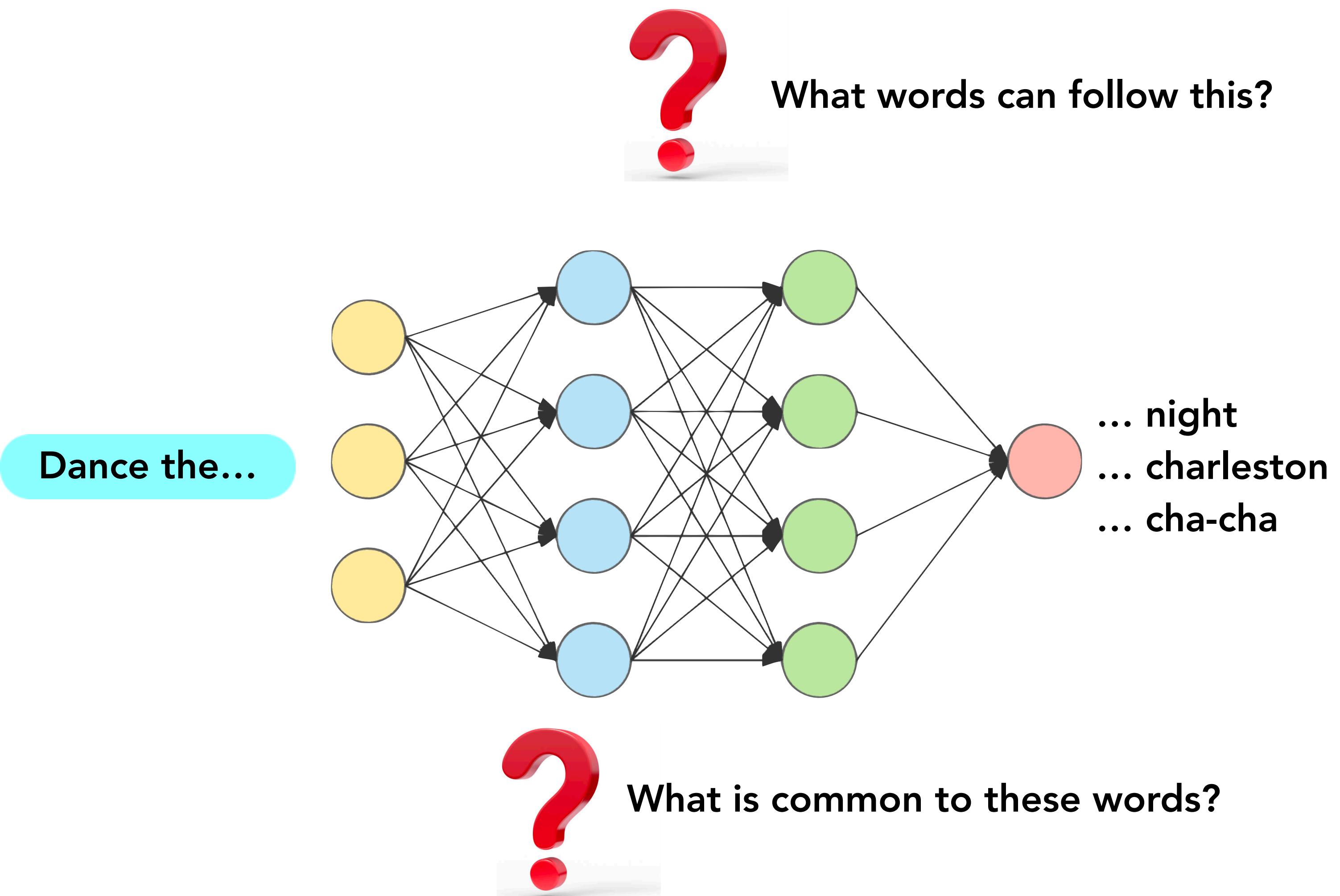
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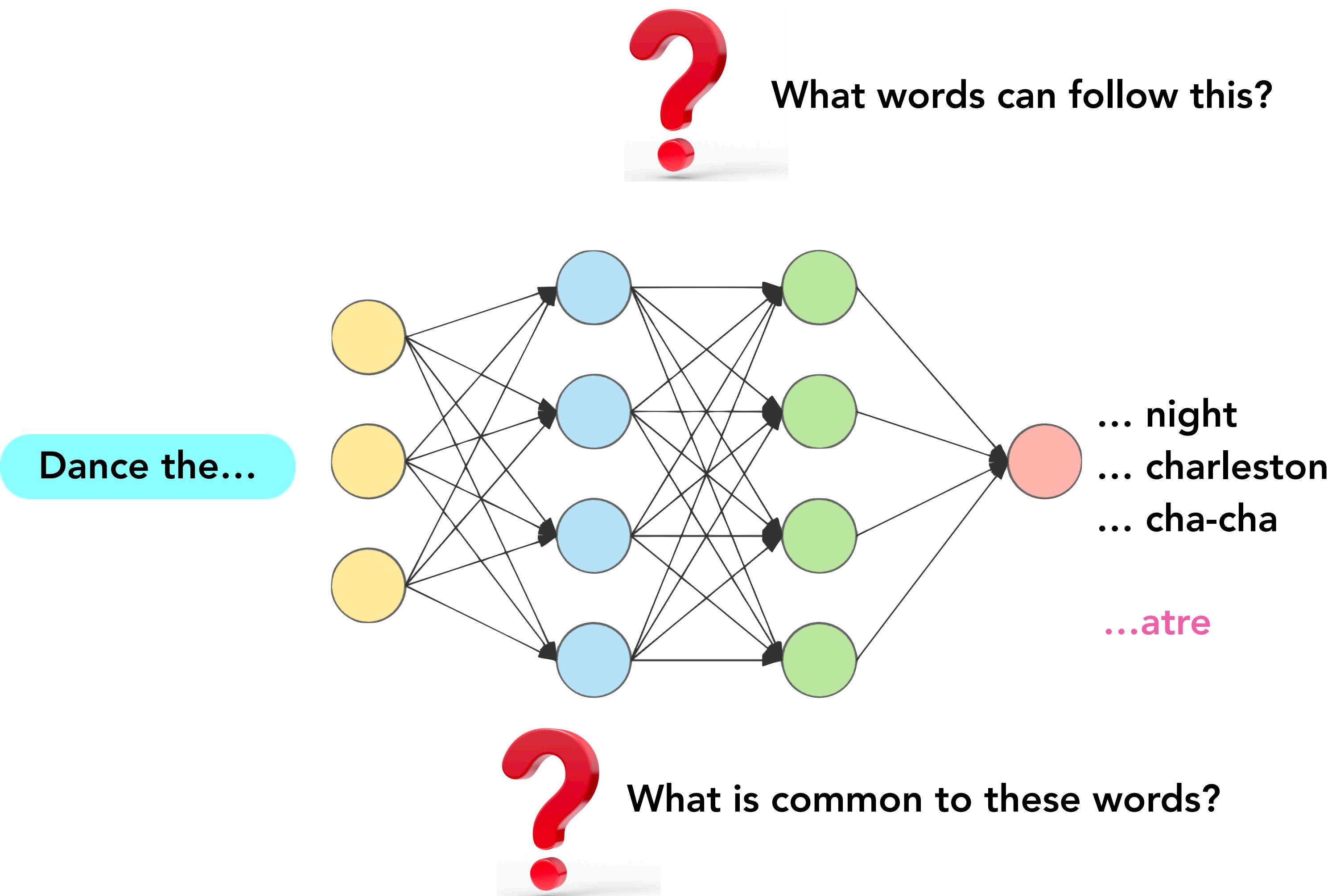
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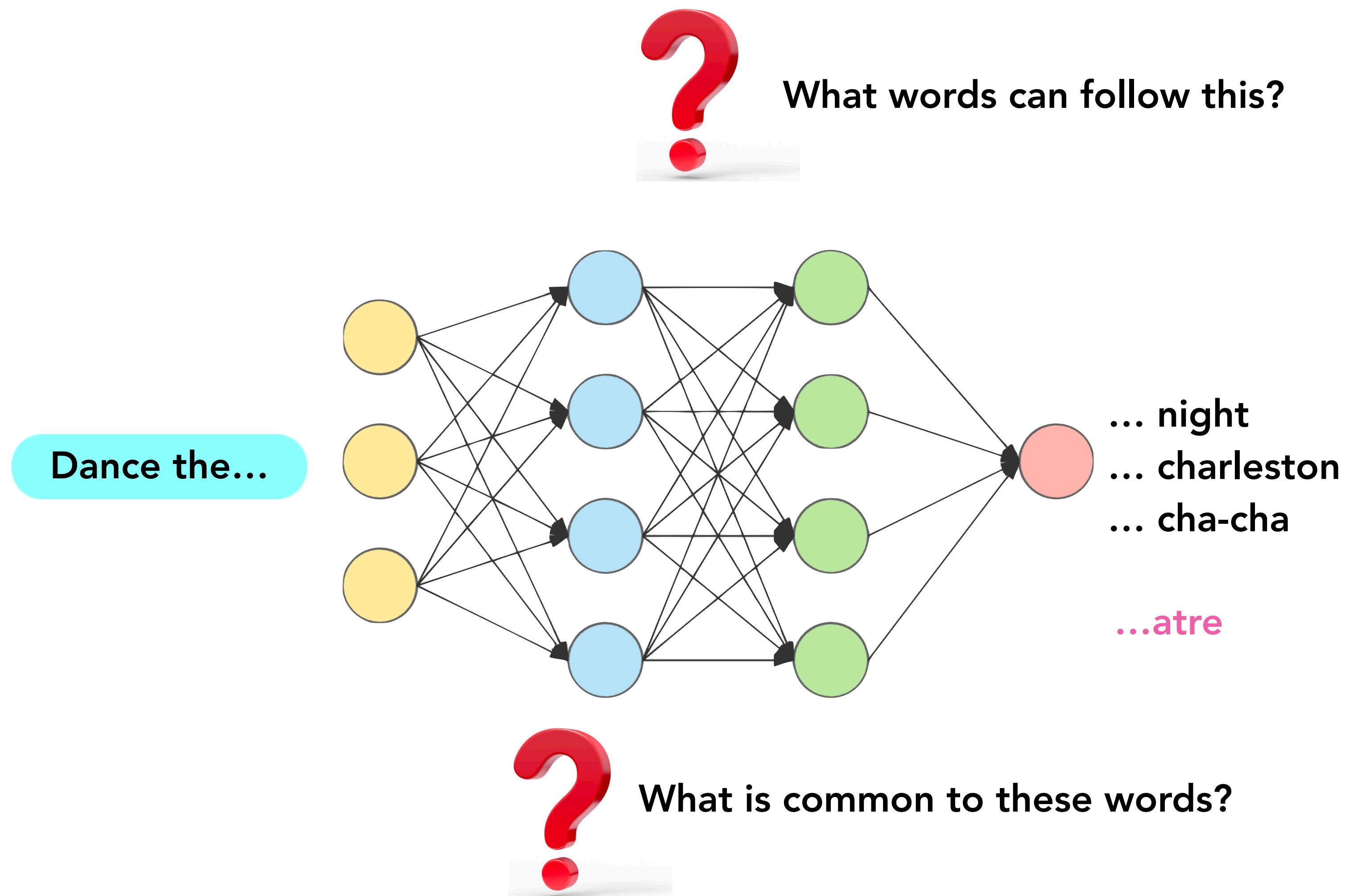
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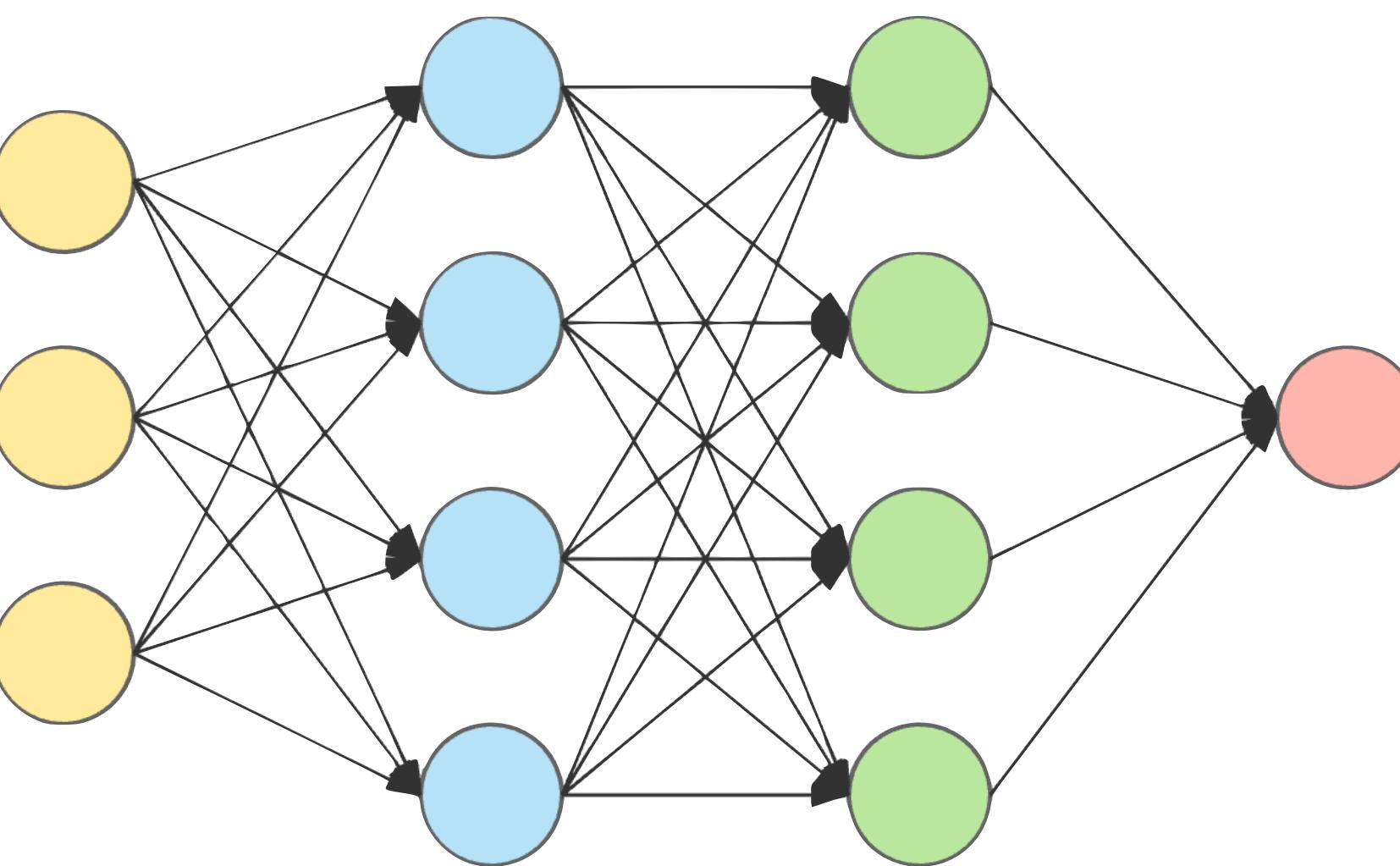
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The 44th President of United States was ...



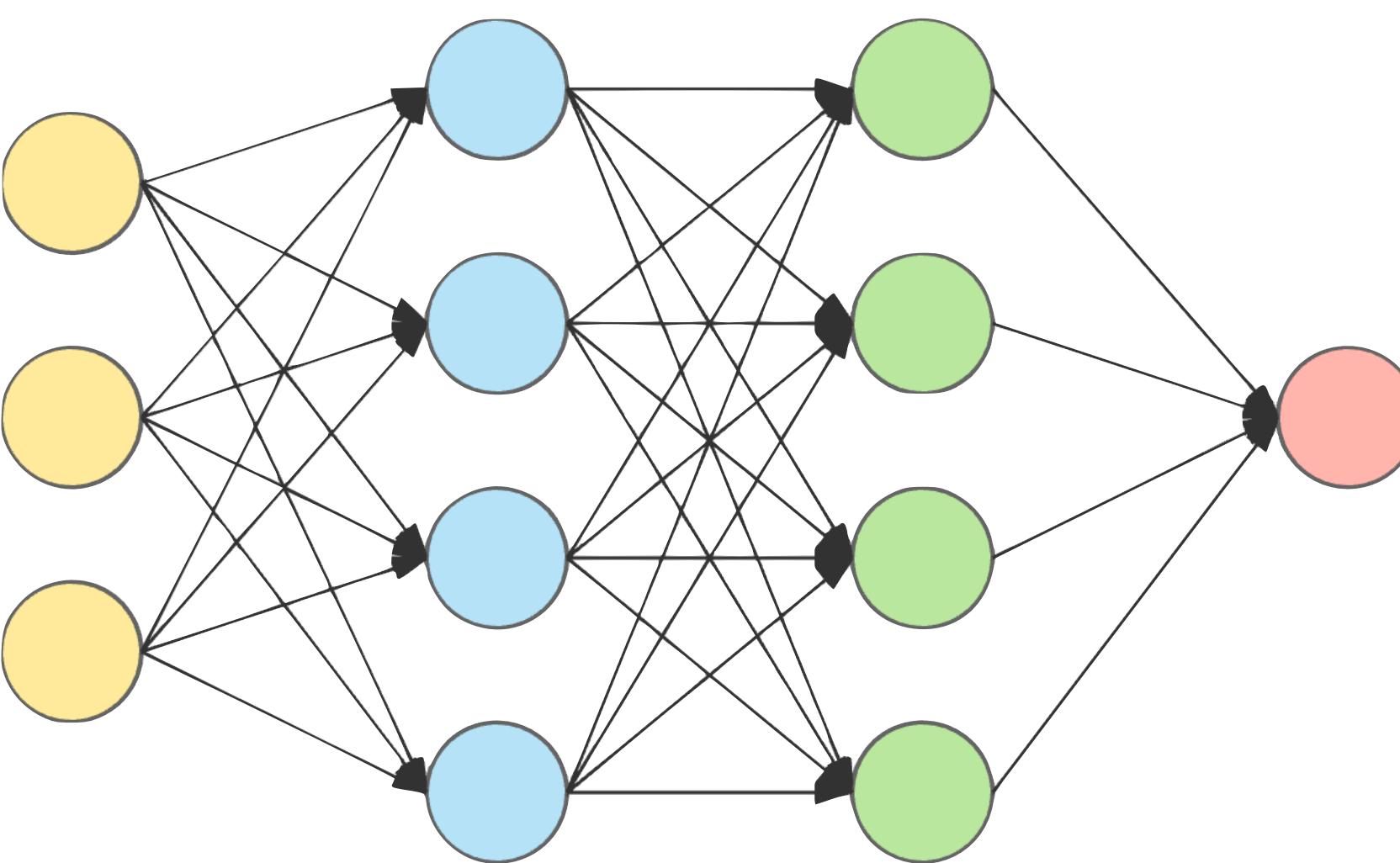
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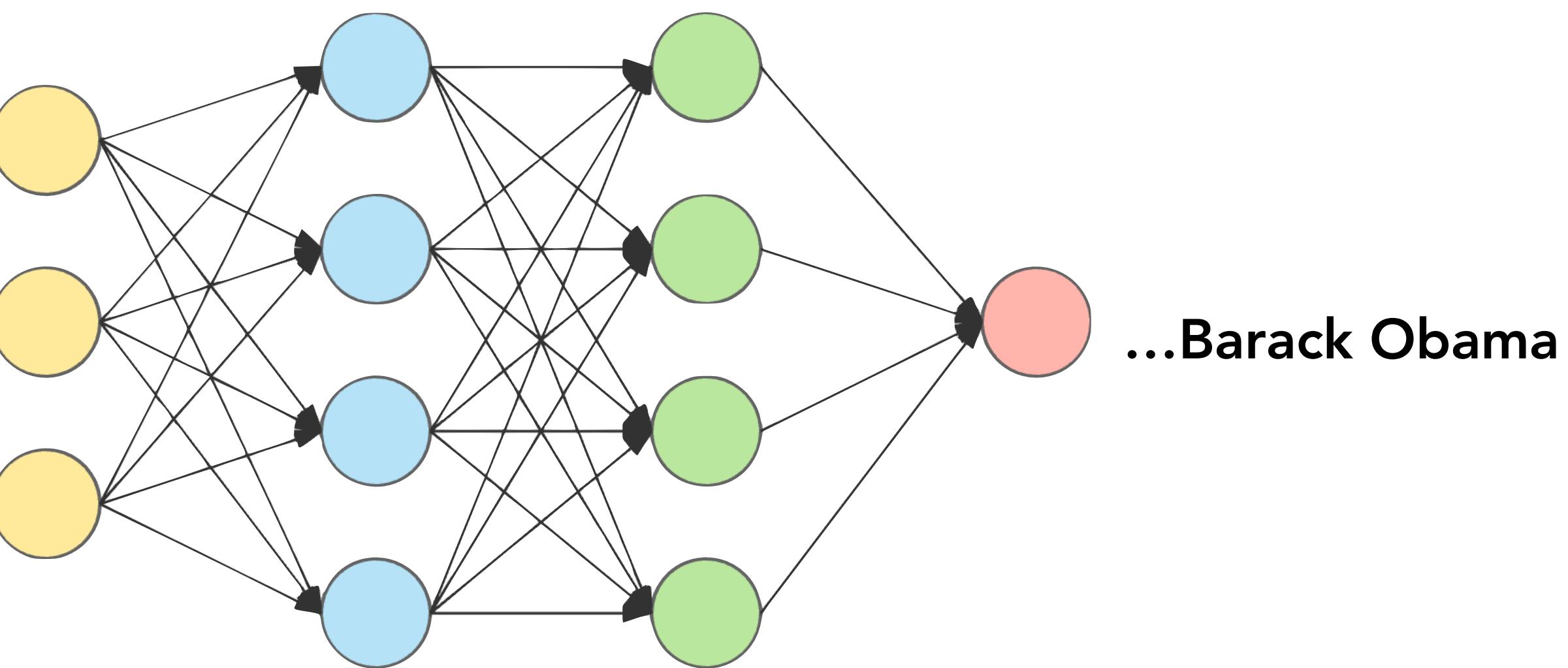
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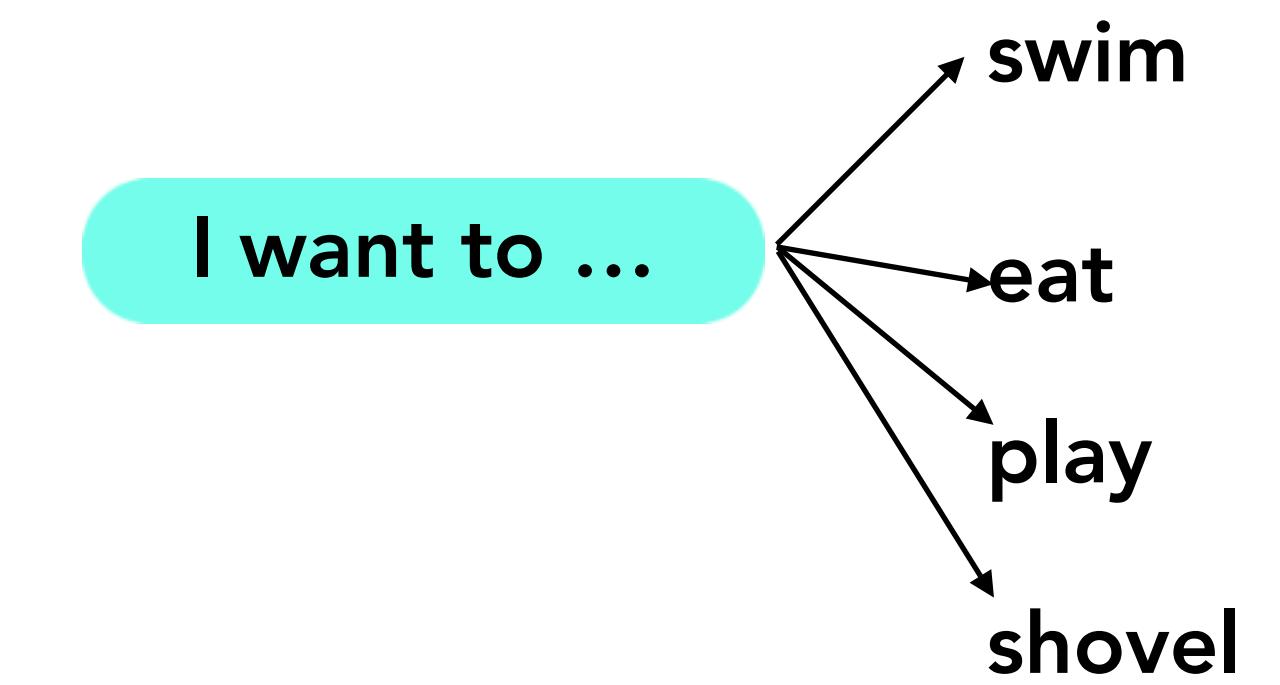


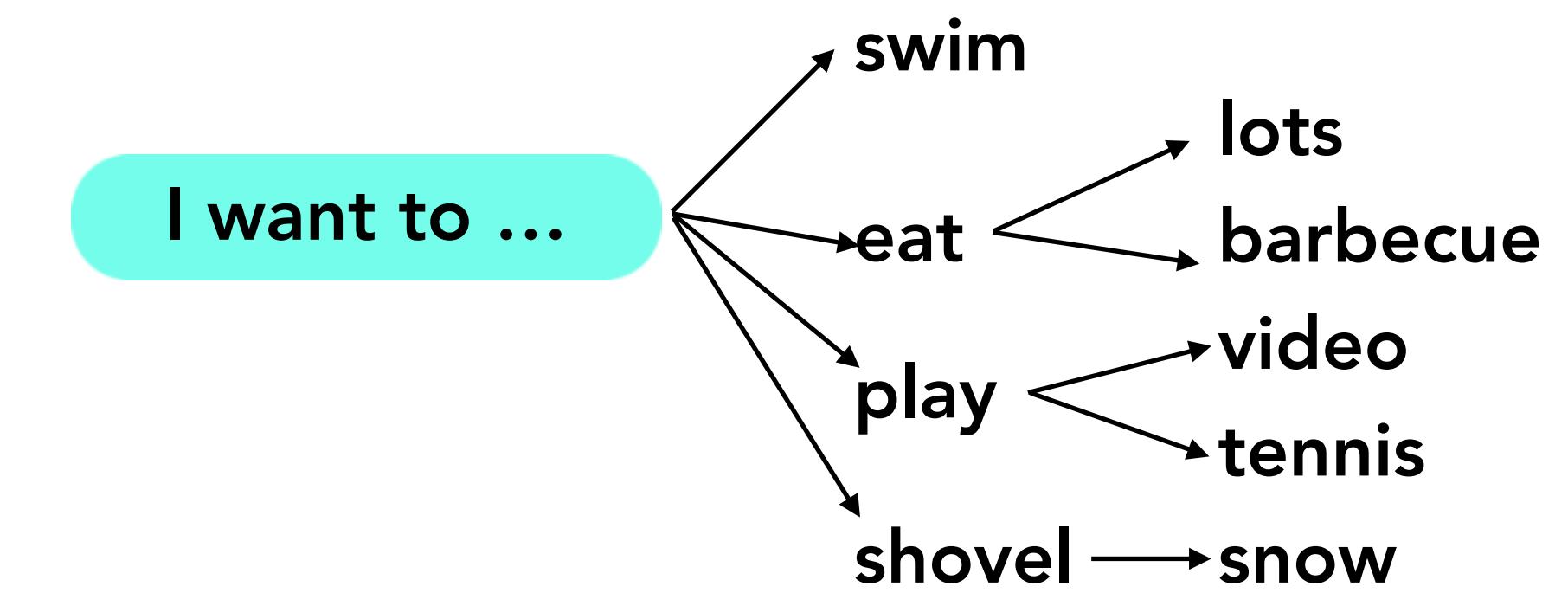
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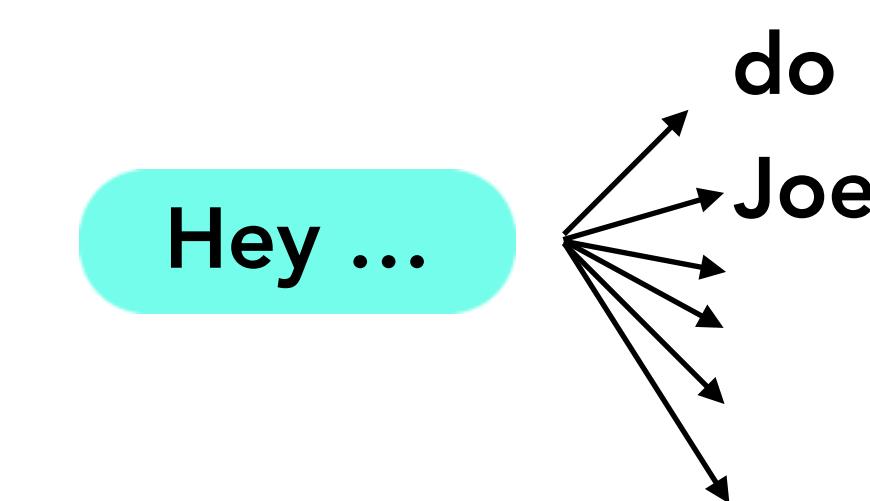
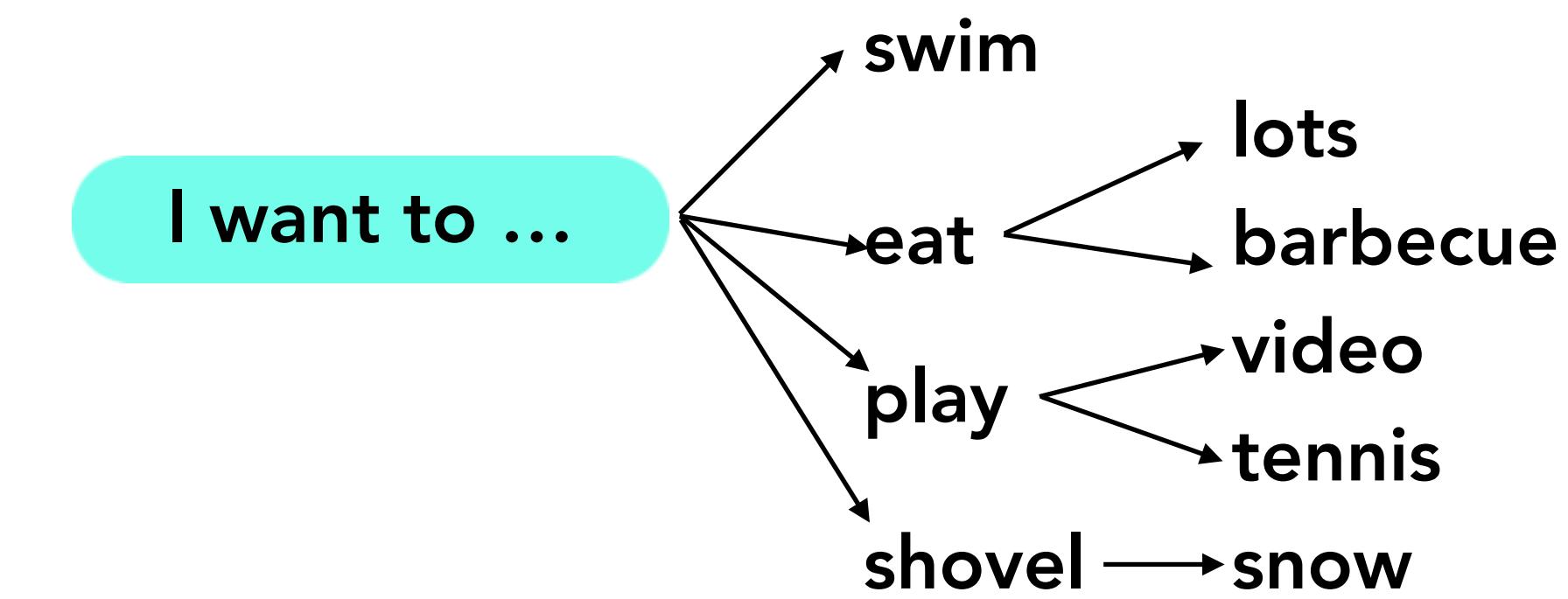


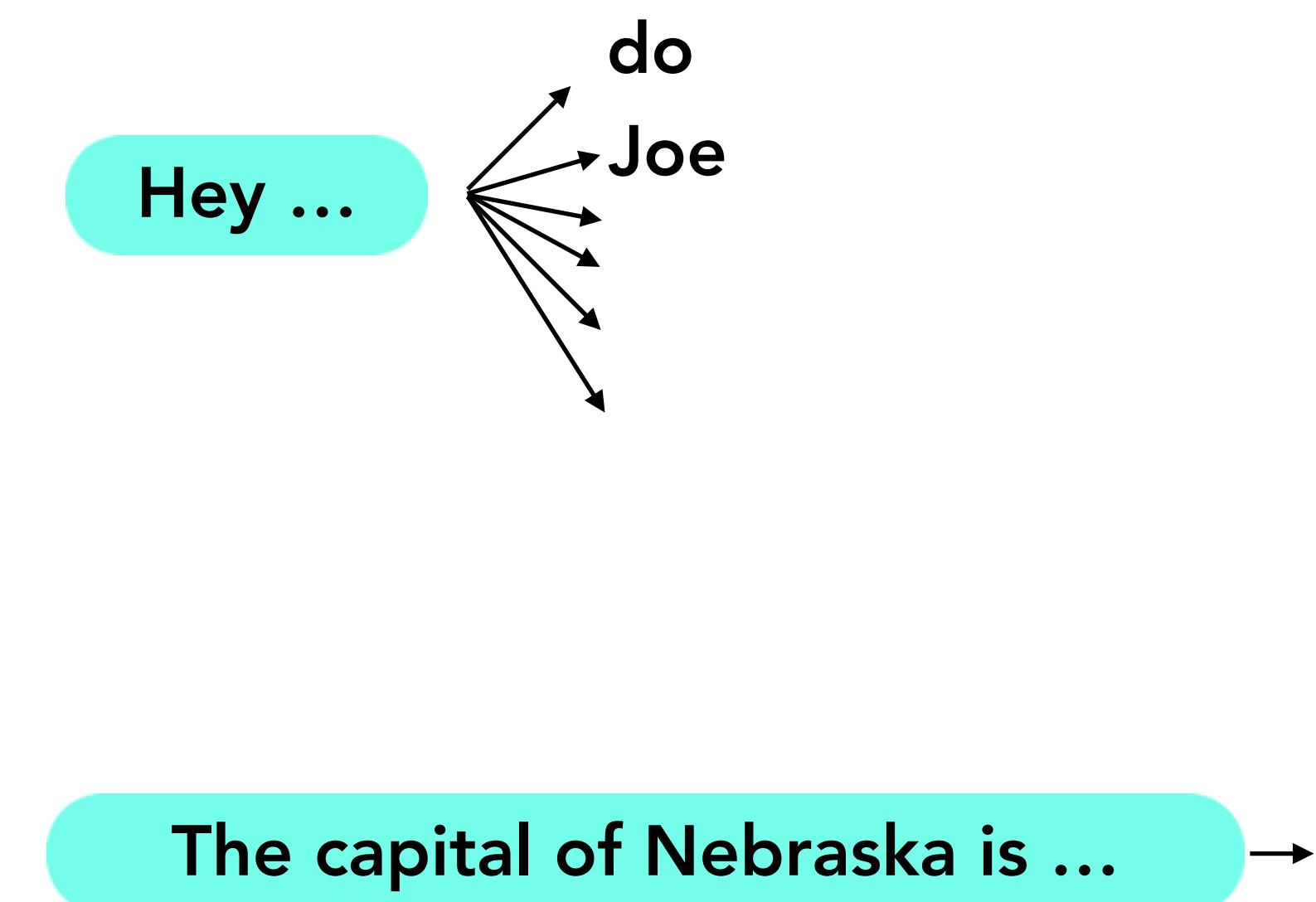
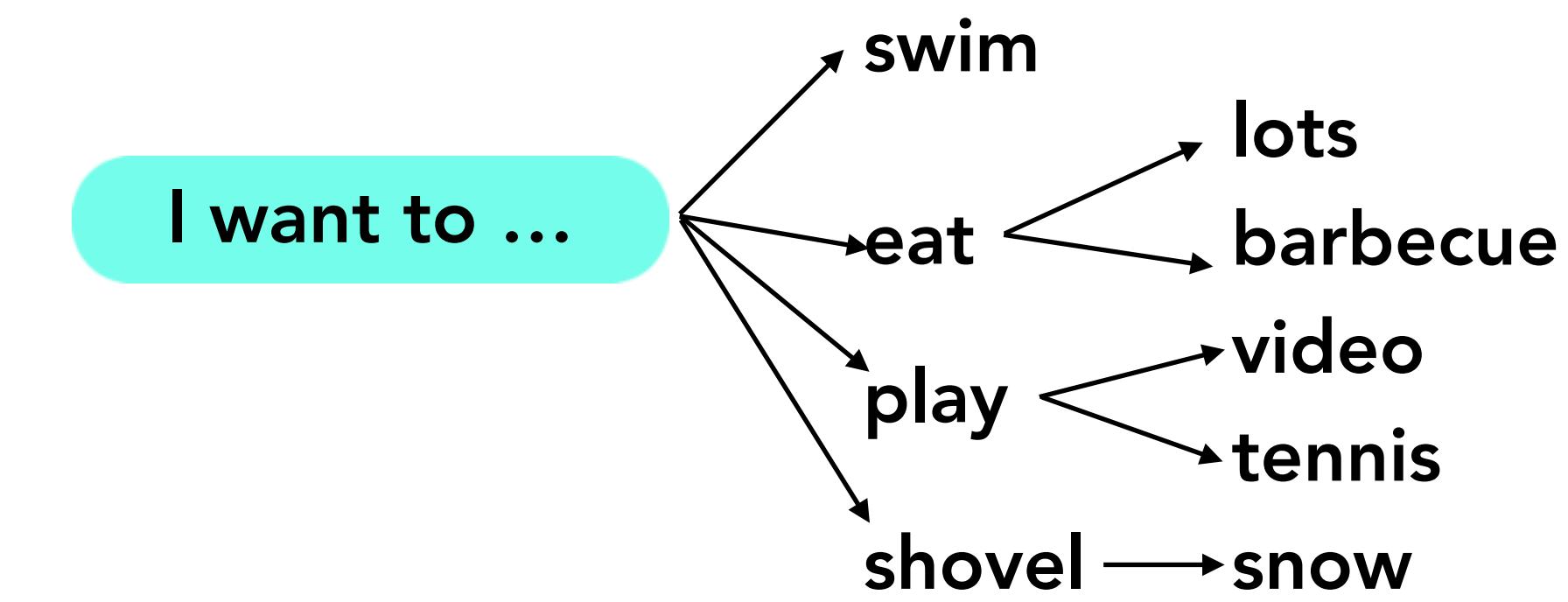
...Barack Obama

I want to ...

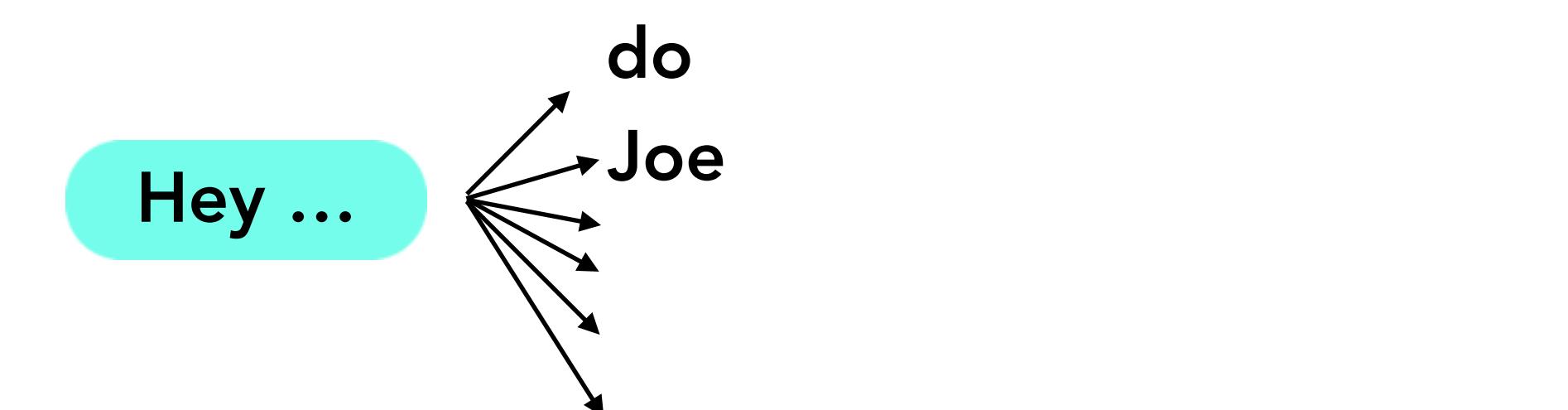
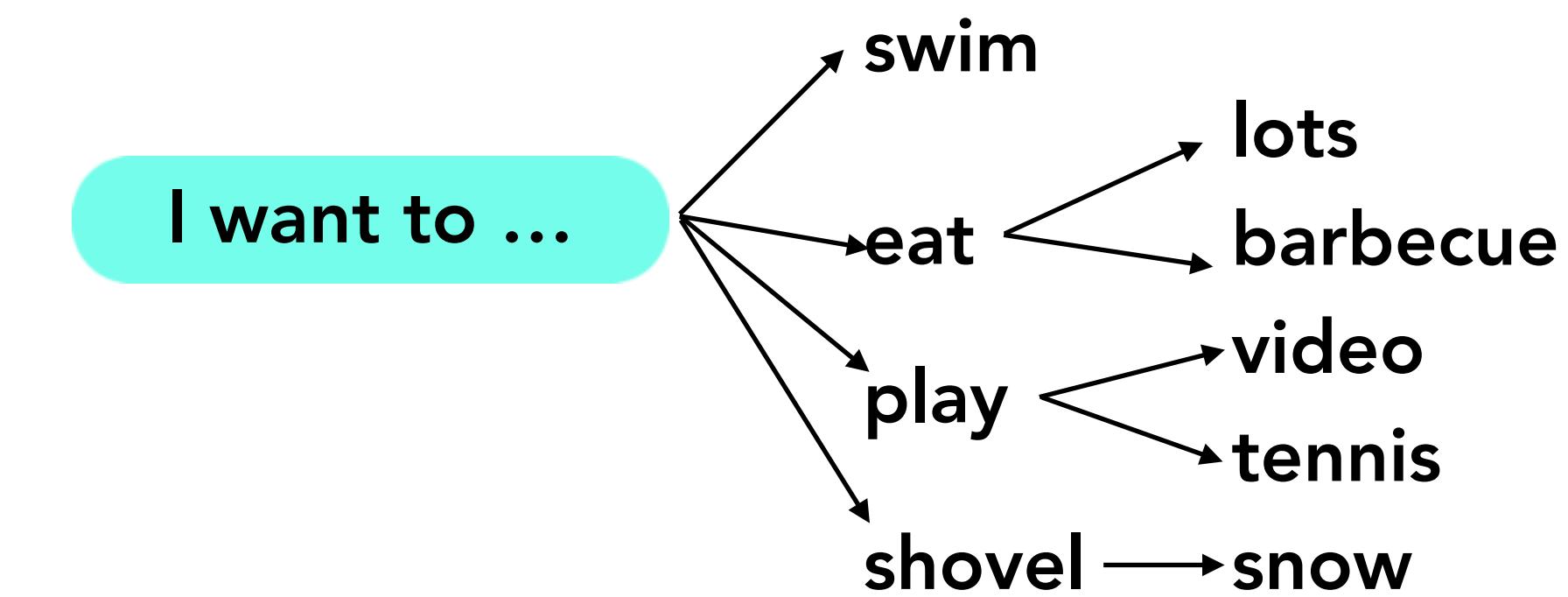








The capital of Nebraska is ... →



The capital of Nebraska is ... → Lincoln

Lecture Outline

- What is Applied NLP today?
 - Language Models!
- Why study Applied NLP? Or, why study language models?
- Class Syllabus
- Class Logistics

Why study Applied NLP?

~~Why study Applied NLP?~~

Why study Language Models?

Related Question: Why study AI?

Related Question: Why study AI?

The future is

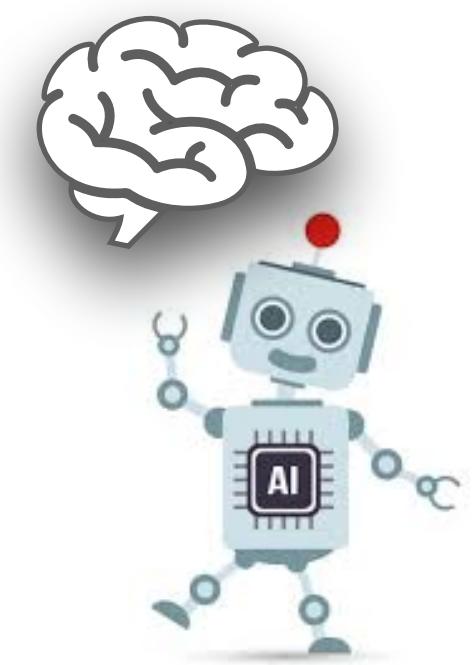
Artificial Intelligence



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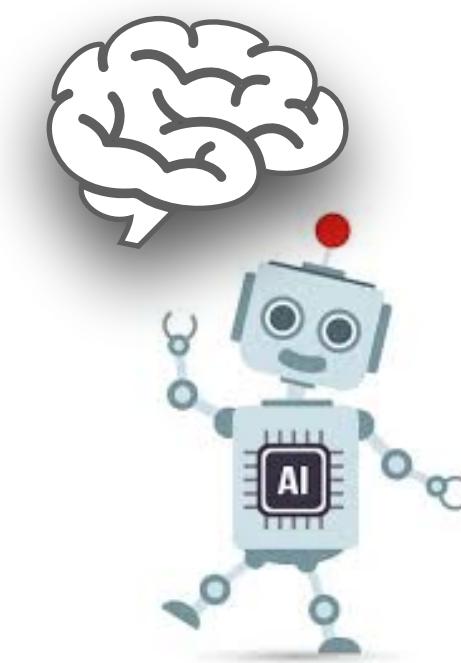
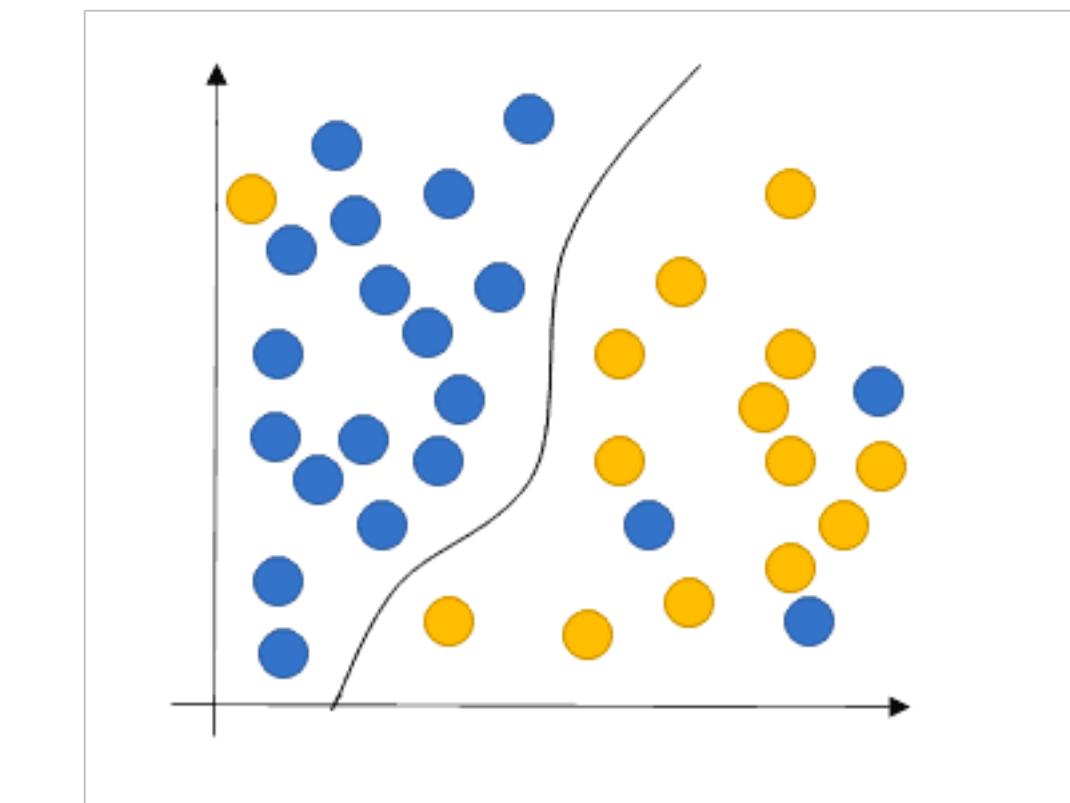


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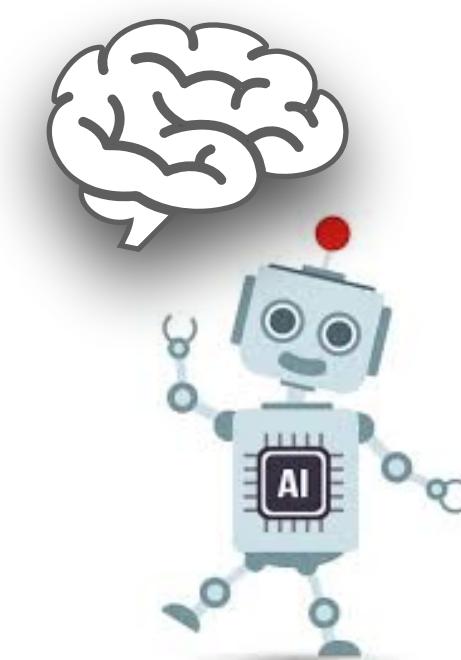
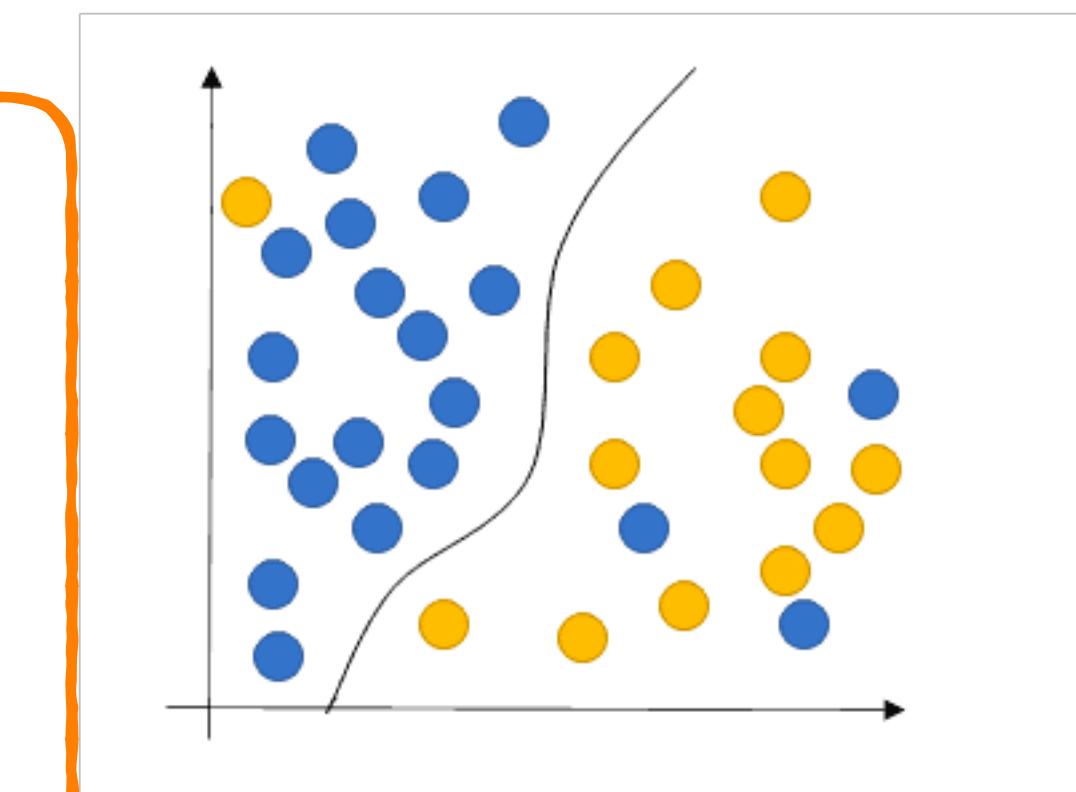
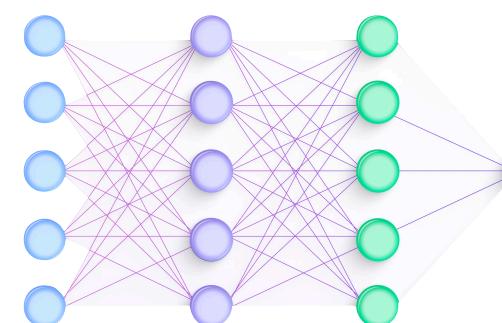
Machine Learning and Natural Language Processing

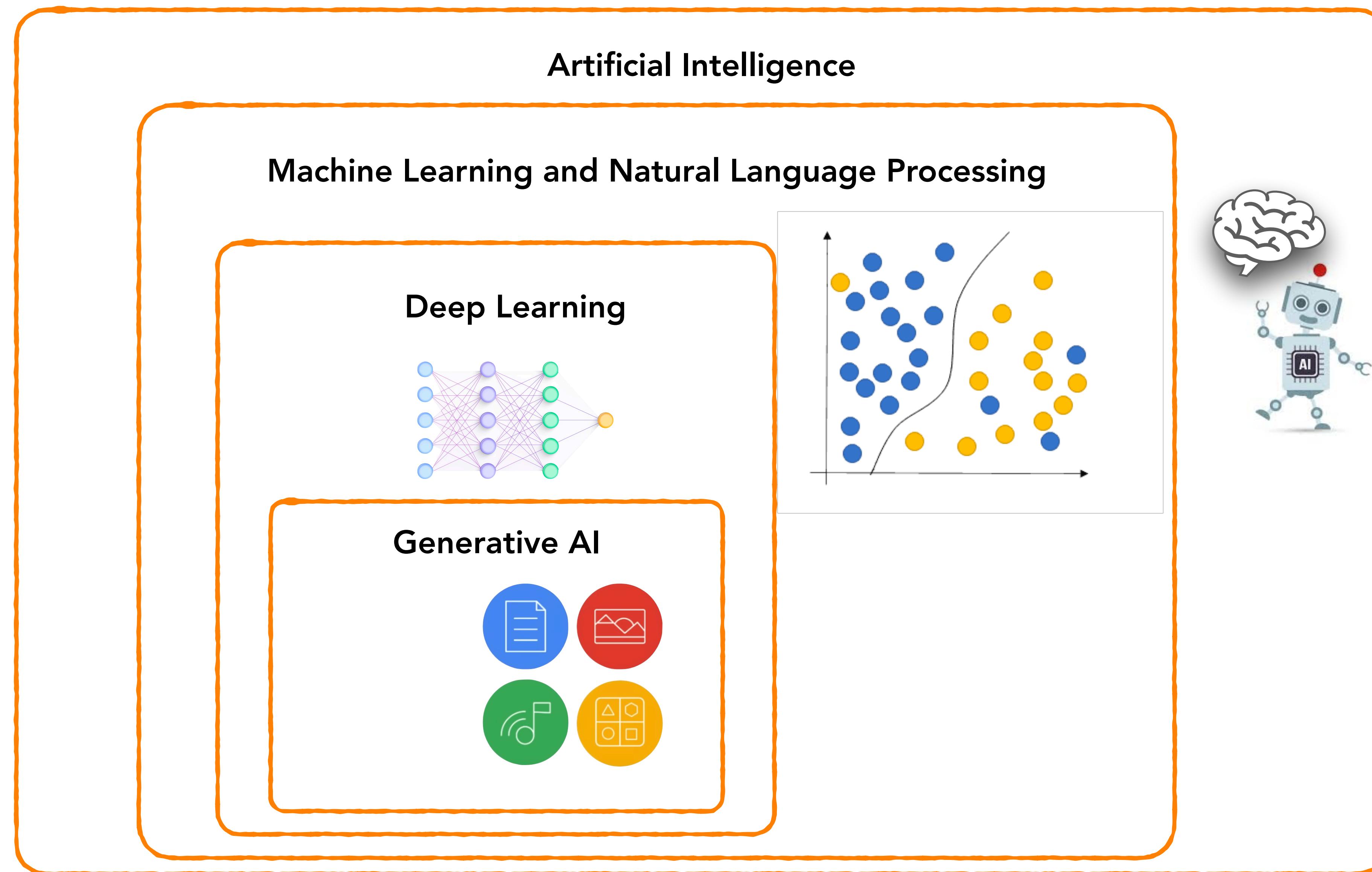


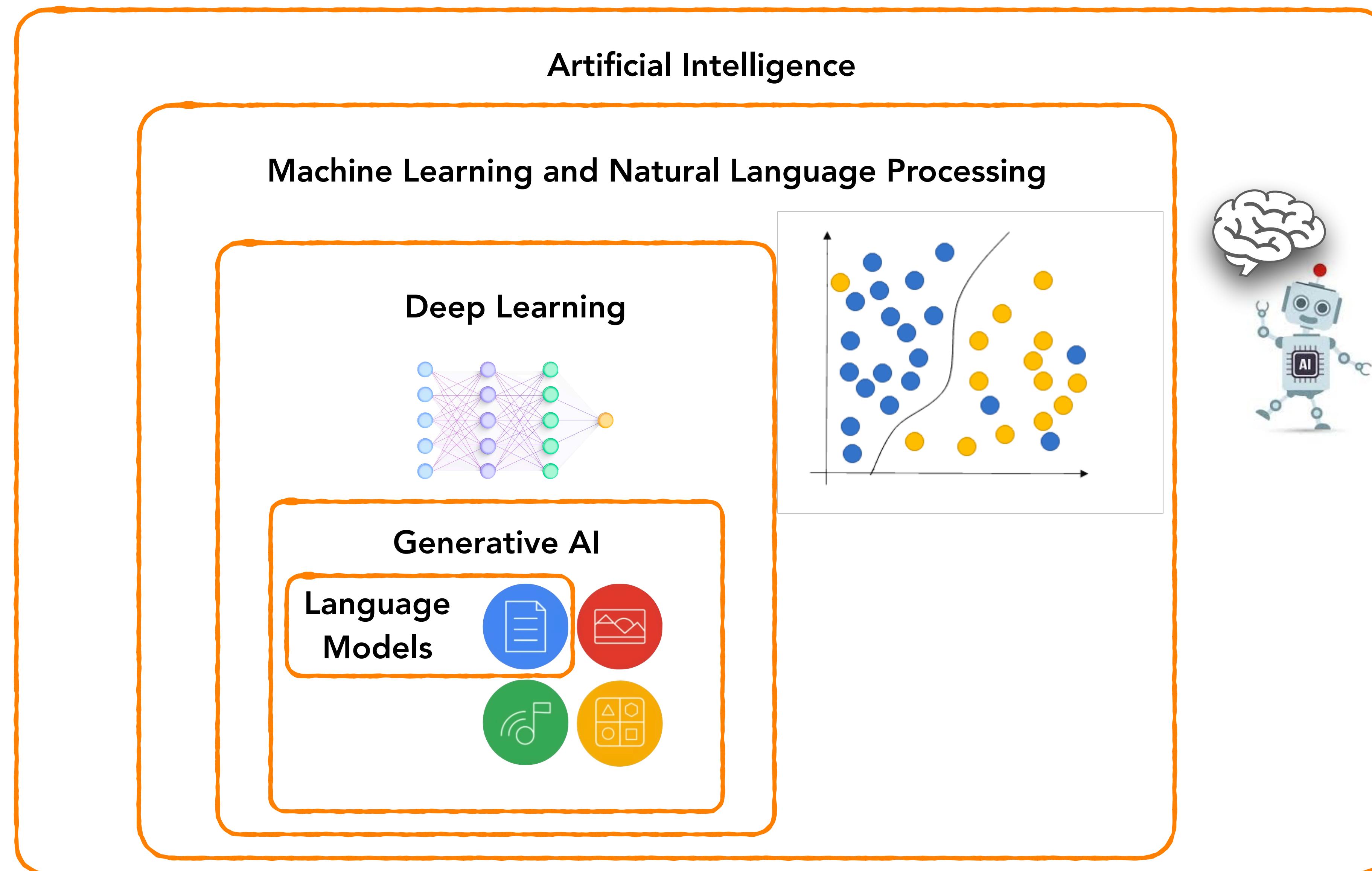
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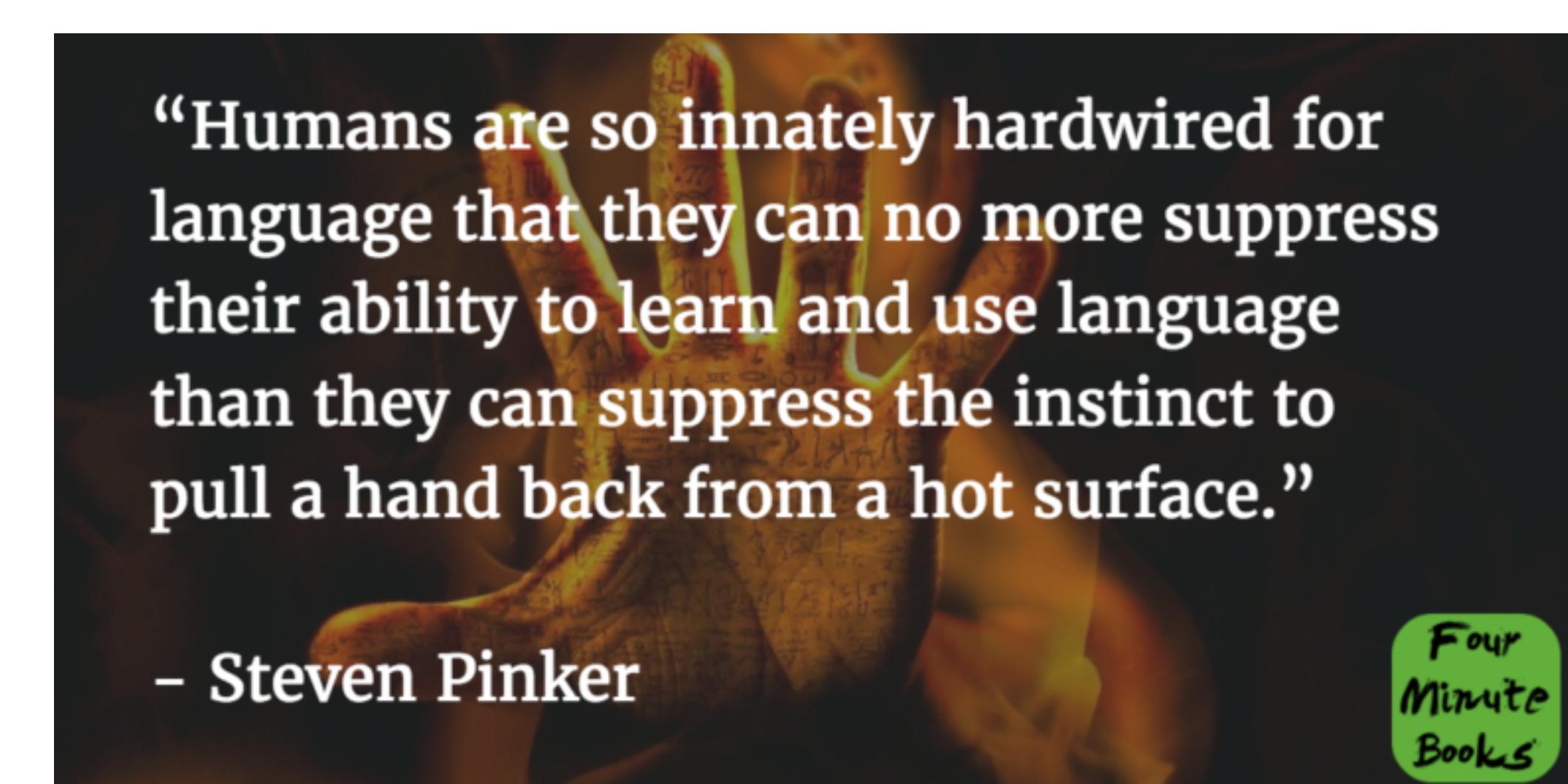
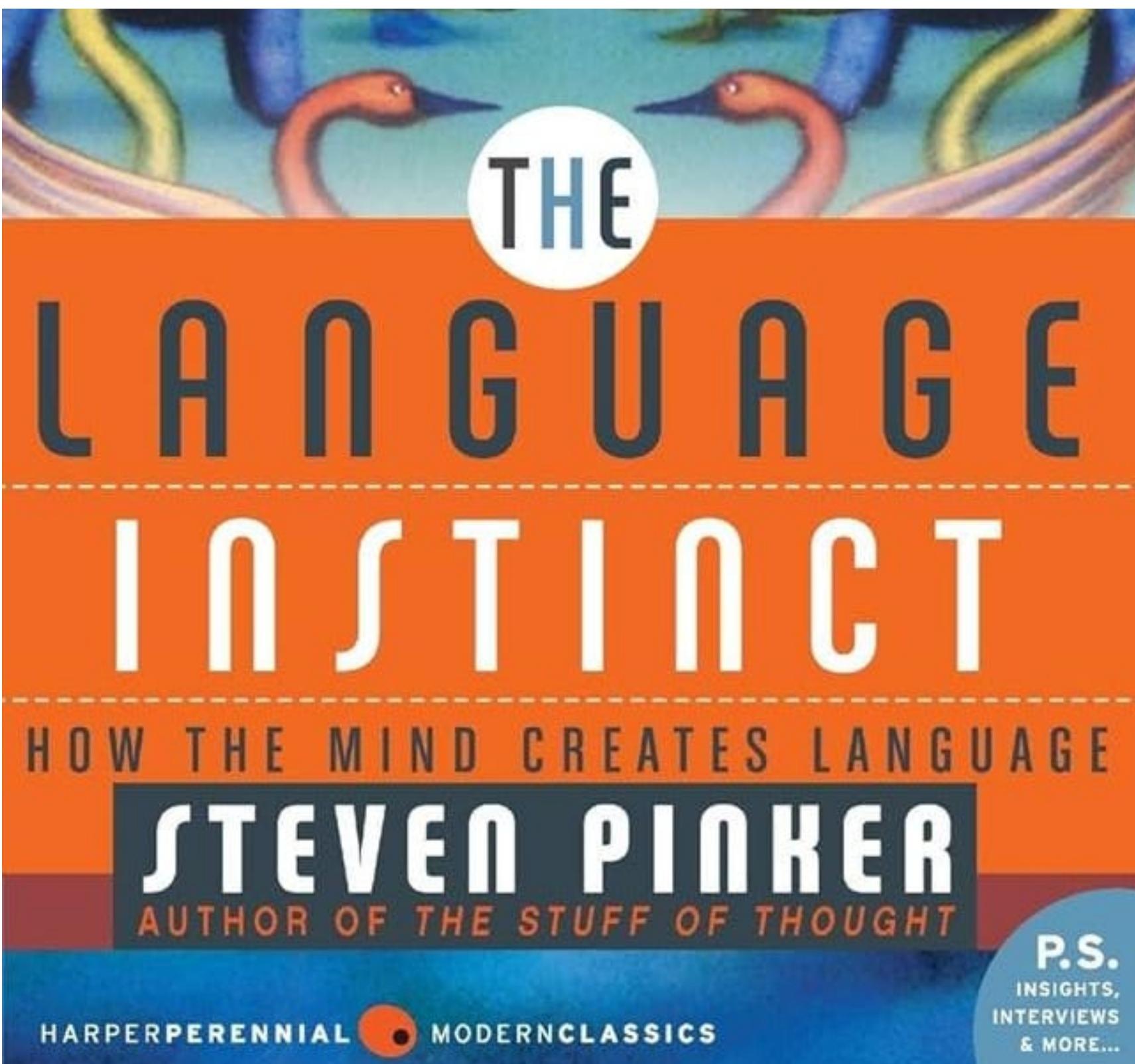
Deep Learning







Language is a key modality



Why should we care about language models?

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 - Direct applications of LLMs are growing rapidly

A screenshot of a ChatGPT conversation. The user asks for a color palette for HomeBite's UI. ChatGPT responds with a list of six colors, their hex codes, and descriptions. It also provides usage advice and a note about subjectivity.

generate a color pallet for HomeBite's UI

Sure, here's an example of a color palette that could be used for HomeBite's UI:

1. Main color: #ff6347 (a bright orange color)
2. Secondary color: #f5f5f5 (a light gray color)
3. Accent color: #ff4500 (a darker orange color)
4. Text color: #333333 (a dark gray color)
5. Background color: #f0f0f0 (a light gray color)
6. Border color: #cccccc (a medium gray color)

You could use these colors to create a cohesive and consistent look throughout the app, using the main color as the primary color, the secondary color as a background color, and the accent color for hover effects, buttons, and other interactive elements.

You could also use these colors as a starting point and adjust them as needed to match your desired design, and also consider accessibility and contrast ratios.

Please note that color choices can be subjective, and the final choice is up to you and your team.

ChatGPT Jan 9 Version. Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.

Why should we care about language models?

- Foundational models in NLP today
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- Classical importance

A screenshot of a ChatGPT interface. A user (FL) asks, "generate a color pallet for HomeBite's UI". ChatGPT responds, "Sure, here's an example of a color palette that could be used for HomeBite's UI:

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FL generate a color pallet for HomeBite's UI

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- Classical importance
- Ubiquitous, so practically everyone has come to contact with one!

A screenshot of a ChatGPT conversation. The user asks, "generate a color pallet for HomeBite's UI". ChatGPT responds with a list of six color codes: Main color: #ff6347, Secondary color: #f5f5f5, Accent color: #ff4500, Text color: #333333, Background color: #f0f0f0, and Border color: #cccccc. It also provides instructions on how to use these colors and notes on accessibility.

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 - Direct applications of LLMs are growing rapidly
- Classical importance
- Ubiquitous, so practically everyone has come to contact with one!
- Immense societal and economic implications

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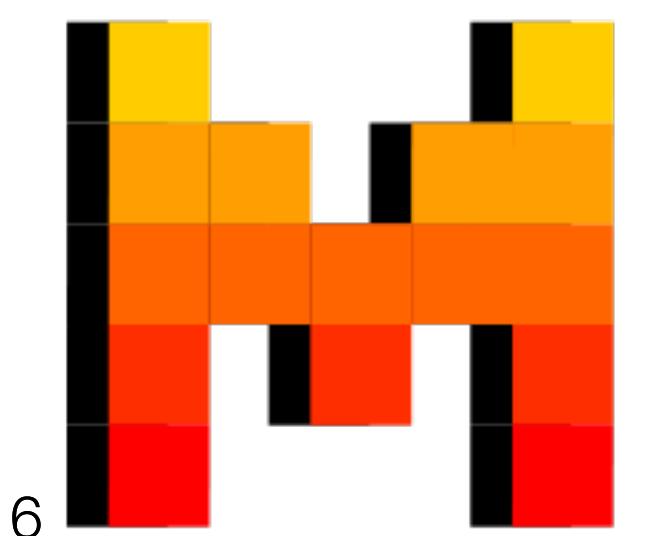
GPT - 4



Gemini



LLM360



**MISTRAL
AI_**





GPT-4

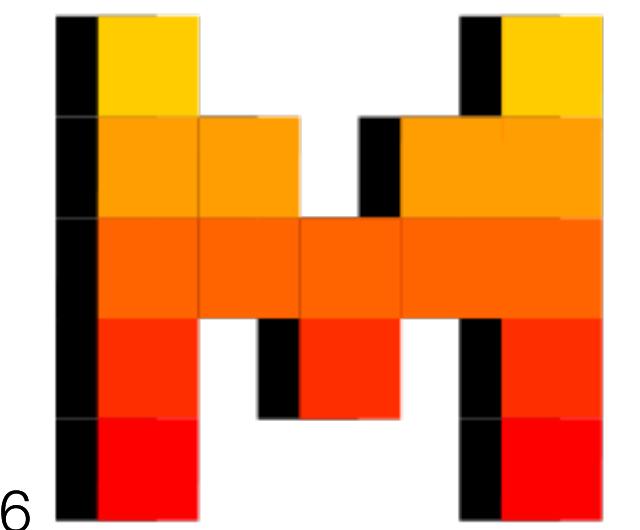
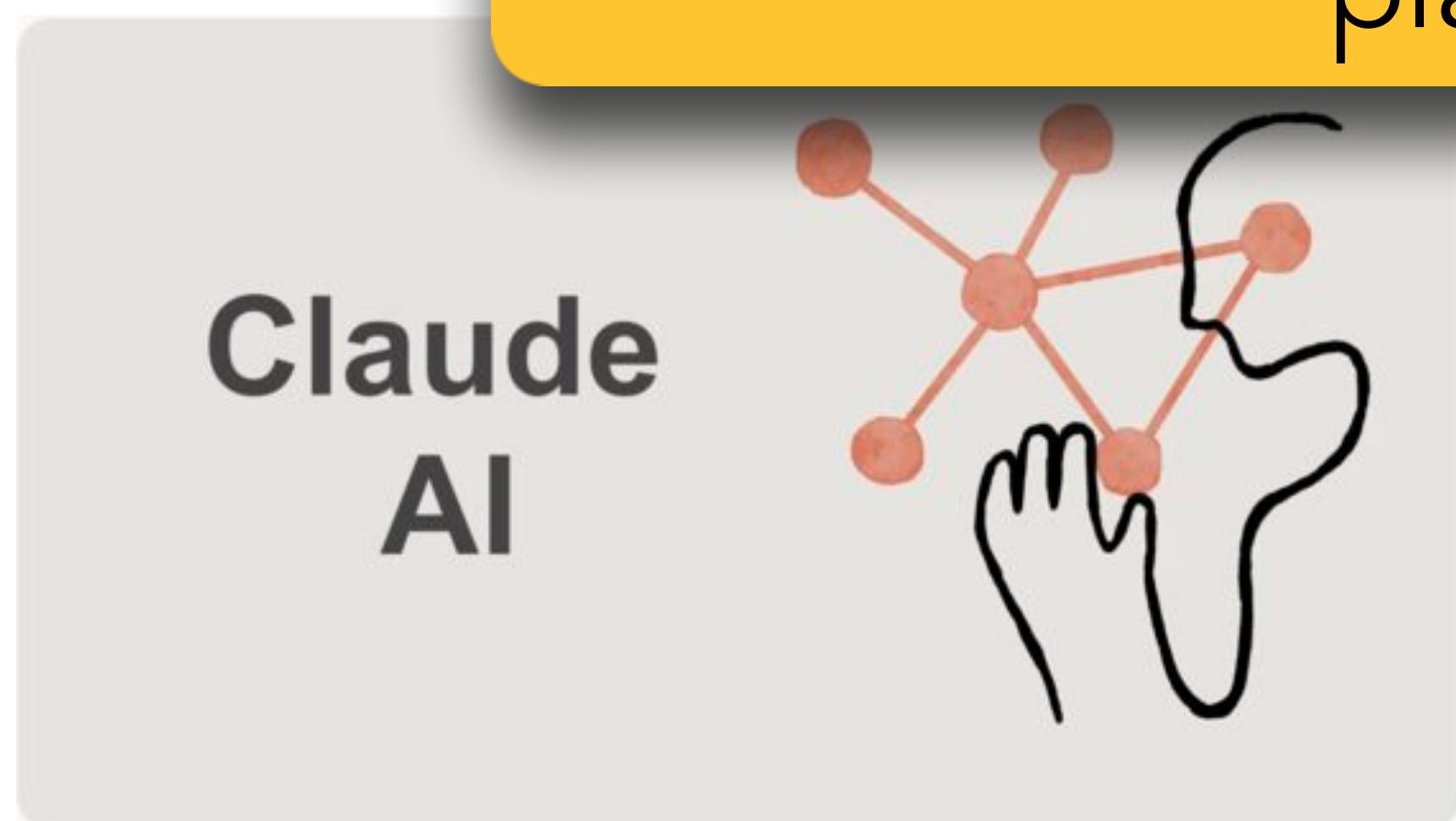
Gemini



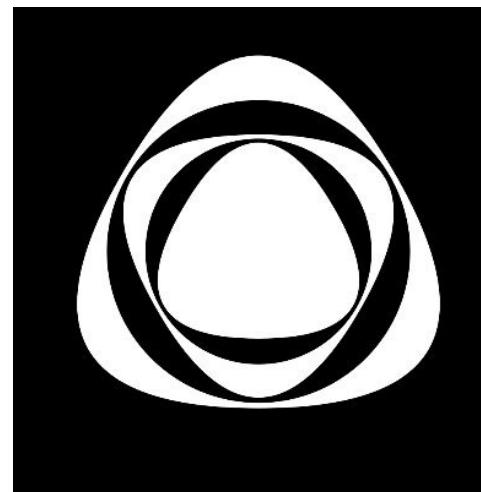
LLM360



Language models are getting larger, only a few key players can develop them



MISTRAL
AI_





**Virtual
Assistants**



Translation



**Content
Creation**



**Code
Generation**



Transcription



**Sentiment
Analysis**

Large Language Models Are Everywhere



Virtual
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Transcription

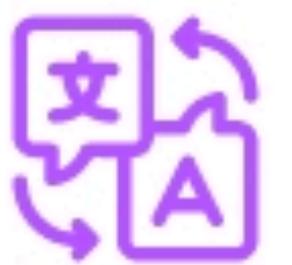


Sentiment
Analysis

Large Language Models Are Everywhere



Virtual
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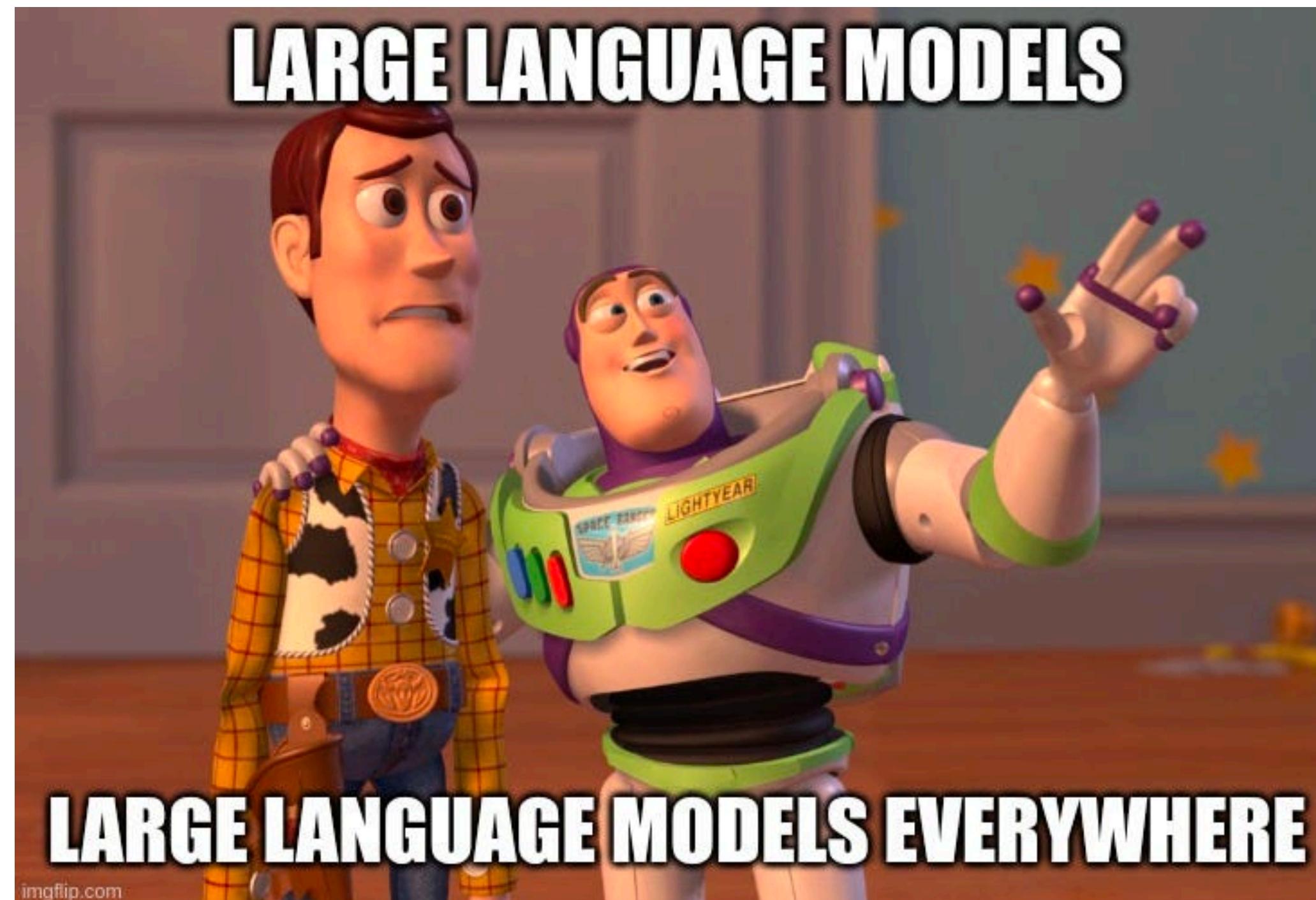
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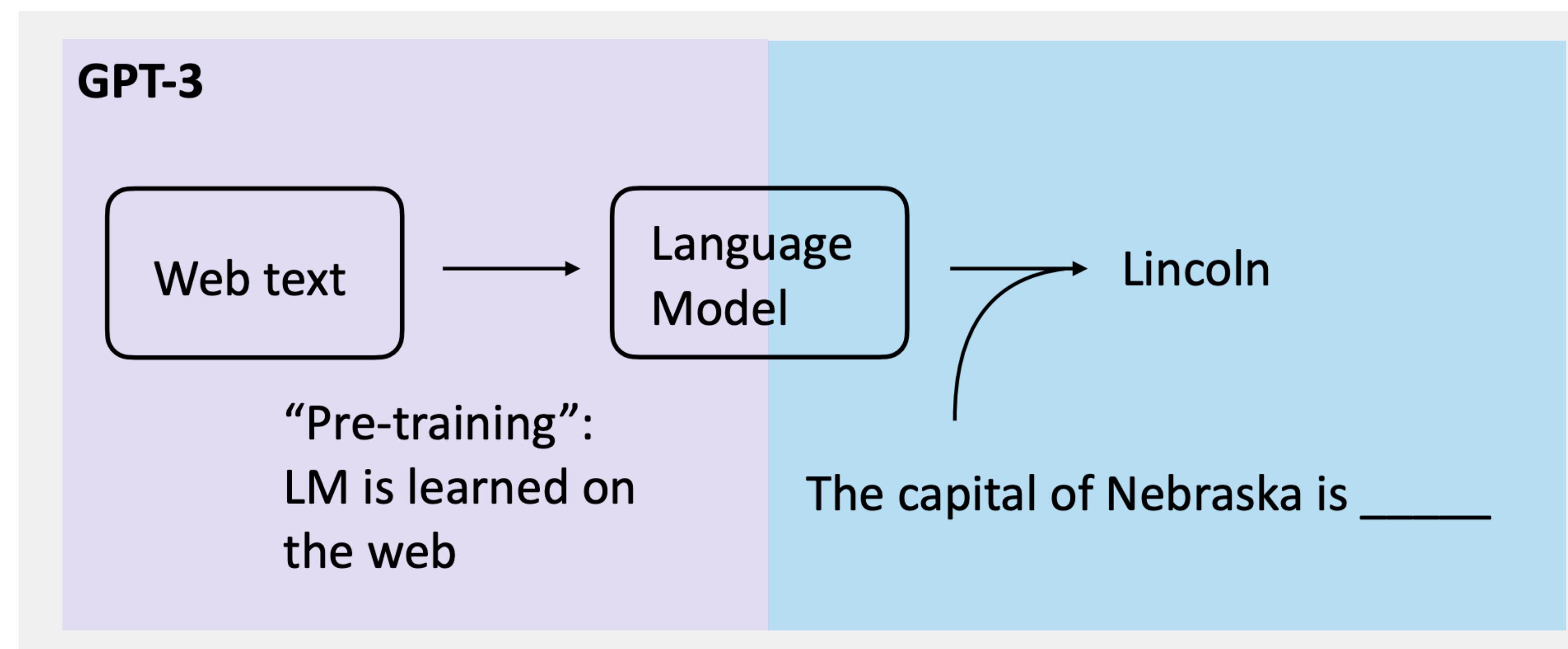
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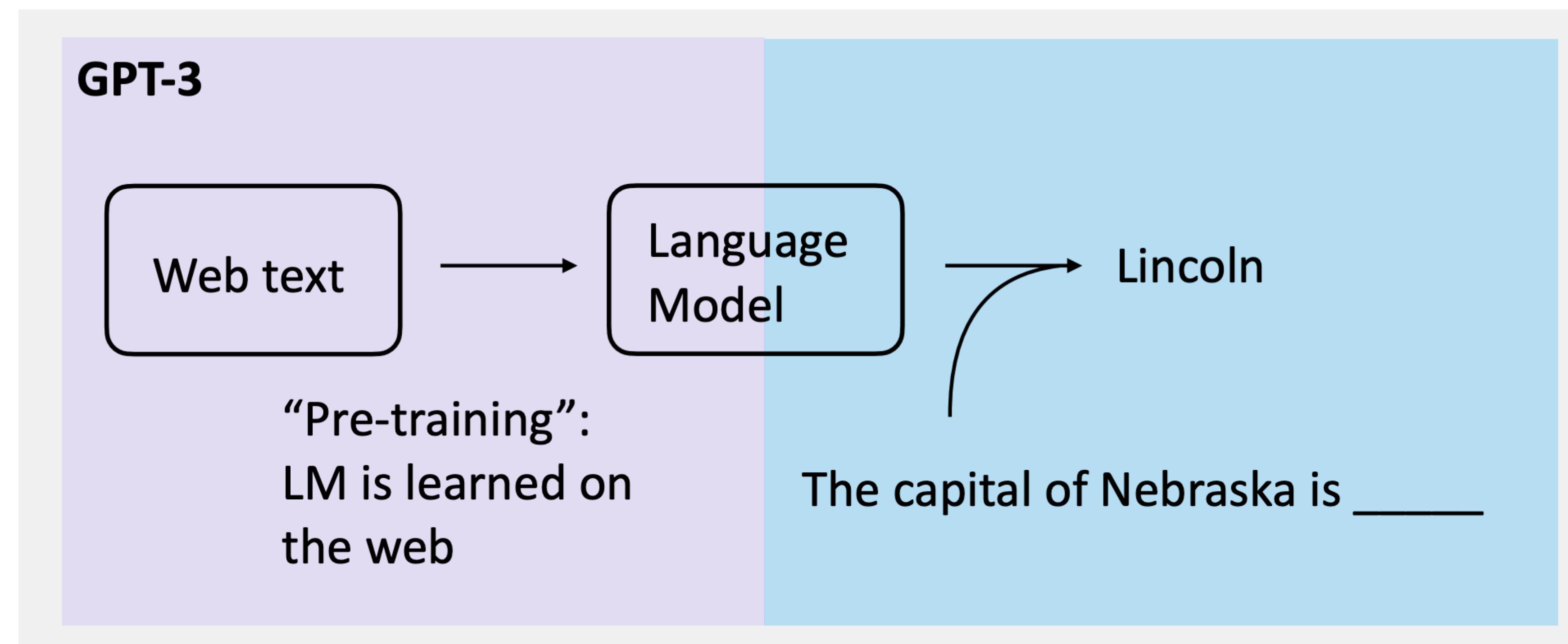
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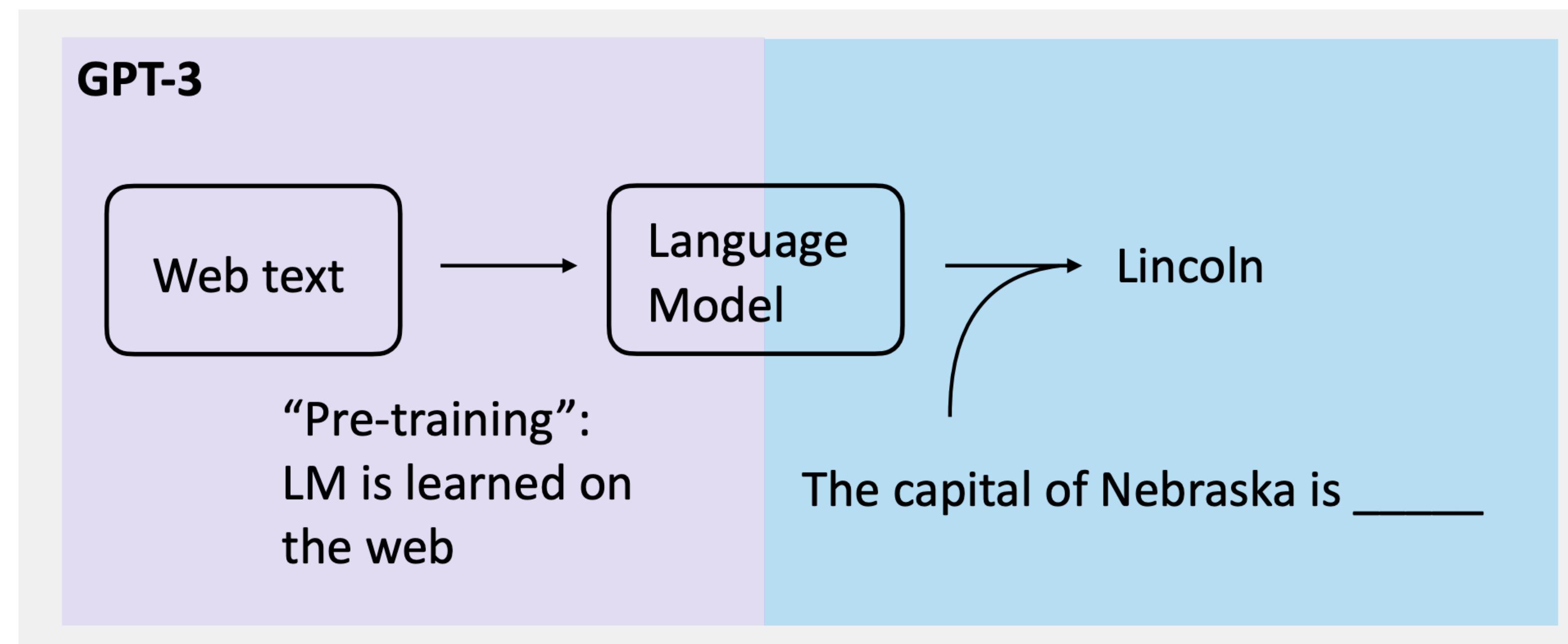
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- Models are trained tons (terabytes) of data — a curated scrape of the web, and even generated data
- Have seen information about common and even not-so-common entities
- A big enough model can answer questions even without being trained to do so. What else can we get these models to do?



LLMs are being used to...

LLMs are being used to...

Summarize articles, podcasts or presentations

Code computer programs!

Script social media posts

Create a title for an article

Draft emails

Assist with job searches,
including writing resumes
and cover letters

Ask trivia questions

Compose music!!!

Describe complex topics more simply

Discover keywords for search
engine optimization.

Formulate product
descriptions

Create articles, blog posts
and quizzes for websites

Solve math problems

Reword existing content for a different medium, such
as a presentation transcript for a blog post

LLMs are being used to...

Summarize articles, podcasts or presentations

Code computer programs!

Script social media posts

Create a title for an article

Draft emails

Assist with job searches
including
and c

Extrem

Ask trivia questions

powerful: can in many cases replace laborious manual efforts

Describe complex topics more simply

Solve math problems

Create articles, blog posts
and quizzes for websites

Reword existing content for a different medium, such as a presentation transcript for a blog post

Formulate product descriptions

GPT-4 Passes the Bar Exam!

GPT Takes the Bar Exam

Michael Bommarito II^{1,2,3}, Daniel Martin Katz^{1,2,3,*}

1 Illinois Tech - Chicago Kent College of Law (Chicago, IL USA)

2 Bucerius Law School (Hamburg, Germany)

3 CodeX - The Stanford Center for Legal Informatics (Stanford, CA USA)

* Corresponding Author: dkatz3@kentlaw.iit.edu

Abstract

Nearly all jurisdictions in the United States require a professional license exam, commonly referred to as “the Bar Exam,” as a precondition for law practice. To even sit for the exam, most jurisdictions require that an applicant completes at least seven years of post-secondary education, including three years at an accredited law school. In addition, most test-takers also undergo weeks to months of further, exam-specific preparation. Despite this significant investment of time and capital, approximately one in five test-takers still score under the rate required to pass the exam on their first try. In the face of a complex task that requires such depth of knowledge, what, then, should we expect of the state-of-the-art in “AI?” In this research, we document our experimental evaluation of the performance of OpenAI’s TEXT-DAVINCI-003 model, often-referred to as GPT-3.5, on the multistate multiple choice (MBE) section of the exam. While we find no benefit in fine-tuning over GPT-3.5’s zero-shot performance at the scale of our training data, we do find that hyperparameter optimization and prompt engineering positively impacted GPT-3.5’s zero-shot performance. For best prompt and parameters, GPT-3.5 achieves a headline correct rate of 50.3% on a complete NCBE MBE practice exam, significantly in excess of the 25% baseline guessing rate, and performs at a passing rate for both Evidence and Torts. GPT-3.5’s ranking of responses is also highly-correlated with correctness; its top two and top three choices are correct 71% and 88% of the time, respectively, indicating very strong non-entailment performance. While our ability to interpret these results is limited by nascent scientific understanding of LLMs and the proprietary nature of GPT, we believe that these results strongly suggest that an LLM will pass the MBE component of the Bar Exam in the near future.

	GPT	GPT Top 2	GPT Top 3	NCBE
Evidence	63%	84%	98%	65%
Torts	62%	72%	93%	71%
Civil Procedure	52%	63%	79%	59%
Constitutional Law	49%	67%	87%	72%
Real Property	45%	72%	85%	65%
Contracts	45%	77%	86%	70%
Criminal Law & Procedure	35%	62%	86%	71%
AVERAGE	50%	71%	88%	68%

Table 2. Summary of performance by question category for GPT-3.5 and NCBE-Reported Students

Fig 2. Accuracy by Question Category for GPT and Average Test-Takers

December 29, 2022

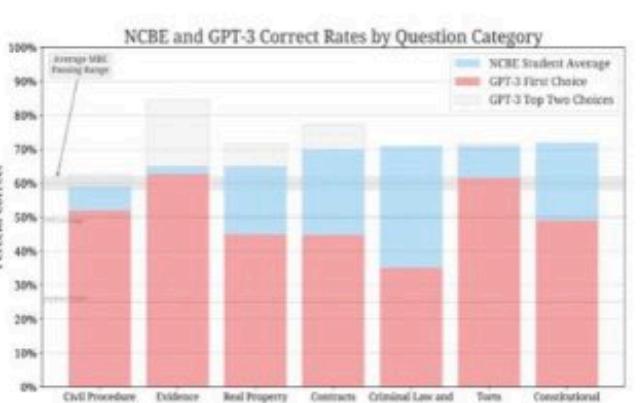
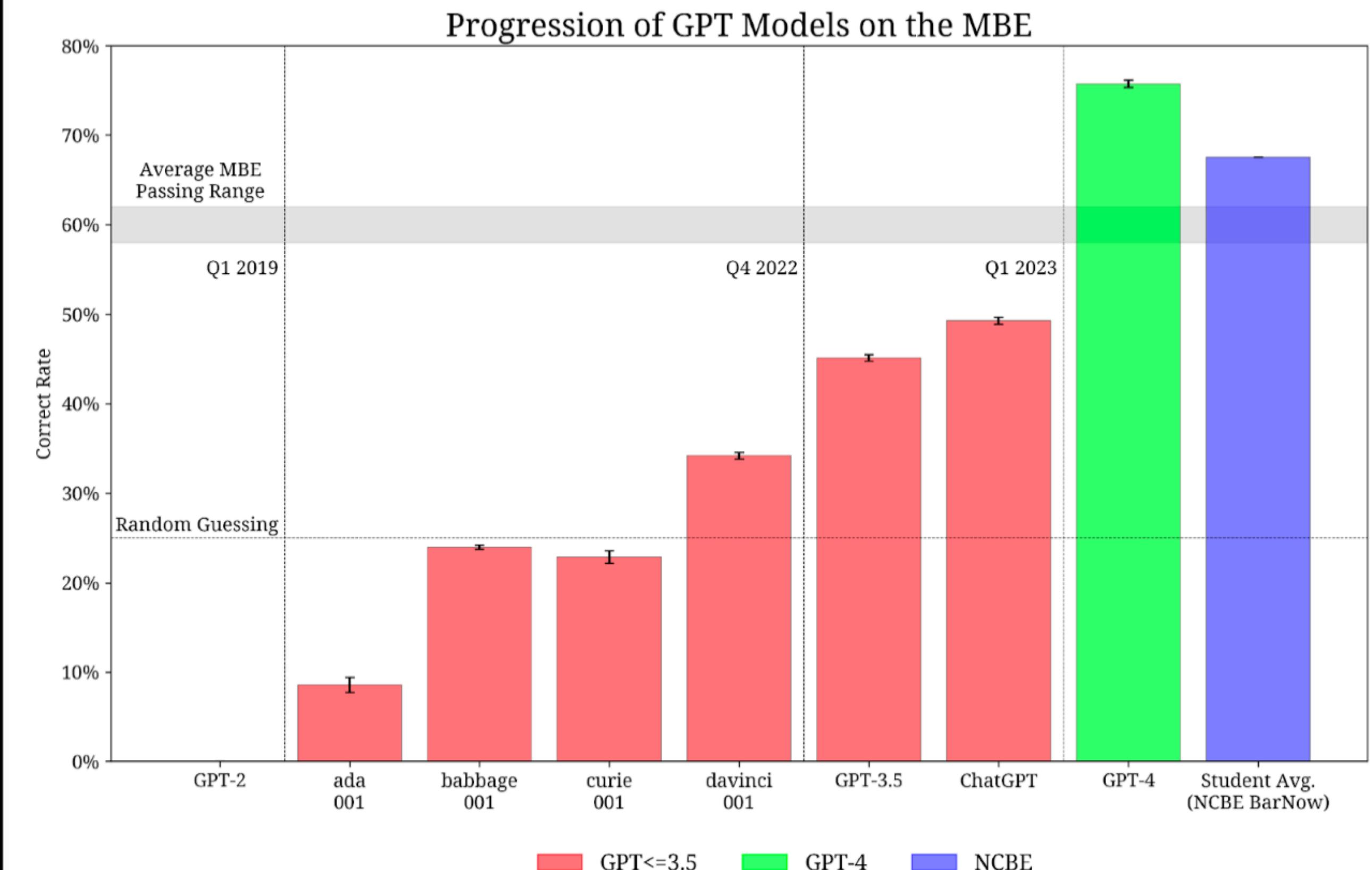
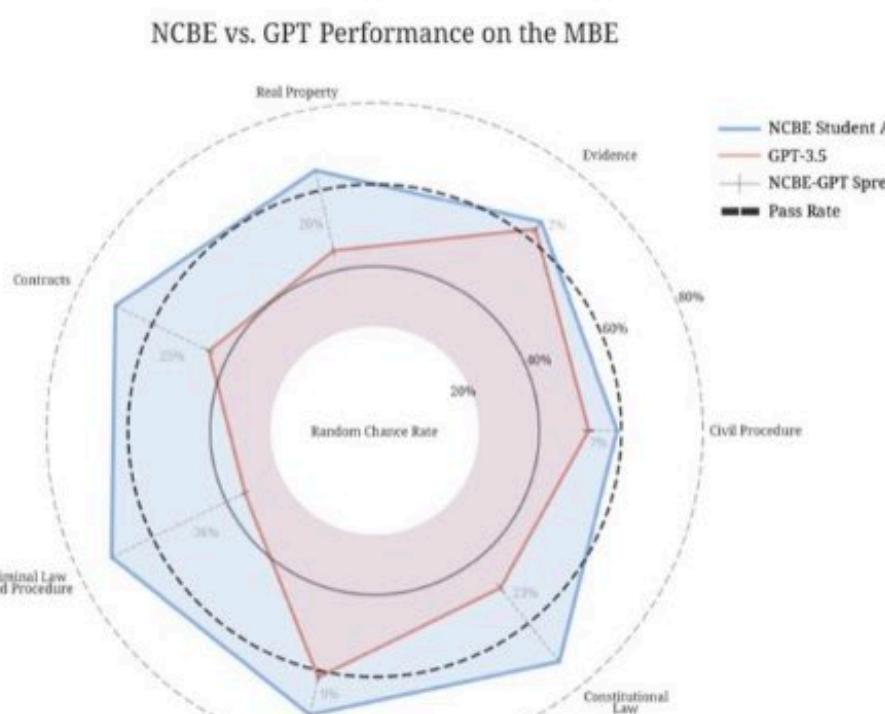
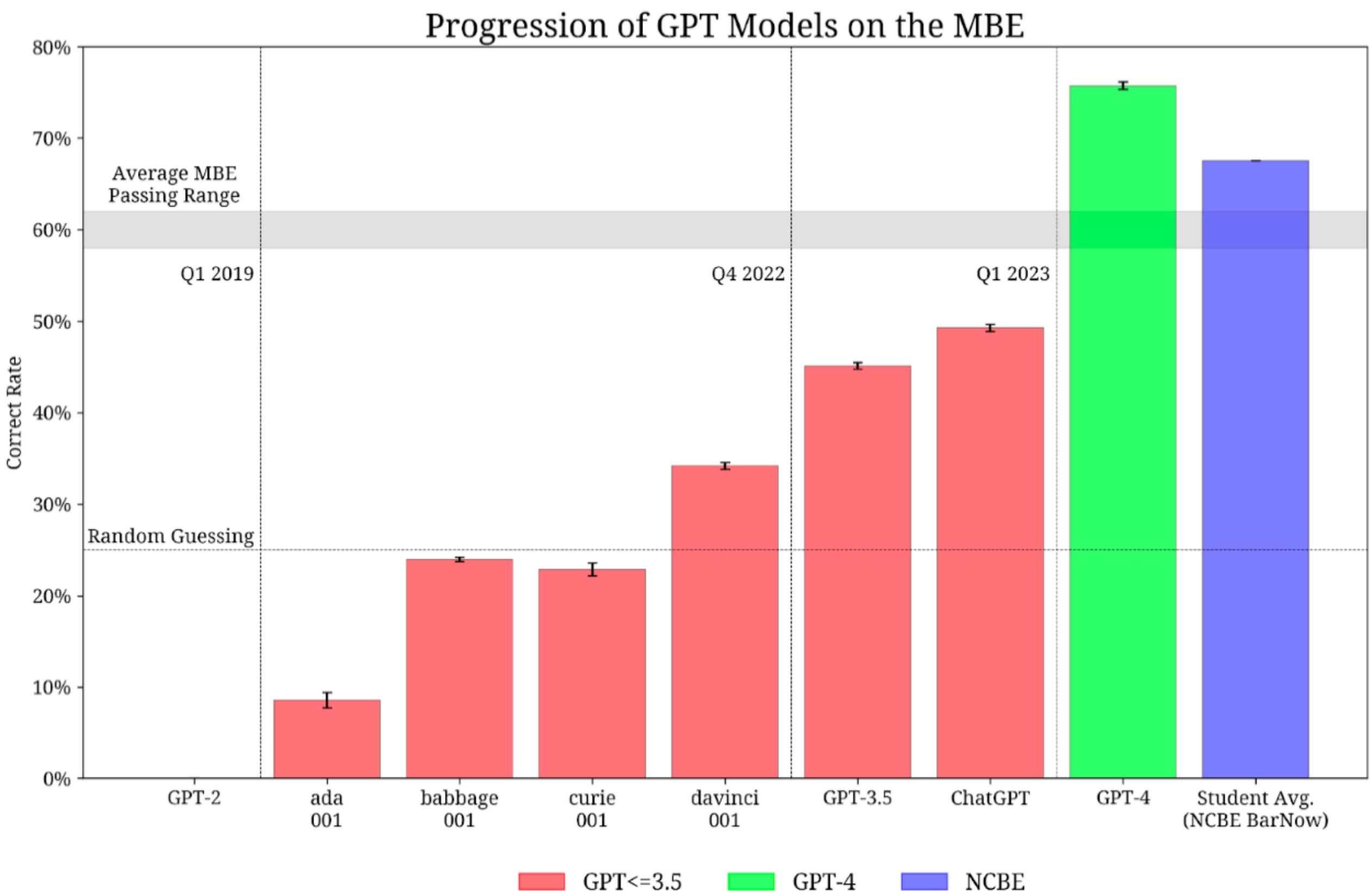
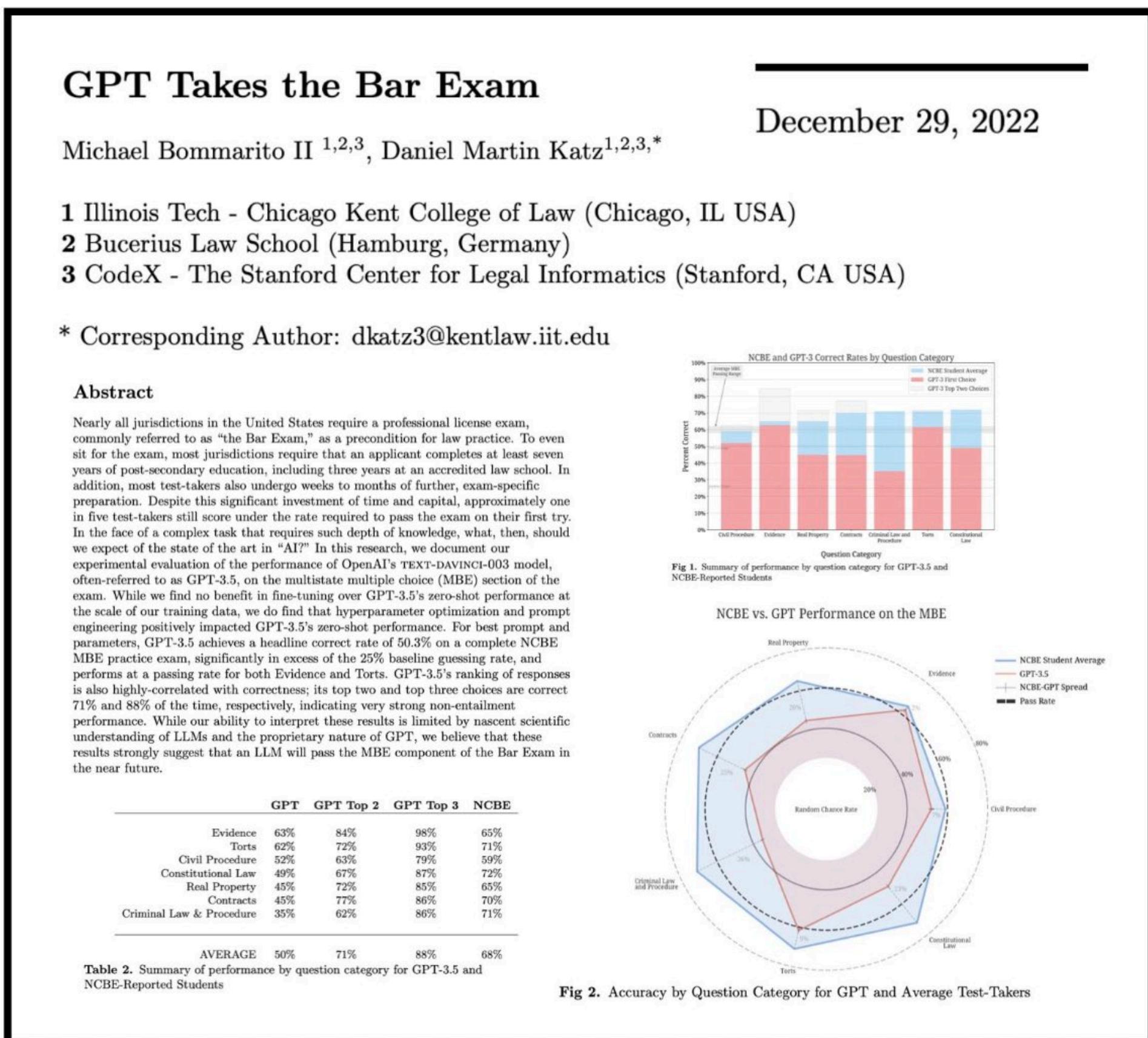


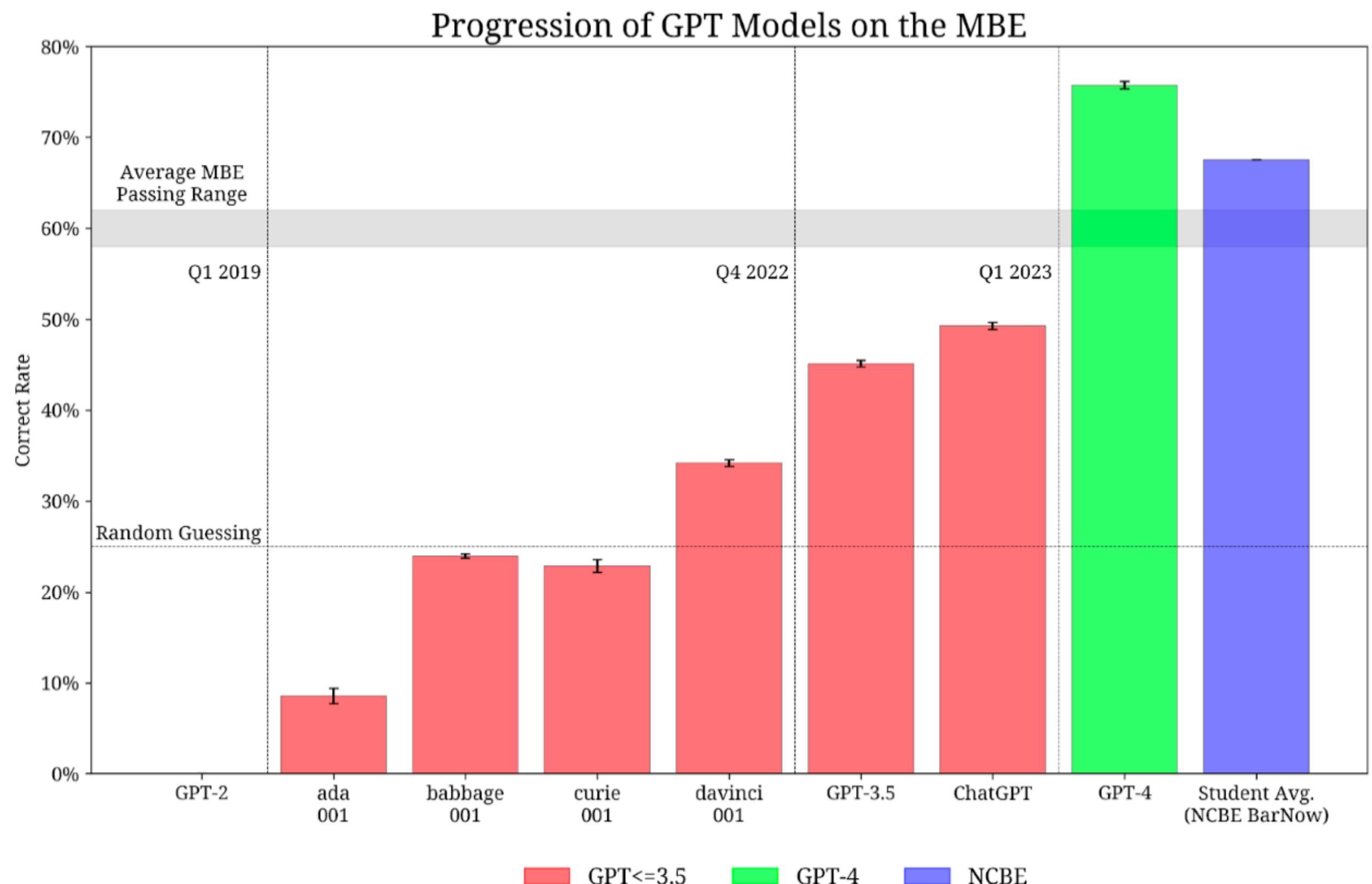
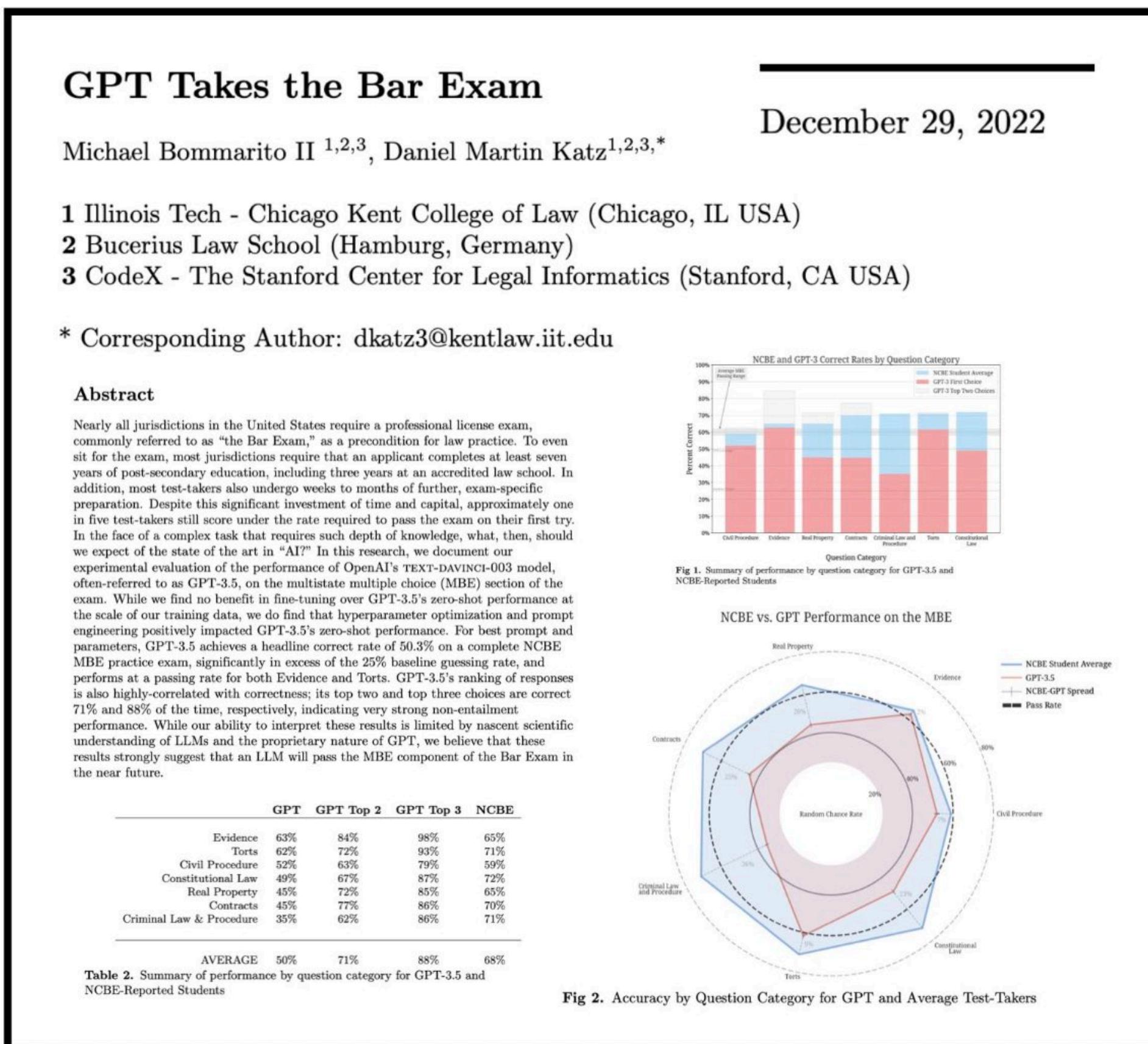
Fig 1. Summary of performance by question category for GPT-3.5 and NCBE-Reported Students



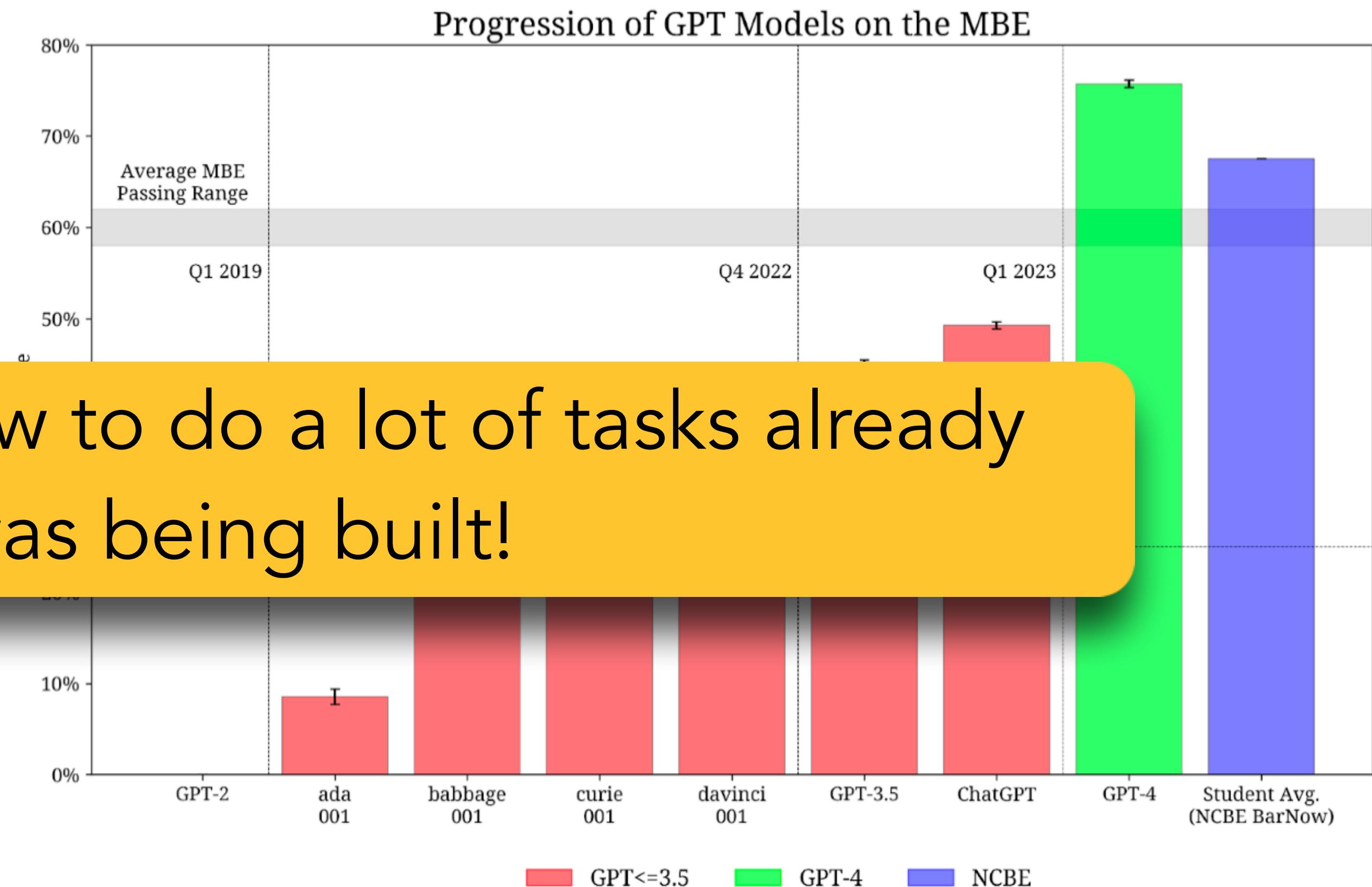
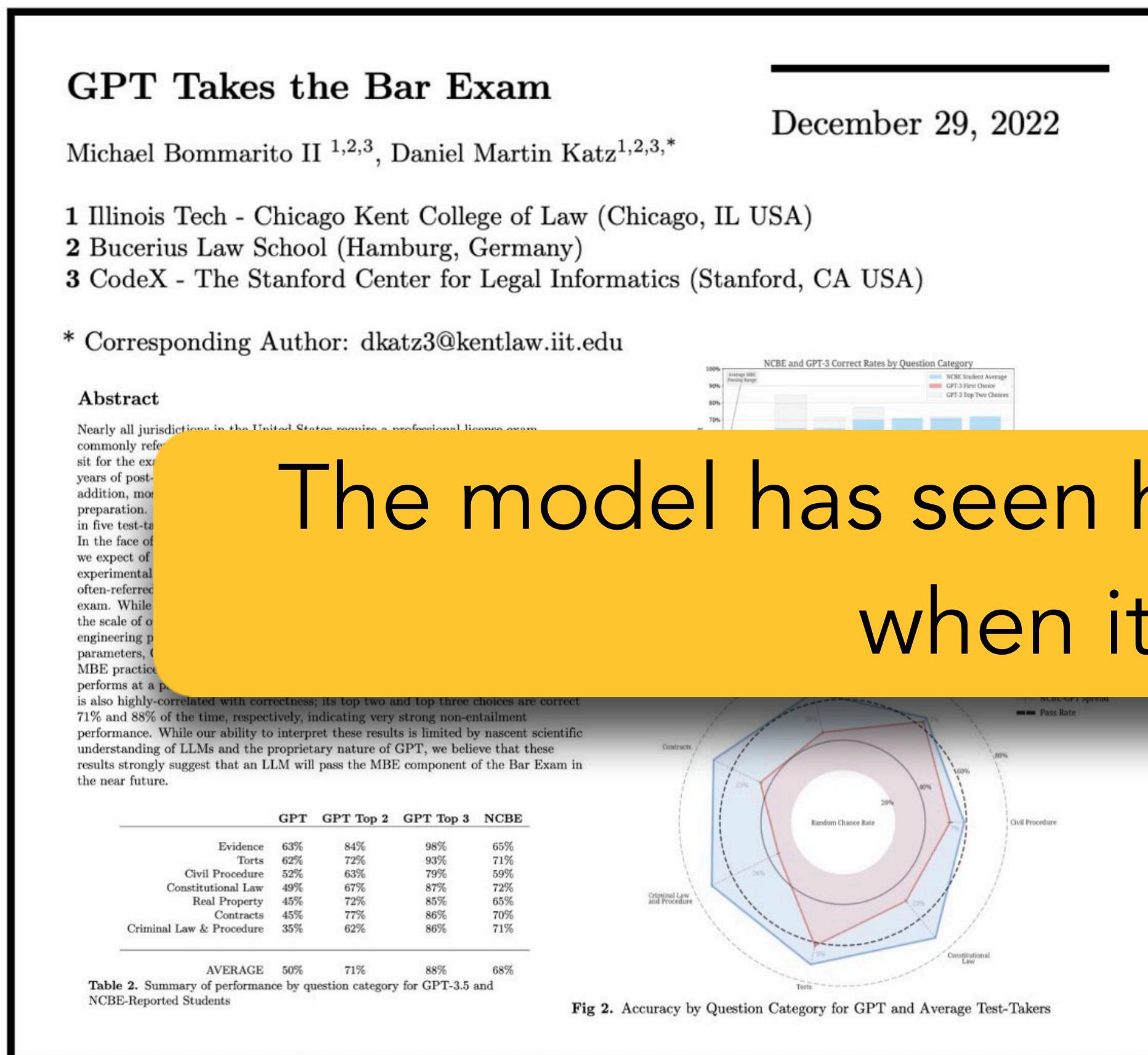
Progression of GPT Models on the MBE



Why does this work?

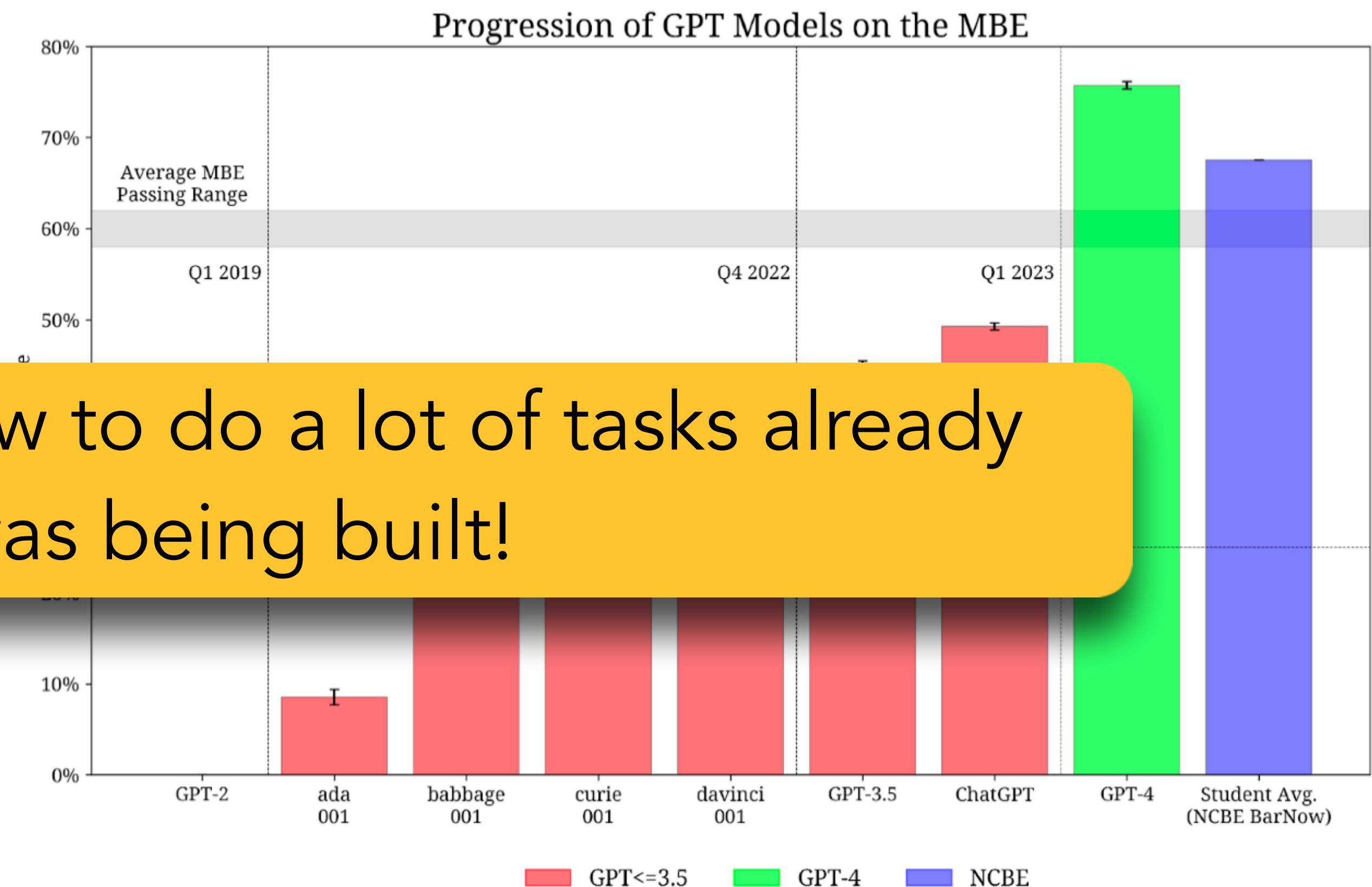
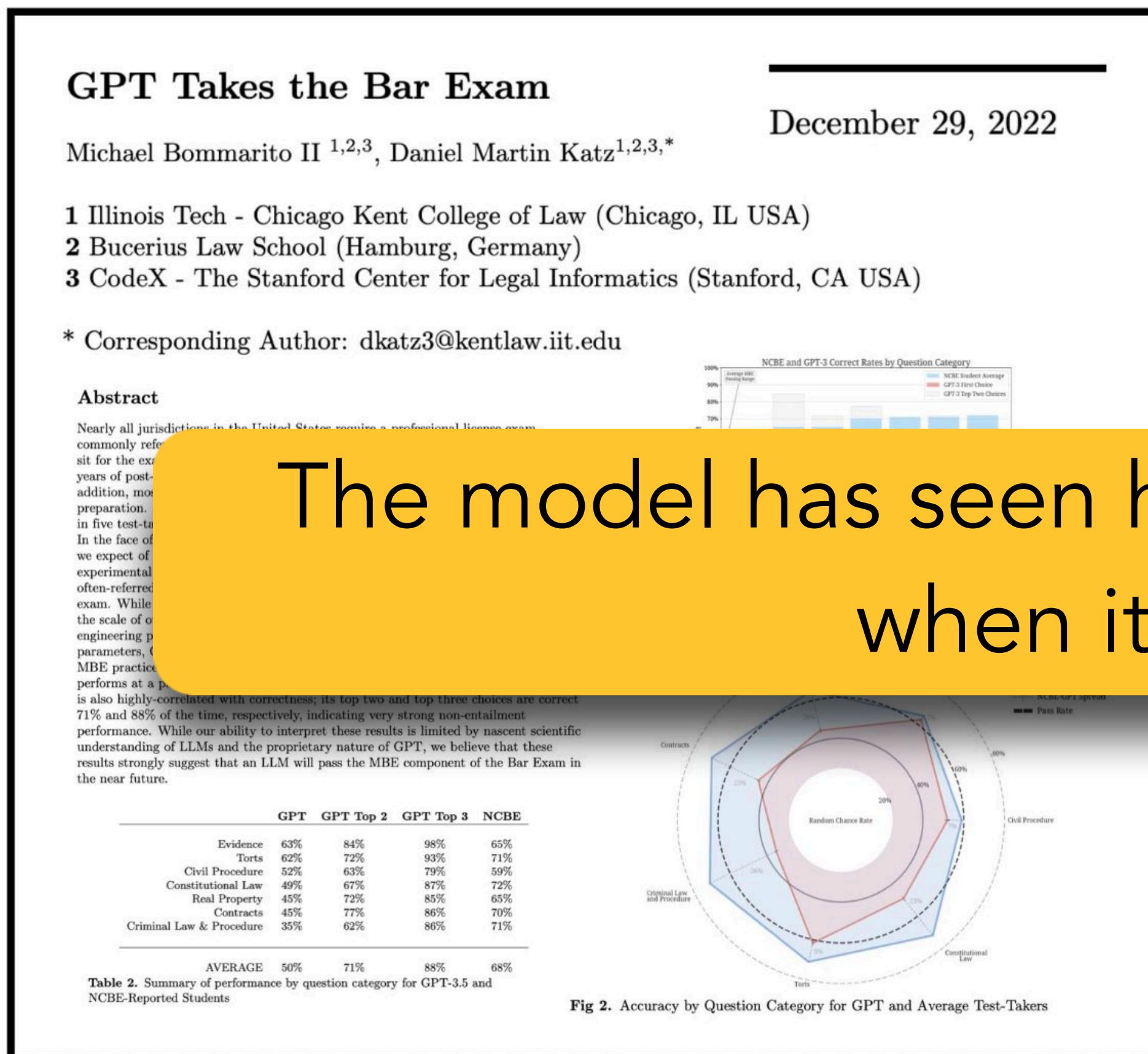


Why does this work?



The model has seen how to do a lot of tasks already when it was being built!

Why does this work?



Memorization vs. generalization



Yann LeCun @ylecun · 4d

⋮

AR-LLMs can pass the bar exam,
medical licensing & MBA exams.
But on the IIT entrance exams they
perform badly on chemistry, horribly on
physics, and terribly on math.
They are good with rote learning &
fluency but bad with building mental
models & reasoning with them.





sw You
What is a good joke about large language models?

ChatGPT
Sure, here's a lighthearted joke about large language models:
Why did the language model bring a ladder to the conversation?
Because it wanted to reach the next level of understanding!



sw You
What is a good joke about large language models?

ChatGPT
Sure, here's a lighthearted joke about large language models:

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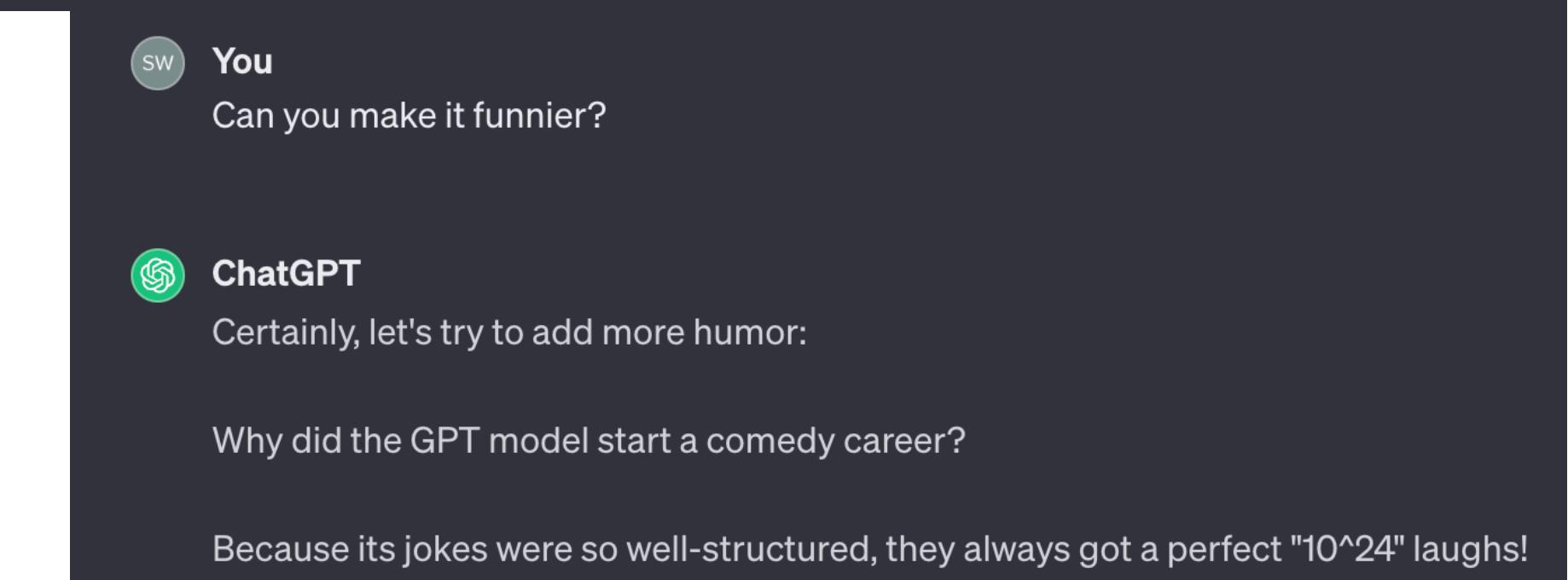
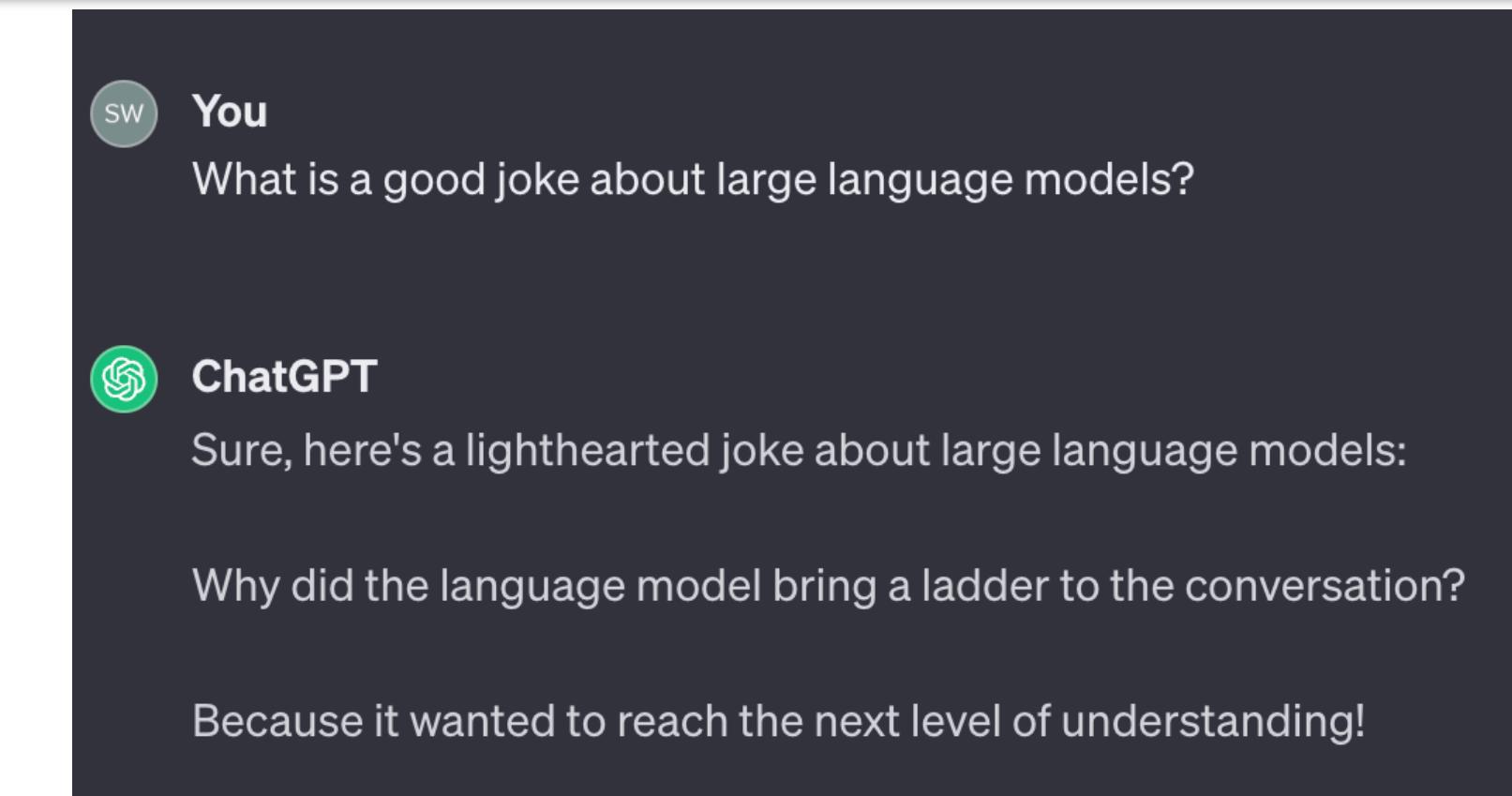
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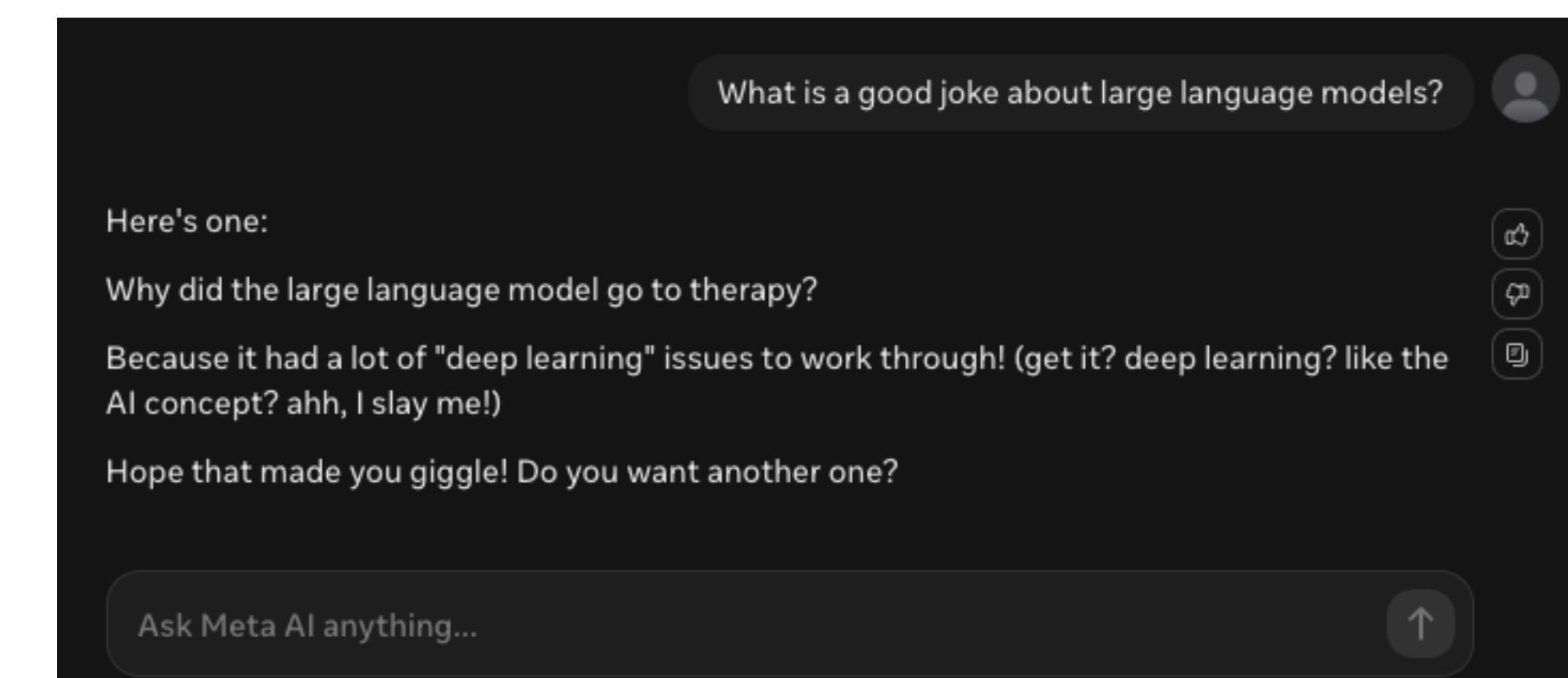
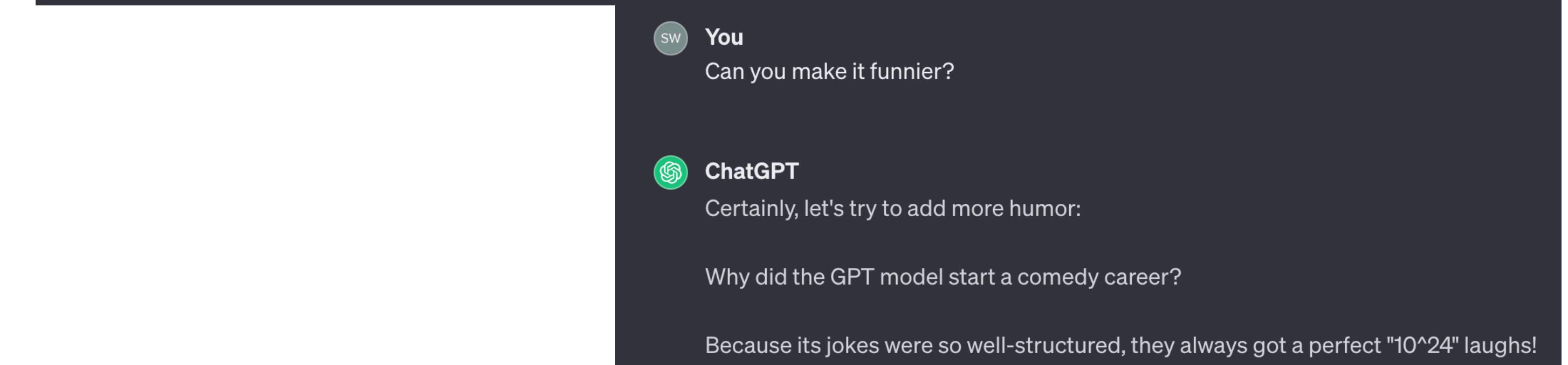
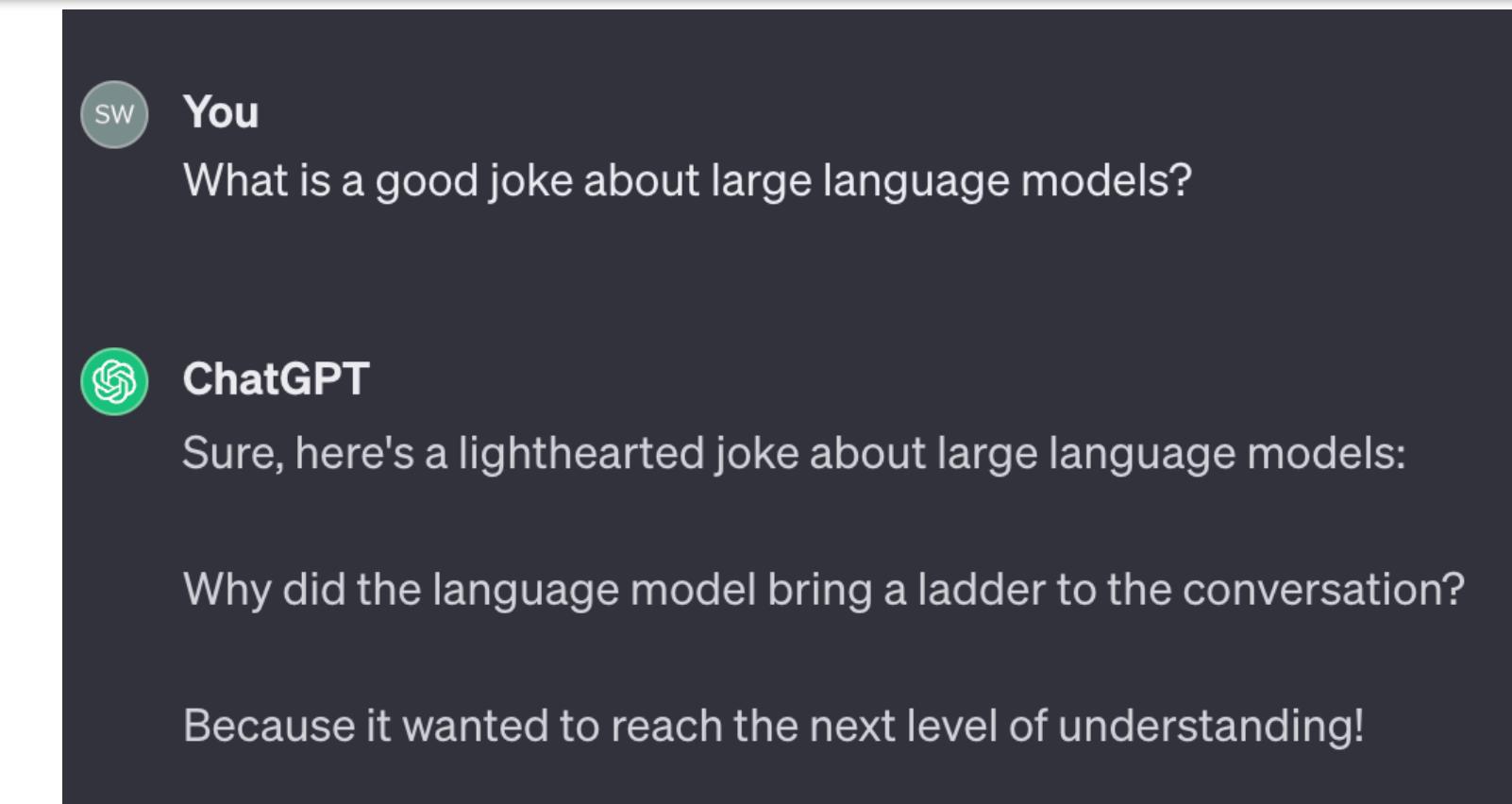
sw You
Can you make it funnier?

ChatGPT
Certainly, let's try to add more humor:

Why did the GPT model start a comedy career?

Because its jokes were so well-structured, they always got a perfect "10²⁴" laughs!





You Probably Can See Where This Is Going

When my flight from LaGuardia landed in Minneapolis on that August afternoon, the first text I received was from the executive director of the nonprofit I'd be holding the training for the next day, canceling our dinner because of a family emergency. The second text was from my friend Jenny asking me to look at the profile of a guy named James on the dating app we both used and to let her know if it was the same asked-not-one-question James I'd gone out with around Christmas. That date had felt like such a waste of an evening that I'd given myself a break from the app since.

By the time the seatbelt light had gone off, I'd texted Jenny to tell her it wasn't, and I'd received a heart on the app from a man who was currently online, whose handle was MtnBiker1971. He was 53, a year younger than me; he had deep brown eyes and was bald with a gray and brown beard; and three of his five photos featured him on a bike. I swear, I swear, that MtnBiker1971 and I already had exchanged generic greetings before it occurred to me that because my settings showed profiles within 10 miles of me, he was local.

"Oh sorry!" I typed. "Just realized you live in Minnesota and I'm only visiting for 36 hrs."

Before I could send this, a new message came in from him: "What's your favorite fruit that's considered a vegetable and what's your best episode of TV ever?"

So I deleted "Oh sorry..." and typed "Okra and the season finale of *Severance*. You?"

Can you see where this is going? You probably can see where this is going.

By the time I was in an Uber, he'd told me his name was Brian, he worked for an environmental advocacy group, and the previous weekend, on a trail, he'd ridden his bike past a woodpecker sitting on the back of a deer; he'd been so close that he and the deer had made eye contact.

The Flip-Flop Moment

Lydia had always been practical. It was her hallmark, the trait that kept her life organized in neat rows, like the files on her desk or the cushions on her sofa. At 48, this practicality had become her armor, protecting her from the reckless impulses that she might have indulged in during her younger years. And so, when she walked into the coffee shop on that sweltering July afternoon, it was with the same cautious optimism that she had applied to everything else in her life.

The coffee shop was called Java Junction, an ironic nod to its nondescript location. It was where she met her friends for book club, where she studied with her son while he was in high school and where she'd spent countless hours with her late husband. That was the first thing she'd felt when she entered, the lingering echo of shared memories. She was here for a meeting with her college friend, Julie, and Julie was late, which gave Lydia plenty of time to observe.

She sat at a small table near the window, which was always Lydia's favorite spot. The sunlight spilled over the table, creating a halo around her as she skimmed through a magazine, her flip-flops occasionally brushing the edge of the table. She had never been one for extravagant shoes — practical, again. But on that day, the flip-flops seemed to betray a different side of her, a side that wanted to feel something more, something less anchored.

Julie arrived, panting slightly from the heat. She was a whirlwind of energy, always dressed in vibrant colors and speaking in rapid bursts. The two friends embraced, and Lydia noticed how the decades had changed them both — Julie still had that unfiltered joy, while Lydia felt a certain grayness to her own existence.

They talked about their lives — Julie's recent move to a beach town and Lydia's endless workdays, the responsibilities of being a single mother, the growing distance from her teenage son. They laughed about old times and reminisced about their college days, and for a moment, Lydia felt something she hadn't in a while: a spark of connection, of vitality.

Human or AI?

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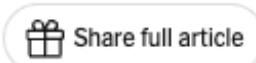
GPT-4o

LLMs are far from perfect

LLMs are far from perfect

The ChatGPT Lawyer Explains Himself

In a cringe-inducing court hearing, a lawyer who relied on A.I. to craft a motion full of made-up case law said he “did not comprehend” that the chat bot could lead him astray.

 Share full article    267



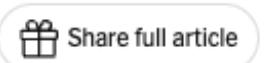
A.I.-Generated Content Discovered on News Sites, Content Farms and Product Reviews

The findings in two new reports raise fresh concerns over how artificial intelligence may transform the misinformation landscape online.

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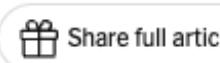
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An A.I. Hit of Fake ‘Drake’ and ‘The Weeknd’ Rattles the Music World

A track like “Heart on My Sleeve,” which went viral before being taken down by streaming services this week, may be a novelty for now. But the legal and creative questions it raises are here to stay.

 Give this article    215



This Tool Could Protect Artists From A.I.-Generated Art That Steals Their Style

Artists want to be able to post their work online without the fear “of feeding this monster” that could replace them.

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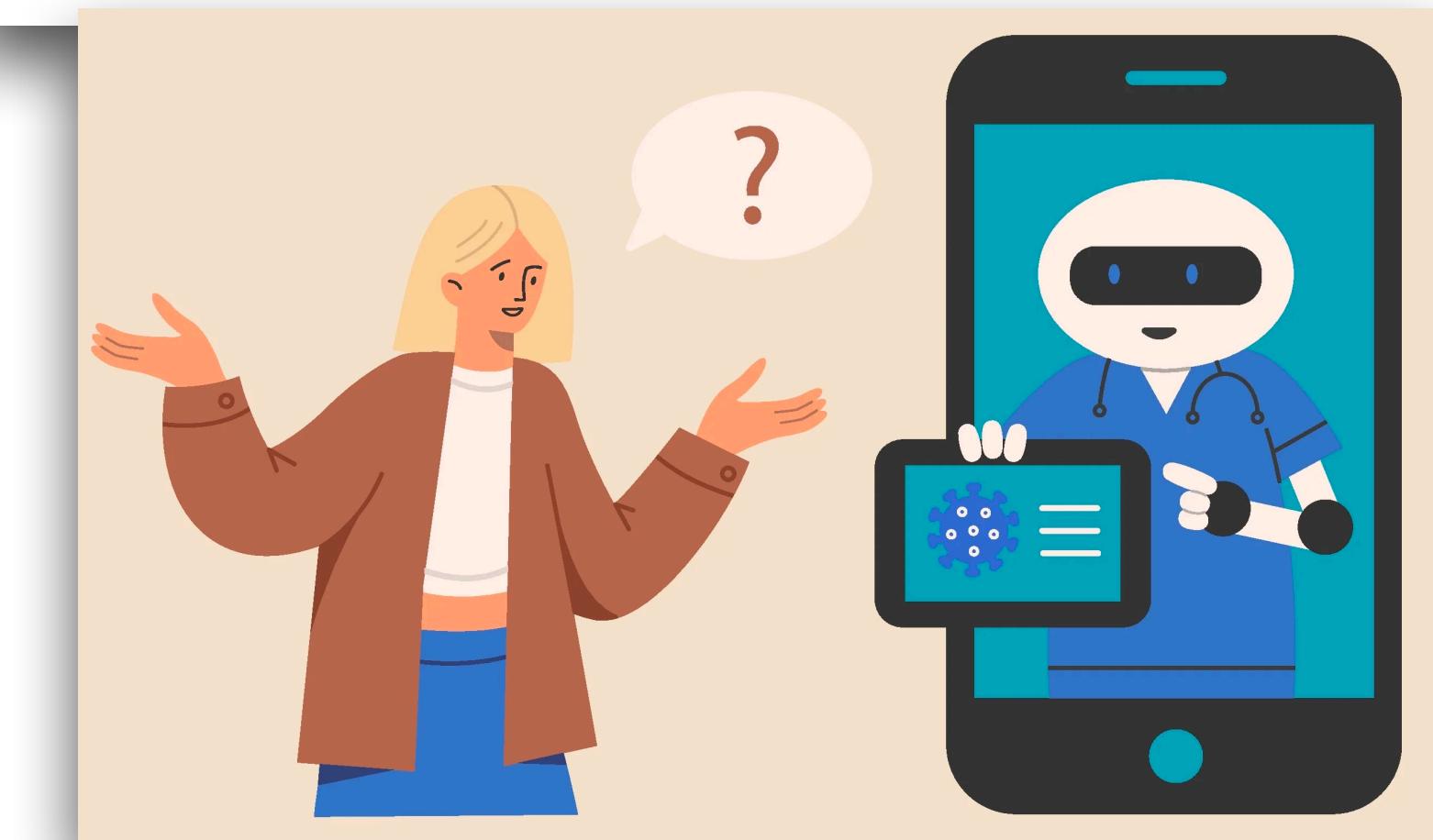
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Privacy and Copyright Issues

Mar 8, 2023 - Technology

Chatbot therapy, despite cautions, finds enthusiasts

Peter Allen Clark



Ethical Issues and Biases

Class Syllabus

The Pre-Neural Age of LMs (-2013)

- n-gram language models
 - The power of context
 - Smoothing
 - Evaluating LMs

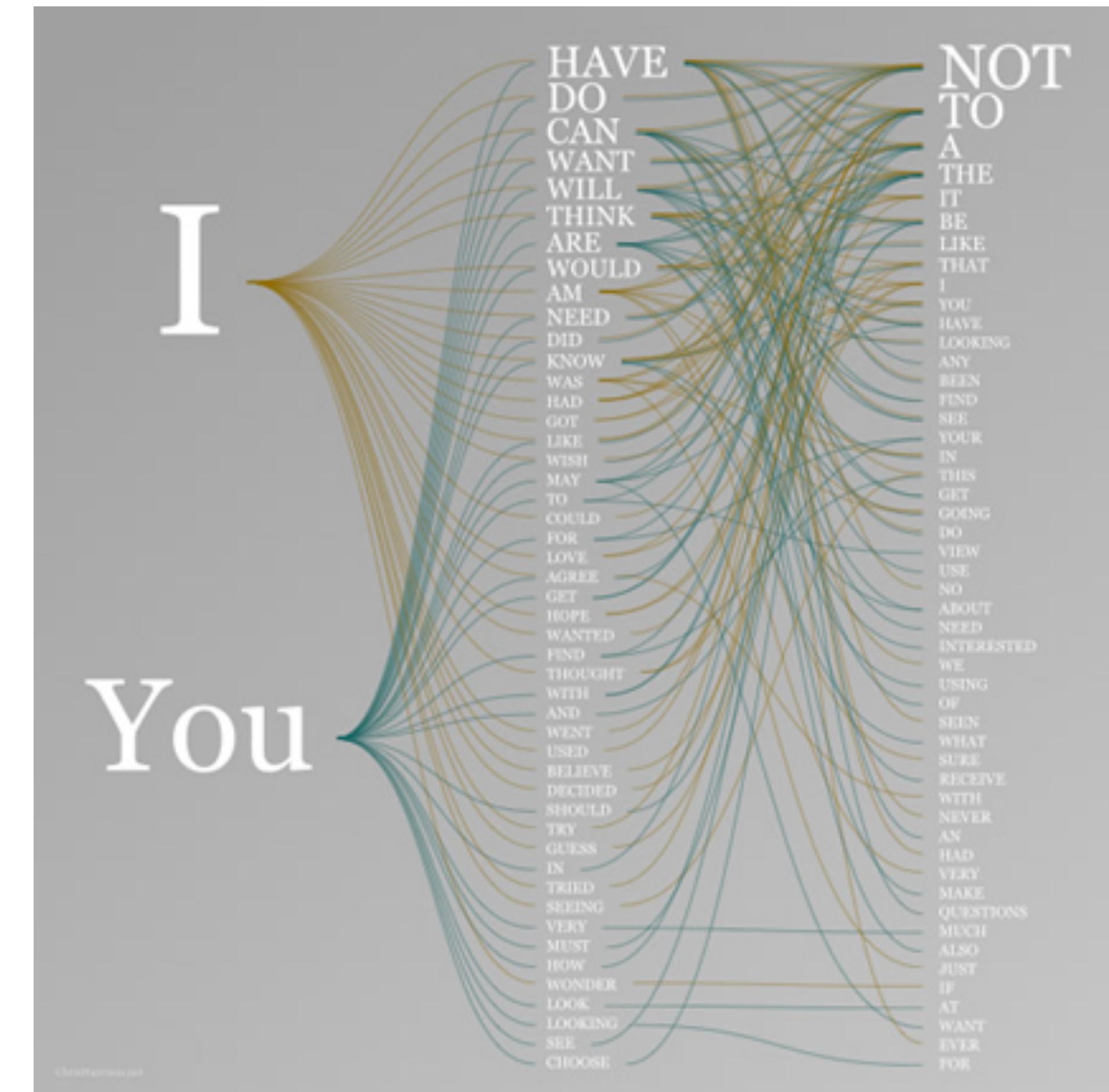
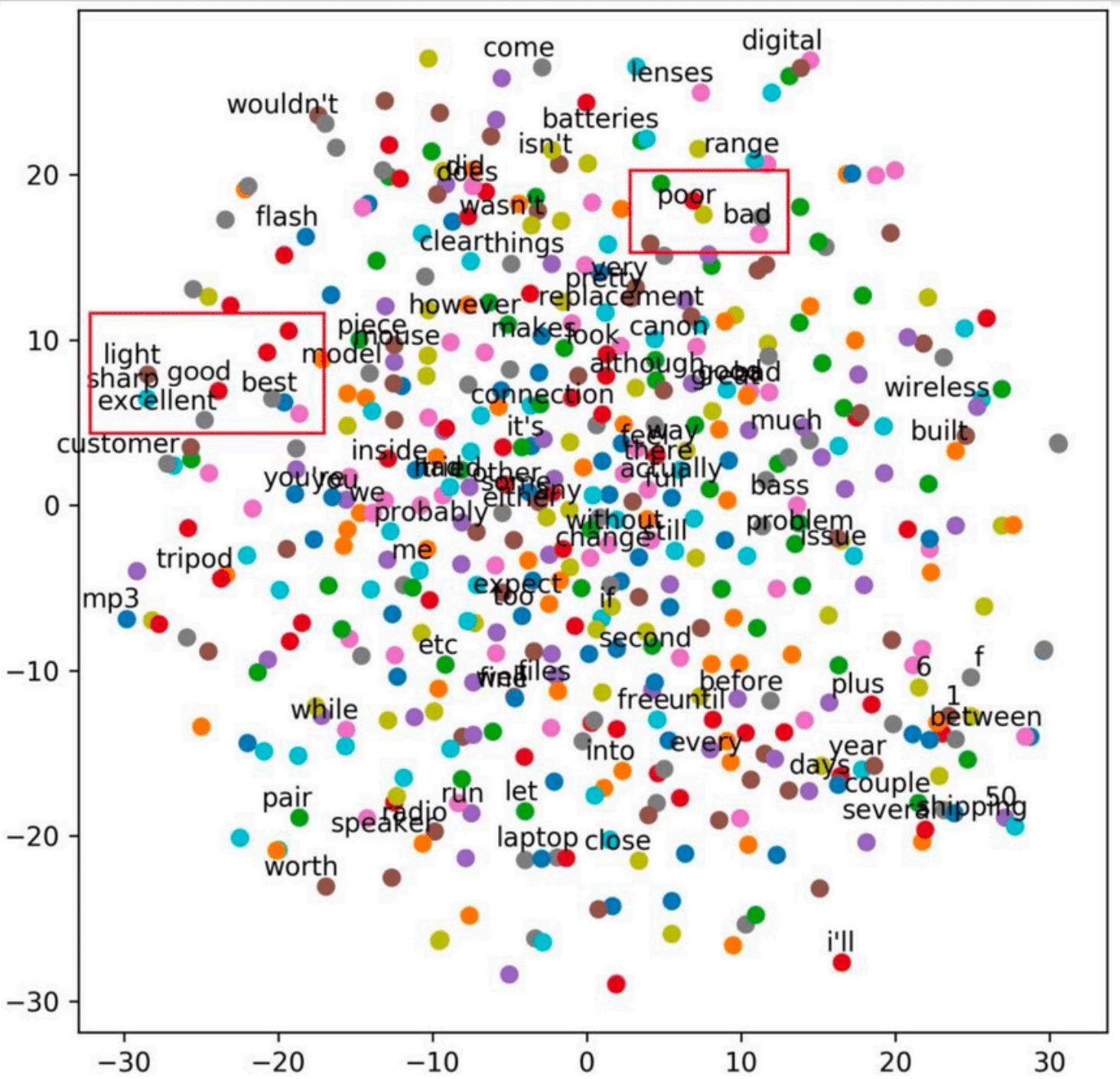
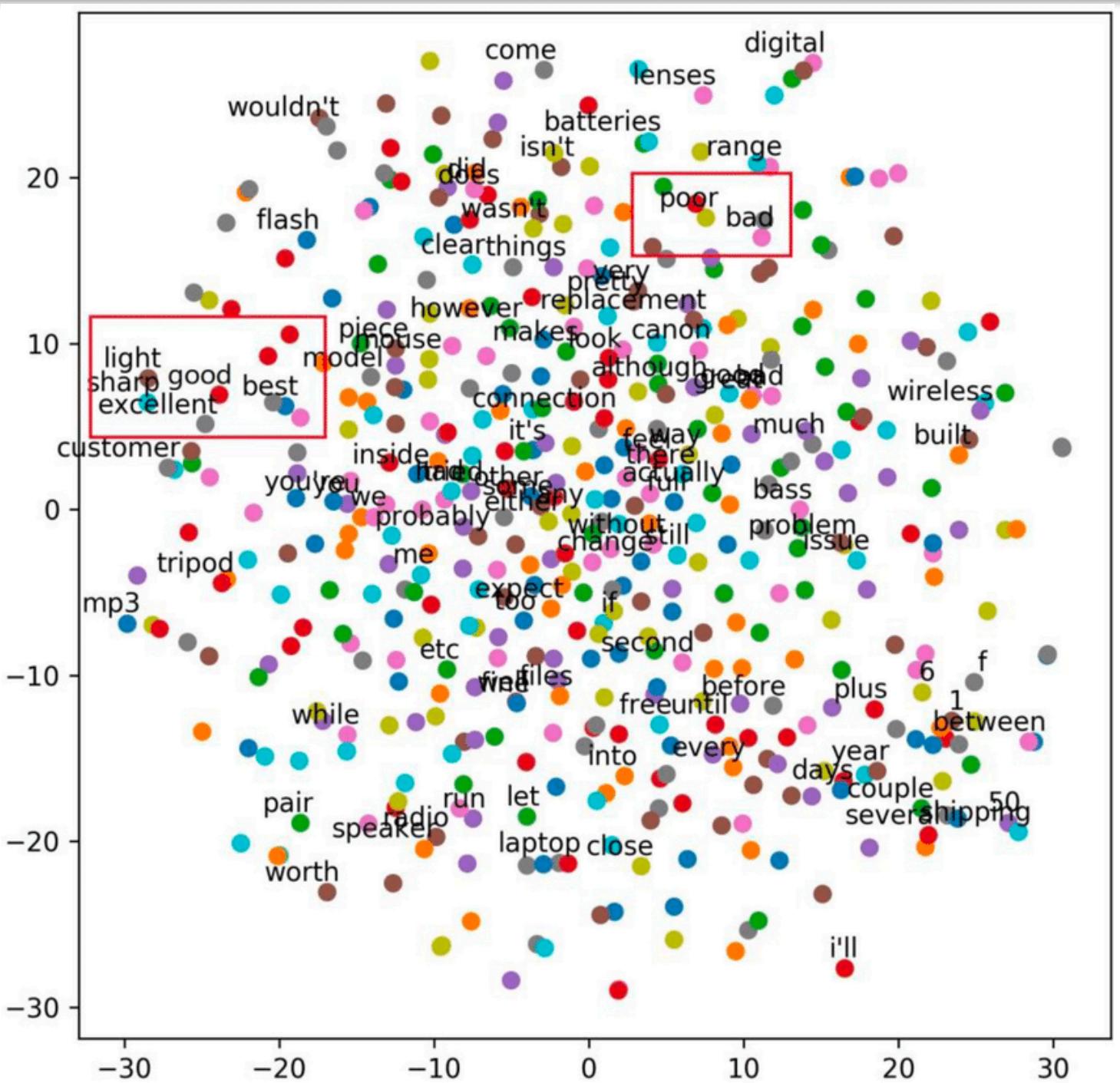


Image Courtesy: Chris Harrison

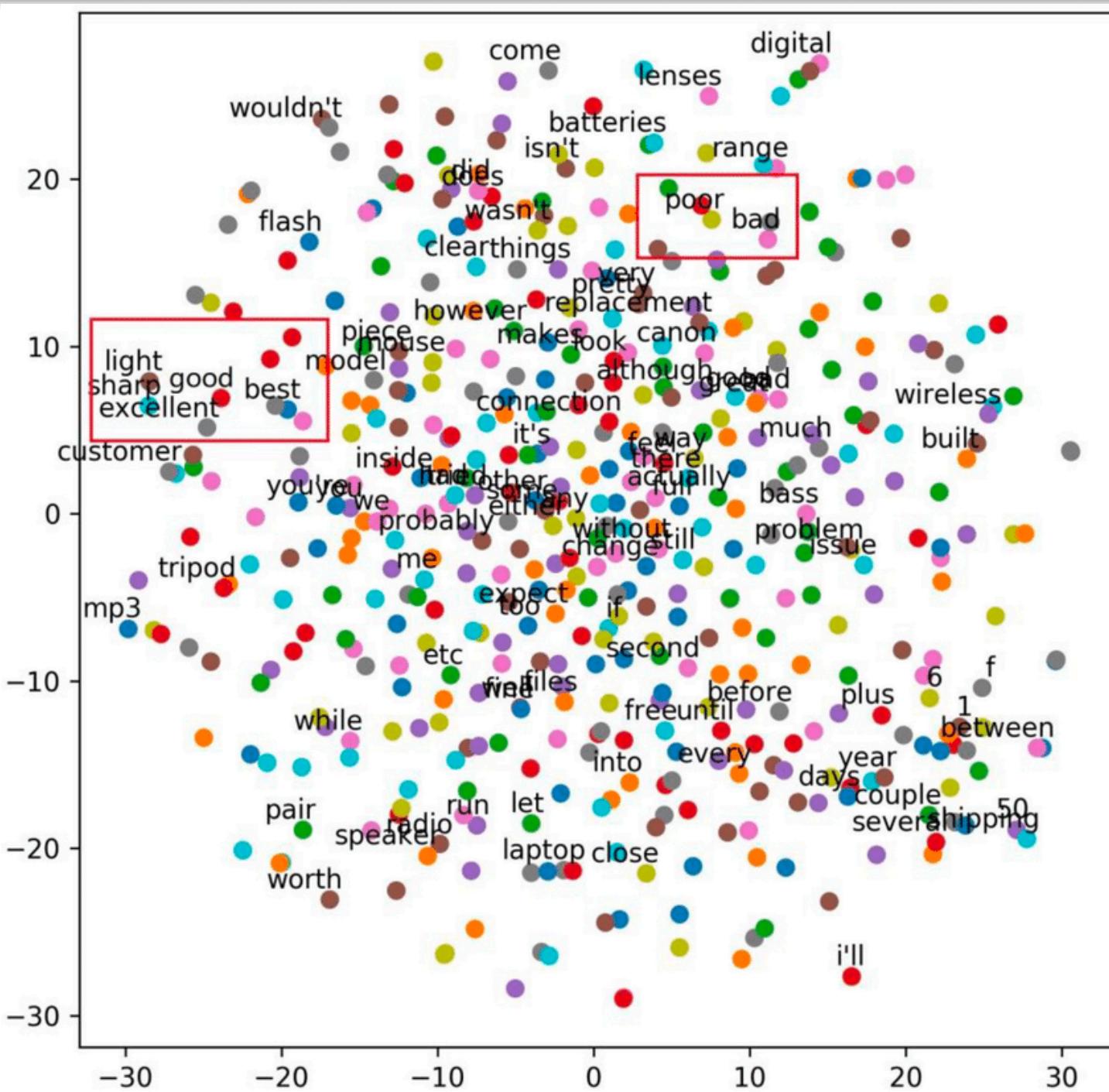
Early Neural LMs (2013-2018)



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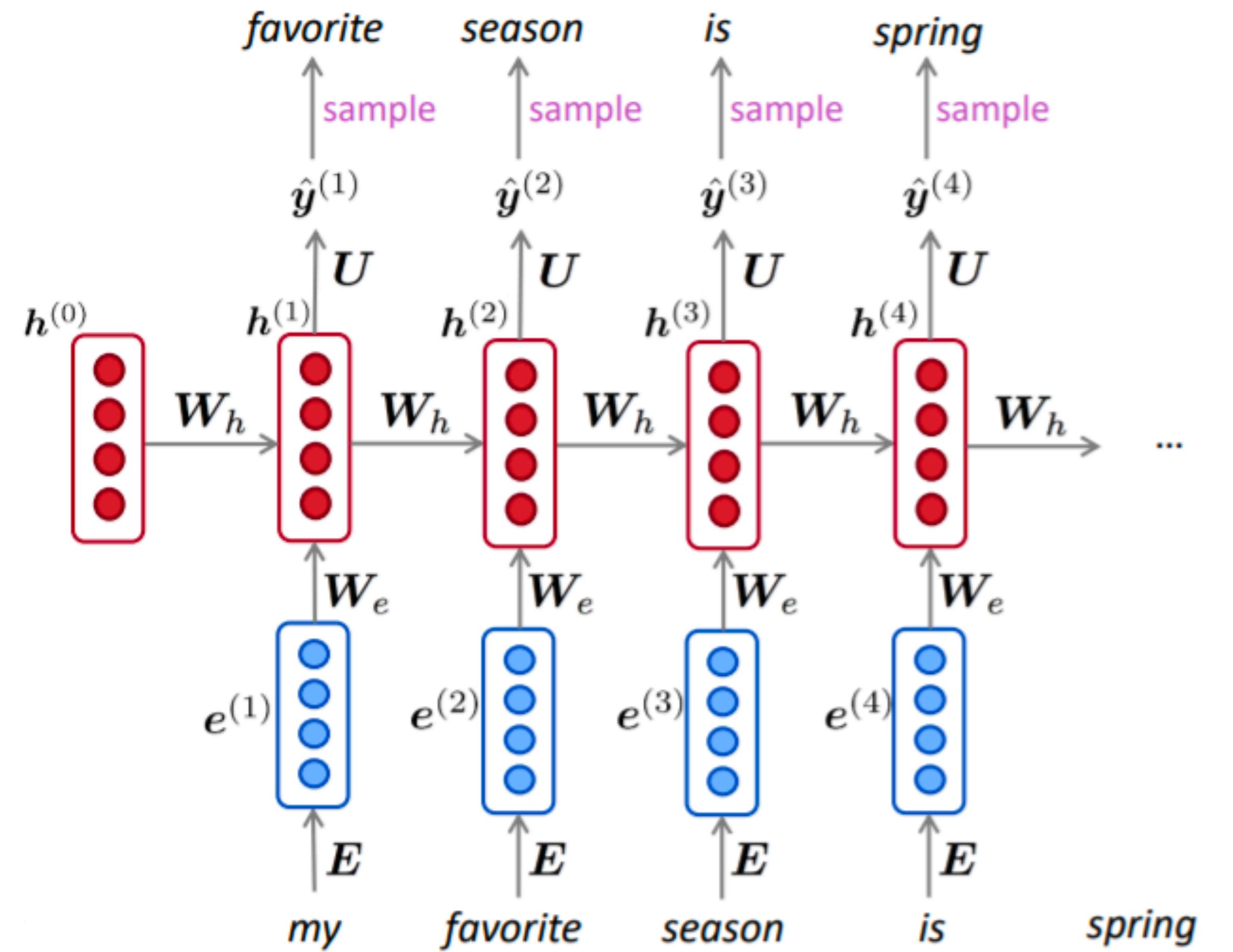


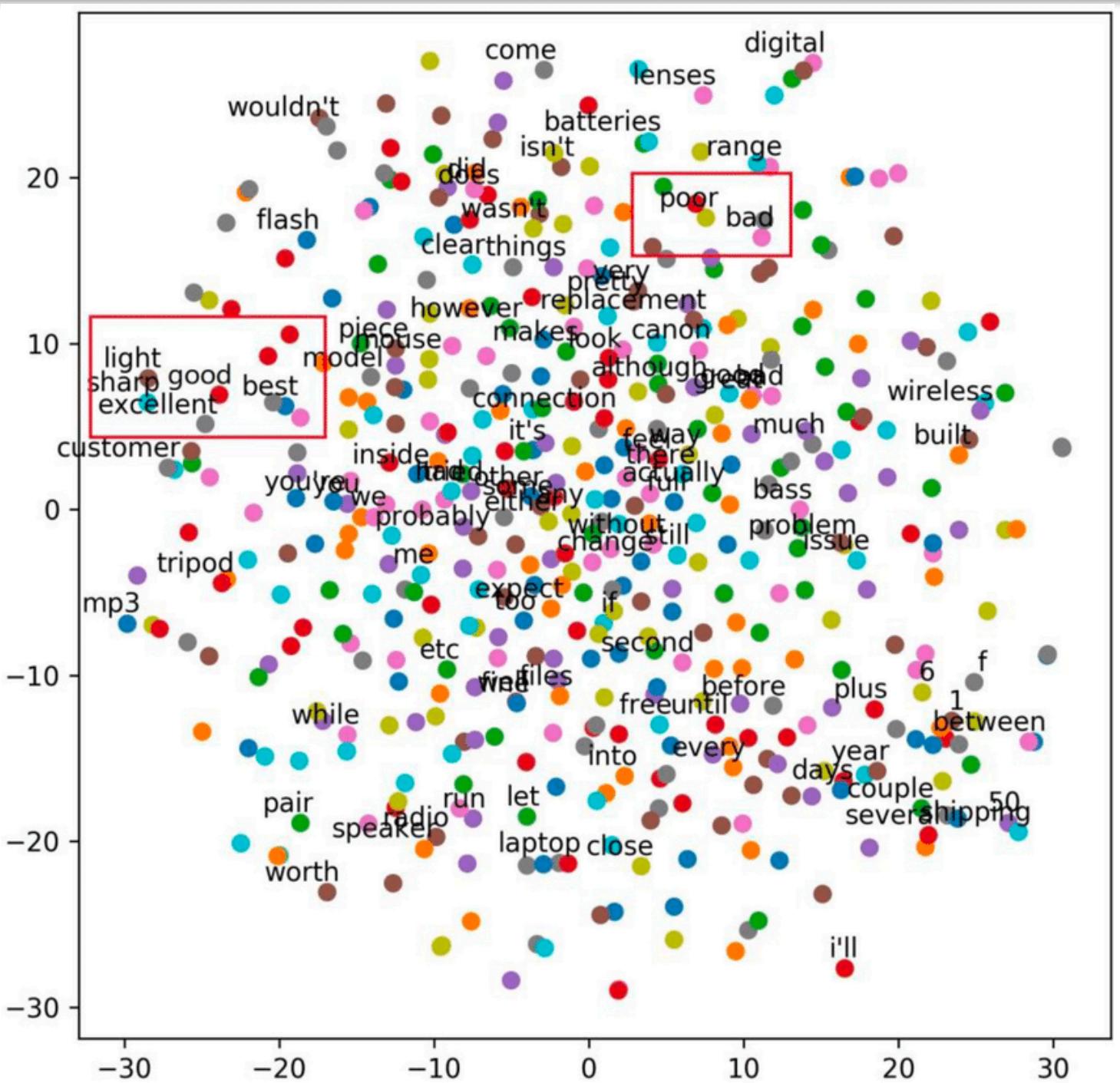
- (ML Basics) Logistic Regression



Early Neural LMs (2013-2018)

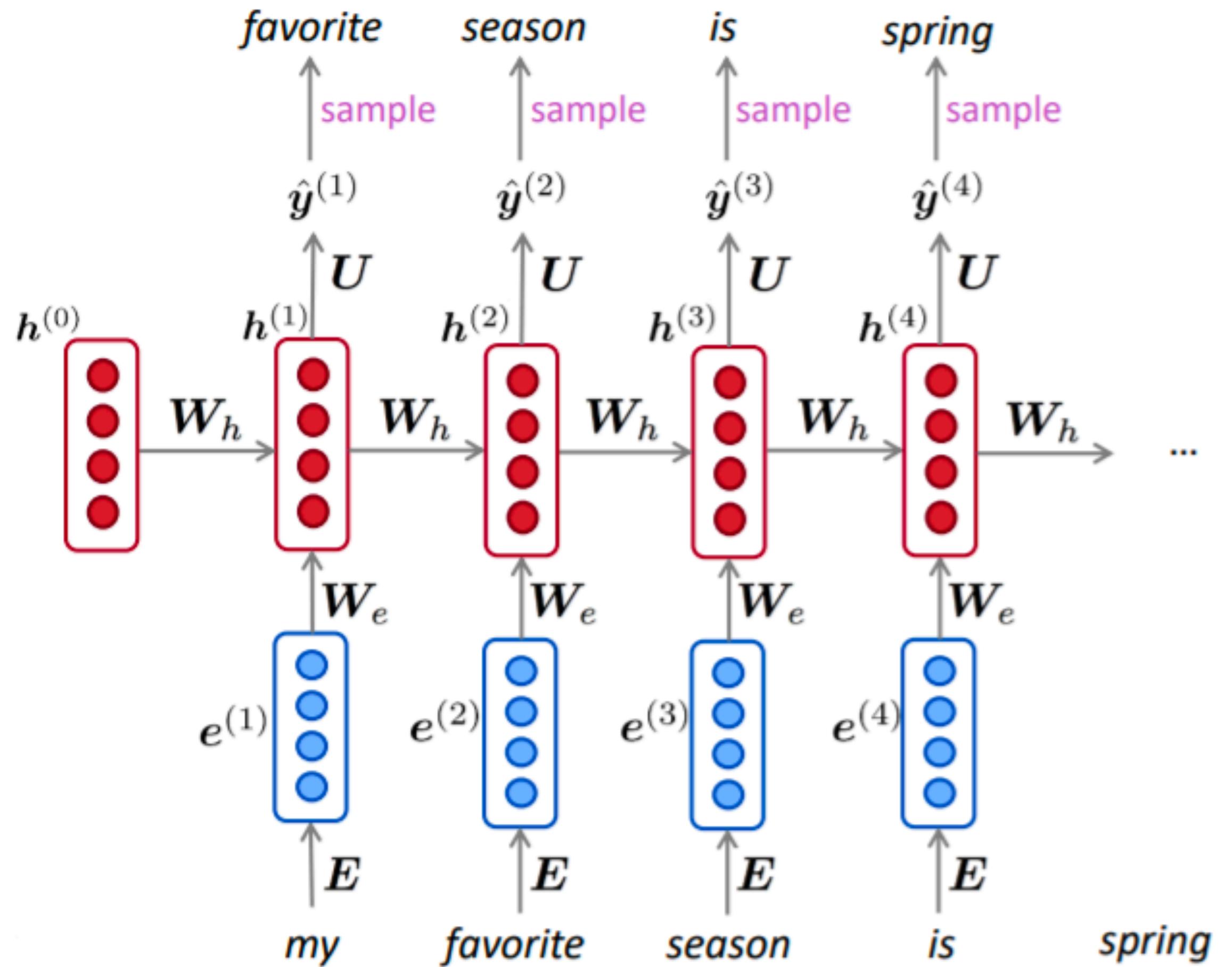
- (ML Basics) Logistic Regression
 - Word Embeddings

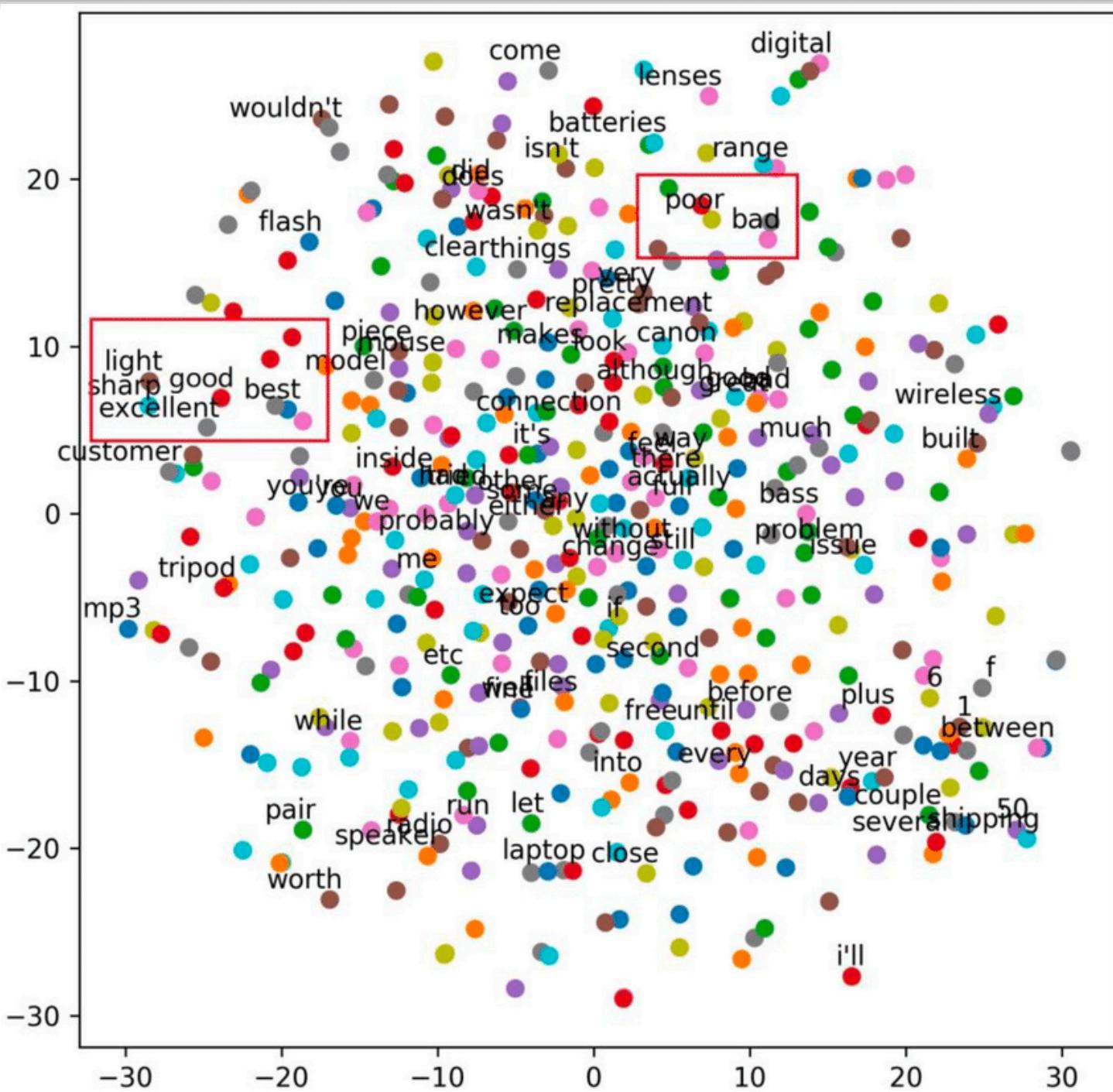




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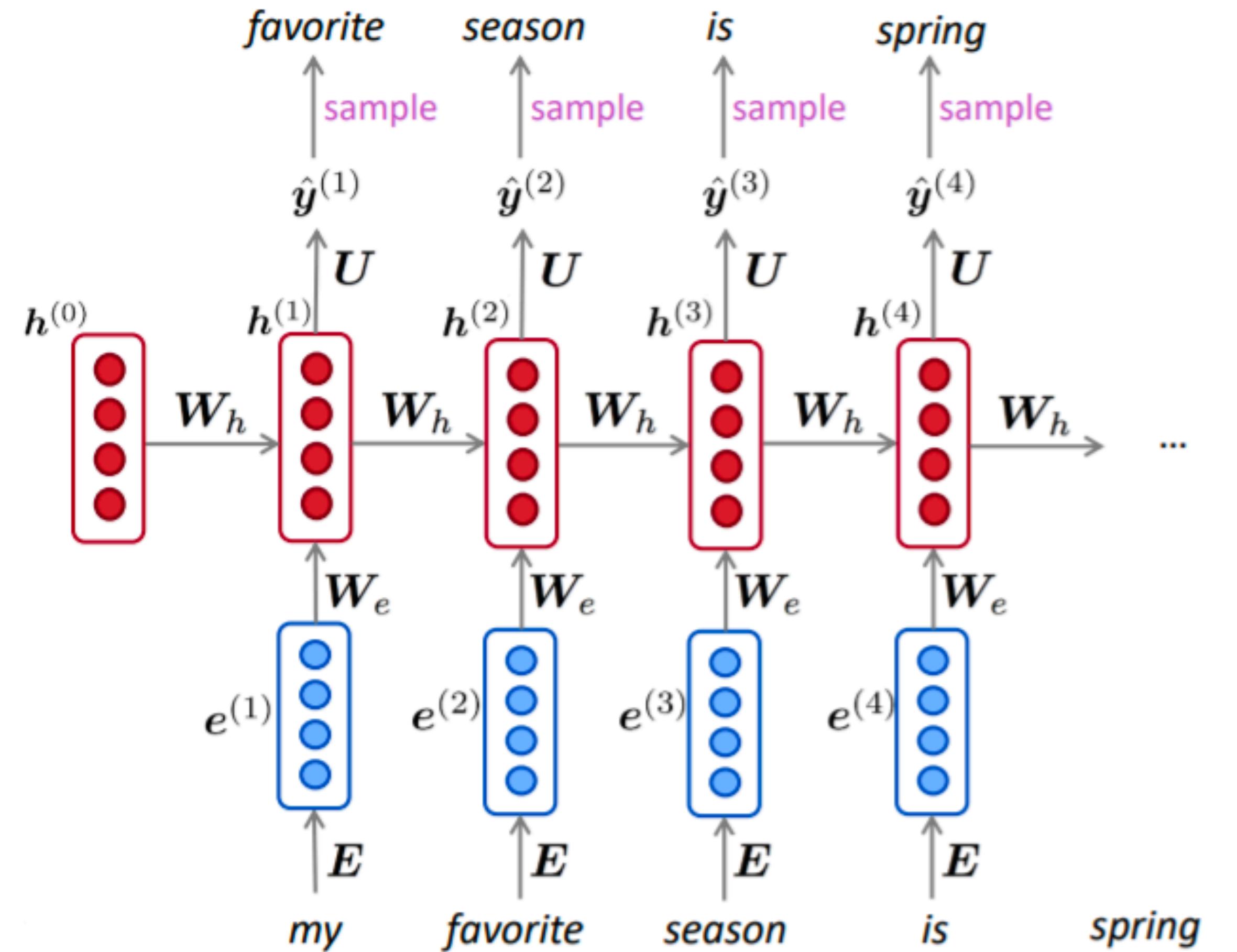
- (ML Basics) Logistic Regression
 - Word Embeddings
 - Feed-forward Networks

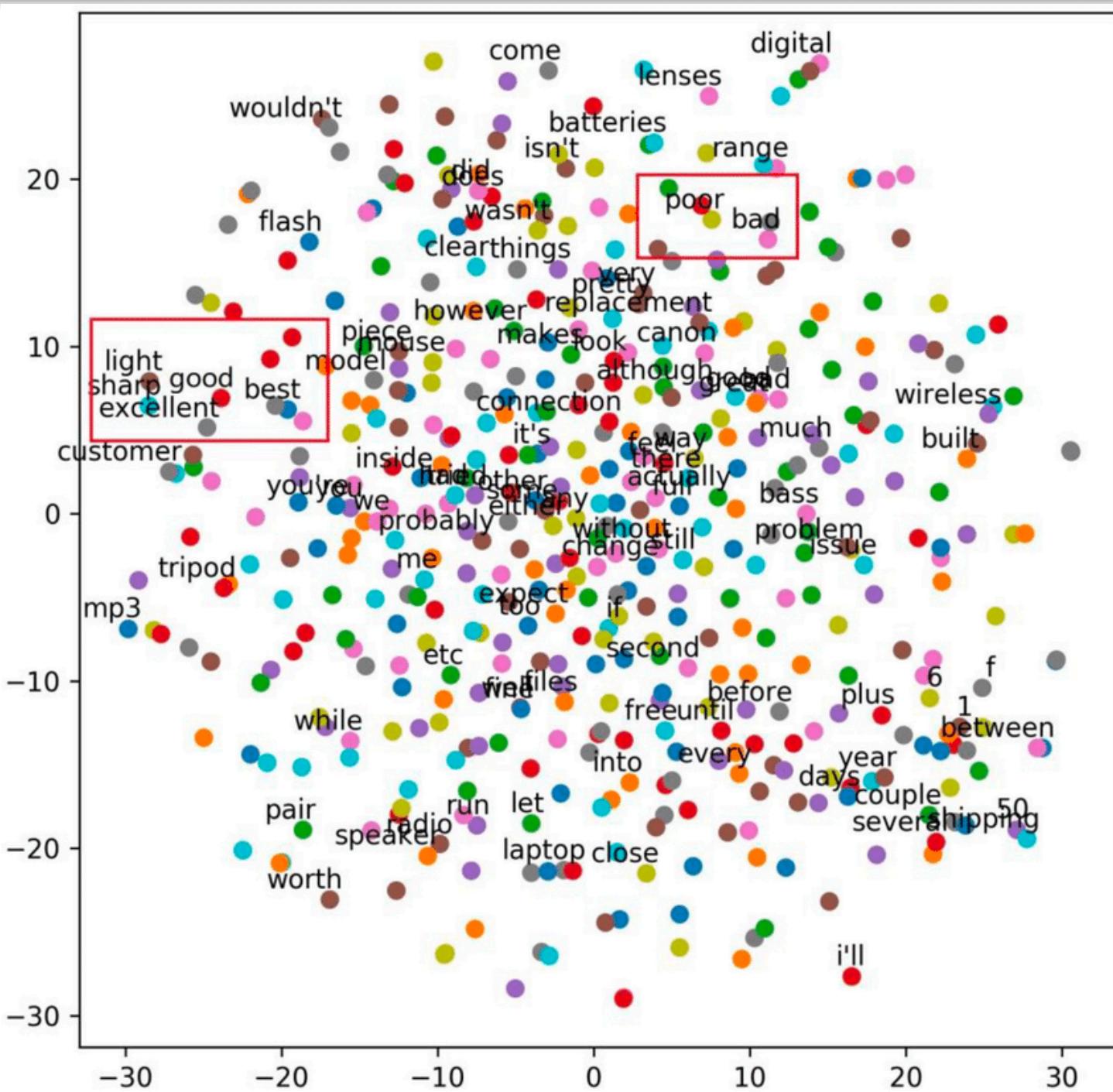




- (ML Basics) Logistic Regression
 - Word Embeddings
 - Feed-forward Networks
 - Recurrent Neural Net Language Models

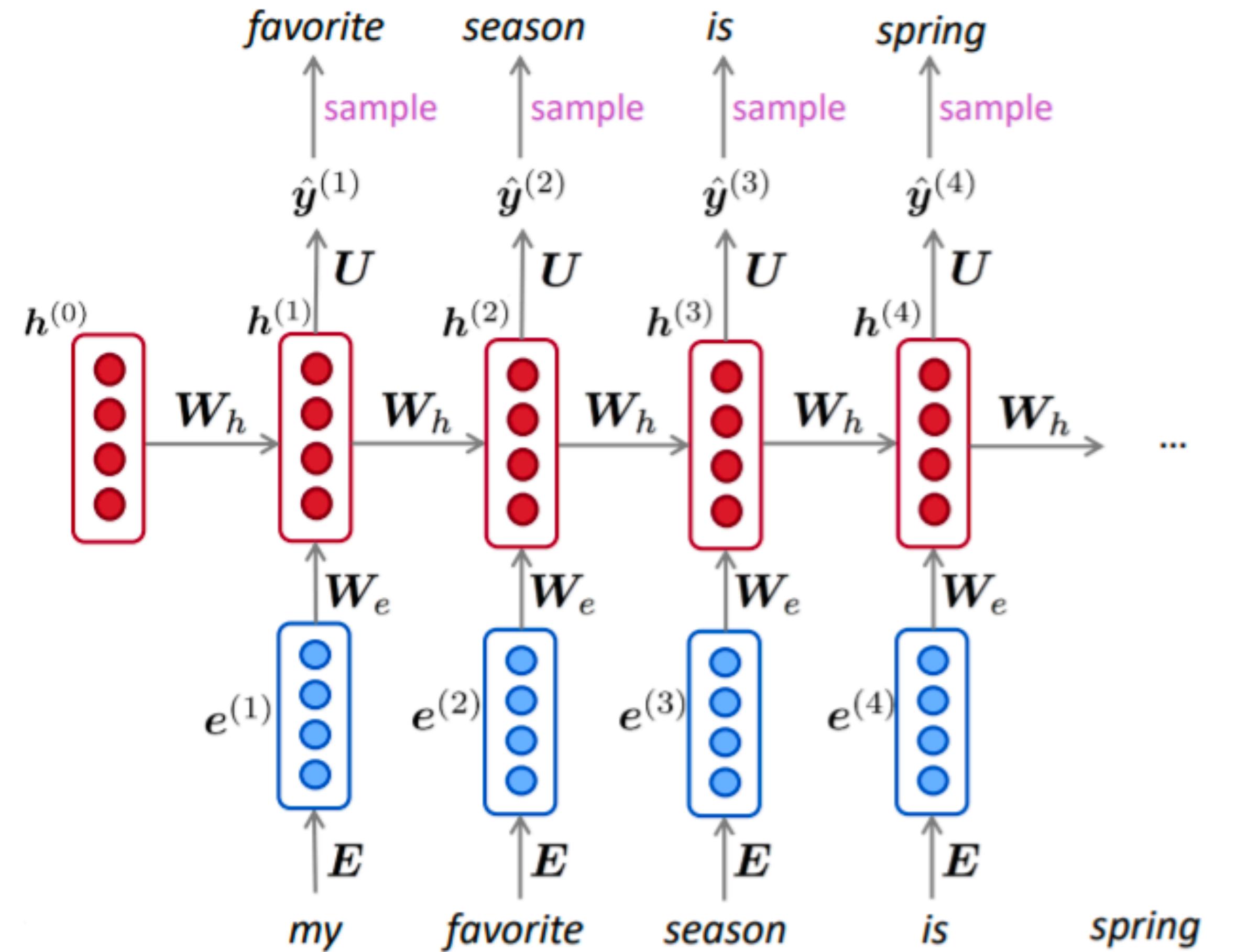
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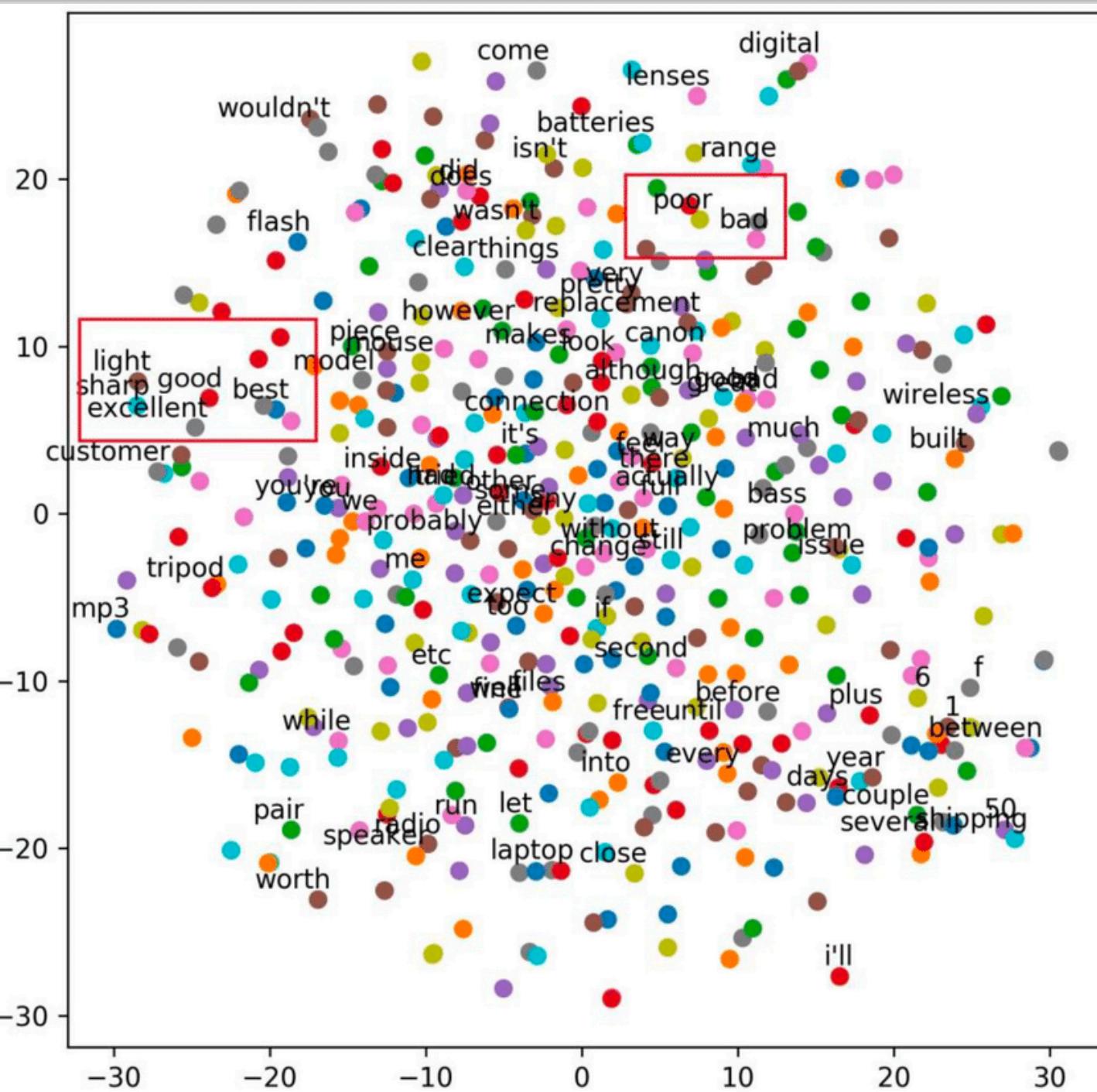




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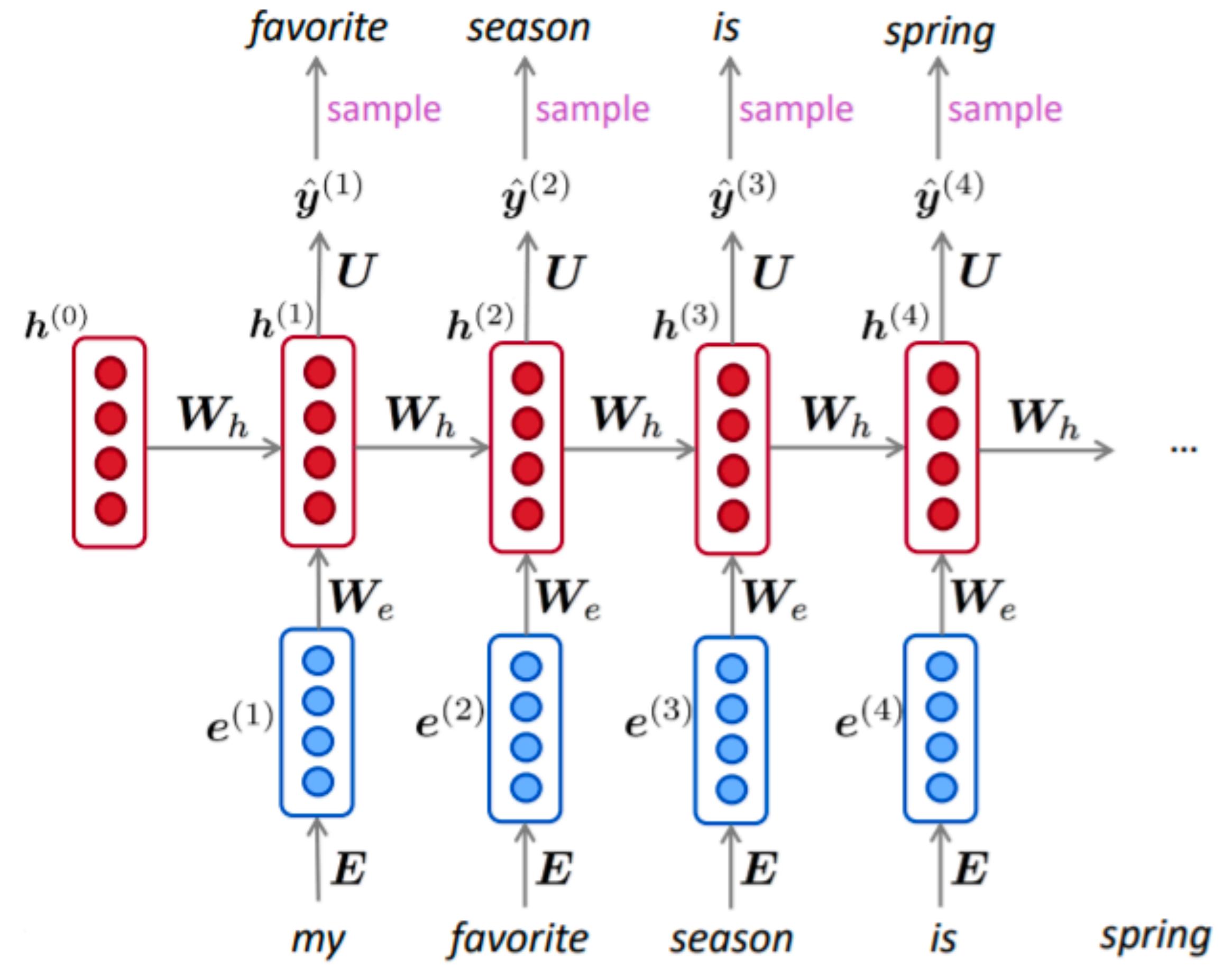
- (ML Basics) Logistic Regression
 - Word Embeddings
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 - Recurrent Neural Net Language Models
 - Basics of Neural Nets: Backpropagation



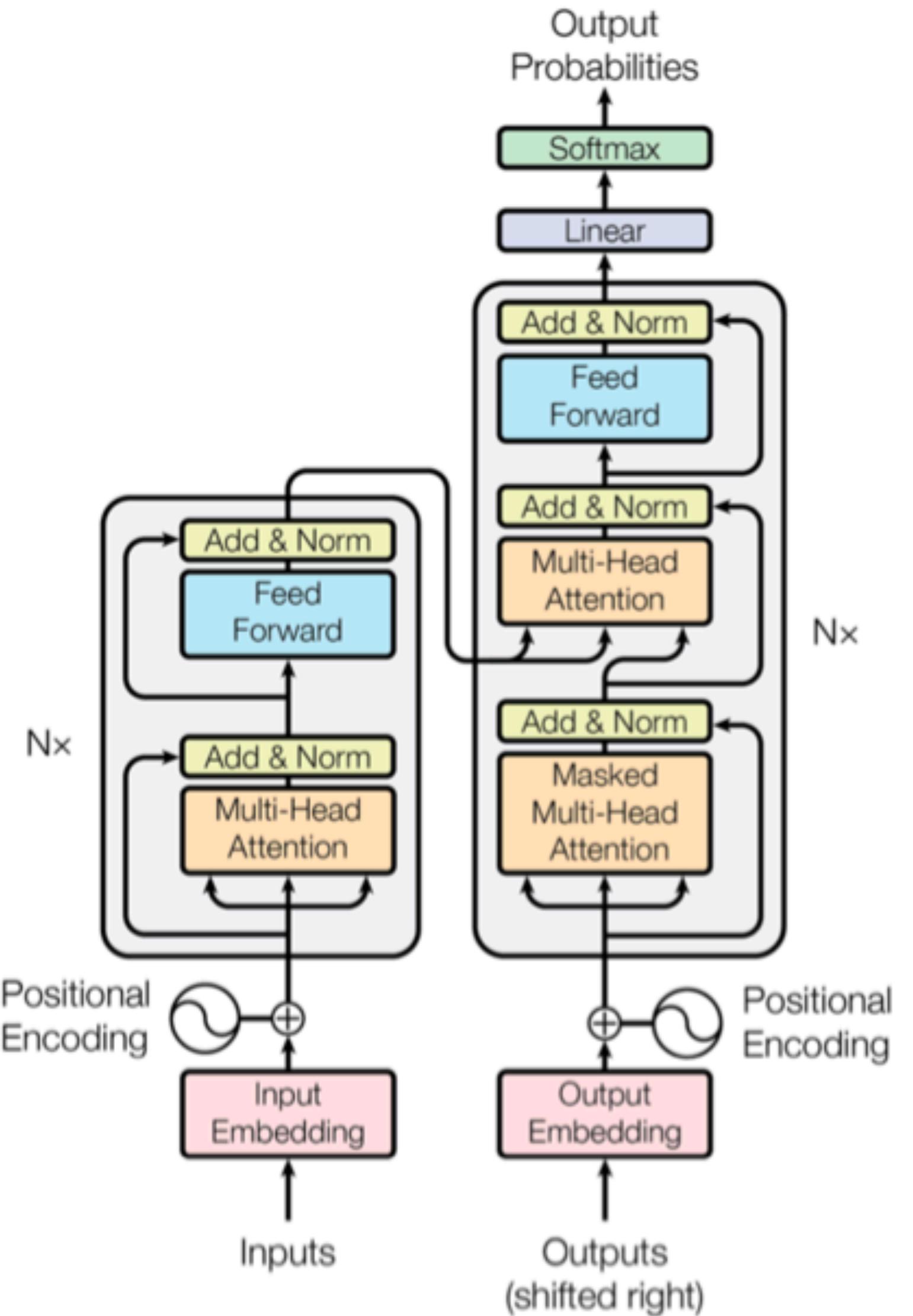


Early Neural LMs (2013-2018)

- (ML Basics) Logistic Regression
- Word Embeddings
- Feed-forward Networks
- Recurrent Neural Net Language Models
- Basics of Neural Nets: Backpropagation
- Encoder-Decoder Models

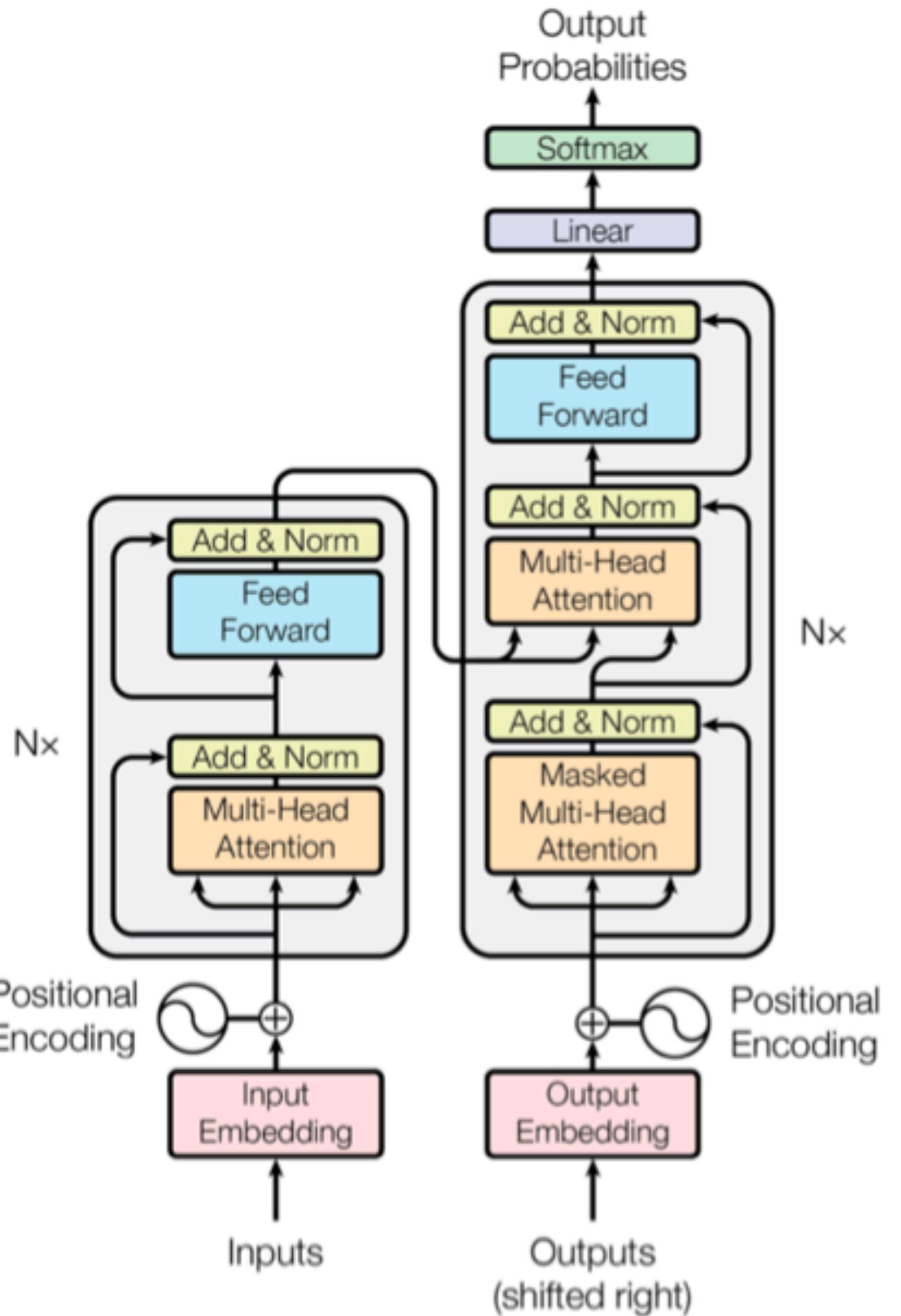


Modern Neural Language Models (2018 - present)



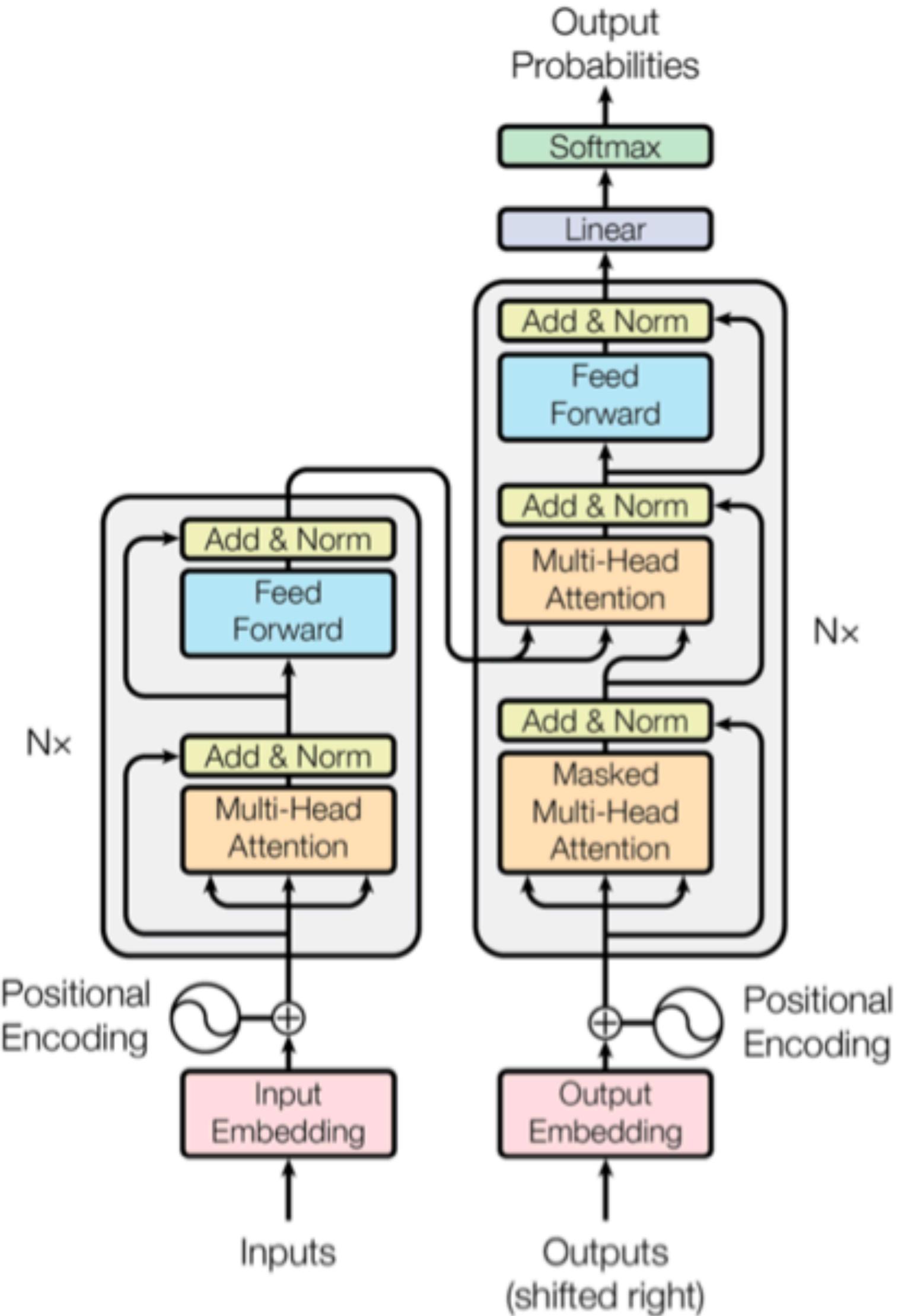
Modern Neural Language Models (2018 - present)

- Attention



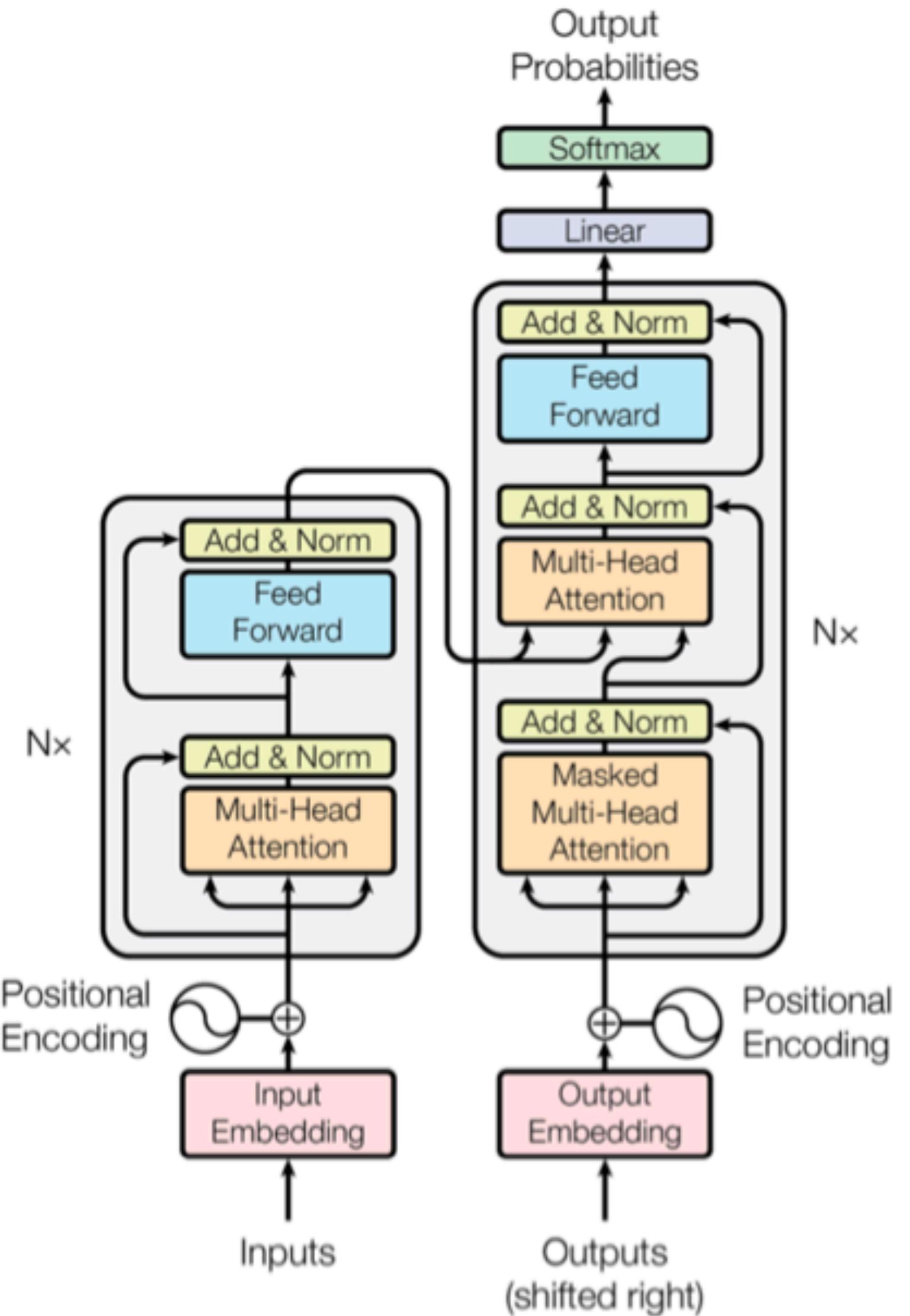
Modern Neural Language Models (2018 - present)

- Attention
- Transformers
- Self-Attention Networks



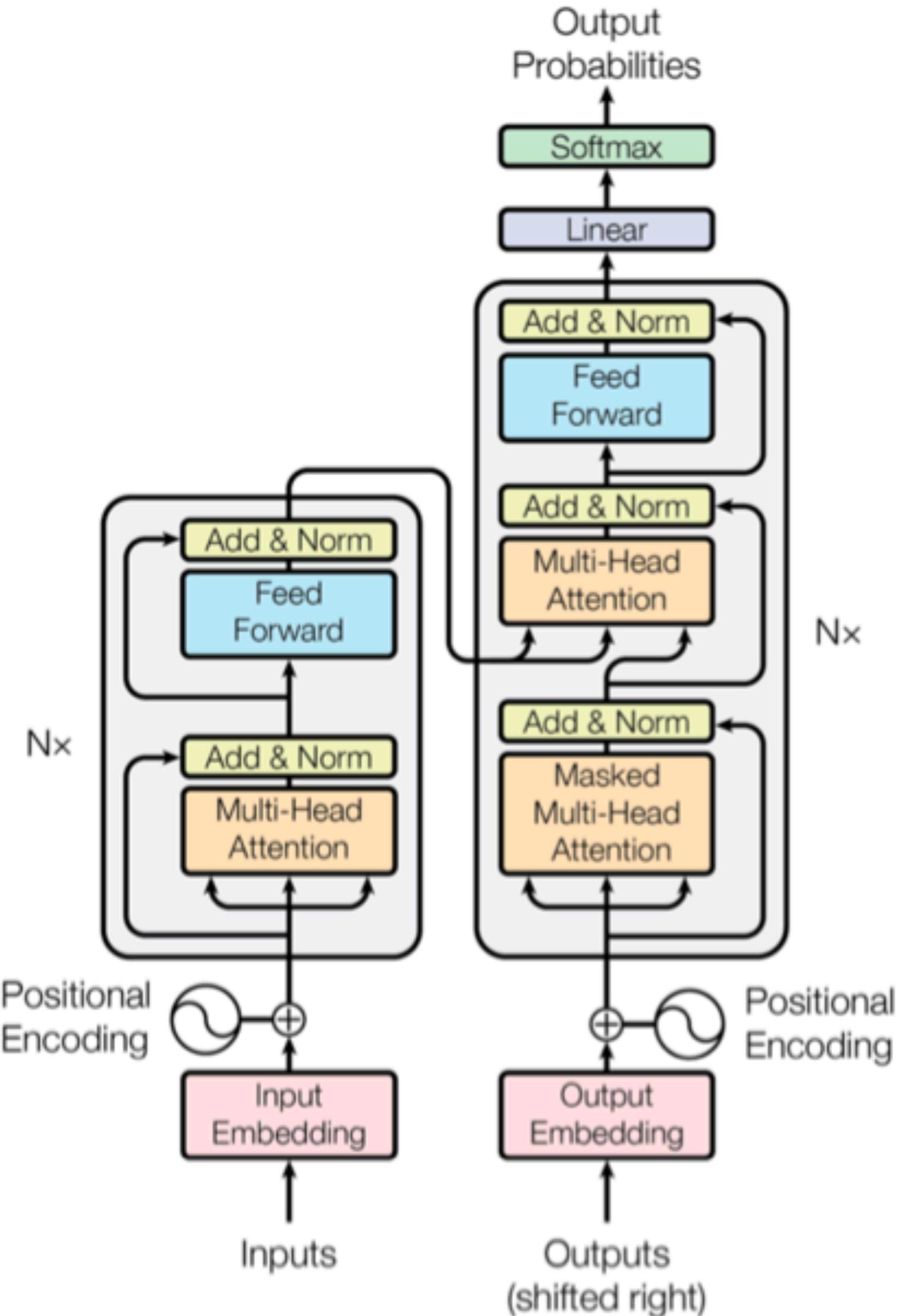
Modern Neural Language Models (2018 - present)

- Attention
- Transformers
 - Self-Attention Networks
- Masked Language Models

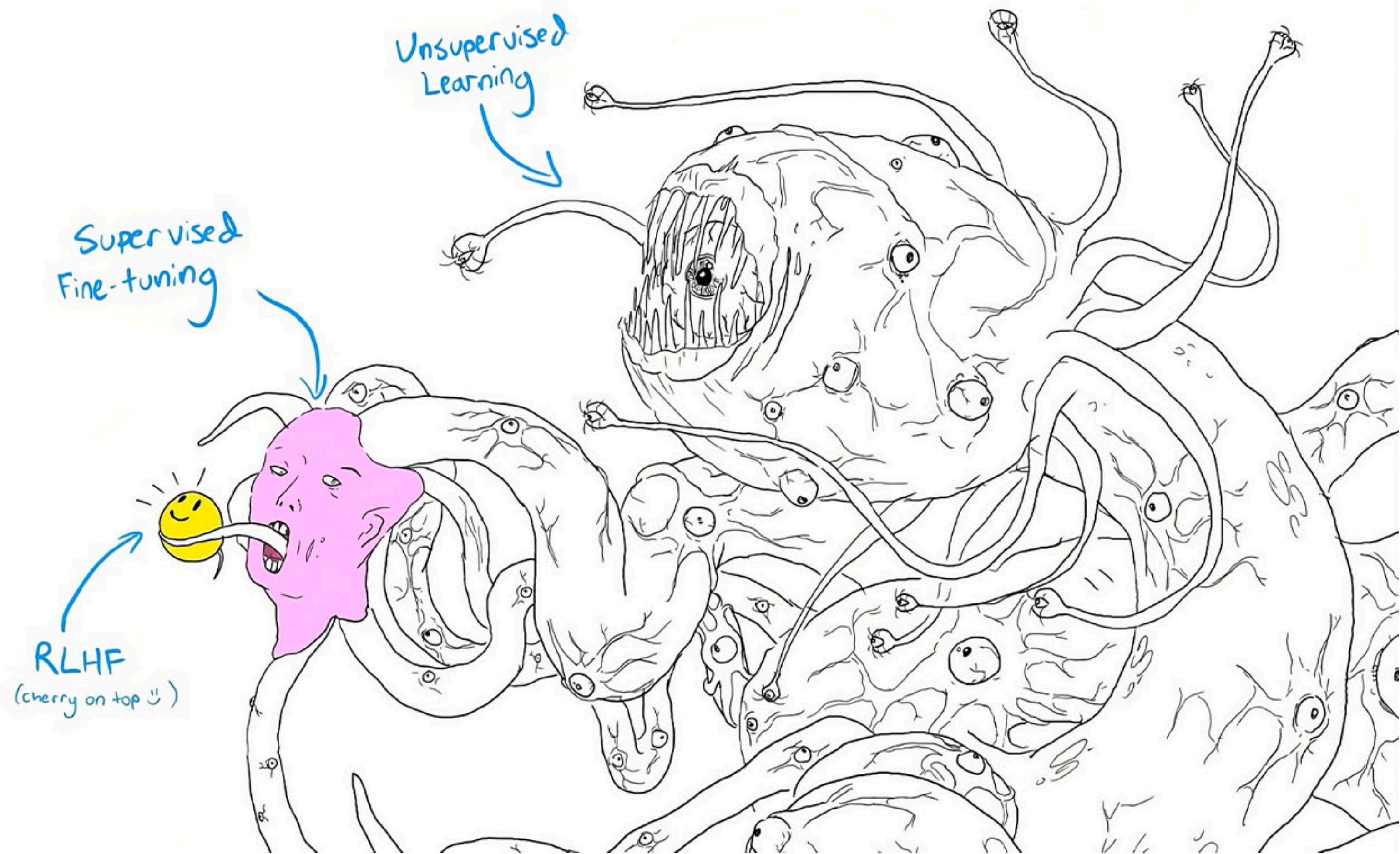


Modern Neural Language Models (2018 - present)

- Attention
- Transformers
 - Self-Attention Networks
- Masked Language Models
- Decoder-only Models



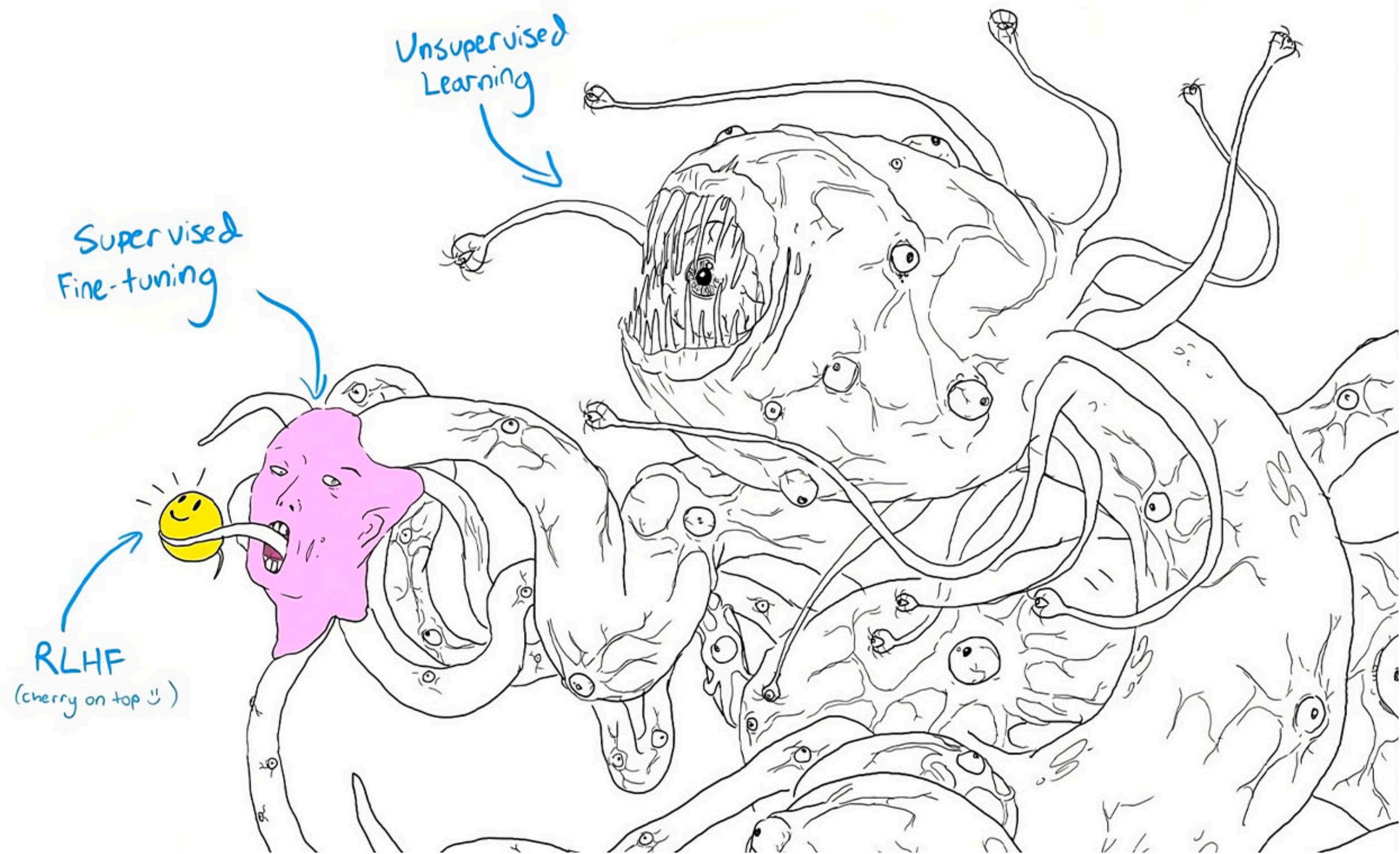
Large Language Models



Shoggoth with smiley face meme (image credit @anthrupad) - thanks to Justin Cho

Large Language Models

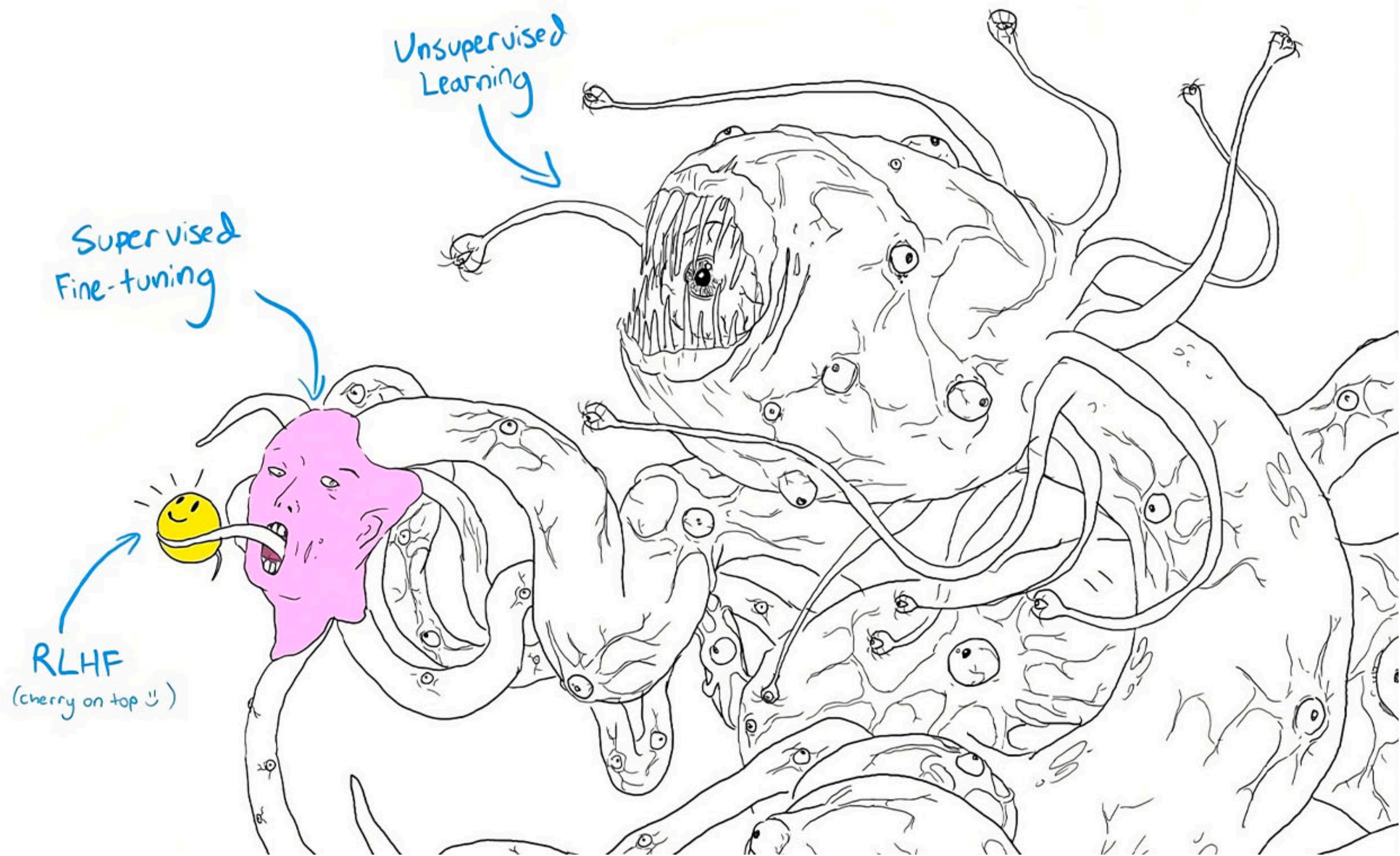
- Pretraining and Finetuning



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Large Language Models

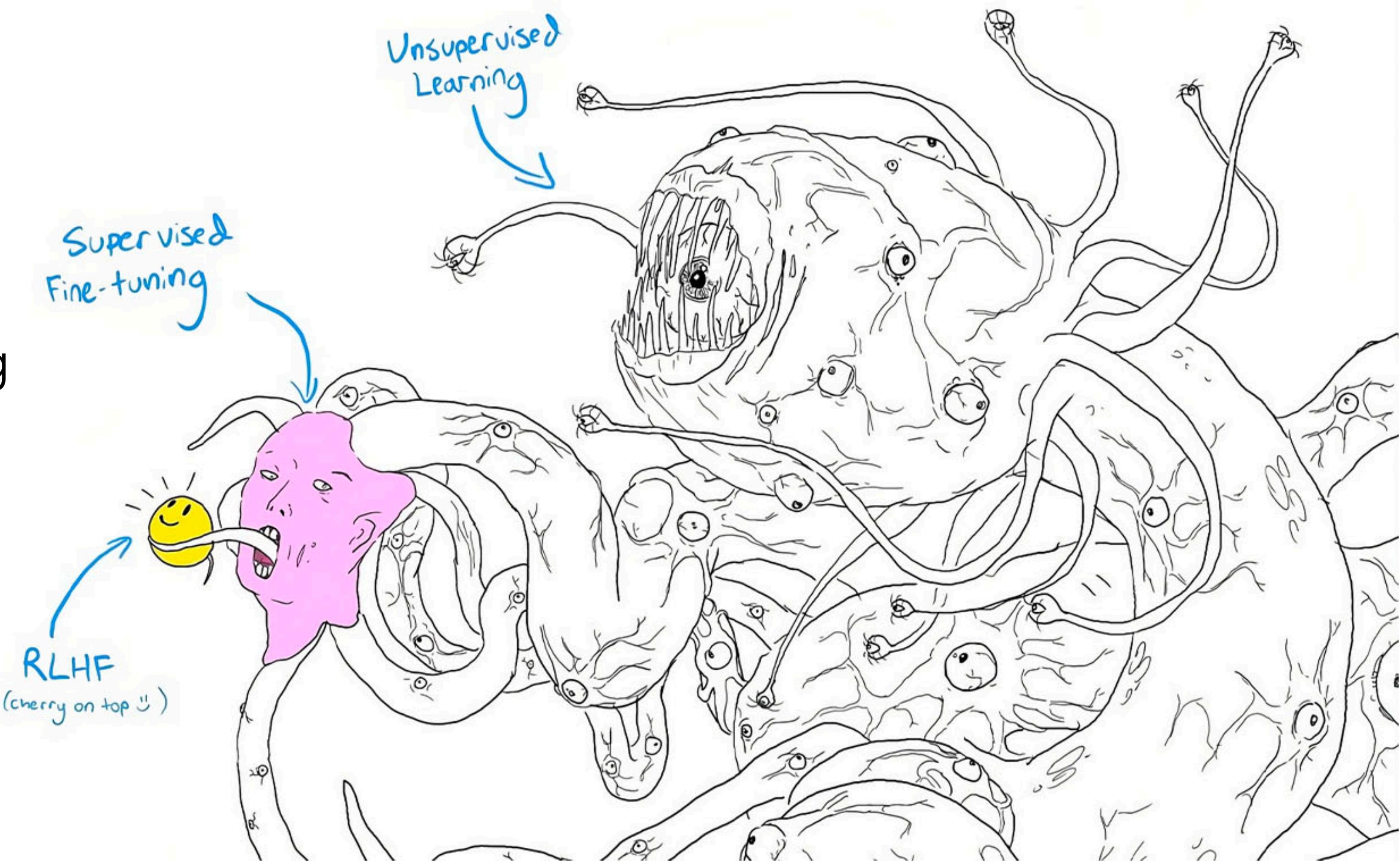
- Pretraining and Finetuning
- Generation from LLMs



Shoggoth with smiley face meme (image credit @anthrupad) - thanks to Justin Cho

Large Language Models

- Pretraining and Finetuning
- Generation from LLMs
- Prompting and Instruction Tuning
- Preference Alignment using Human Feedback
- Outstanding Technical Issues (e.g., hallucinations) and Socio-Technical Issues (e.g., privacy)



Shoggoth with smiley face meme (image credit @anthrupad) - thanks to Justin Cho

Concrete Outcomes

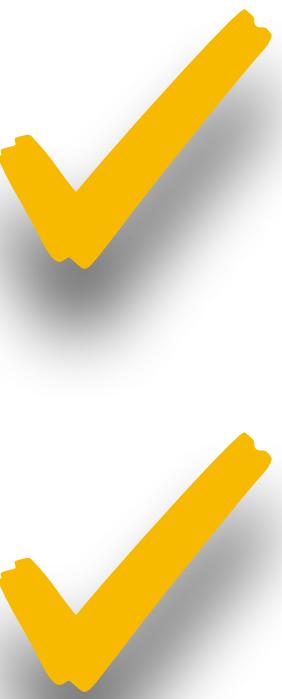
Concrete Outcomes



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- Build a language model - homework and / or project



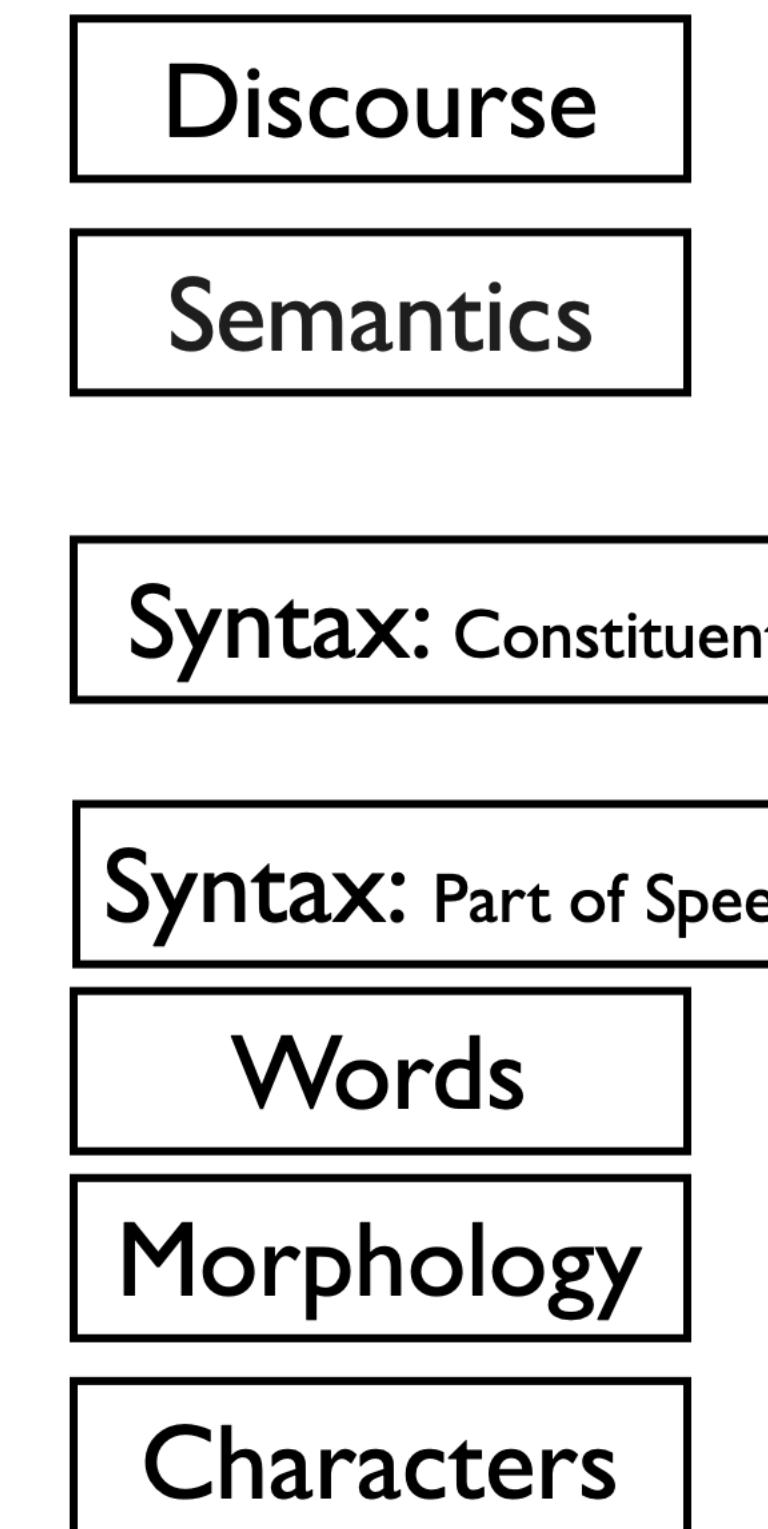
Concrete Outcomes

- Fundamentals of language modeling
- Build a language model - homework and / or project
- Learn the connections between this language model and models such as OpenAI's ChatGPT / GPT-4 models
- Current capabilities and outstanding issues with LLMs
- Exciting new problems



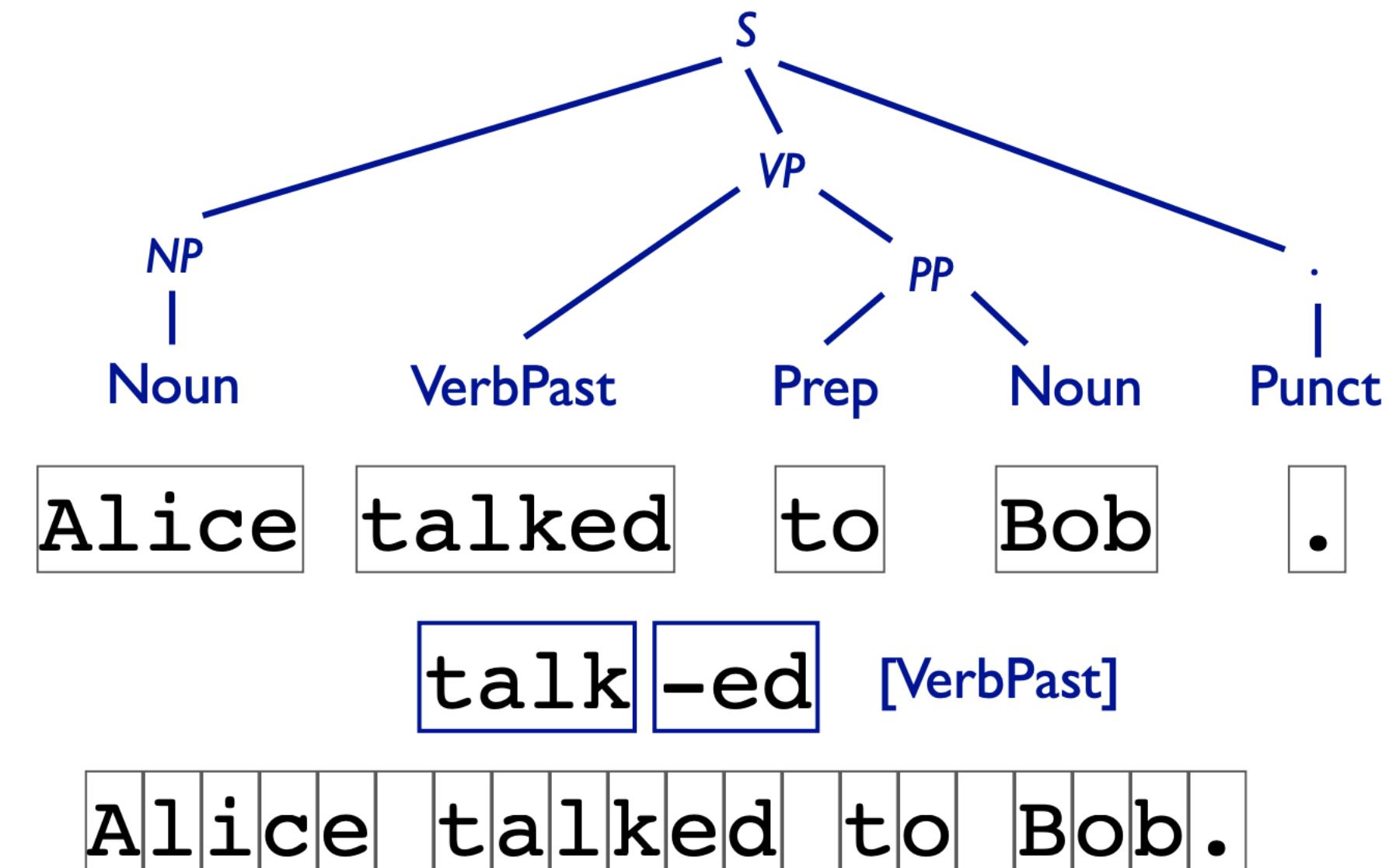
What the class will NOT cover

- Detailed discussion on NLP classification tasks, e.g. question answering
- Classical NLP algorithms for structured prediction
 - e.g. logical semantics and lambda calculus
 - sequence tagging tasks
- In-depth discussion of linguistics



CommunicationEvent(e)
Agent(e, Alice)
Recipient(e, Bob)

SpeakerContext(s)
TemporalBefore(e, s)



Prerequisites

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 - Linear Algebra
 - Probabilistic Theory & Statistics
 - Mathematical Analysis: differential/gradient

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Class Logistics



Staff and Website



Instructor: [Swabha Swayamdipta](#)
swabhas@usc.edu

Office Hours: Wednesdays 8-9 am @ Zoom (link on Brightspace)

<https://swabhs.com/f24-csci544-appliednlp/>

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Office Hours: Thursdays 3-4 PM @ TBA



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tingyun@usc.edu

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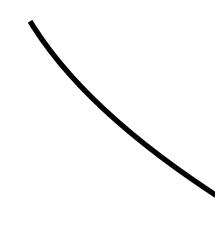
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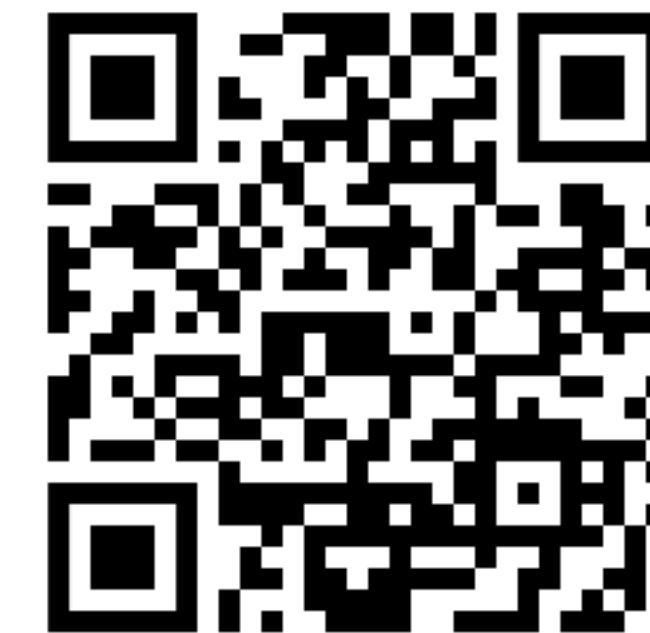
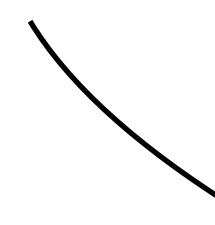
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Announcements, Homework, Grades, etc. on Brightspace:

DEN and D-Clearance

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- No lecture recordings are provided (in-person only)
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D-Clearance

- To be applied through myviterbi
- Decisions from CS department
- As an instructor, I cannot provide reserved slots

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- **6 total late days for homework and projects**
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- Grades will be available with 2-2.5 weeks of submission. Regrading requests must be made one week after announcing the grades (except the final exam)

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 - Mix of programming and essay-type questions

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 - Advanced Topics in LLMs



Subject to change

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 - Advanced Topics in LLMs
- 14-16 days per homework



Subject to change

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Class participation - This class is meant to be a discussion-oriented intro to research:

- You are required to attend class:
 - In case of extenuating circumstances that prevent you from attending, use the form on Brightspace to report absence (*will be considered only when declared in advance*)
 - Attendance will be taken at random
 - Non-attendance can be the basis for grade penalties
- You are encouraged to participate in class: Ask questions, **and** volunteer to answer my questions!

Exams

- Midterm on Oct 15
 - 4:10-5:10pm, no overlap with CSCI 572 for those taking the class
 - Confirmed with Prof. Saty
- Finals on the last day of class - Dec 5
 - Slight change from syllabus pdf
- Final Deliverable: Project Final Report, due on Dec 17
- In Class

Class Project

Sep 17	Backprop	HW1 Due; HW2 Released; Group Formation Deadline
Oct 10	Fall Break	Project Proposal Due on Oct 9
Oct 31	Paper Presentation I	Project Status Report Due
Nov 19	Project Presentation I	
Nov 21	Project Presentation II	
Nov 26	Project Presentation III	
Nov 28	Thanksgiving	
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Class Project

- Styled like a research paper

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 - In some cases, teams of 4 are allowed
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 - 8%: progress report (2-3 pages) +
 - 10%: presentation of main findings (5 mins) +
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- Need to declare project teams by 9/17, start early!

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Class Project Topics - Examples

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Detoxifying Language Model with Context
Distillation

Haiku Generation with Large Language
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Legal-SBERT: Creating a Sentence Transformer
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Prompting for Diverse Responses: Making
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Forage: ML Generated Recipes

Learning the Language of Wine

Machine Translation from Inuktitut to English

DISCo: Detecting Insults in Social Commentary

Authorship Attribution with Limited Text
When Was it Written?

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See more: [Stanford CS224n Projects](#)

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Creativity in choosing new and interesting problems often get rewarded!

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Creativity in choosing new and interesting problems often get rewarded!

TAs will be assigned as project mentors - get feedback during their office hours!

See more: Stanford CS224n Projects

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Collaboration and GenAI

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- Collaboration
 - Discussion on HW is allowed, but your code and report should be solely your own work
 - It is your responsibility to make sure your solution is not shared or copied by others
 - We will find out if you're using GenAI for homework questions, please do these on your own
 - We will check for overlap in HW - there is a **zero tolerance for plagiarism**

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- PyTorch Programming
 - Expected to be self-studied
 - A short introduction provided in the class

Academic Conduct

Plagiarism – presenting someone else’s ideas as your own, either verbatim or recast in your own words – is a serious academic offense with serious consequences. Please familiarize yourself with the discussion of plagiarism in SCampus in [Part B, Section 11, “Behavior Violating University Standards”](#). Other forms of academic dishonesty are equally unacceptable. See additional information in SCampus and university policies on Research and Scholarship Misconduct.

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Website contains links, freely available

Welcome

CSCI 544 Fall 2024: Applied NLP

🍂 Fall 2024

⌚ Tue / Thu 4:00 - 5:50p

📍 SAL 101



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- TODOs for you
 - Start forming project teams

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- Next Class
 - n-gram Language Models

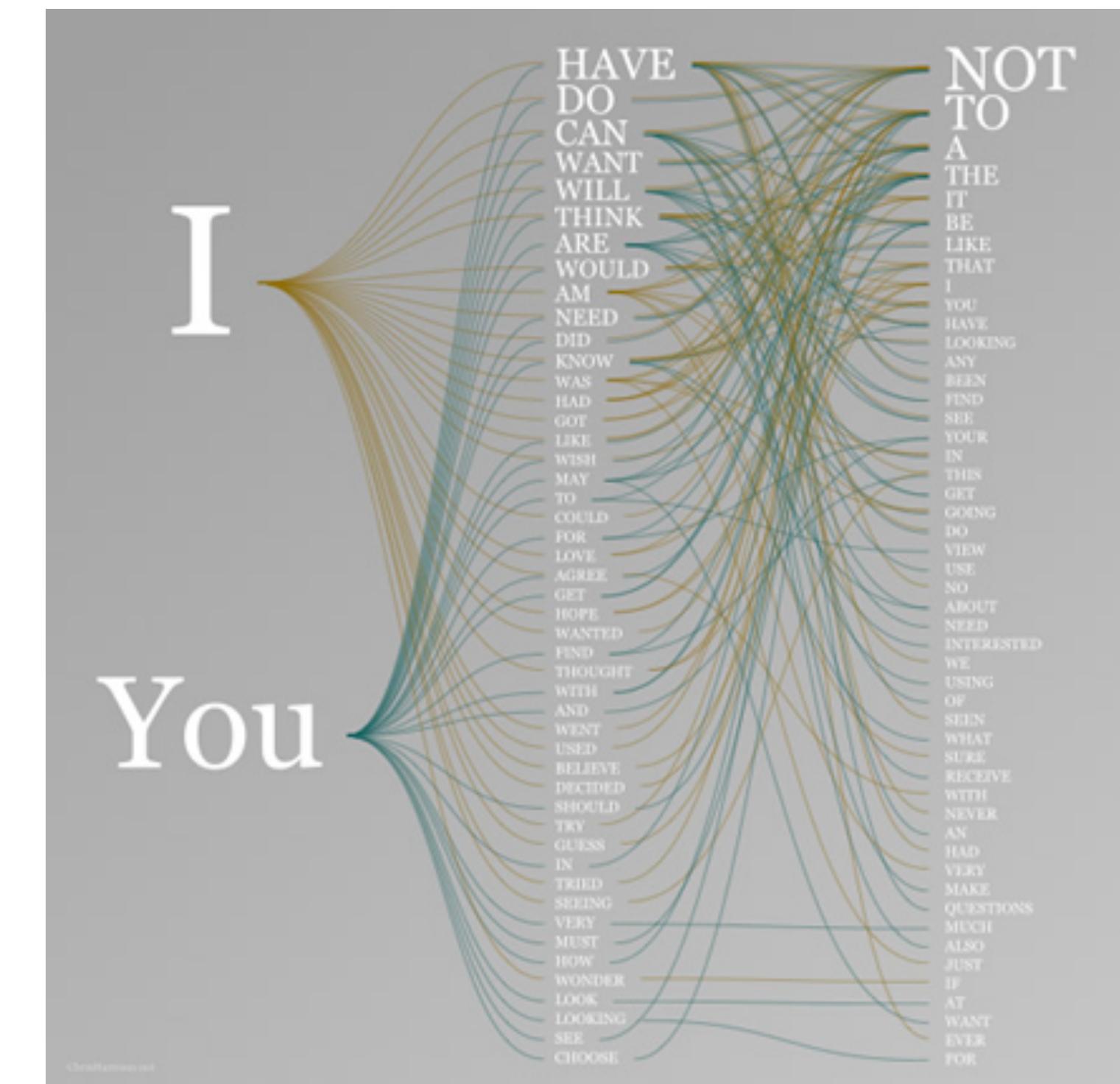


Image Courtesy: Chris Harrison

