Announcements

- Homework 9 due tomorrow, Nov 17 at 11:59pm PT
- Project 5 due Friday, Nov 27 at 11:59pm PT
- Homework 10 will be released tomorrow
 - due Friday, Dec 1 at 11:59pm PT
- Review session next Tuesday, Nov 21
- Special Topic Guest Lecture on Nov 28!

Nov 28 Special Topic Lecture on Generative Al

Guest Lecturer: Katherine Lee

- Katherine is a research scientist at Google DeepMind. Her work has provided essential empirical evidence and measurement for grounding discussions around concerns that language models infringe copyright, and about how language models can respect an individuals' right to privacy and control of their data. Additionally, she has proposed methods of reducing memorization. Her work has received recognition at ACL, USENIX, and ICLR.
- katelee168.github.io
- genlaw.github.io
- Topic: Generative AI and its legal implications
- Date: Tuesday, Nov 28 (after Thanksgiving week)
- Please attend!

CS 188: Artificial Intelligence Applications



[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.]





Ketrina Yim CS188 Artist

Today

- Applications and analysis of supervised deep learning
- Intro to unsupervised learning
- Multi-modal AI
- Tracking and forecasting progress
- Frontier applications of AI
- Al ethics and regulation
- Where to go next

Recap of Supervised Learning with Neural Networks

Optimize probability of label given input $\max_{w} ll(w) = \max_{w} \sum_{i} \log P(y^{(i)}|x^{(i)};w)$

Continuous optimization

Gradient ascent: take step in steepest uphill direction Backpropagation computes gradient efficiently (out of scope)

Deep neural nets

Last layer = logistic regression Many layers before this last layer: learns "features" of input Universal function approximation theorem:

a large enough 2 layer neural network can represent any continuous function with arbitrary accuracy

Deep Learning for Image Classification



Deep Learning for Language Generation



How well does deep learning work?

Computer Vision



Object Detection and Image Classification



Traditional Computer Vision

Manual Feature Design



Image

Histogram of Gradients (HoG)

[HoG: Dalal and Triggs, 2005]

ImageNet Error Rate 2010-2014



ImageNet Error Rate 2010-2014



ImageNet Error Rate 2010-2014



ImageNet Error Rate 2010-2014



ImageNet Error Rate 2010-2014





Credit: paperswithcode.com

Language Understanding: Performance

DATASET	METRIC	OUR RESULT	PREVIOUS RECORD	ΗυΜΑΝ
Winograd Schema Challenge	accuracy (+)	70.70%	63.7%	92%+
LAMBADA	accuracy (+)	63.24%	59.23%	95%+
LAMBADA	perplexity (-)	8.6	99	~1-2
Children's Book Test Common Nouns (validation accuracy)	accuracy (+)	93.30%	85.7%	96%
Children's Book Test Named Entities (validation accuracy)	accuracy (+)	89.05%	82.3%	92%
Penn Tree Bank	perplexity (-)	35.76	46.54	unknown
WikiText-2	perplexity (-)	18.34	39.14	unknown

[Radford et al, 2019]

Protein Prediction: AlphaFold

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nature > news > article

NEWS · 30 NOVEMBER 2020

'It will change everything': DeepMind's AI makes gigantic leap in solving protein structures

Google's deep-learning program for determining the 3D shapes of proteins stands to transform biology, say scientists.

Ewen Callaway



A protein's function is determined by its 3D shape. Credit: DeepMind

Protein Prediction: AlphaFold



Computational prediction

AlphaFold at CASP 2020 Competition





Recall: neural networks learn features

Features learned in image classification network:



Early layers similar to features in the human visual system



Features learned in language models:



ig.ft.com/generative-ai

Words cluster by similarity:



Signs of sensible algebra in word feature 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



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

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Deep Unsupervised Learning

- Do we always need to solve some task to learn features?
- Can't we learn general-purpose features?
- Key hypothesis:
- Task 1 | IF neural network smart enough to predict:
 - Next frame in video
 - Next word in sentence
 - Generate realistic images
 - ``Translate'' images
 - ••••

Task 2THEN same neural network is ready to do Deep Supervised Learningfrom very small data-set

Transfer from Unsupervised Learning



Example Setting



Unsupervised Sentiment Neuron

This is one of Crichton's best books. The characters of Karen Ross, Peter Elliot, Munro, and Amy are beautifully developed and their interactions are exciting, complex, and fast-paced throughout this impressive novel. And about 99.8 percent of that got lost in the film. Seriously, the screenplay AND the directing were horrendous and clearly done by people who could not fathom what was good about the novel. I can't fault the actors because frankly, they never had a chance to make this turkey live up to Crichton's original work. I know good novels, especially those with a science fiction edge, are hard to bring to the screen in a way that lives up to the original. But this may be the absolute worst disparity in quality between novel and screen adaptation ever. The book is really, really good. The movie is just dreadful.

Pre-Training and Fine-Tuning

Pre-Train: train a large model with a lot of data on a supervised pretext 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

Image Pre-Training: Predict Missing Patch




Pre-Trained Model (SimCLR) + Linear Classifier



[Chen et al, 2020]

Pre-Training and Fine-Tuning: Language Assistants

ChatGPT

Plan a trip

to explore the Madagascar wildlife on a budget

Write a text message

asking a friend to be my plus-one at a wedding

Help me pick an outfit that will look good on camera

Tell me a fun fact about the Roman Empire

What is the population of Berkeley?



Pre-Training and Fine-Tuning: Language Assistants

- 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

Recall: RL Fine-Tuning for Language Assistants

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

Pre-Training and Fine-Tuning

Pre-Train: train a large model with a lot of data on a supervised pretext task

- Predict next word / patch of image
- Predict missing word / patch of image
- Predict if two images are related (contrastive learning)
- 2a Fine-Tune: continue training the same model on task you care about



The three settings we explore for in-context learning

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

1	Translate English to French:	← task description
2	cheese =>	← prompt

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

1	Translate English to French:	← task description
2	sea otter => loutre de mer	←— example
3	cheese =>	←— prompt

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

Translate English to French:	\longleftarrow task description
sea otter => loutre de mer	← examples
peppermint => menthe poivrée	<
plush girafe => girafe peluche	←
cheese =>	←— prompt

Prompt without training:

[Language Models are Few-Shot Learners, Brown et al, 2020]

Prompt without training:

Control desired output via examples

Standard Prompting

Example Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Example Output

A: The answer is 11.

Prompt

The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Response

Chain of thought prompting

Example Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Example Output

Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 <mark>= 11.</mark> The answer is 11.

Prompt

The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Response



The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23-20 = 3. They bought 6 more apples, so they have 3+6=9. The answer is 9.

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Language models build a structured concept space



Can other data (images/audio/...) be put in this space?



Can we build a single model of all data types?



Can we build a single model of all data types?



A dog jumping over a

hurdle at a dog show.

image? Answer in emojis.

A: 🍏 🌙 🍻 為 🍑 🟐 🚣.

Q: Miami Beach borders which ocean? A: Atlantic. Q: What is 372 x 18? A: 6696.Q: Write a Haiku about embodied LLMs. A: Embodied language. Models learn to understand. The world around them.

[PaLM-E, Driess et al, 2023]

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Tracking Progress

 How well AI can do human tasks



Forecasting Progress

Scaling Laws extrapolate:

- If we [make model bigger / add more data / ...]
- What would accuracy become?



data:



compute:

Forecasting Progress

Scaling Laws extrapolate:

- If we [make model bigger / add more data / ...]
- What would accuracy become?
- But some capabilities emerge unexpectedly



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Applications of Text Models: Mathematics

Question: A line parallel to y = 4x + 6 passes through (5, 10). What is the y-coordinate of the point where this line crosses the y-axis?

Model output: The line is parallel to y = 4x + 6, which means that it has the same slope as y = 4x + 6. Since the line passes through (5, 10), we can use the point-slope form of a line to find the equation of the line:

$$y - 10 = 4(x - 5)$$

 $y - 10 = 4x - 20$
 $y = 4x - 10$

Now that we have the equation of the line, we can find the y-coordinate of the point where the line crosses the y-axis by substituting x = 0 into the equation:

$$y = 4 \cdot 0 - 10 = -10$$
.

[Solving Quantitative Reasoning Problems with Language Models, Lewkowycz et al, 2022] https://minerva-demo.github.io/

Applications of Text Models: Mathematics



[Solving Quantitative Reasoning Problems with Language Models, Lewkowycz et al, 2022] https://minerva-demo.github.io/

Applications of Text Models: Mathematics

Incorrect Answer: reasoning mistake (but looks worryingly plausible!)

Question: At each basketball practice last week, Jenny made twice as many free throws as she made at the previous practice. At her fifth practice she made 48 free throws. How many free throws did she make at the first practice?

Model output: At the first practice, Jenny made $\frac{48}{2} = 24$ free throws. Final Answer: The final answer is 24.

Applications of Text Models: Programming

```
def incr_list(l: list):
"""Return list with elements incremented by 1.
>>> incr_list([1, 2, 3])
[2, 3, 4]
>>> incr_list([5, 3, 5, 2, 3, 3, 9, 0, 123])
[6, 4, 6, 3, 4, 4, 10, 1, 124]
"""
```

return [i + 1 for i in 1]

```
def solution(lst):
"""Given a non-empty list of integers, return the sum of all of the odd elements
that are in even positions.
Examples
solution([5, 8, 7, 1]) =⇒12
solution([3, 3, 3, 3, 3]) =⇒9
solution([30, 13, 24, 321]) =⇒0
"""
return sum(lst[i] for i in range(0,len(lst)) if i % 2 == 0 and lst[i] % 2 == 1)
```

[Evaluating Large Language Models Trained on Code, Chen et al, 2021]



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TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

mixing sparkling chemicals as mad scientists shopping for groceries working on new AI research

as a 1990s Saturday morning cartoon as digital art in a steampunk style

DALL·E 2



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TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

mixing sparkling chemicals as mad scientists shopping for groceries working on new AI research

as a 1990s Saturday morning

cartoon as digital art in a steampunk style

DALL·E 2



••••



 \rightarrow

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

mixing sparkling chemicals as mad scientists shopping for groceries working on new AI research

as kids' crayon art on the moon in the 1980s underwater with 1990s technology DALL·E 2





 \rightarrow

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

mixing sparkling chemicals as mad scientists shopping for groceries working on new AI research

as kids' crayon art on the moon in the 1980s underwater with 1990s technology DALL·E 2



 \rightarrow

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

that is a portal to another

dimension that looks like a monster as a planet in the universe

as digital art in the style of Basquiat drawn on a cave wall

DALL·E 2



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Applications of Image-Text Models: Visual Dialogue

Alayrac et al, 2022



Applications: Robotics + Language

[Do As I Can, Not As I Say: Grounding Language in Robotic Affordances, Ahn et al, 2022]





Traditional Robotic Automation

Highly structured environments

Pre-programmed, deterministic

Next Generation: Al Robotic Automation

Less structured environments

Intelligent, reactive behaviors

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Al Ethics Ever More Important

Why?

- AI is making decisions, at scale
- Any kind of issues (e.g. bias or malignant use) could significantly affect people

- Many open questions:
 - Who is responsible?
 - How to diagnose and prevent?

Some experts you'll want to learn from



Prof. Rediet Abebe Harvard Soc.



Prof. Rachel Thomas Queensland Univ.



Prof. Moritz Hardt MPI



Prof. Ruha Benjamin Princeton Univ.



Dr. Joy Buolamwini MIT, Algo. Justice League



Dr. Abeba Birhane Mozilla, Trinity Col.

Also: Data C104 Human Contexts and Ethics of Data

Some Key AI Ethics Topics

- Disinformation
- Bias and fairness
- Privacy and surveillance
- Metrics
- Algorithmic colonialism

Source: Rachel Thomas (@math_rachel)

AI Regulation

How should we regulate AI?

After years of speculation about mounting potential divergence in regulatory approaches, we're starting to see regulatory approaches stabilise and settle into a handful of distinct approaches.



AI Regulation

How should we regulate AI?

US Executive Order on AI

UK AI Safety Summit



OCTOBER 30, 2023

FACT SHEET: President Biden Issues Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence

BRIEFING ROOM > STATEMENTS AND RELEASES


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Where to Go Next?



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
 - Data Science: data 100, data 102
 - Data / Ethics: data c104
 - Probability: ee126, stat134
 - Optimization: ee127
 - Cognitive modeling: cog sci 131
 - Machine learning theory: cs281a/b
 - Computer vision: cs280
 - Reinforcement Learning: cs285
 - Robotics: cs287, cs287h
 - NLP: cs288
 - ... and more; ask if you're interested



Lightweight Opportunities to Keep Learning









- Andrew Ng weekly newsletter: The Batch: https://www.deeplearning.ai/thebatch/
- Jack Clark weekly newsletter:

Import AI: https://jack-clark.net/

Rachel Thomas AI Ethics course:

Course website: ethics.fast.ai

Pieter Abbeel podcast:

The Robot Brains Podcast: https://therobotbrains.ai

What will be Al's impact in the future?

- You get to determine that!
- As you apply AI
- As researchers / developers
- As auditors and regulators
- As informed public voices

Next

Help us out with some course evaluations please!

Nov 21: Review

• Nov 28: Generative AI Special Topic Lecture – please attend!

• After: good luck on the exam and have a great winter break!

