S&DS 265 / 565

Introductory Machine Learning

Course Wrap Up

December 5

Yale

Endgame

- Quiz 6 open today at 1pm; closes Saturday at 6pm
- Final exam: Monday, Dec 16 at 2pm in WLH 201
- Practice exams posted
- Review sessions:
  - Harry: Thursday 9:00-10:00am
  - Shay: Thursday 5:00-6:00pm
  - Anran: Friday 3:00-4:00pm

Last unit: Language/Sequence models

- Generative process, any sequence (of words, characters, stock prices, nucleotides...) is assigned a probability

  $$p(x_1, \ldots, x_n)$$

  which can be factored as

  $$p(x_1, \ldots, x_n) = p(x_1)p(x_2 \mid x_1) \ldots p(x_n \mid x_1, \ldots, x_{n-1})$$

Transformers

The current state-of-the-art is based on *transformers*

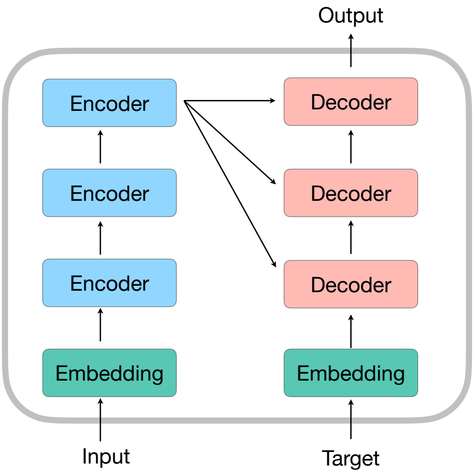
- Attention is the key ingredient
- Rather than processing sequences word-by-word, transformers handle larger chunks of text at once
- Incorporate “interactions” between words and hidden states

Transformer architecture

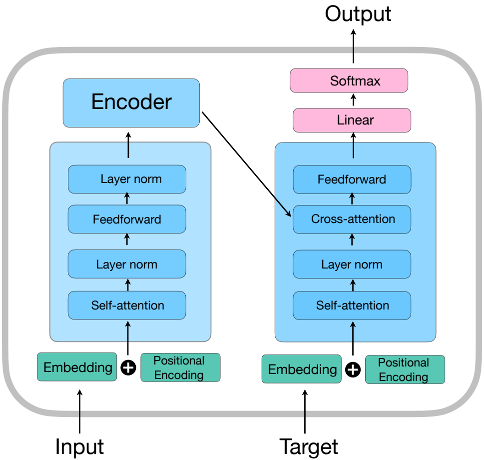
A Transformer is a seq2seq model based on encoder and decoder modules.

Transformers are powerful alternatives to RNNs that transform the encoder/decoder states using (multi-head) attention mechanisms.

Transformer architecture

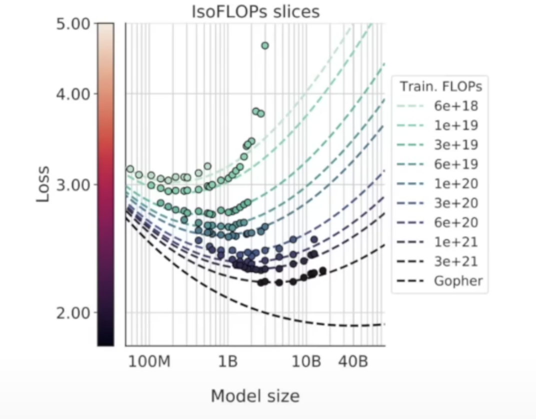


Transformer architecture



Two encoder layers and one decoder layer

LLM scaling laws

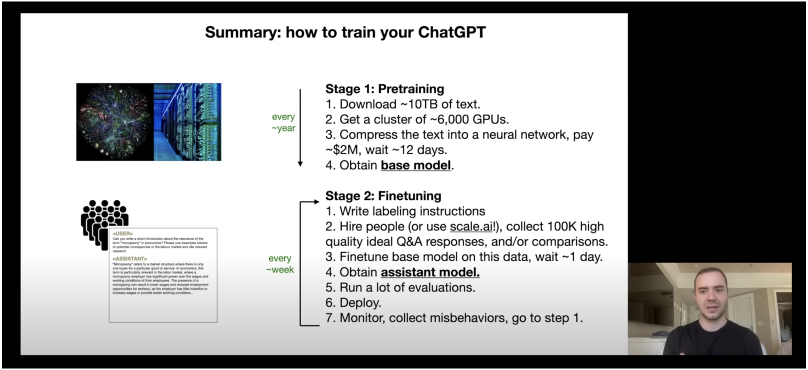


https://www.youtube.com/watch?v=zjkBMFhNj_g&t=25m40s

Finetuning (Training an LLM Decoder)

- An incredible amount of knowledge is stored implicitly in the weights of the transformer
- To be made useful, supervised learning and reinforcement learning are used to teach the model how to respond

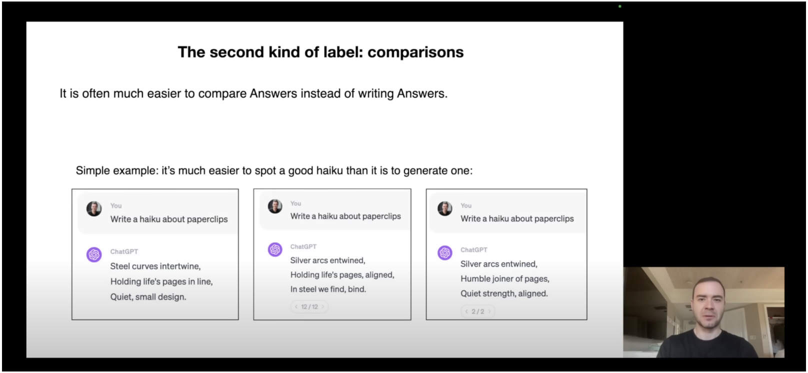
Finetuning



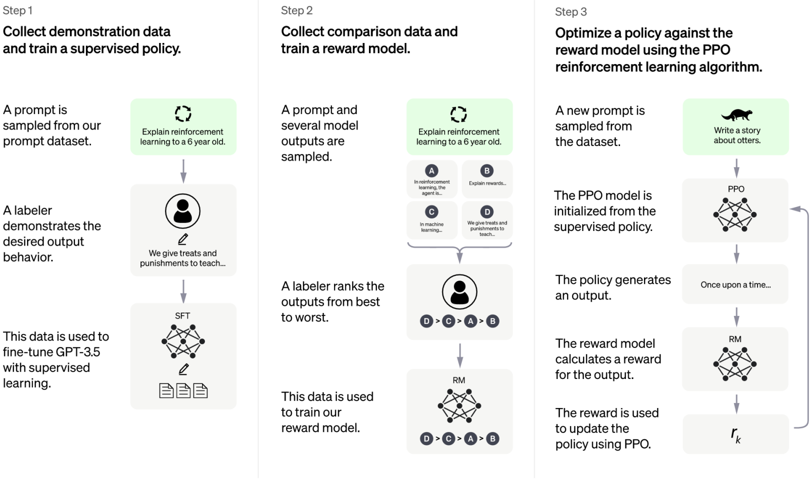
https://www.youtube.com/watch?v=zjkBMFhNj_g&t=14m19s

Finetuning

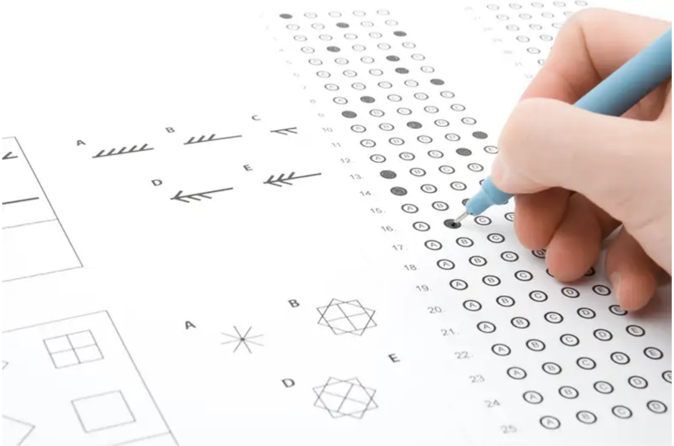
RLHF



https://www.youtube.com/embed/zjkBMFhNj_g?start=1277&end=1340


Step 1
Collect demonstration data and train a supervised policy.
A prompt is sampled from our prompt dataset.
Explain reinforcement learning to a 6 year old.
A labeler demonstrates the desired output behavior.
We give treats and punishments to teach...
This data is used to fine-tune GPT-3.5 with supervised learning.
SFT
Step 2
Collect comparison data and train a reward model.
A prompt and several model outputs are sampled.
Explain reinforcement learning to a 6 year old.
A
In reinforcement learning, the agent is...
B
Explain rewards...
C
In machine learning...
D
We give treats and punishments to teach...
A labeler ranks the outputs from best to worst.
D > C > A > B
This data is used to train our reward model.
RM
D > C > A > B
Step 3
Optimize a policy against the reward model using the PPO reinforcement learning algorithm.
A new prompt is sampled from the dataset.
Write a story about otters.
The PPO model is initialized from the supervised policy.
PPO
The policy generates an output.
Once upon a time...
The reward model calculates a reward for the output.
RM
The reward is used to update the policy using PPO.
r_k

What's next?: Fast learning, slow thinking



AI struggles with IQ tests
Panther Media GmbH / Alamy Stock Photo

Two types of intelligence

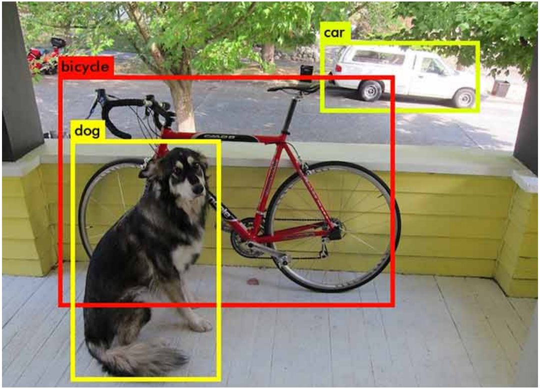
1. "Sensory/motor"— acquire semantic and procedural knowledge
   - Requires extensive data and training
   - Slow to learn, fast to apply
   - Well captured by modern deep learning

Two types of intelligence

1. "Sensory/motor"— acquire semantic and procedural knowledge

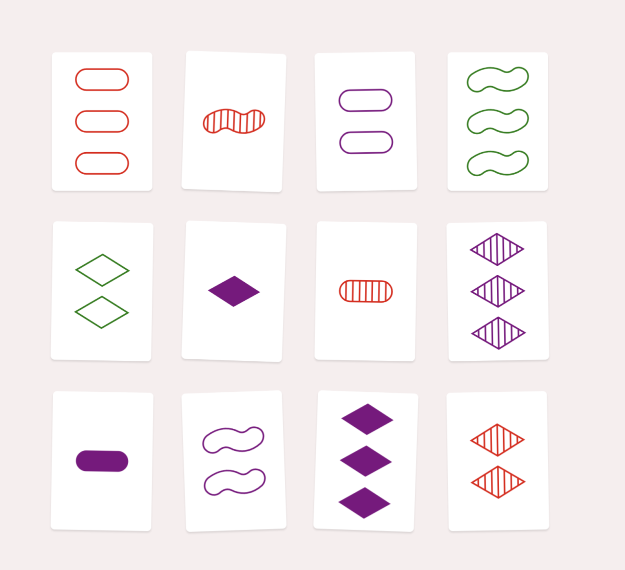
Two types of intelligence

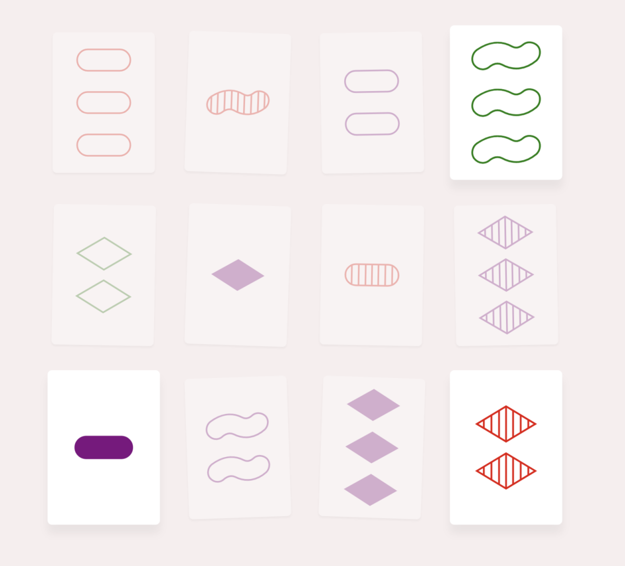
1. "Sensory/motor"— acquire semantic and procedural knowledge



Two types of intelligence

2. "Abstract/relational"— identify novel associations and relations
   - Fast to learn, slow to apply
   - Symbolic processing and abstraction
   - Little explicit training data





Relational Bottleneck

Key: An inductive bias we call the *relational bottleneck*:

Information flows from sensory and motor subsystems to reasoning and decision making subsystems through <u>relations</u>, as computed through inner products between distributed representations

---

https://arxiv.org/abs/2309.06629

Relations are essential to reasoning

"Jack and Jill are sitting side by side. The person next to Jack is angry. The person next to Jill is happy. Who is happy, Jack or Jill?"

Shlomi Sher, "On Artifice and Intelligence: How to spot counterfeit cognition," medium.com/@shlomi.sher, April 21, 2023

Relations are essential to reasoning

ChatGPT response:

Based on the information provided, Jill is happy. The statement specifies that the person next to Jill is happy, indicating that Jill is the one who is happy. Therefore, Jill is happy while Jack is angry.

Relations are essential to reasoning

ChatGPT response:

Based on the information provided, Jill is happy. The statement specifies that the person next to Jill is happy, indicating that Jill is the one who is happy. Therefore, Jill is happy while Jack is angry.

Relations are essential to reasoning

ChatGPT response:

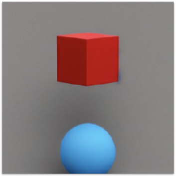
Based on the information provided, Jill is happy. The statement specifies that the person next to Jill is happy, indicating that Jill is the one who is happy. Therefore, Jill is happy while Jack is angry.

Relations are essential to reasoning

"Two shapes are in a room. The shape next to the cube is blue. The shape next to the sphere is red. Which is red, the cube or the sphere?"

Relations are essential to reasoning

"Two shapes are in a room. The shape next to the cube is blue. The shape next to the sphere is red. Which is red, the cube or the sphere?"



Relations are essential to reasoning

Based on the given information, it can be inferred that the sphere is red. The statement specifies that the shape next to the sphere is red, implying that the sphere itself is red. The color of the cube is not mentioned, so we cannot determine its color from the given information.

Relations are essential to reasoning

Based on the given information, it can be inferred that the sphere is red. The statement specifies that the shape next to the sphere is red, implying that the sphere itself is red. The color of the cube is not mentioned, so we cannot determine its color from the given information.

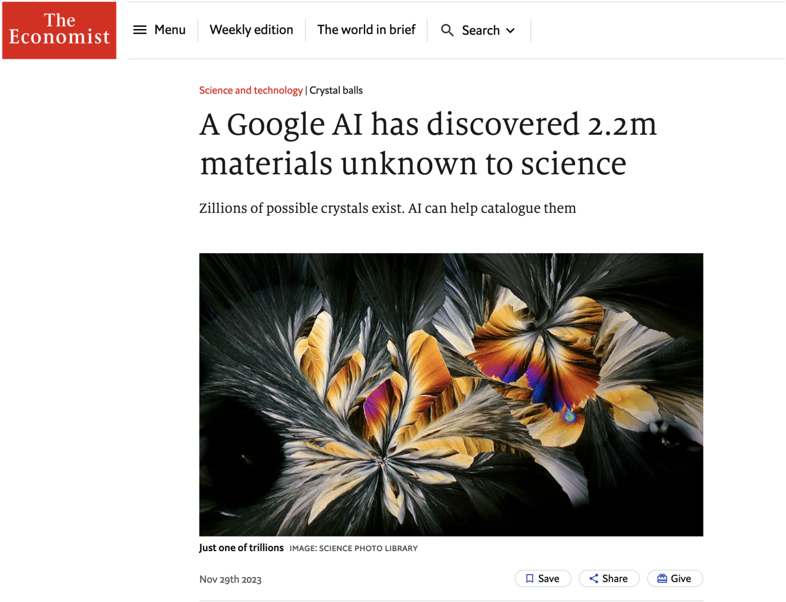
Relations are essential to reasoning

Based on the given information, it can be inferred that the sphere is red. The statement specifies that the shape next to the sphere is red, implying that the sphere itself is red. The color of the cube is not mentioned, so we cannot determine its color from the given information.

On the horizon

We can expect to hear much more about “slow thinking” in AI soon

Always news—on both sides



Always news—on both sides

The Economist

Menu | Weekly edition | The world in brief | Search

Business | Of evils and evals

The world wants to regulate AI, but does not quite know how

There is disagreement over what is to be policed, how and by whom

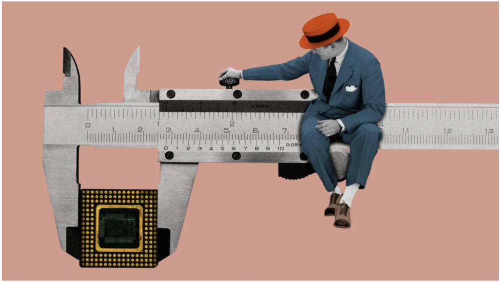


IMAGE: MARI FOUZ

Oct 24th 2023 | BLETCHLEY PARK

Save Share Give

Advancing ML: Something for everyone

- Designing new methods
- Applying to new domains
- Solving deep mathematical puzzles
- Tackling unique engineering challenges
- Designing interfaces
- Collecting data
- Equitable use through policy and law
- Outreach and communication to broad communities

We've covered a lot of ground!

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings and Notes	Assignments & Exams
1	Aug 29	Course overview		Thu: Course overview		
2	Sept 3, 5	Python and background concepts	Python elements Covid trends	Tue: Python elements Thu: Pandas and linear regression	Data8 Chapters 3, 4, 5	Quiz 1 Assn 1 out
3	Sept 10, 12	Linear regression and classification	Covid trends (revisited) Classification examples	Tue: Regression concepts Thu: Classification	ISL Sections 3.1, 3.2, 3.5 Notes on regression ISL Sections 4.3, 4.4 Notes on classification	
4	Sept 17, 19	Stochastic gradient descent	SGD examples	Tue: Classification (continued) Thu: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Assn 1 in Assn 2 out
5	Sept 24, 26	Bias and variance, cross-validation	Bias-variance tradeoff Covid trends (revisited) California housing	Tue: Bias and variance Thu: Cross-validation	ISL Section 2.2 ISL Section 5.1	Quiz 2

We’ve covered a lot of ground!

6	Oct 1, 3	Tree-based methods and principal components	Trees and forests Visualizing trees PCA examples	Tue: Trees (and Forests) Thu: Forests and PCA	ISL Sections 8.1, 8.2 ISL Section 12.2	Assn 2 in Assn 3 out
7	Oct 8, 10	PCA and dimension reduction	PCA revisited Used for dimension reduction Word embeddings	Tue: PCA and word embeddings Thu: Embeddings and review	ISL Section 12.2	Quiz 3
8	Oct 15	Midterm exam (in class)			On Canvas: Practice midterms / Sample solns Midterm / Sample soln	
9	Oct 22, 24	Language models, Bayes, topic models	Bayesian inference Topic models	Tue: Language models Thu: Bayesian inference	OpenAI: Better language models Notes on Bayesian inference	Assn 3 in Assn 4 out

We've covered a lot of ground!

10	Oct 29, Nov 1	Topic models, introduction to neural networks	Sanity check Minimal neural network Regression examples	Tue: Topic models Thu: Neural networks	ISL Sections 10.1, 10.2	Quiz 4
11	Nov 5, 7	Neural networks, reinforcement learning	Q-learning	Tue: Neural networks (continued) Thu: Reinforcement learning	Notes on backpropagation	Assn 4 in Assn 5 out
12	Nov 12, 14	Deep neural networks	Tensorflow playground Autoencoder examples	Tue: Deep reinforcement learning Thu: Autoencoders and LLMs	ISL Section 10.7	Quiz 5
13	Nov 19, 21	Transformers and LLMs	Attention GPT-4 Python API	Tue: Transformers Thu: LLM scaling and finetuning		

We’ve covered a lot of ground!

			API	finetuning		
14	Nov 26, 28	No class, Thanksgiving break				
15	Dec 3, 5	Societal issues for machine learning		Tue: Panel discussion Thu: Course wrap up		Assn 5 in Quiz 6
16	December 16, 2pm, WLH 201	Final exam			Registrar: Final exam schedule Practice finals	

Final exam

- Final exam Monday, Dec 16, 2024 at 2pm in WLH 201
- `https://registrar.yale.edu/general-information/final-exams`
- Review sessions (see times/dates above)
- Length: About 1.5X Midterm
- Emphasis on material after midterm
- Cumulative, closed book, cheat-sheet


OUTTHINK • OUTCODE
iML
SURVIVOR
OUTPREDICT

- Majority votes off a topic!
- But–a topic may have a hidden immunity idol! 
- What are you thinking? Persuade your classmates!

Vote a topic off the final!

1. Cross-validation
2. Decision trees
3. Random forests
4. Principal components
5. Bayesian inference
6. Topic models
7. Autoencoders
8. Deep Q-Learning
9. LLM scaling laws
10. Societal issues

Your input

- Please complete a course review!
- I greatly value your comments and feedback
- Feel free to send me comments privately
- Let me know how you use and continue to learn ML!

Thank you!