

S&DS 265 / 565
Introductory Machine Learning

Course Wrap Up

December 7

Yale

Endgame

- Quiz 6 open today at 1pm; closes Friday at 6pm
- Final exam: Friday, Dec 15 at 2pm in SSS 114
- Practice exams posted
- Review sessions:
 - ▶ Regina: Wednesday (Dec 13): 5-7pm Bass L73
 - ▶ Kaylee: Thursday: (Dec 14) 5-7pm KT 211
 - ▶ Hannah: Thursday: (Dec 14) 7-9pm KT 211

Last unit: Language/Sequence models

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

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

which can be factored as

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

Transformers

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

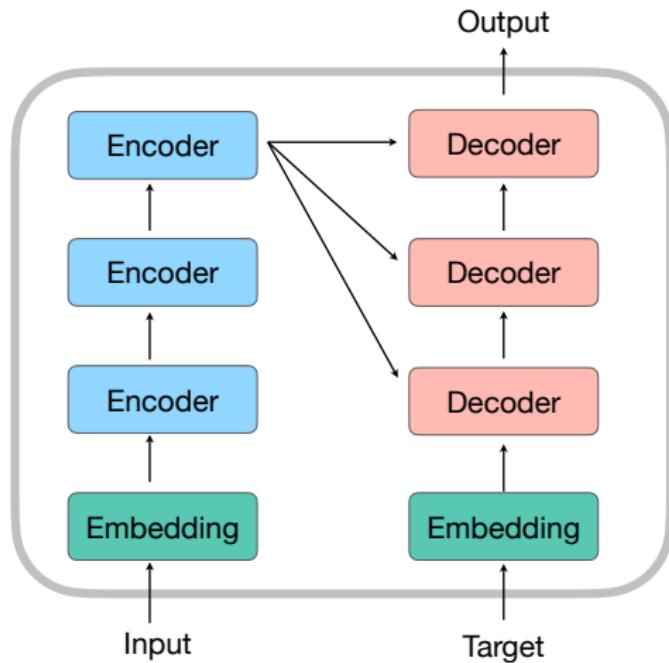
- Attention is the key ingredient
- Rather than processing sequences word-by-word, transformers handle larger chunks of text at once
- Incorporate “interactions” between words and hidden states

Transformer architecture

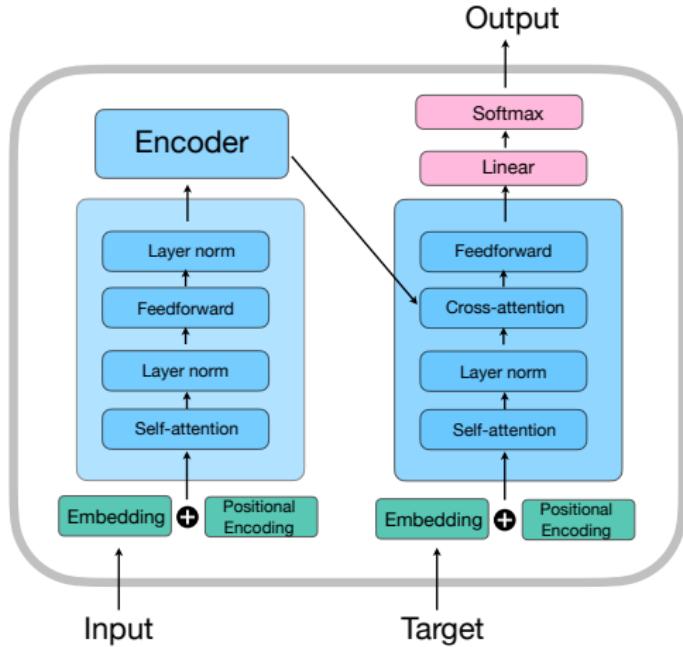
A Transformer is a seq2seq model based on encoder and decoder modules.

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

Transformer architecture

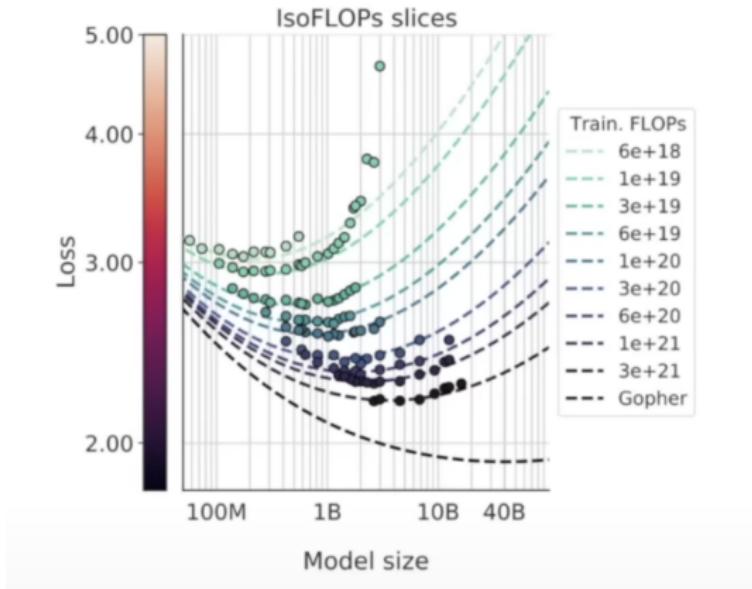


Transformer architecture



Two encoder layers and one decoder layer

LLM scaling laws: Bigger is better

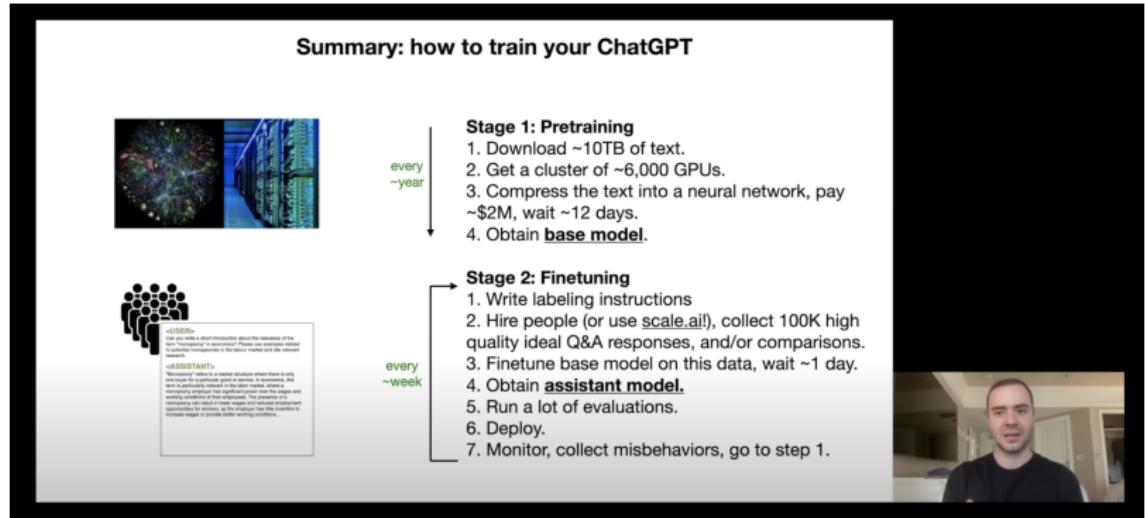


https://www.youtube.com/watch?v=zjkBMFhNj_g&t=25m40s

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

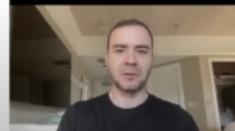
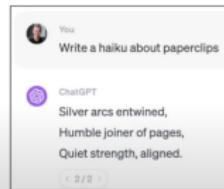
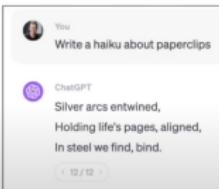
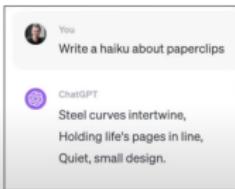
Finetuning

RLHF

The second kind of label: comparisons

It is often much easier to compare Answers instead of writing Answers.

Simple example: it's much easier to spot a good haiku than it is to generate one:



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.



We give treats and punishments to teach...



SFT

📄📄📄

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.

Explain reinforcement learning to a 6 year old.

- A Explain reinforcement learning to a 6 year old.
- 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

RM

📄📄📄

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.

Write a story about otters.



Once upon a time...



PPO


The PPO model is initialized from the supervised policy.

The policy generates an output.



RM

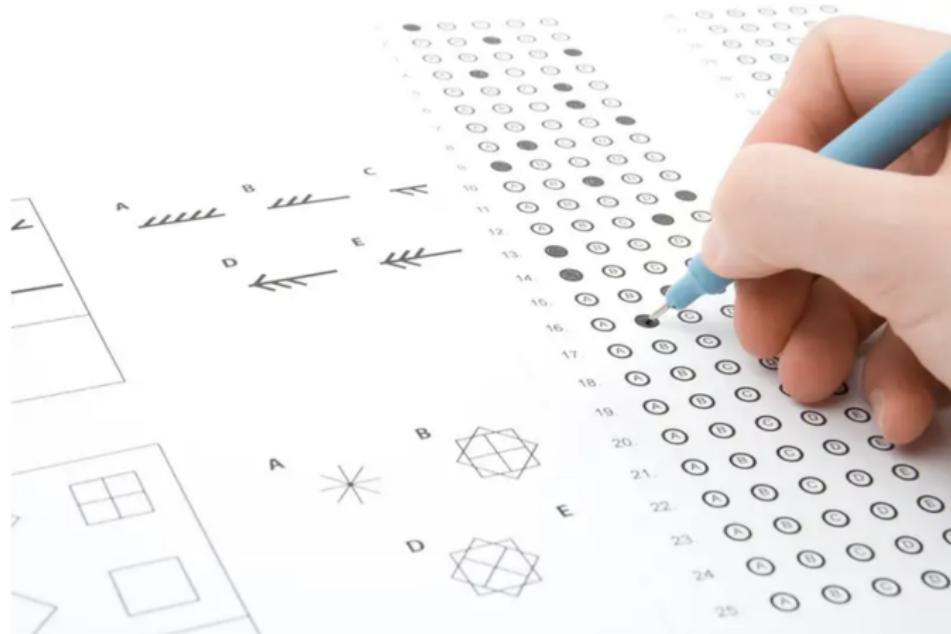
Once upon a time...

The reward model calculates a reward for the output.

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

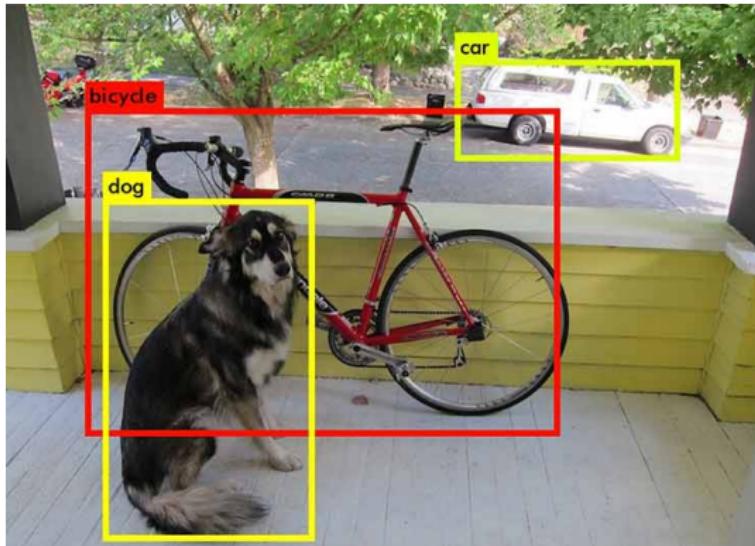
Two types of intelligence

- ① “Sensory/motor”— acquire semantic and procedural knowledge



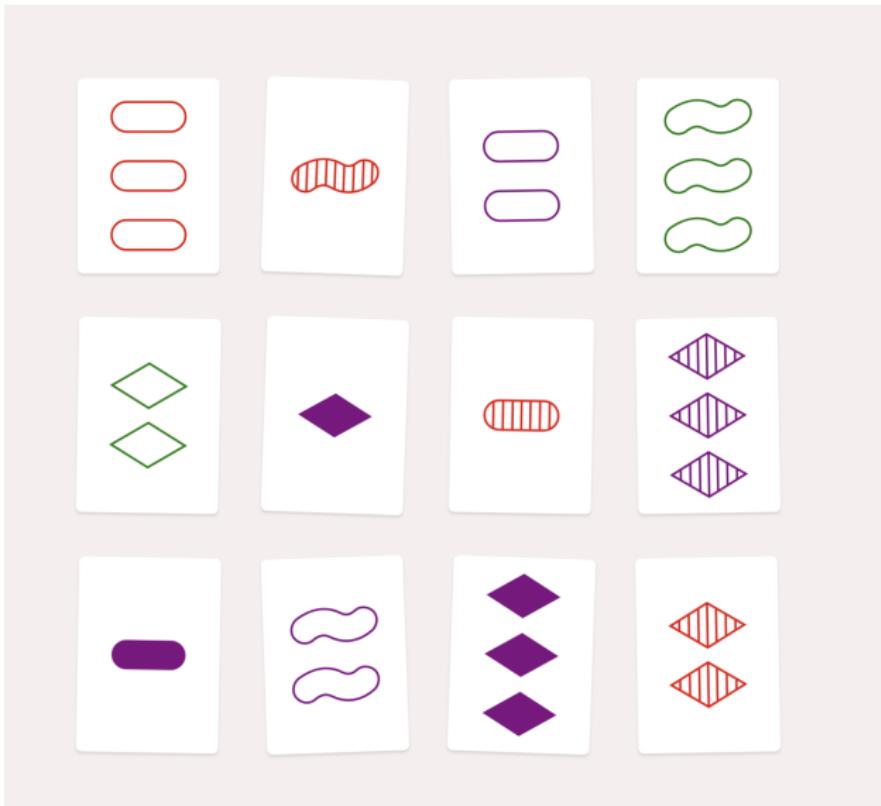
Two types of intelligence

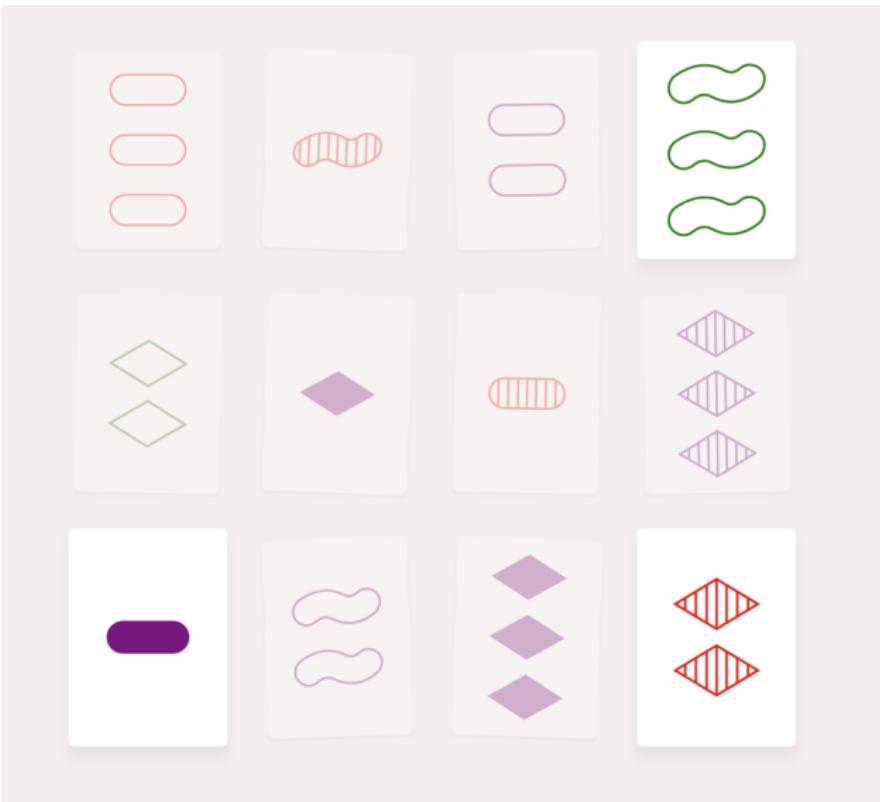
- ① “Sensory/motor”— acquire semantic and procedural knowledge



Two types of intelligence

- ② “Prefrontal”— 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 relations, as computed through inner products between distributed representations

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?”



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

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ChatGPT response:

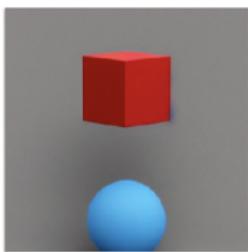
-  Based on the information provided, Jill is happy. The statement specifies that the person next to Jill is happy, indicating that Jill is the one who is happy. Therefore, Jill is happy while Jack is angry.

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.

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On the horizon

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

Always news—on both sides

The
Economist

≡ Menu

Weekly edition

The world in brief

Search ▾

Science and technology | Crystal balls

A Google AI has discovered 2.2m materials unknown to science

Zillions of possible crystals exist. AI can help catalogue them



Just one of trillions IMAGE: SCIENCE PHOTO LIBRARY

Nov 29th 2023

Save

Share

Give

Always news—on both sides

The
Economist

≡ Menu | Weekly edition | The world in brief | Q, 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

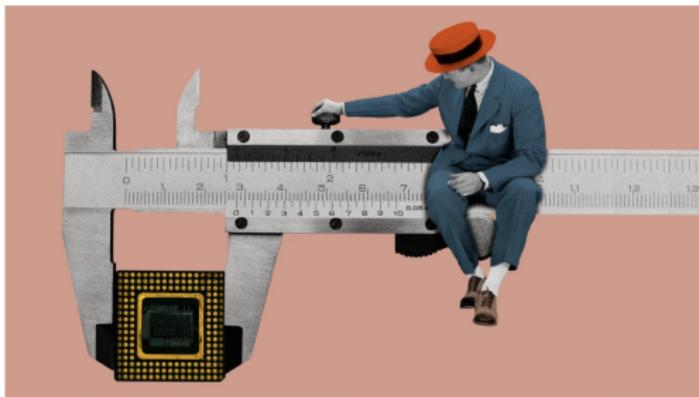


IMAGE: MARI FOUZ

Oct 24th 2023 | BLETCHLEY PARK

Save

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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!

Calendar Fall 2023

Lectures: Tuesday/Thursday 11:35-12:50pm

Davies Auditorium

Complementary readings marked ISL refer to sections in the book [An Introduction to Statistical Learning](#) (Python version, July 2023). Assignments and quizzes are posted and due on Thursday in a given week.

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings and Notes	Assignments & Exams
1	Aug 31	Course overview		Thu: Course overview		
2	Sept 5, 7	Python and background concepts	CO Python elements CO Covid trends	Tue: Python elements Thu: Pandas and linear regression	Data8 Chapters 3, 4, 5	Quiz 1 CO Assn 1 out
3	Sept 12, 14	Linear regression and classification	CO Covid trends (revisited) CO 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 19, 21	Stochastic gradient descent	CO SGD examples	Tue: Classification (continued) Thu: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Assn 1 in CO Assn 2 out

We've covered a lot of ground!

5	Sept 26, 28	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
6	Oct 3, 5	Tree-based methods and principal components	Trees and forests Visualizing trees PCA examples	Tue: Trees and Forests Thu: PCA	ISL Sections 8.1, 8.2 ISL Section 12.2	Assn 2 in Assn 3 out
7	Oct 10, 12	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 17	Midterm exam (in class)			On Canvas: Practice midterms / Sample solns Midterm / Sample soln	

We've covered a lot of ground!

10	Oct 31, Nov 2	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 7, 9	Neural networks, reinforcement learning	 Q-learning	Tue: Neural networks Thu: Reinforcement learning	Notes on backpropagation	Assn 4 in  Assn 5 out
12	Nov 14, 16	Deep neural networks	Tensorflow playground  Autoencoder examples	Tue: Deep reinforcement learning Thu: Deep networks and autoencoders	ISL Section 10.7	Quiz 5
13	Nov 21, 23	No class, Thanksgiving break				

We've covered a lot of ground!

14	Nov 28, 30	Transformers and ChatGPT	 GPT-4 Python API	Tue: Autoencoders and transformers Thu: Transformers (continued)		
15	Dec 5, 7	Societal issues for machine learning		Tue: Panel discussion Thu: Course wrap up		Assn 5 in Quiz 6
16	Fri, Dec 15, 2pm, SSS 114	Final exam			Registrar: Final exam schedule Practice finals	

Final exam

- Final exam Friday, Dec 15, 2023 at 2pm in SSS 114
- <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

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!