

S&DS 265 / 565
Introductory Machine Learning

Course Wrap Up

Thursday, December 9

Yale

Reminders

- Assignment 7 out (neural nets and RL)
- New due date: Tuesday December 14
- Assignment 6 will be graded by today
- Quiz 4: Open until 1pm today
- Final exam, Dec 21 at 7pm (cumulative, 3 hours, cheat sheet, practice exam end of this week)

For today

- Addendum on RL
- Follow up from last class
- Examples of recent ML research
- Course summary
- Final exam

When does learning take place?

The Bellman equation tells us:

Learning takes place when expectations are violated. The receipt of the reward itself does not cause changes.

A Neural Substrate of Prediction and Reward

Wolfram Schultz, Peter Dayan, P. Read Montague*

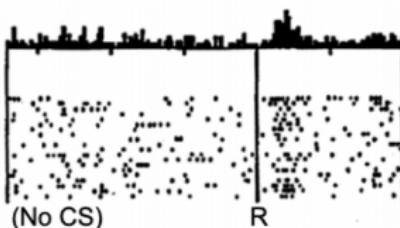
The capacity to predict future events permits a creature to detect, model, and manipulate the causal structure of its interactions with its environment. Behavioral experiments suggest that learning is driven by changes in the expectations about future salient events such as rewards and punishments. Physiological work has recently complemented these studies by identifying dopaminergic neurons in the primate whose fluctuating output apparently signals changes or errors in the predictions of future salient and rewarding events. Taken together, these findings can be understood through quantitative theories of adaptive optimizing control.

Science 1997

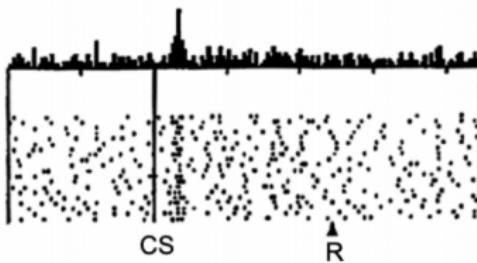
Neuroscience connection

Do dopamine neurons report an error
in the prediction of reward?

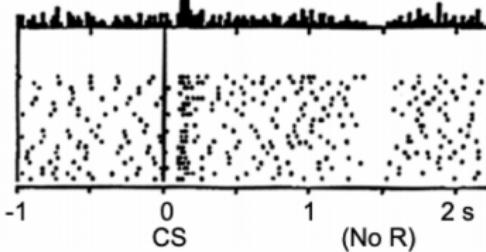
No prediction
Reward occurs



Reward predicted
Reward occurs



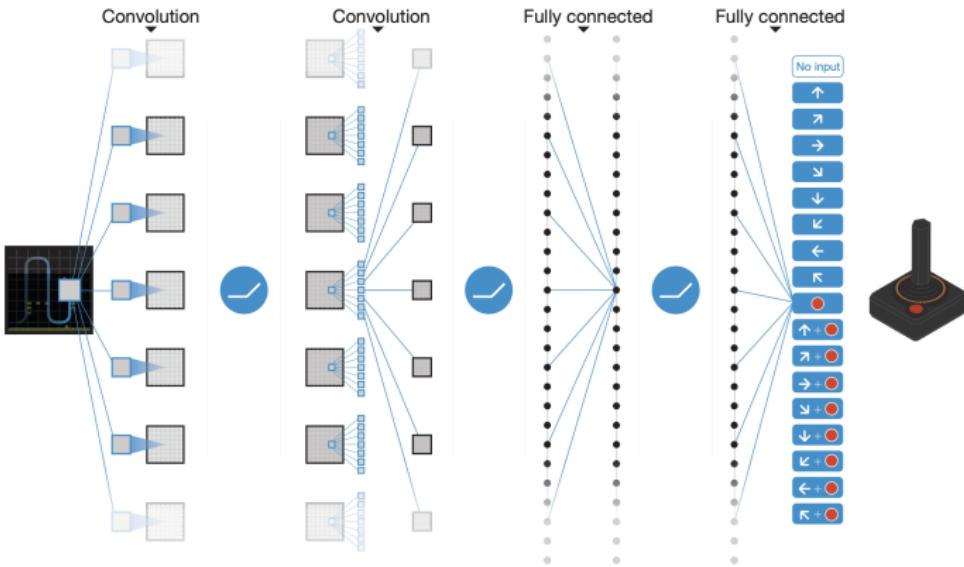
Reward predicted
No reward occurs



Space Invaders

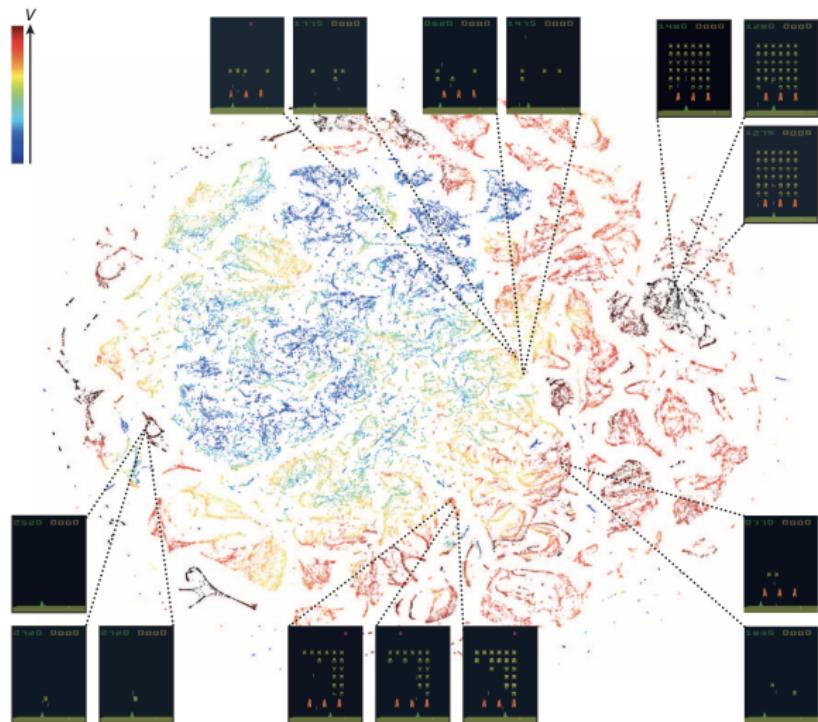


Second generation DQN



<https://storage.googleapis.com/deepmind-data/assets/papers/DeepMindNature14236Paper.pdf>

Second generation DQN: Interpretation



Follow up from Tues



1 hr 16 min

PLAY ►

Is A.I. the Problem? Or Are We?

The Ezra Klein Show

Society & Culture

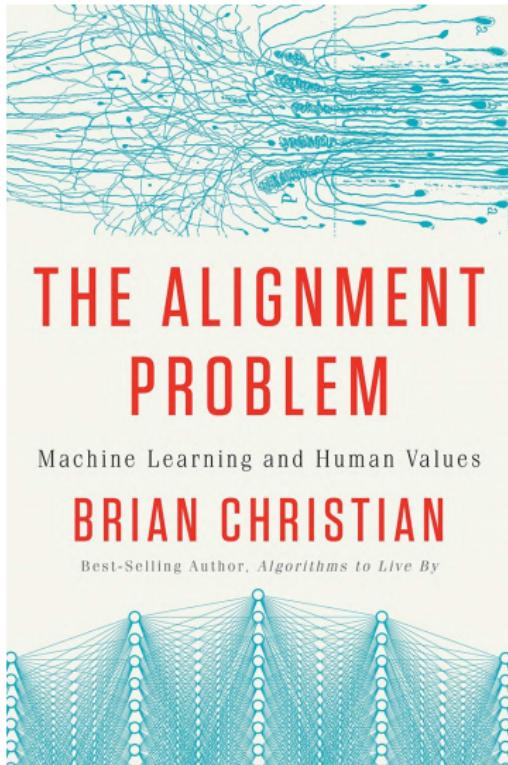
[Listen on Apple Podcasts ↗](#)



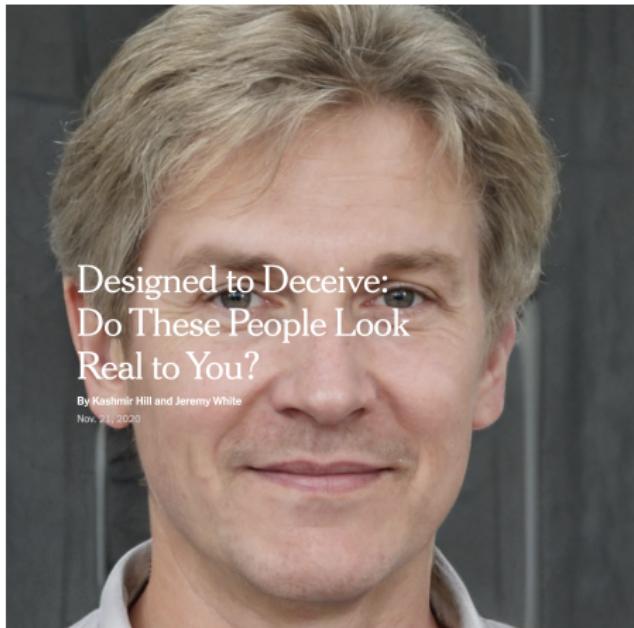
If you talk to many of the people working on the cutting edge of artificial intelligence research, you'll hear that we are on the cusp of a technology that will be far more transformative than simply computers and the internet, one that could bring about a new industrial revolution and usher in a utopia — or perhaps pose the greatest threat in our species's history.

Others, of course, will tell you those folks are nuts.

Follow up from Tues



Follow up from Tues



Designed to Deceive:
Do These People Look
Real to You?

By Kashmir Hill and Jeremy White

Nov. 21 | 2020

[https://www.nytimes.com/interactive/2020/11/21/science/
artificial-intelligence-fake-people-faces.html?](https://www.nytimes.com/interactive/2020/11/21/science/artificial-intelligence-fake-people-faces.html?)

Follow up from Tues



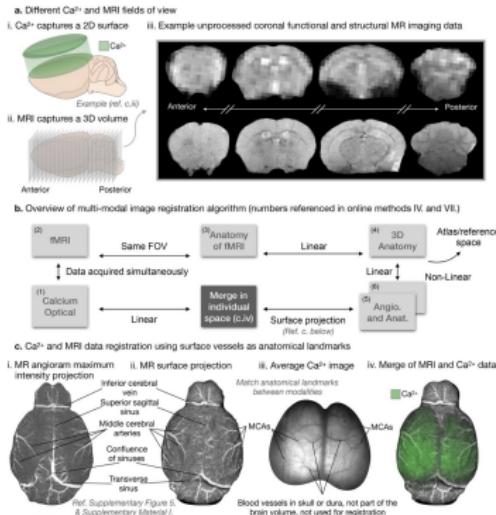
The image shows the header of the Yale Jackson Institute for Global Affairs website. It features a dark blue header bar with the institute's name in white. Below the header is a large banner with a globe in the center, set against a background of a circuit board pattern. A search bar and a menu icon are visible in the top left corner of the banner.

Jackson Institute establishes Schmidt Program on Artificial Intelligence, Emerging Technologies, and National Power

December 8, 2021 | by Yale Jackson

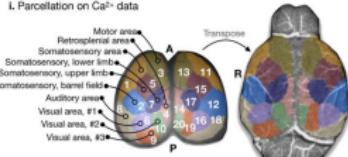
Some recent projects in Yale SML group

ML for brain imaging data

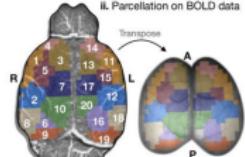


a. Representative Ca^{2+} and BOLD parcellation results transposed between Ca^{2+} and BOLD space

i. Parcellation on Ca^{2+} data

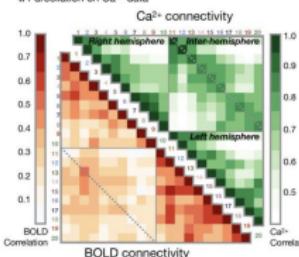


ii. Parcellation on BOLD data

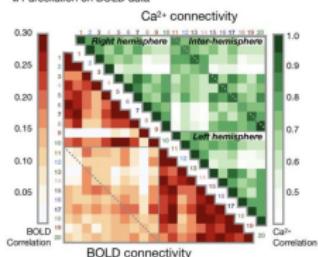


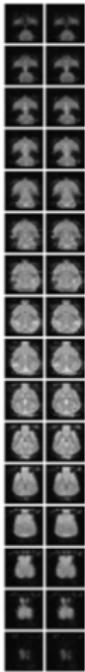
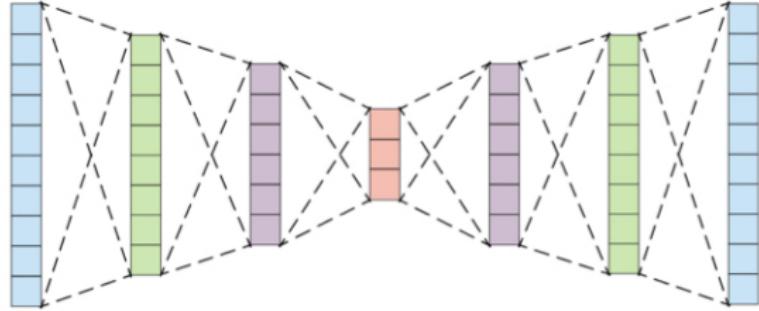
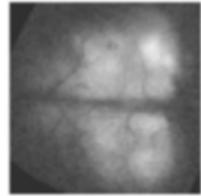
b. Average ($N=6$) Ca^{2+} and BOLD connectivity matrices

i. Parcellation on Ca^{2+} data



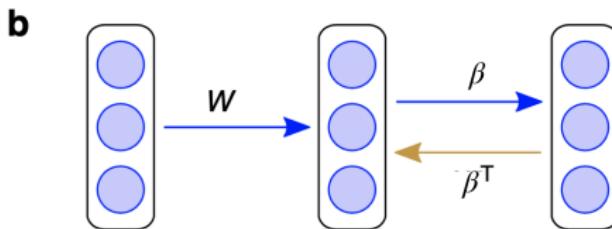
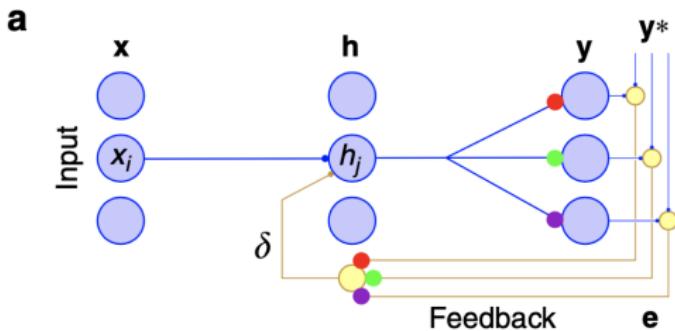
ii. Parcellation on BOLD data



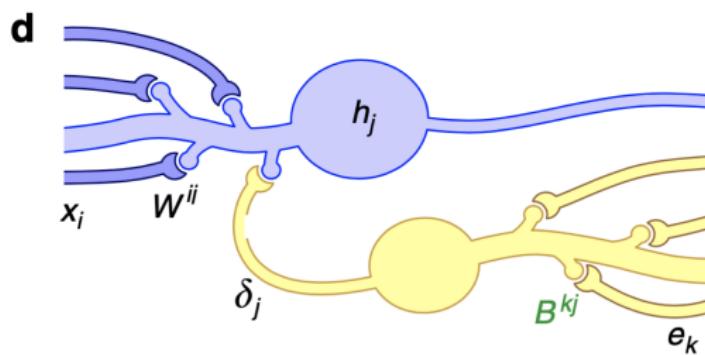
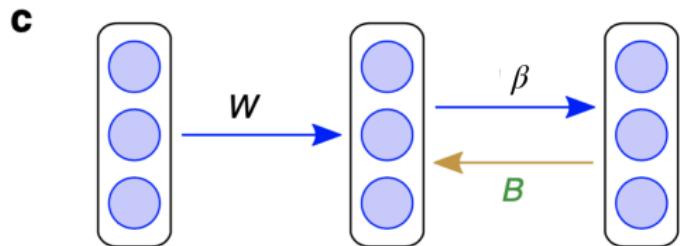


- U-net architecture with GANs
- 34 million parameters

Proposal from DeepMind



Proposal from DeepMind



Proposal from DeepMind

Convergence and Alignment of Gradient Descent with Random Backpropagation Weights

Ganlin Song · Ruitu Xu · John Lafferty

Thu Dec 09 04:30 PM -- 06:00 PM (PST) @ None #None

Poster

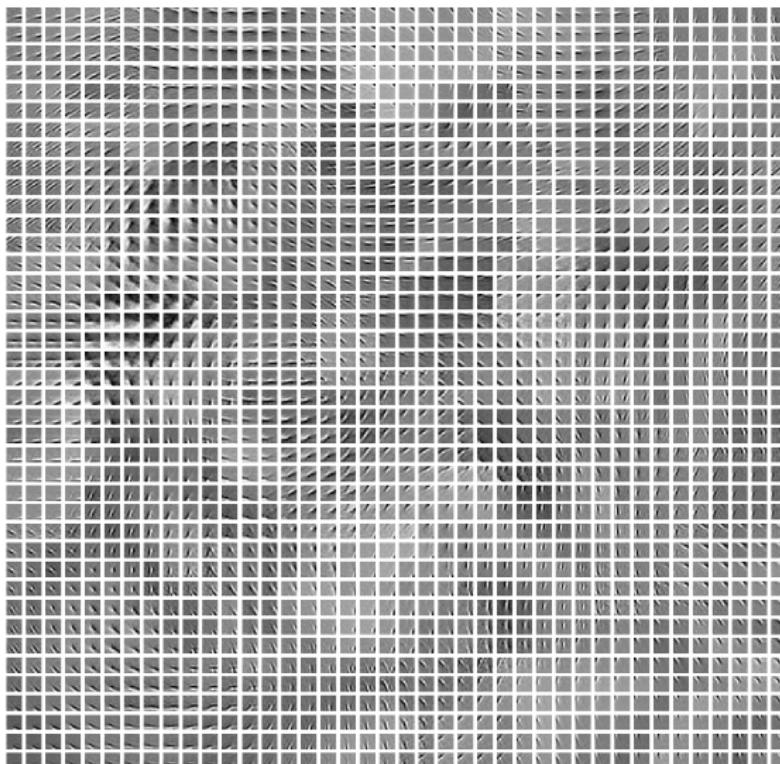
In Poster Session 7 »

Stochastic gradient descent with backpropagation is the workhorse of artificial neural networks. It has long been recognized that backpropagation fails to be a biologically plausible algorithm. Fundamentally, it is a non-local procedure---updating one neuron's synaptic weights requires knowledge of synaptic weights or receptive fields of downstream neurons. This limits the use of artificial neural networks as a tool for understanding the biological principles of information processing in the brain. Lillicrap et al. (2016) propose a more biologically plausible "feedback alignment" algorithm that uses random and fixed backpropagation weights, and show promising simulations. In this paper we study the mathematical properties of the feedback alignment procedure by analyzing convergence and alignment for two-layer networks under squared error loss. In the overparameterized setting, we prove that the error converges to zero exponentially fast, and also that regularization is necessary in order for the parameters to become aligned with the random backpropagation weights. Simulations are given that are consistent with this analysis and suggest further generalizations. These results contribute to our understanding of how biologically plausible algorithms might carry out weight learning in a manner different from Hebbian learning, with performance that is comparable with the full non-local backpropagation algorithm.

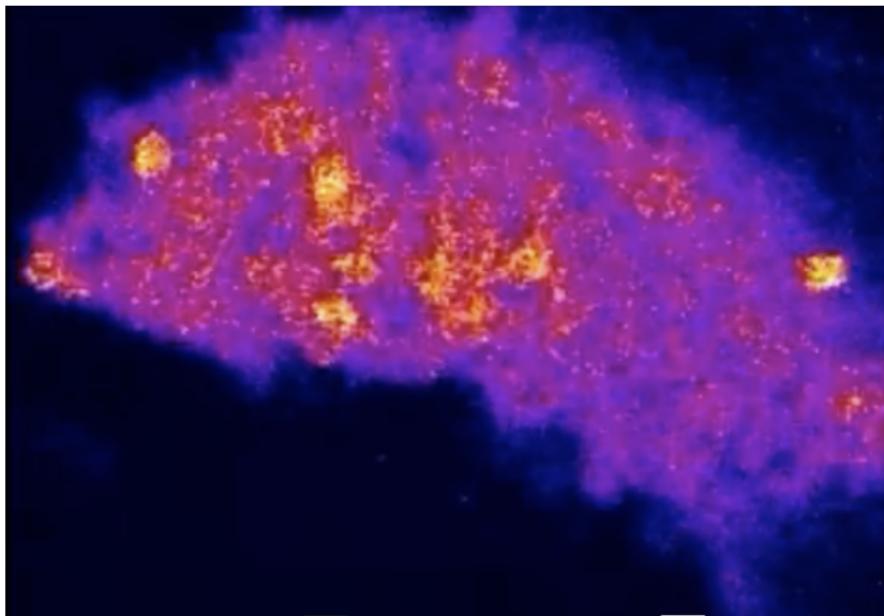
Keywords: Deep Learning · Optimization

[[OpenReview](#)] [[Visit Poster at Spot B2 in Virtual World](#)]

Topographic maps of neural tunings

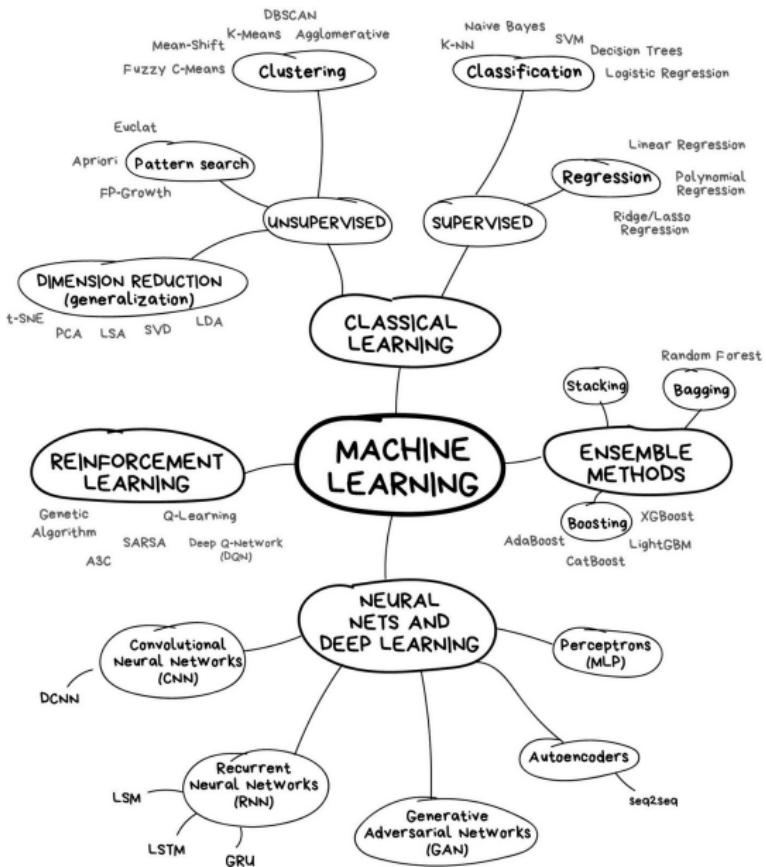


Sparse representations in memory systems



"Sparse, decorrelated odor coding in the mushroom body enhances learned odor discrimination," Lin et al., Nature Neuroscience (2014). Long line of work: Kanerva (1988), Marr (1969), Treves and Rolls (1991), Vinje and Gallant (2000), Hromadka et al. (2008), Crochet et al. (2011), Perez-Orive et al. (2002), Ito et al. (2008), Stettler and Axel (2009), Honegger et al. (2008).

We've covered a lot of ground!



| | | | | | |
|----|---------------|--------------------------------------|--|--|--|
| 3 | Sept 14, 16 | Linear regression and classification | <ul style="list-style-type: none">○ Covid trends (revised)○ Classification examples | Tue: <ul style="list-style-type: none">○ Assn1 out | Sept 16: Classification concepts Notes on regression Sept 16: Classification Notes on classification |
| 4 | Sept 21, 23 | Stochastic gradient descent | <ul style="list-style-type: none">○ SGD examples | Tue: Quiz 1 Thu: Assn 1 in <ul style="list-style-type: none">○ Assn2 out | Sept 21: Classification (continued) Sept 23: Stochastic gradient descent |
| 5 | Sept 28, 30 | Bias and variance, cross-validation | <ul style="list-style-type: none">○ Bias-variance tradeoff○ Covid trends (revised)○ California housing | | Sept 28: Bias and variance Sept 30: Cross-validation |
| 6 | Oct 5, 7 | Tree-based methods | <ul style="list-style-type: none">○ Trees and forests○ Visualizing trees | Tue: Assn 2 in <ul style="list-style-type: none">○ Assn3 out | Oct 5: Trees Oct 7: Forests |
| 7 | Oct 12, 14 | PCA and dimension reduction | <ul style="list-style-type: none">○ PCA examples○ PCA revisited○ Used for regression | Tue: Quiz 2 Thu: Assn 3 in <ul style="list-style-type: none">○ Assn4 out | Oct 12: PCA Oct 14: PCA and review |
| 8 | Oct 19 | Midterm exam (in class) | | | On Canvas: Practice midterm / Sample soln Midterm / Sample soln |
| 9 | Oct 26, 28 | Language models, word embeddings | <ul style="list-style-type: none">○ Word embeddings | | Oct 26: Language models Oct 28: Word embeddings |
| 10 | Nov 2, 4 | Bayesian inference, topic models | <ul style="list-style-type: none">○ Mixtures○ Bayesian inference○ Topic models | Tue: Assn 4 in <ul style="list-style-type: none">○ Assn5 out | Nov 2: Bayesian inference Notes on Bayesian inference Nov 4: Bayes and topic models |
| 11 | Nov 9, 11 | Introduction to neural networks | <ul style="list-style-type: none">○ Minimal neural network○ Regression examples | Thu: Assn 5 in <ul style="list-style-type: none">○ Assn6 out | Nov 9: Topic models Nov 11: Neural networks |
| 12 | Nov 16, 18 | Deep neural networks | <ul style="list-style-type: none">○ Tensorflow playground○ Autoencoder examples | Tue: Quiz 3 | Nov 16: Neural networks (continued) Notes on backpropagation Nov 18: Autoencoders |
| 13 | Nov 19-28 | No class, Thanksgiving break | | | |
| 14 | Nov 30, Dec 2 | Reinforcement learning | <ul style="list-style-type: none">○ Q-learning | Tue: Assn 6 in <ul style="list-style-type: none">○ Assn7 out | Nov 30: Reinforcement learning Dec 2: Deep reinforcement learning |
| 15 | Dec 7, 9 | Societal issues for machine learning | | Tue: Quiz 4 | Dec 7: Societal issues |

Many other topics we haven't touched

- Graphical models
- Collaborative filtering
- Generalized adversarial networks
- Kernel methods
- New types of generative models
- Causal inference and machine learning
- ...

Final exam

- Final exam Tuesday, December 21, 2021 at 7pm
- https://registrar.yale.edu/general-information/final-exams
- Review sessions, time and place TBA
- Length: About 1.5X Midterm
- Practice exams posted
- Any topic could be on exam...except

Vote a topic off the exam!



Nominations?

Your input

- Please complete a course review!
- I value your comments and feedback

Thank you!