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Learning Machine Learning

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This presentation will give you overview on what PACMANN AI learn and our learning style

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I. The Basic

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You want to learn the basic math and computer sciences foundation to learn Machine Learning

I. The Noob and tWhiner

- Single Variable Calculus
- Multivariable Calculus
- Linear Algebra
- Probability and Statistics

- Introduction to Computer Sciences
- Introduction to Statistical Learning

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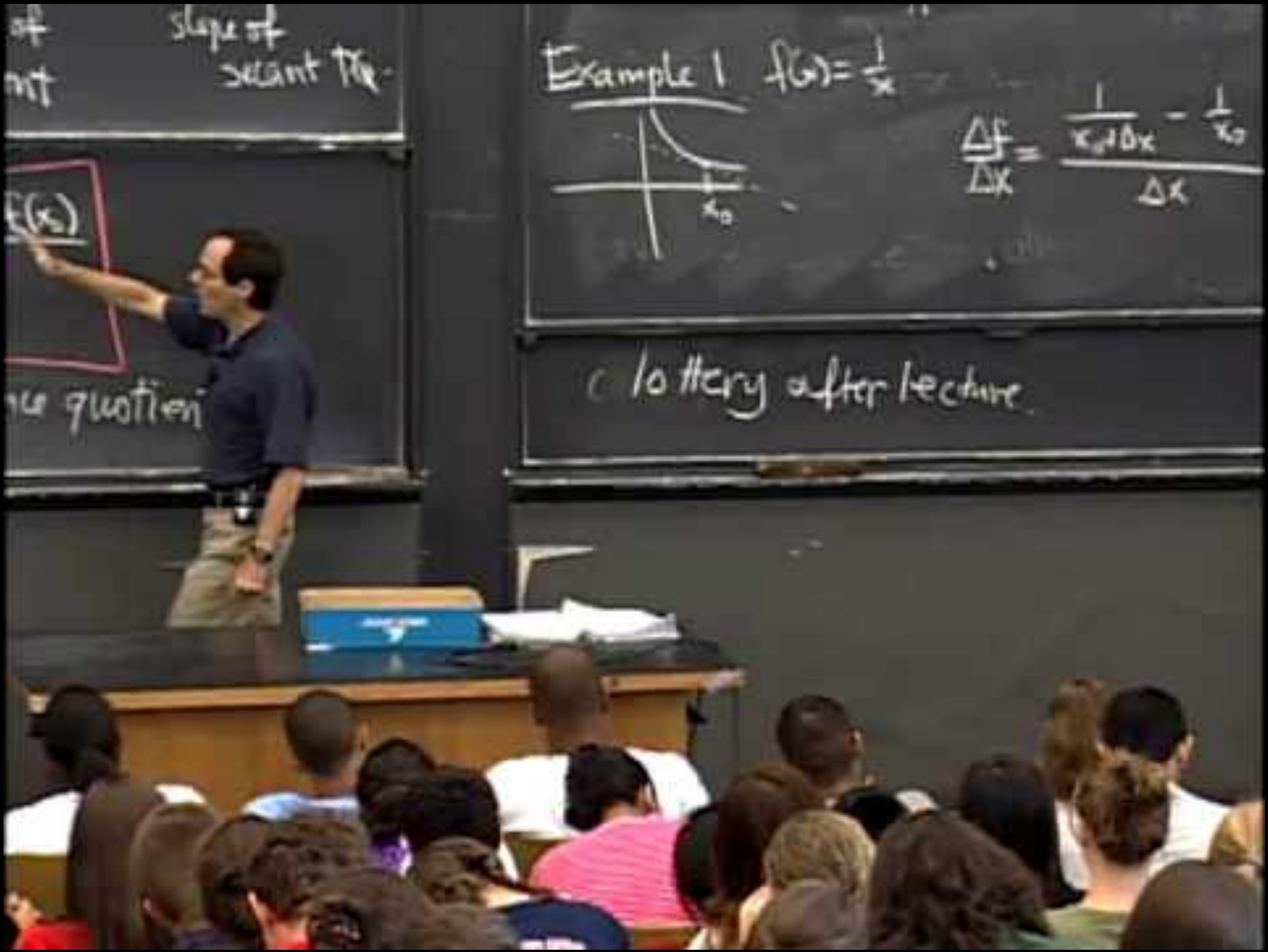
Single Variable Calculus MIT



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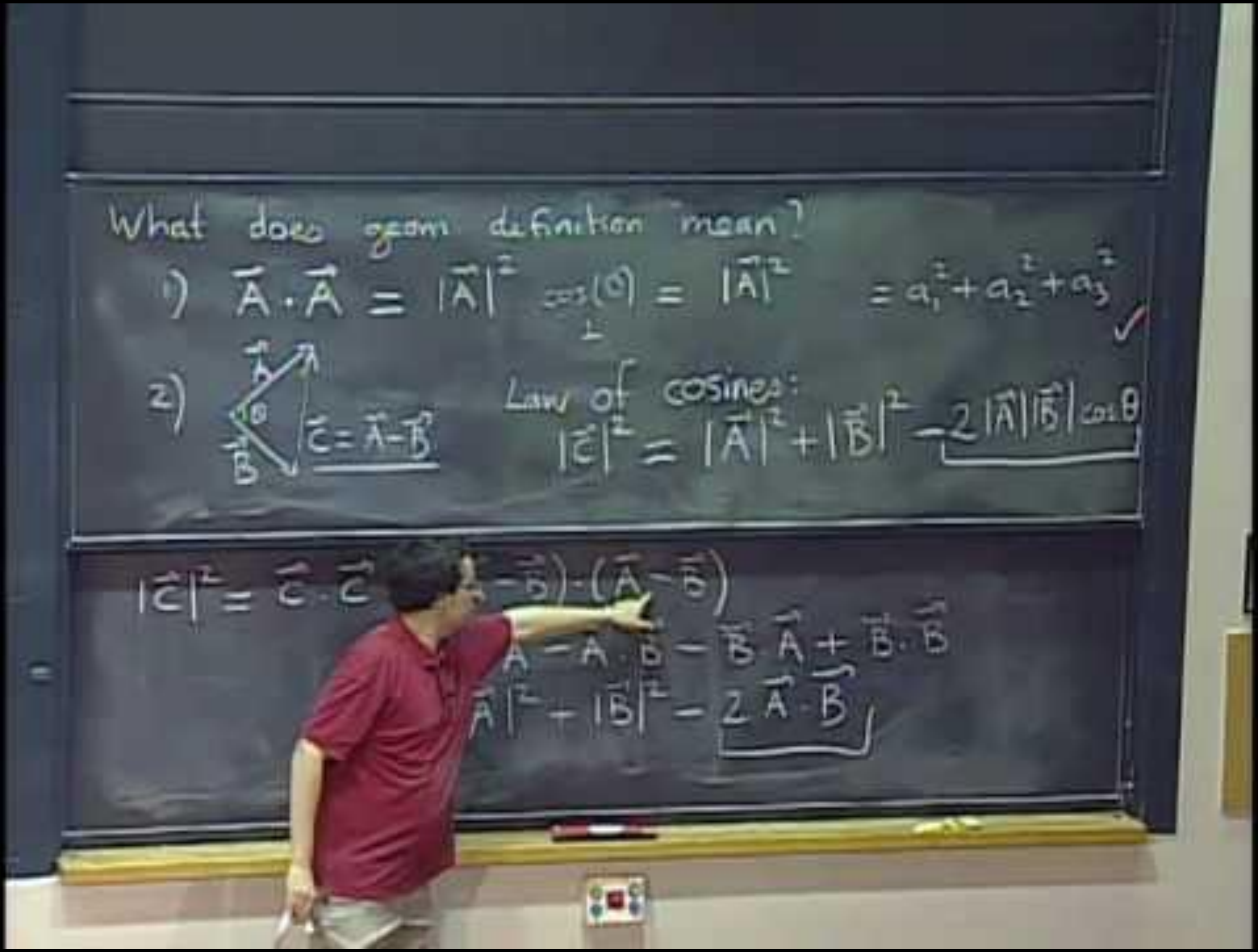
Multivariable Calculus MIT



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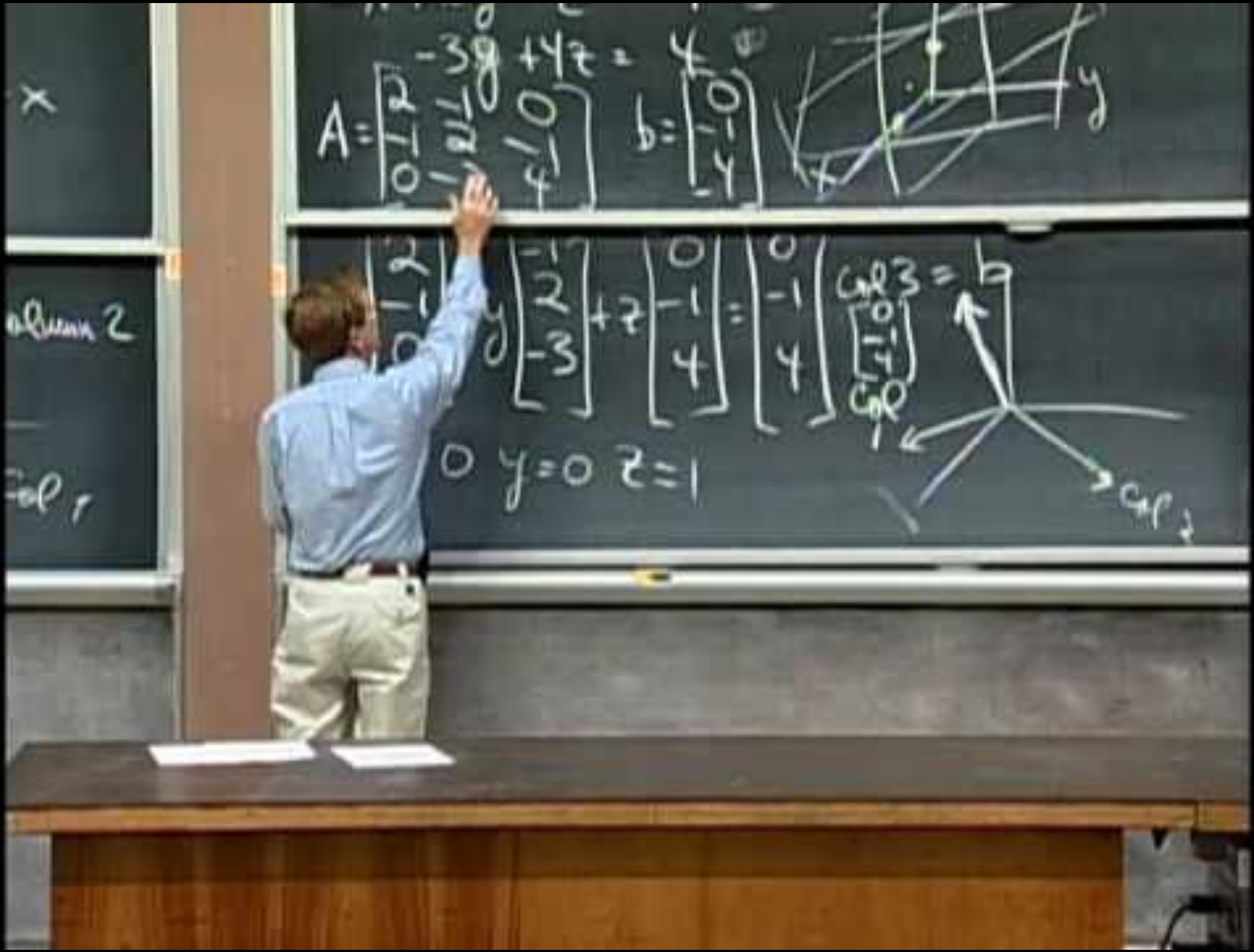
Linear Algebra MIT



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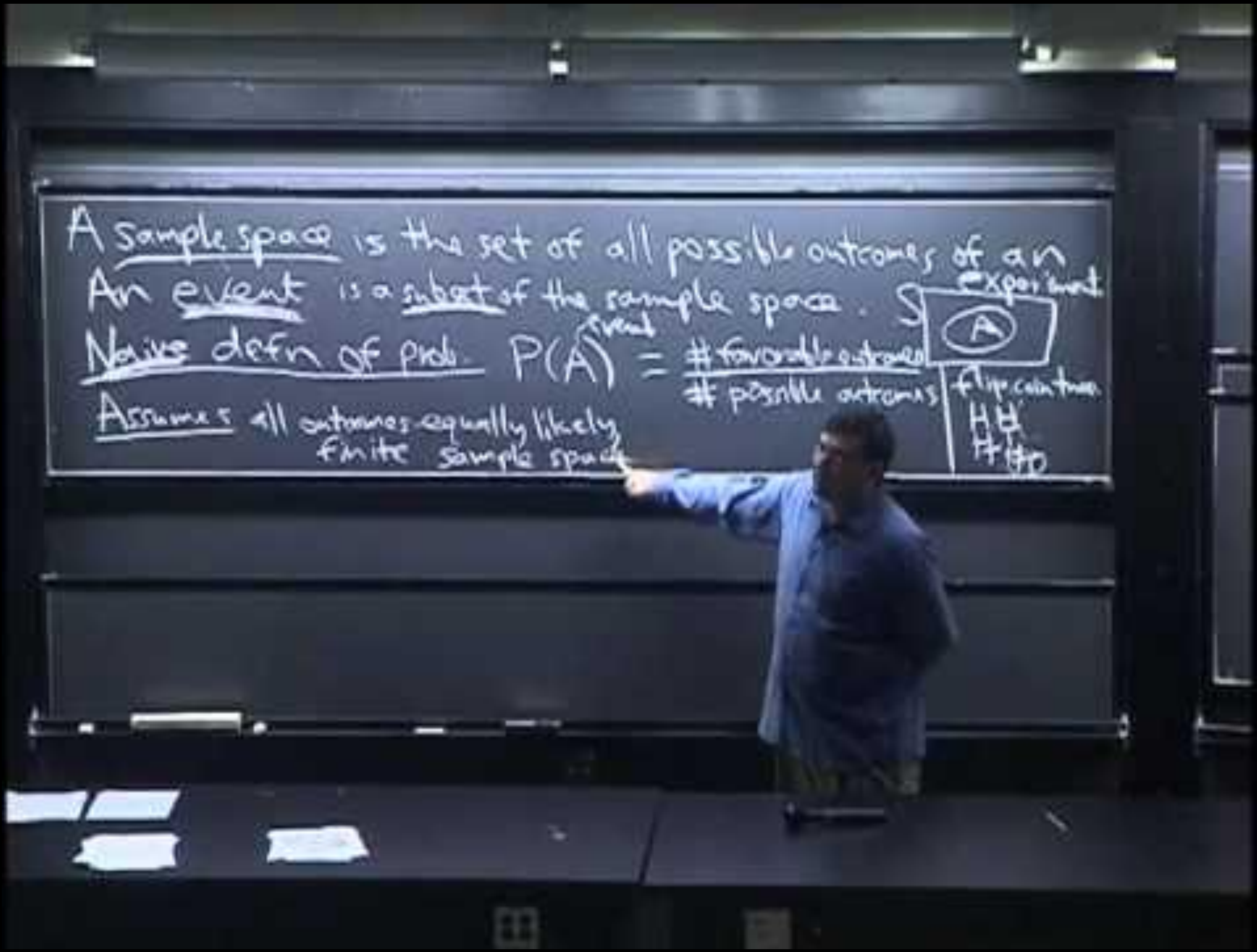
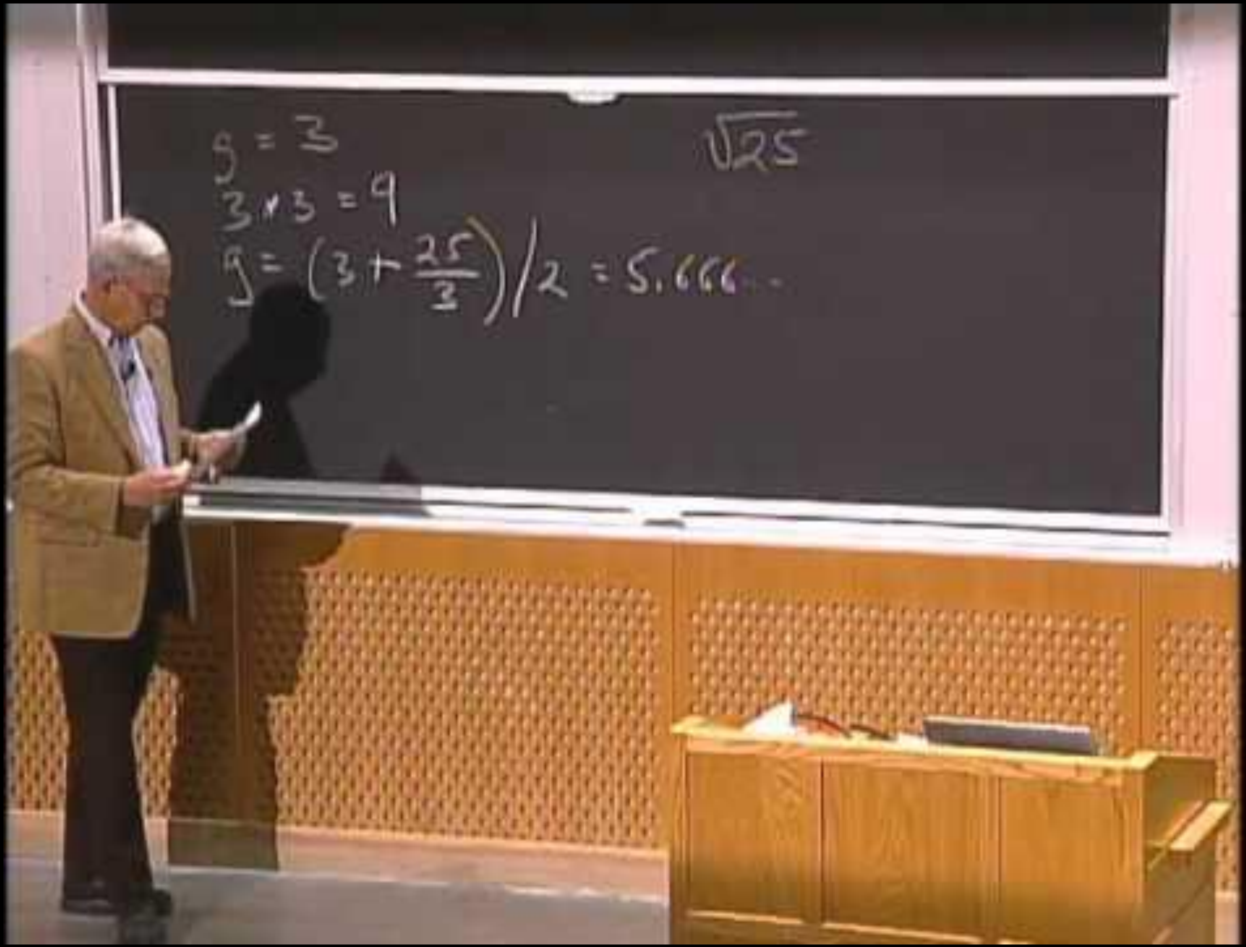
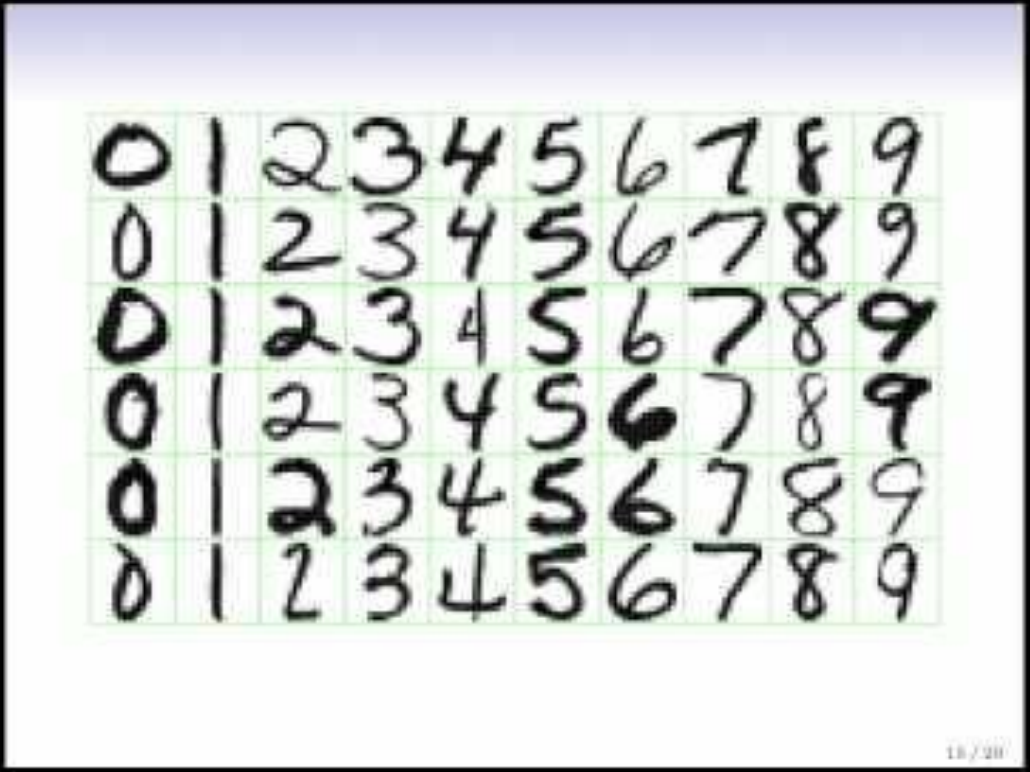
Probability and Statistics Harvard



Introduction to Comp Science and Programming MIT



Introduction to Statistical Learning (This Course)



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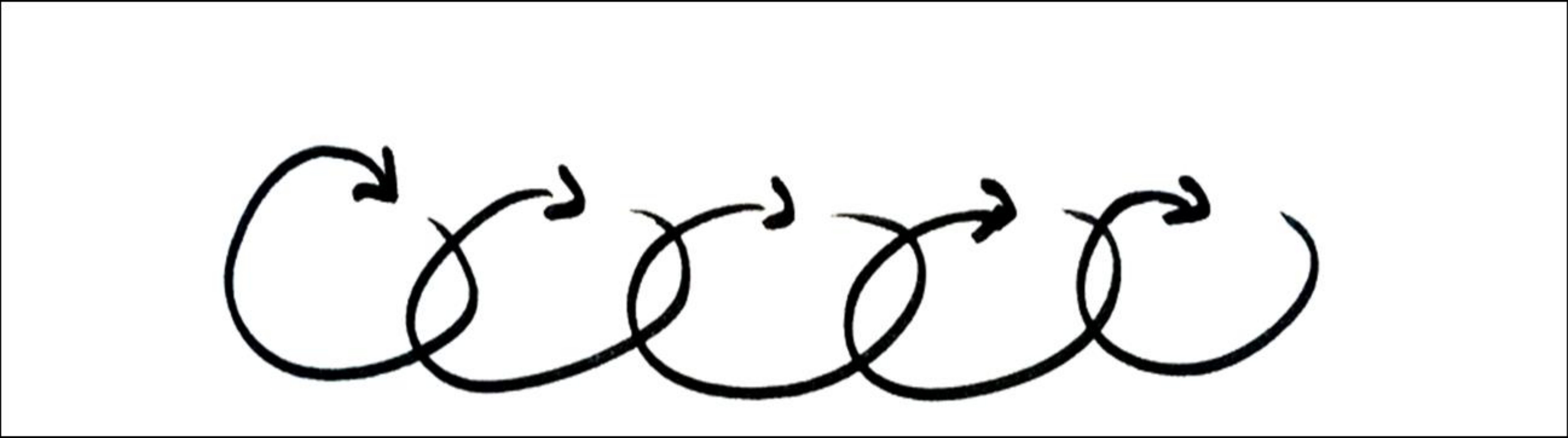

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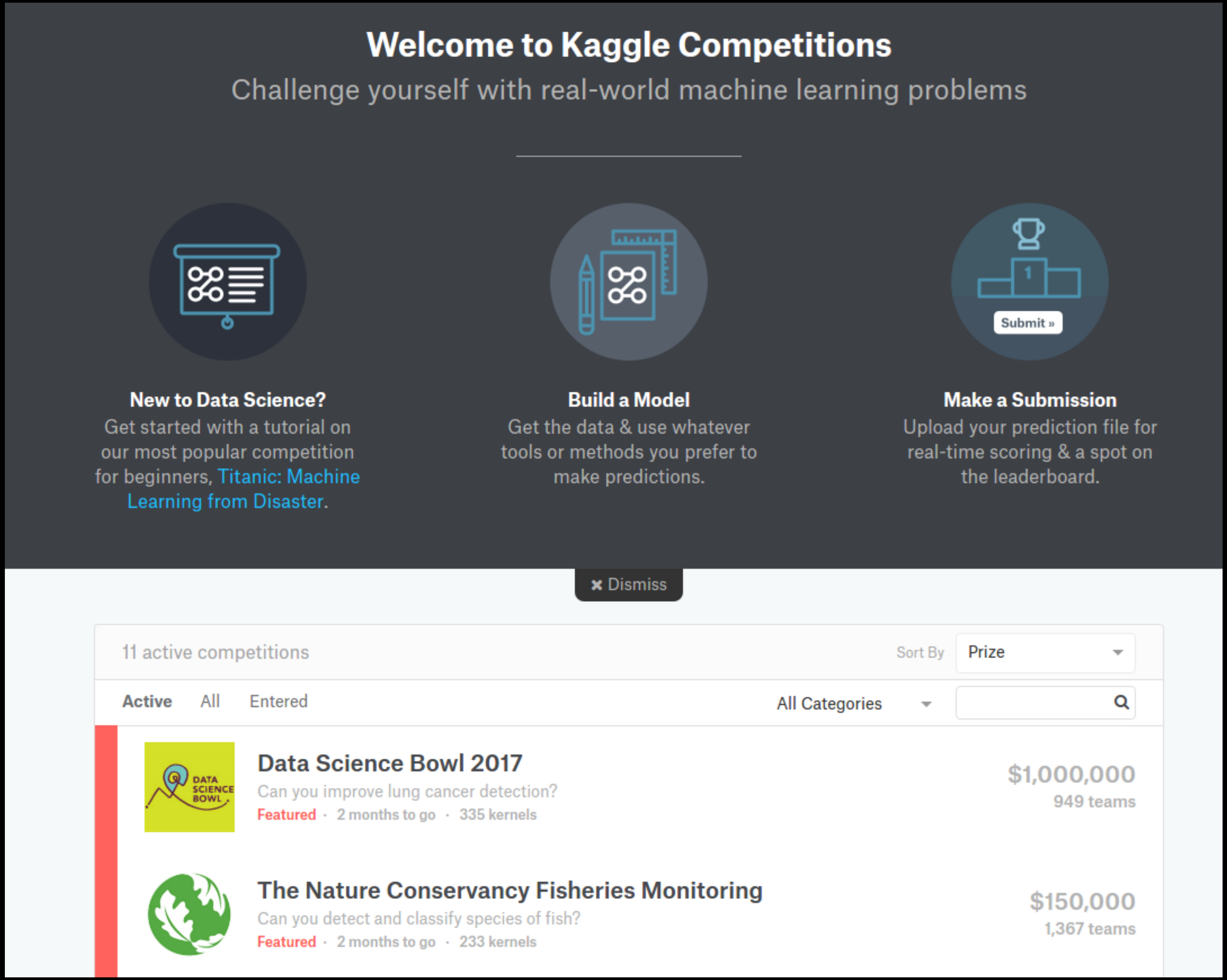

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II. The Learner

- Convex Optimization

- Machine Learning
- Machine Learning
- Machine Learning
- Machine Learning
- Machine Learning

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You want to learn all general machine learning course

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Introduction to Machine Learning Andrew Ng, Stanford

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Machine Learning Abu Mostafa, CalTech

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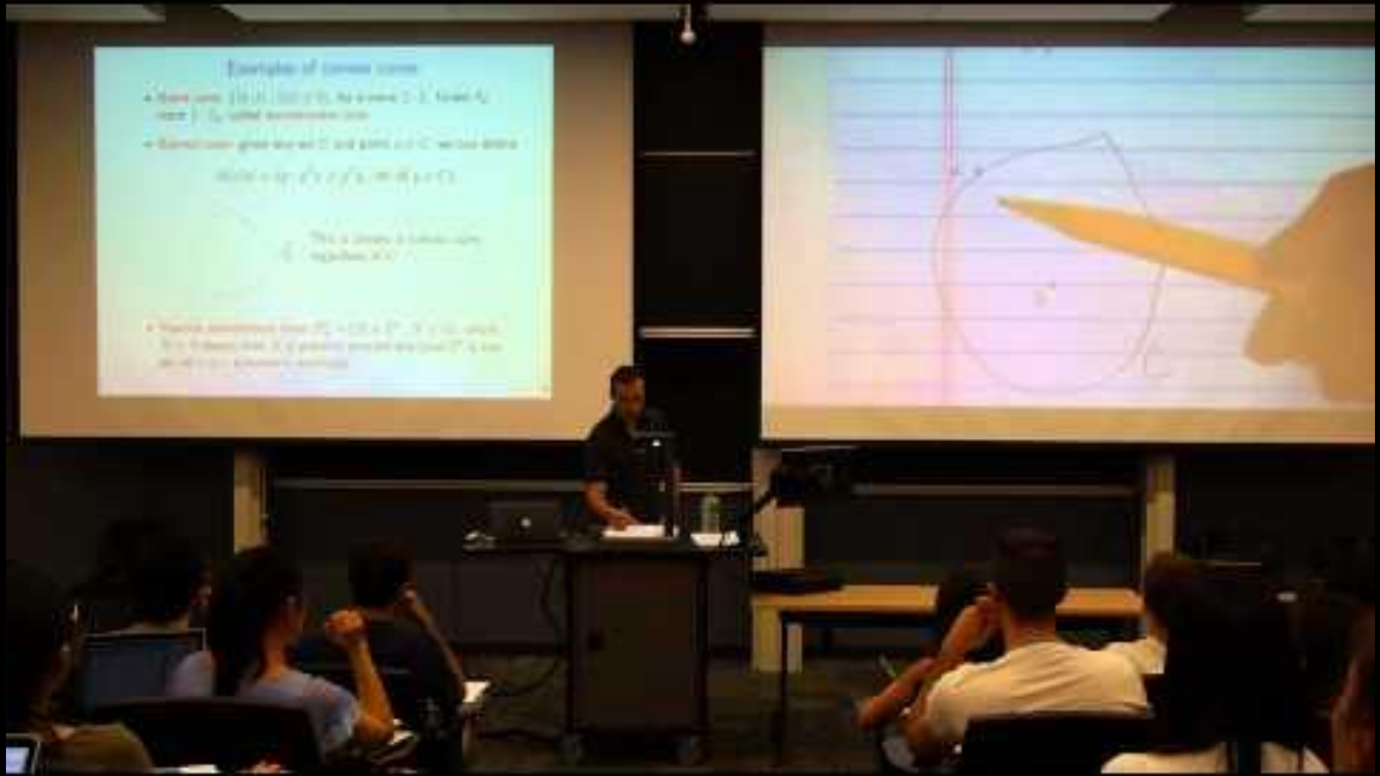
Convex Optimization Ryan Tibshirani, Carnegie Mellon PhD Level



Machine Learning Nando de Freitas, Oxford PhD Level

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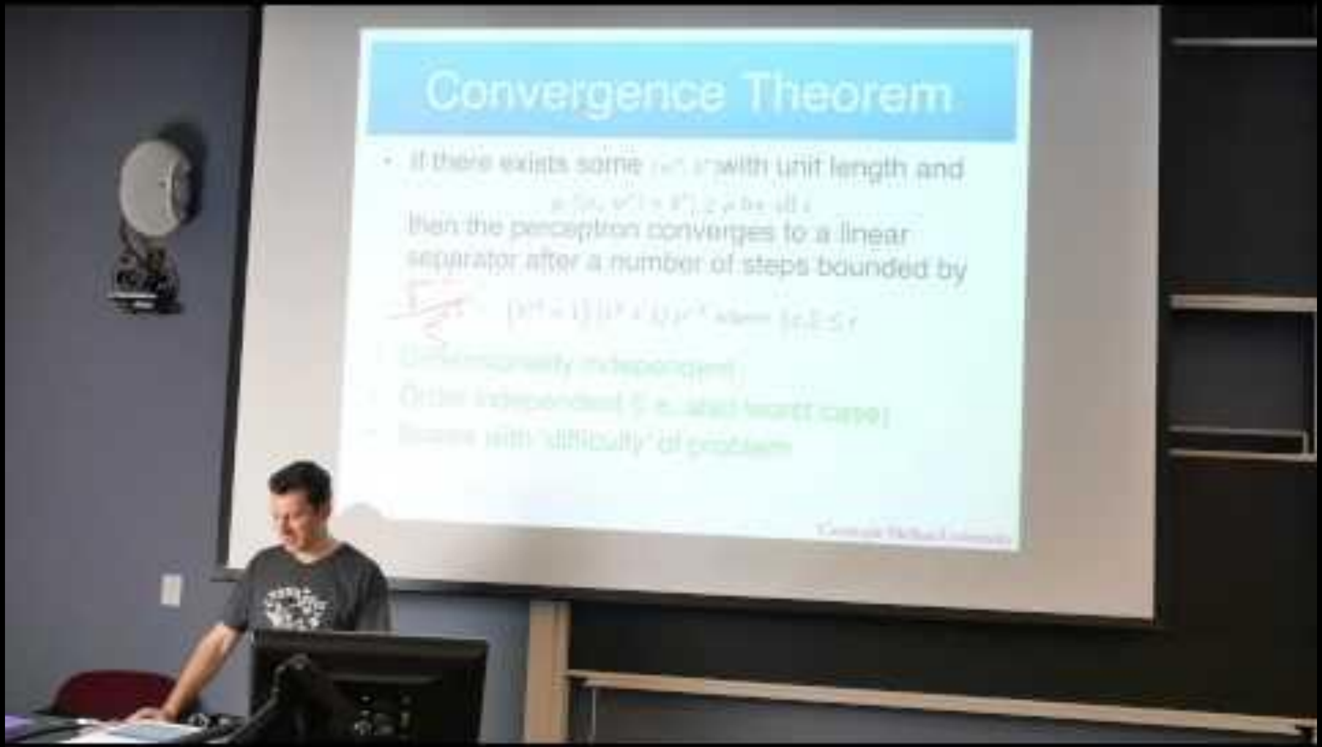
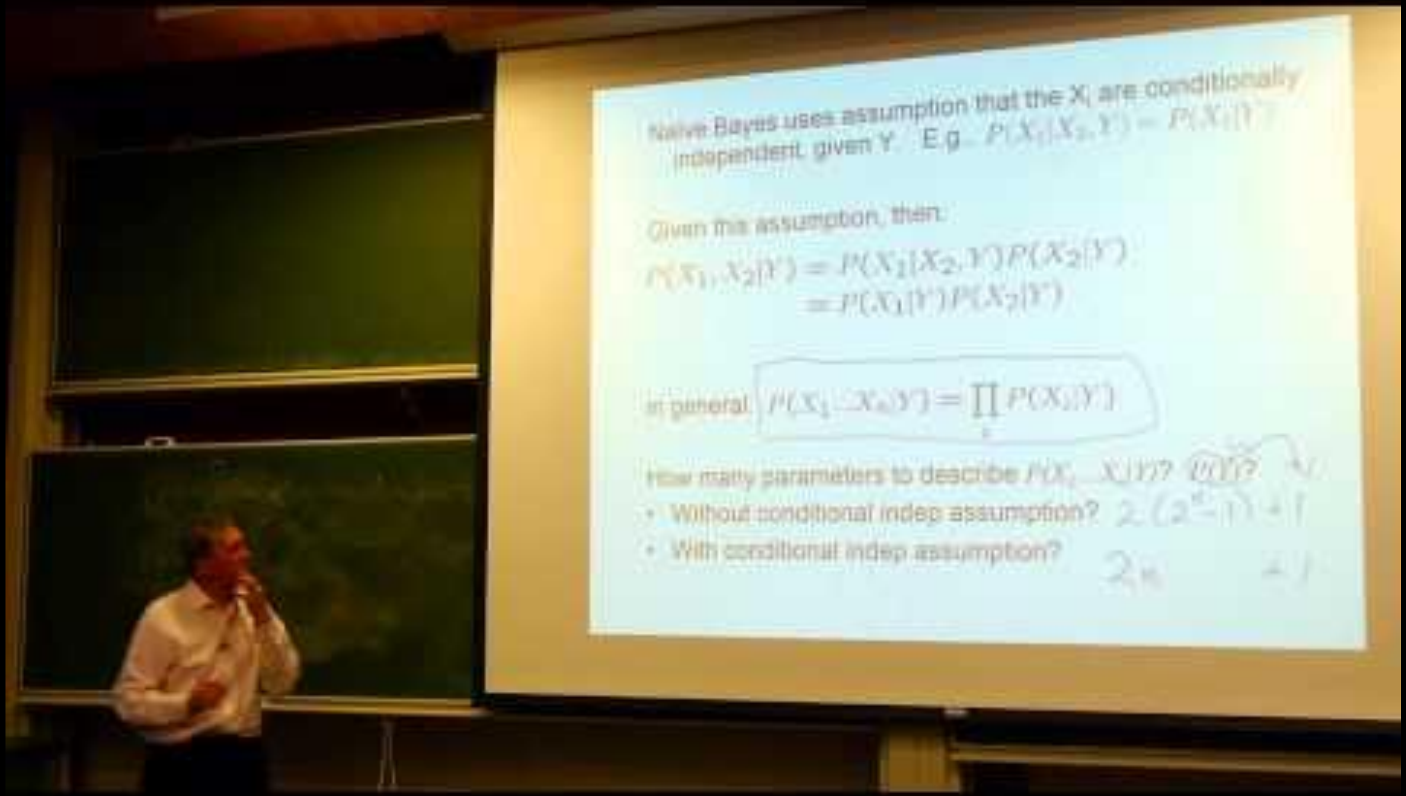
Introduction to Machine Learning Alex Smola, Carnegie Mellon PhD Level



Introduction to Machine Learning Tom Mitchell, Carnegie Mellon PhD Level



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Advance Introduction to Machine Learning Alex Smola, PhD Level

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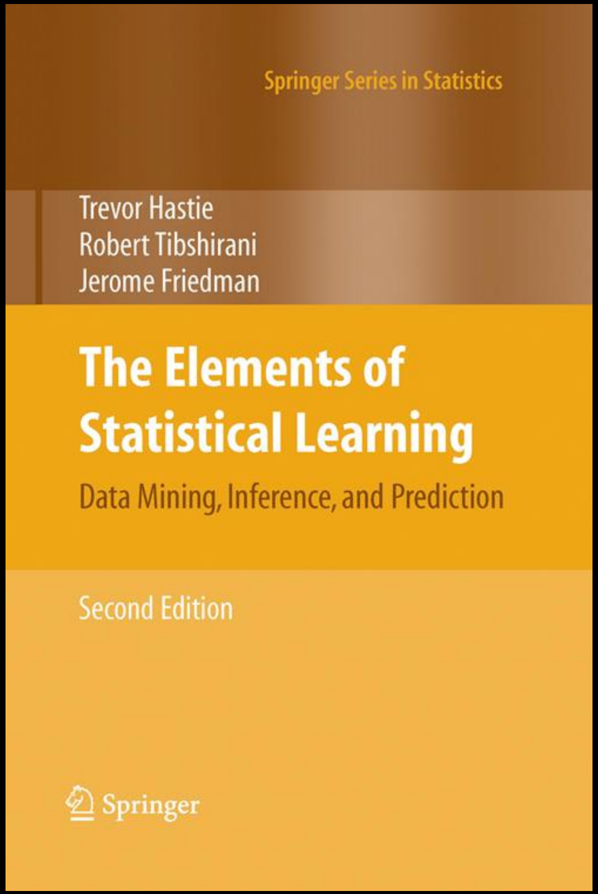

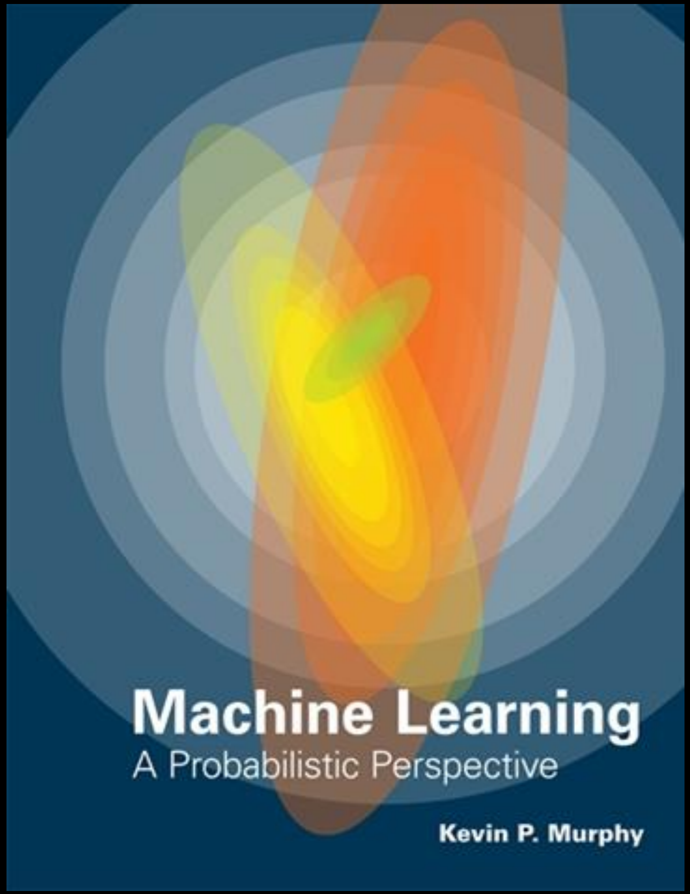

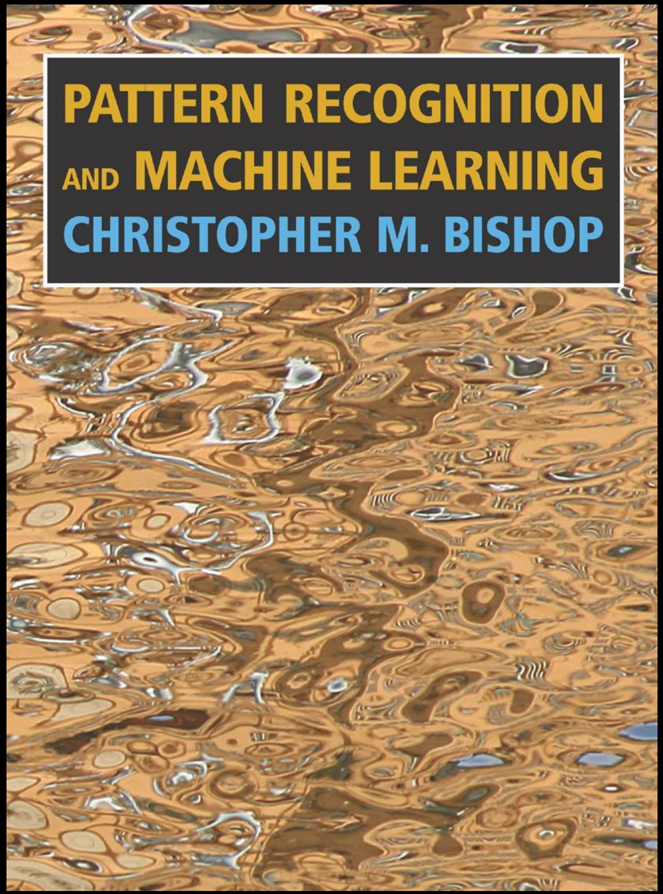

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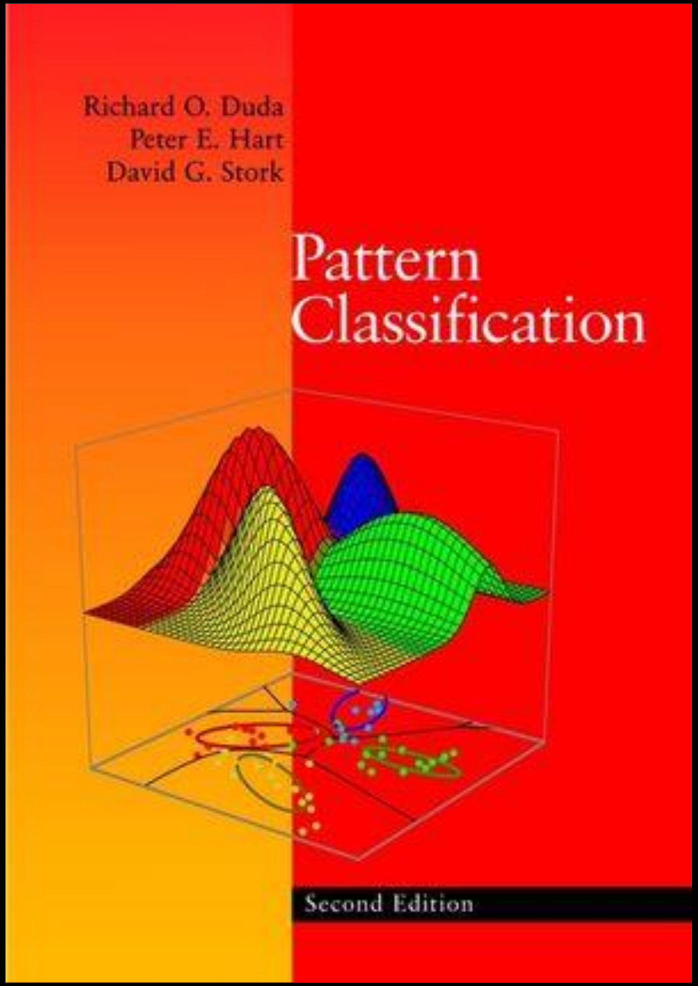

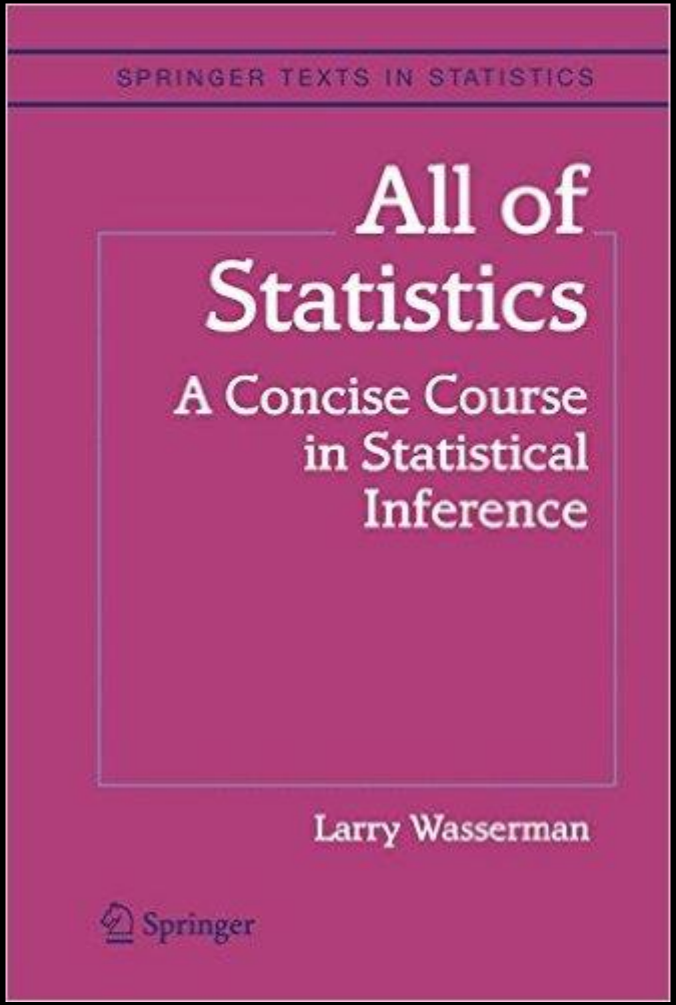

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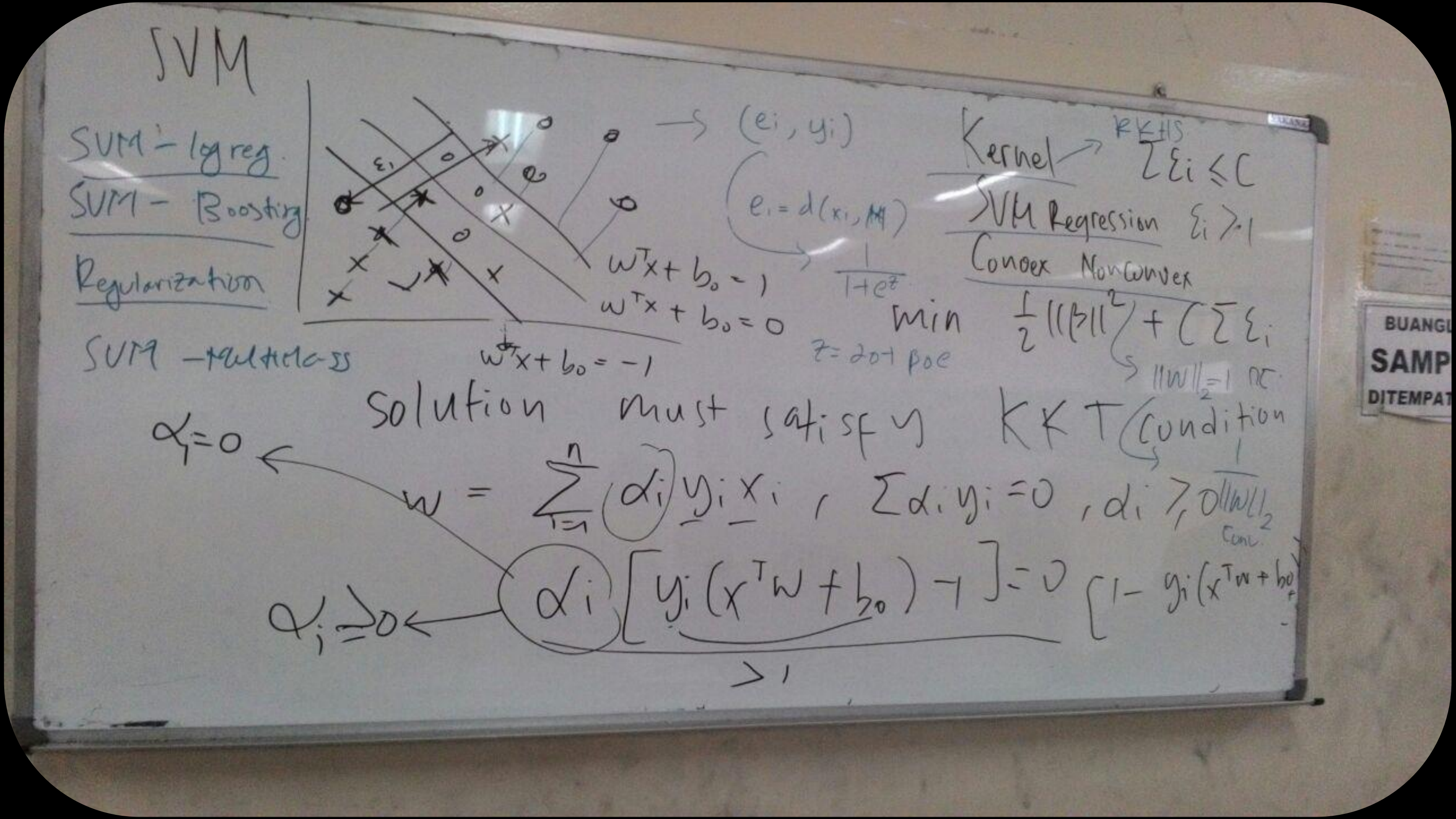

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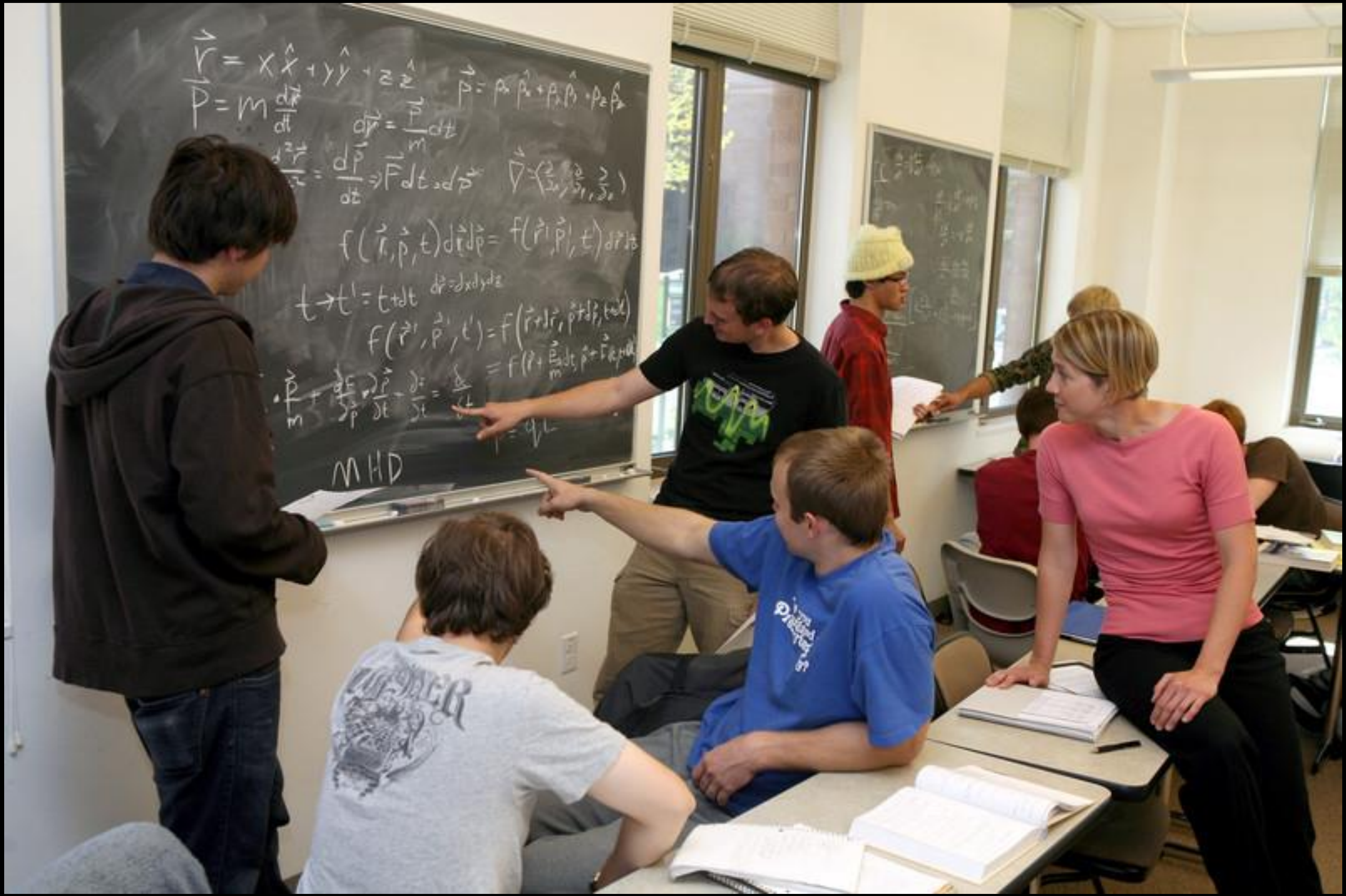
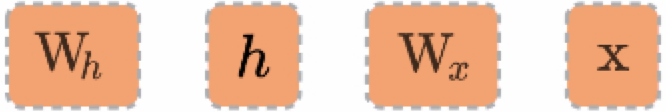


The Strategy

A graph is created on the fly

```
from torch.autograd import Variable

x = Variable(torch.randn(1, 10))
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))
```



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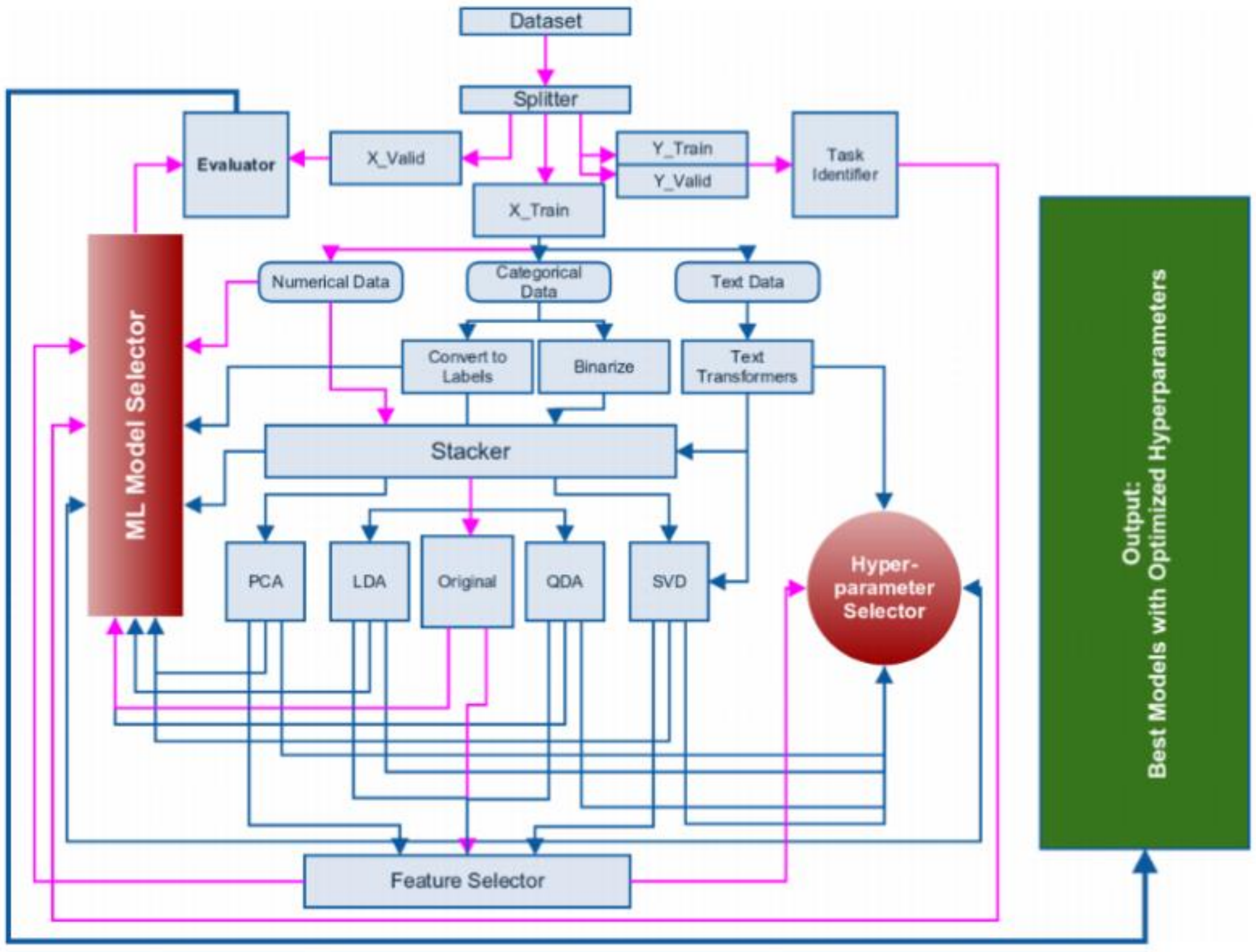

FIGURE FROM: A. THAKUR AND A. KROHN-GRIMBERGHE, AUTOCOMPETE: A FRAMEWORK FOR MACHINE LEARNING COMPETITIONS, AUTOML WORKSHOP, INTERNATIONAL CONFERENCE ON MACHINE LEARNING 2015.

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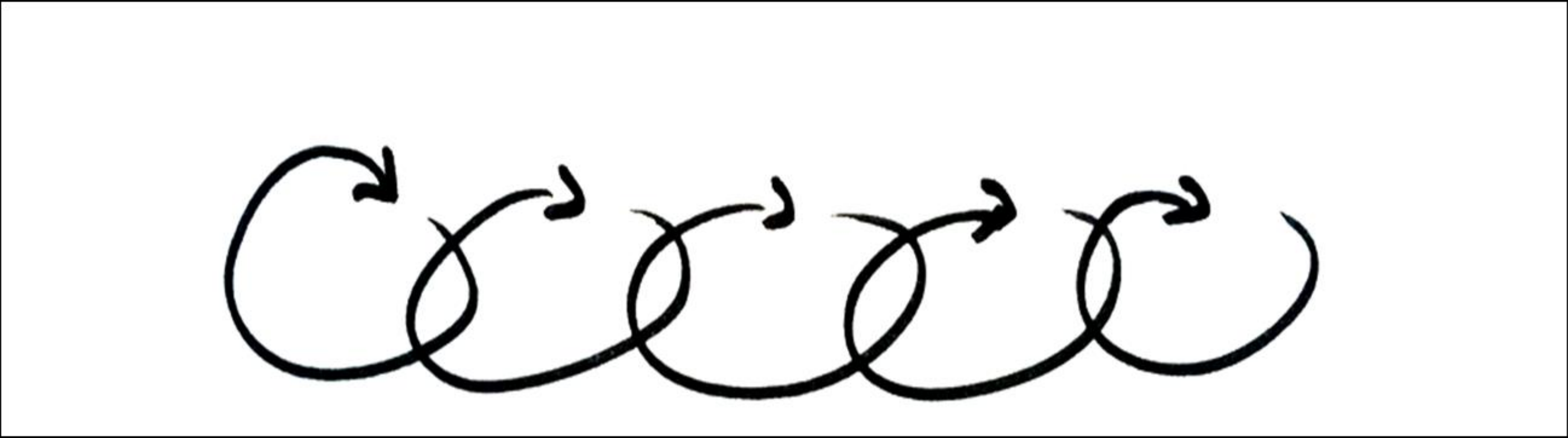

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III. The Theorist

- Theoretical Machine Learning
- Statistical Machine Learning
- Regularization Machine Learning
- Intermediate Statistics

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You want to learn machine learning theory, so you can sleep well

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Machine Learning Shai David, Waterloo PhD level

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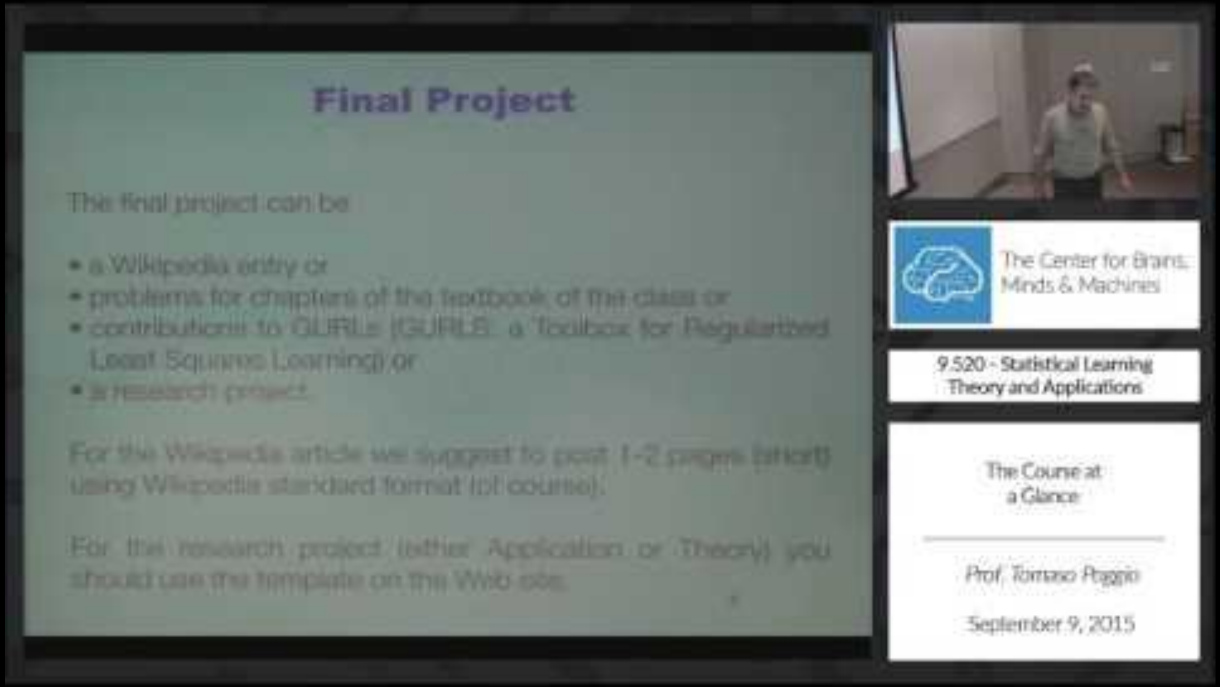
Regularization Machine Learning Paggio, MIT PhD level



Intermediate Statistics, Larry Wasserman Carnegie Mellon PhD level

Statistical Machine Learning, Larry Wasserman Carnegie Mellon PhD level

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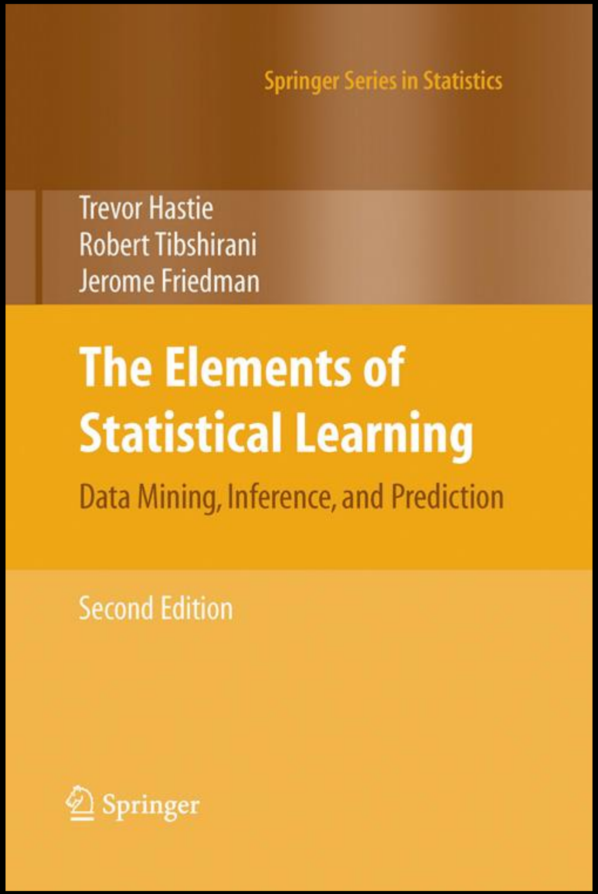

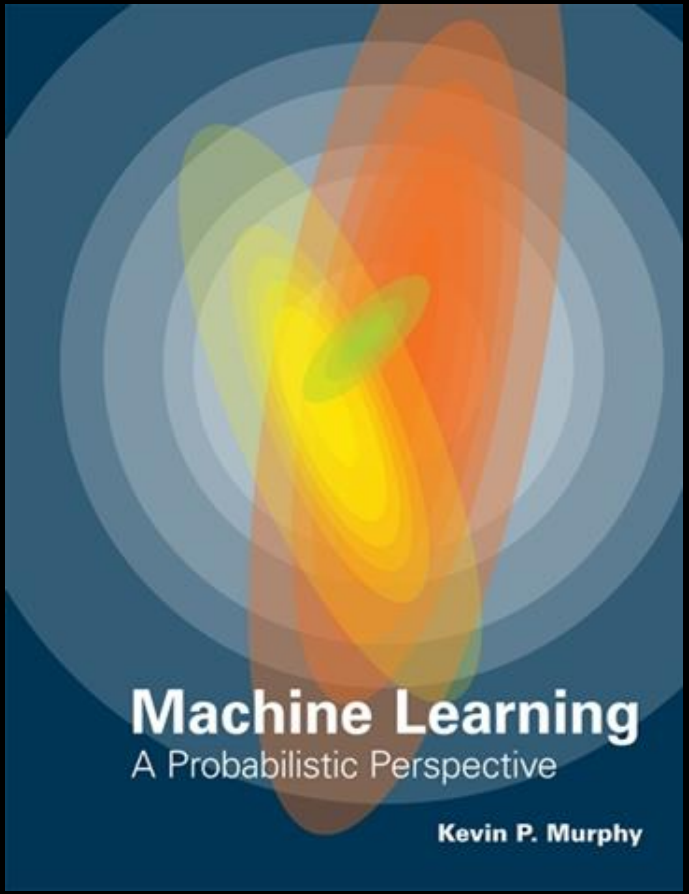

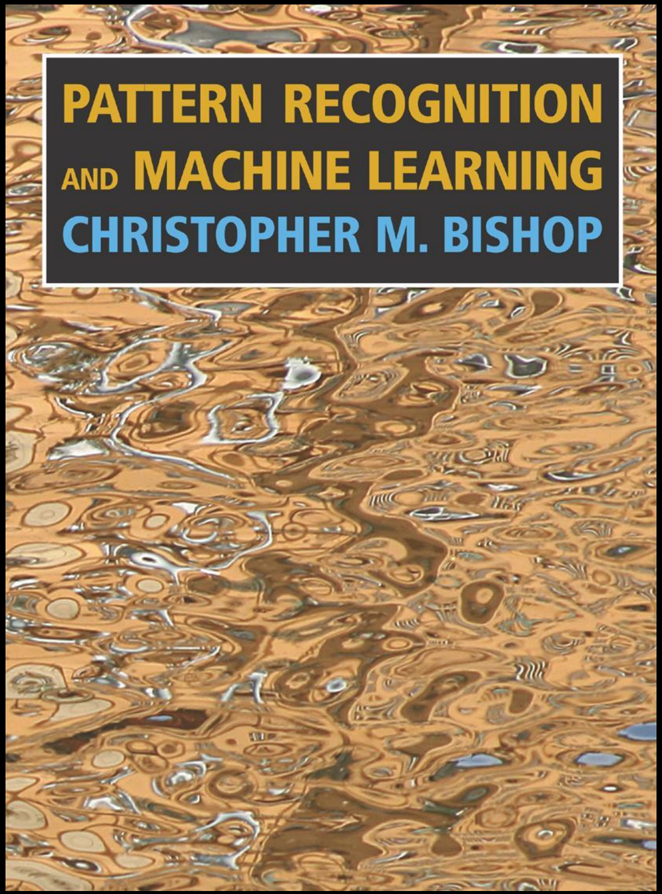

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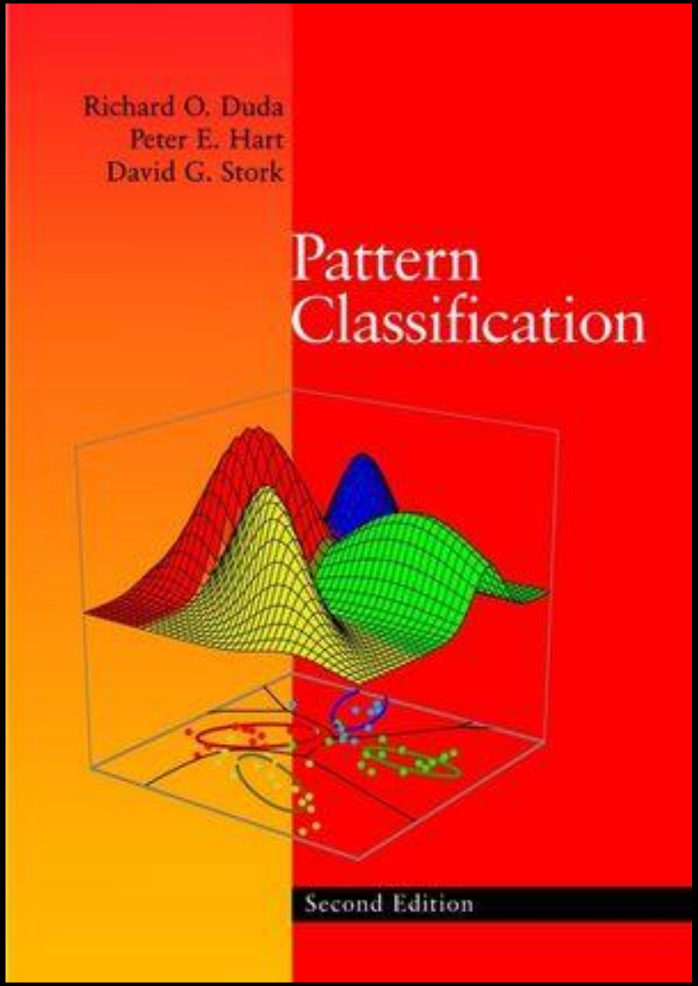

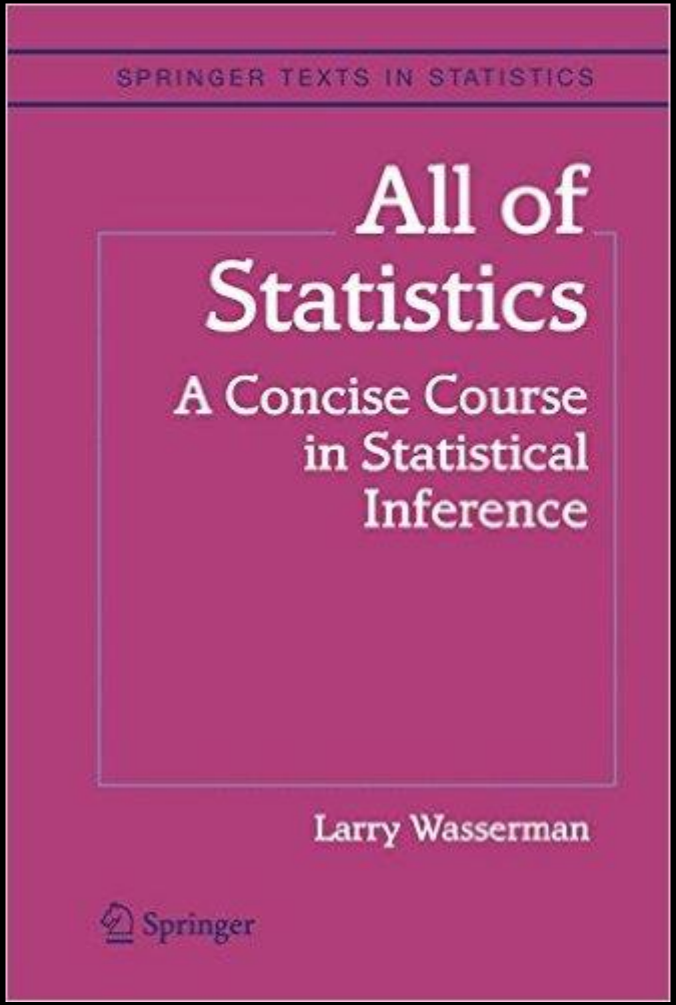

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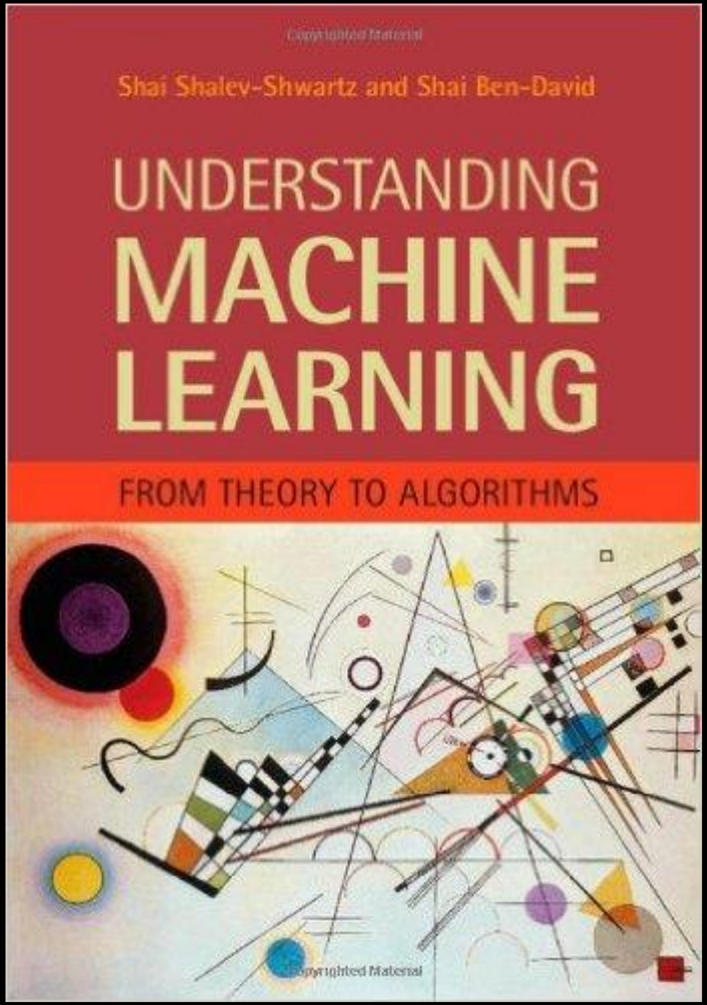

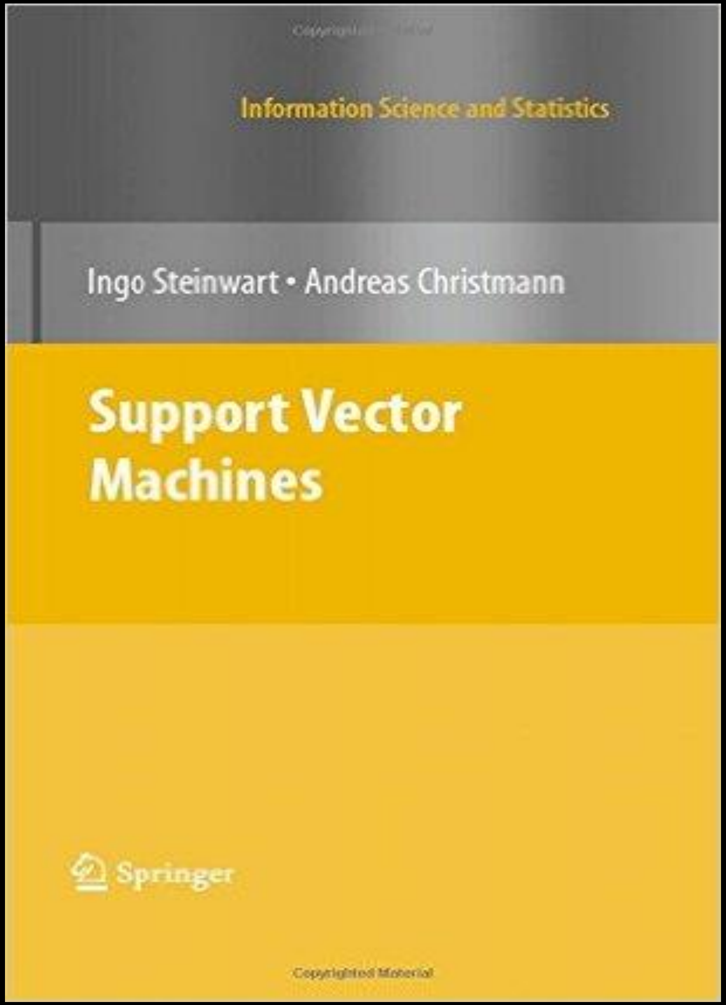

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11. $\int_0^\infty e^{-x} x^n \, dx = \underline{|n}$ and hence

$$\int_0^\infty x^{n-1}\left\{\phi(0) - \frac{x}{\underline{|1}}\phi(1) + \frac{x^2}{\underline{|2}}\phi(2) - \&c\right\} dx = \underline{|n-1}\,\phi(-n)$$

Sol. $\int_0^\infty e^{-x} x^n \, dx = e^{-x}\left\{x^n + nx^{n-1} + n(n-1)x^{n-2} + \&c\right\}$

when $x = 0$ $= \underline{|n}$ by IV 10 Cor.

$$f(0)\int_0^\infty e^{-x} x^{n-1} dx = \underline{|n-1}\, f(0)$$

$$\frac{f'(0)}{\underline{|1}}\int_0^\infty e^{-rx} x^{n-1} dx = \frac{\underline{|n-1}}{r^n}\cdot\frac{f'(0)}{\underline{|1}}$$

$$\frac{f''(0)}{\underline{|2}}\int_0^\infty e^{-r^2x} x^{n-1} dx = \frac{\underline{|n-1}}{r^{2n}}\cdot\frac{f''(0)}{\underline{|2}}$$

and so on.

Adding up all the results we have

$$\int_0^\infty x^{n-1}\left\{f(1) - \frac{x}{\underline{|1}} f(r) + \frac{x^2}{\underline{|2}} f(r^2) - \&c\right\} dx = \underline{|n-1}\, f\left(\frac{1}{r^n}\right)$$

Let $f(r^n) = \phi(n)$ then $f\left(\frac{1}{r^n}\right) = \phi(-n)$.

Cor 1. $\int_0^\infty x^{n-1}\left\{\phi(0) - x\phi(1) + x^2\phi(2) - \&c\right\} dx = \frac{\pi\,\phi(-n)}{\sin \pi n}$

Cor 2. $\int_0^\infty x^{n-1}\left\{\phi(0) - \frac{x^2}{\underline{|2}}\phi(2) + \frac{x^4}{\underline{|4}}\phi(4) - \&c\right\} dx = \underline{|n-1}\,\phi(-n) \times \cos\frac{\pi n}{2}$

Cor 3. $\int_0^\infty \left\{\phi(0) - \frac{x}{\underline{|1}}\phi(1) + \frac{x^2}{\underline{|2}}\phi(2) - \&c\right\} \cos nx \, dx$

$= \phi(-1) - n^2\phi(-3) + n^4\phi(-5) - \&c.$

Cor 4. $\int_0^\infty \left\{\phi(0) - x^2\phi(2) + x^4\phi(4) - \&c\right\} \cos nx \, dx$

$= \frac{\pi}{2}\left\{\phi(-1) - \frac{n}{\underline{|1}}\phi(-2) + \frac{n^2}{\underline{|2}}\phi(-3) - \frac{n^3}{\underline{|3}}\phi(-4) + \&c\right\}$

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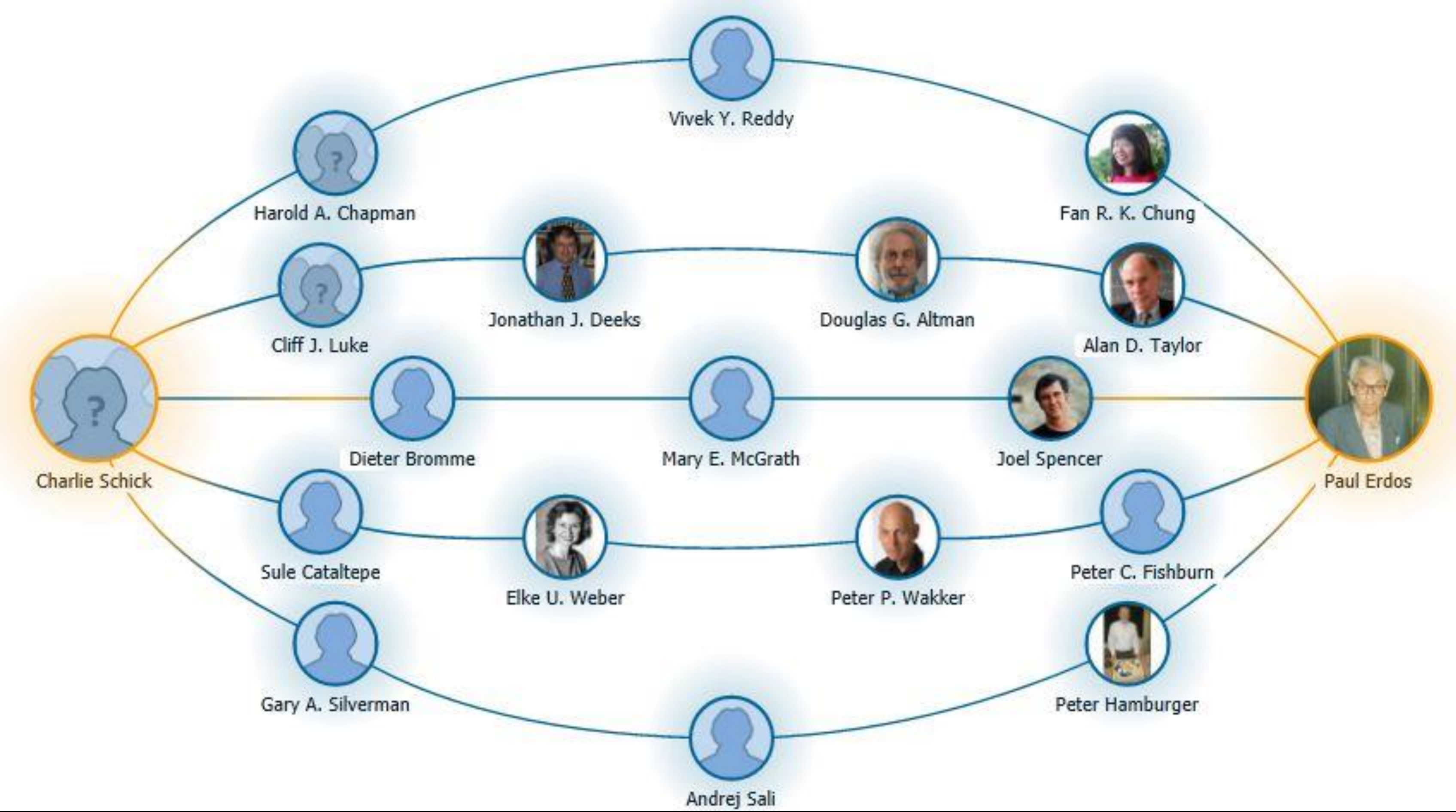

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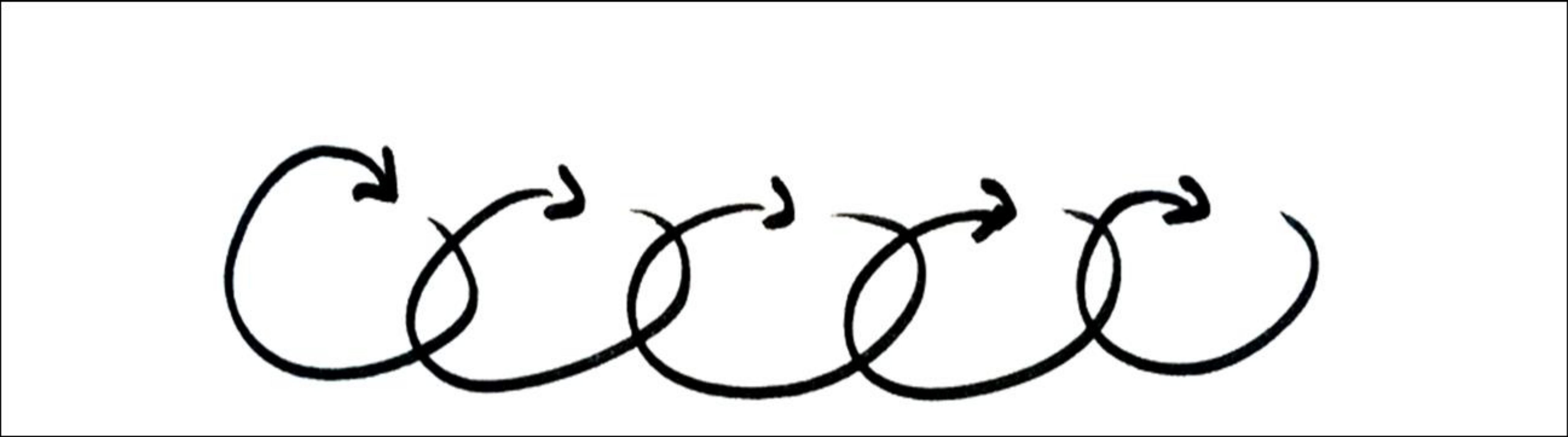

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IV. The Specialist

- Deep Learning
- Reinforcement Learning
- Computer Vision
- Natural Language Processing

You want to have a special ability on one or two subject, so you can get a job

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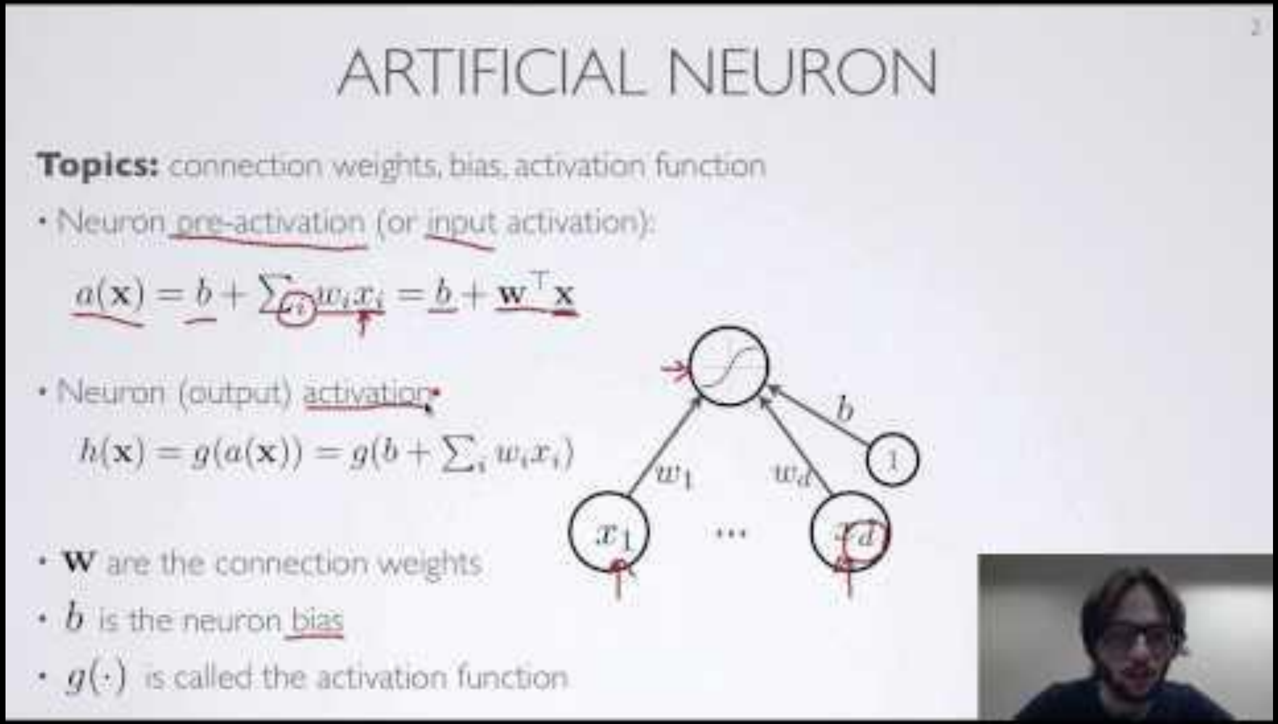
Neural Networks Hugo Larochelle, Montreal Univ PhD level



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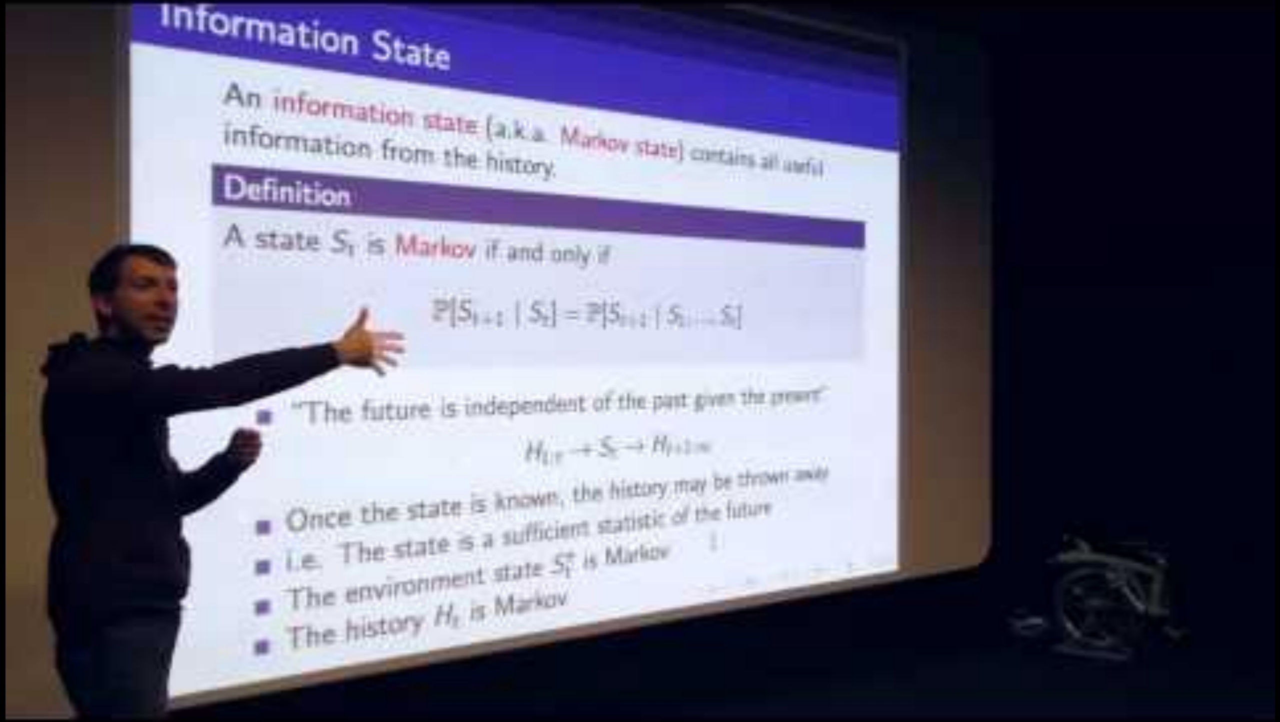
Reinforcement Learning David Silver, UCL
PhD level



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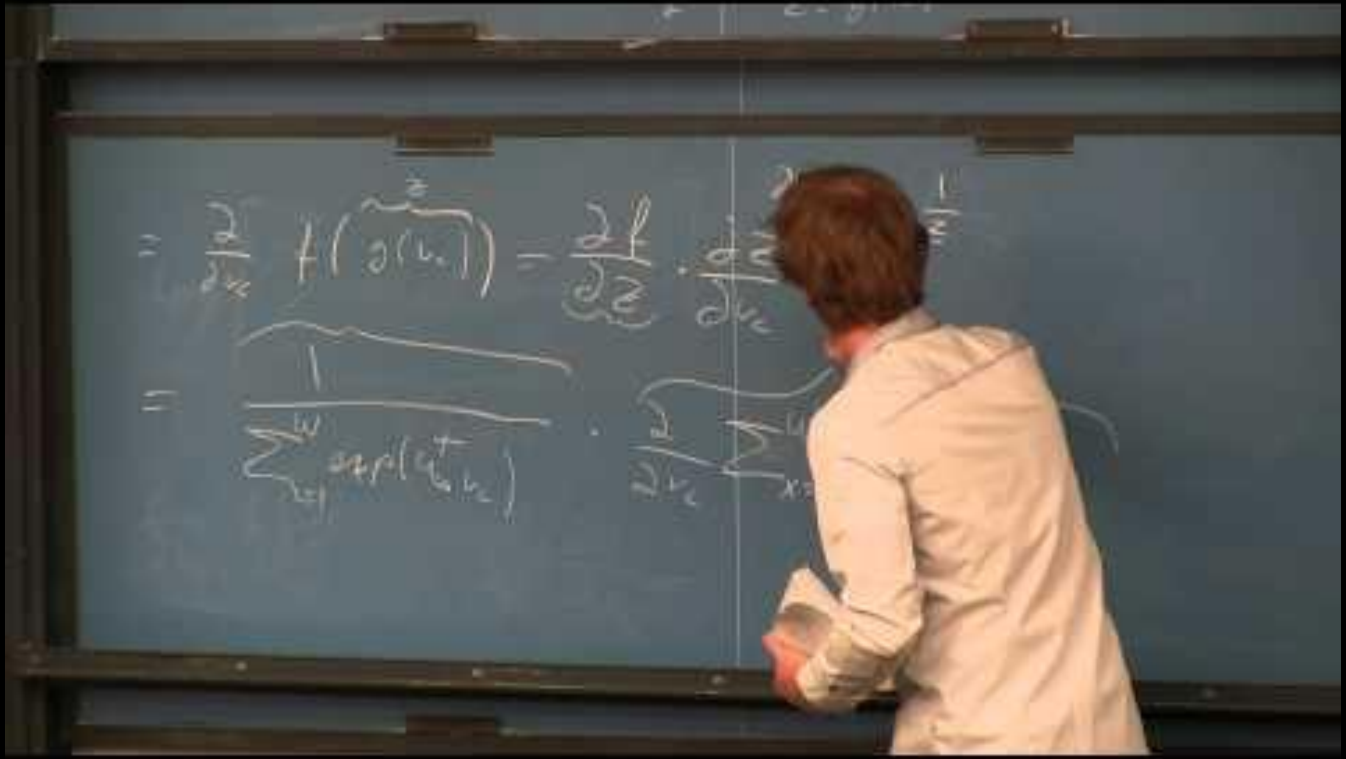
Deep Learning Vision Andrei Karpathy,
Stanford PhD level

Deep Learning NLP Richard Socher, Stanford
PhD level



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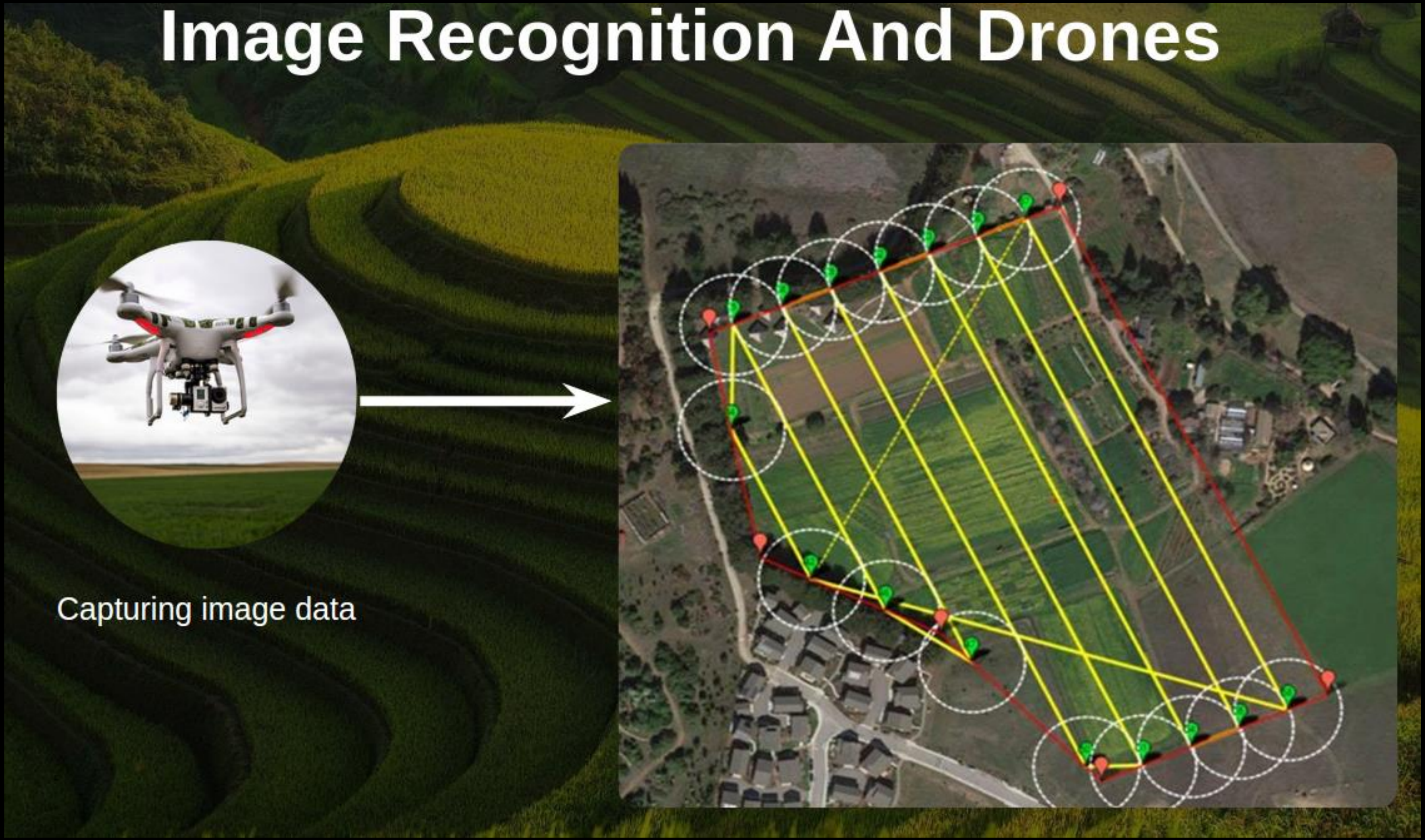

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The Strategy

True startup story

- Startup builds exchange for ads on webpages
- Clients bid on opportunities, market takes a cut

- System gets popular
- Stuff works better if ads and pages are matched
    - Programmer adds a few IF … THEN … ELSE clauses (system improves)
    - Programmer adds even more clauses (system sort-of improves, ruleset is a mess)
    - Programmer discovers decision trees (lots of rules, but they work better)
    - Programmer discovers boosting (combining many trees, works even better)
- Startup is bought … (machine learning system is replaced entirely)

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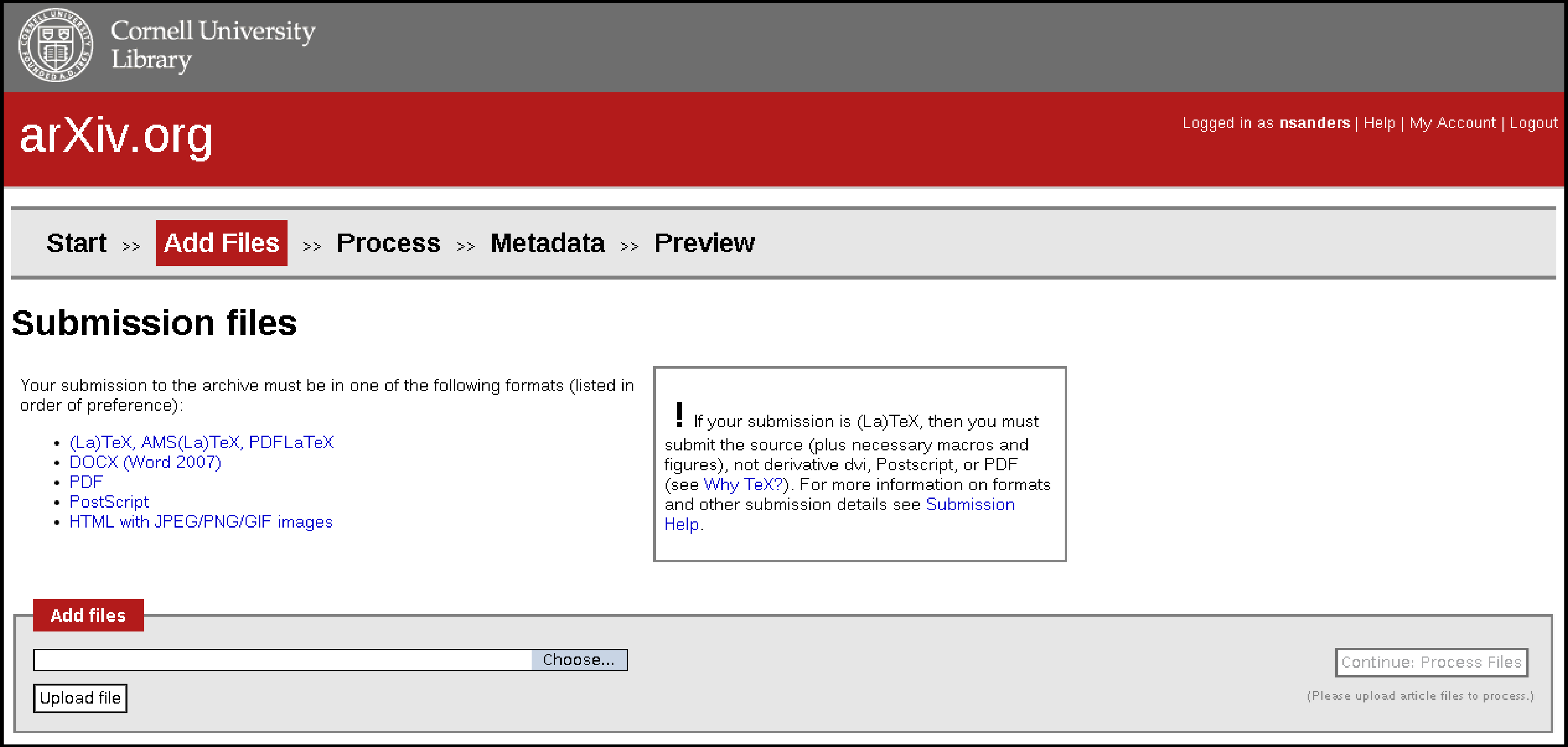

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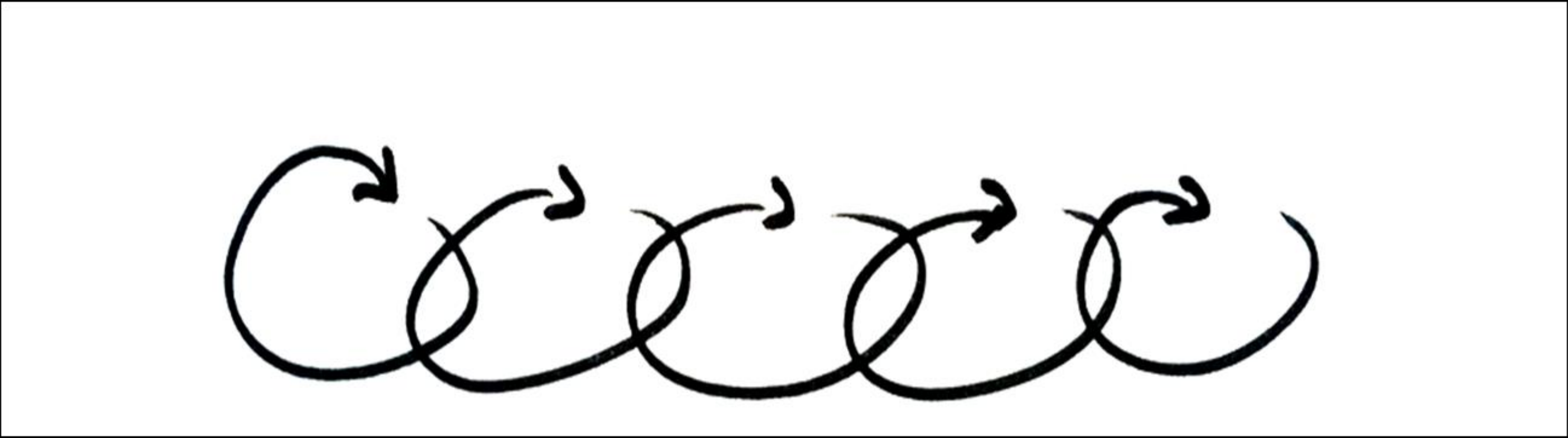

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IV. The Researcher

- Track down interesting paper
- Replicate some research
- Read the journals
- Get a PhD?

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Arxiv Sanity Preserver
Built by @karpathy to accelerate research.
Serving last 25909 papers from cs.[CV|CL|LG|NE]/stat.ML

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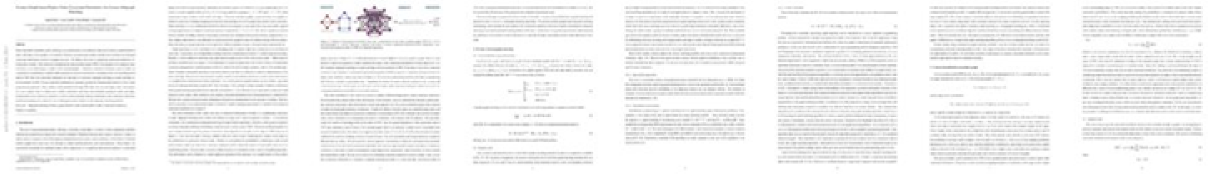

Many algorithms formulate graph matching as an optimization of an objective function of pairwise quantification of nodes and edges of two graphs to be matched. Pairwise measurements usually consider local attributes but disregard contextual information involved in graph structures. We address this issue by proposing contextual similarities between pairs of nodes. This is done by considering the tensor product graph (TPG) of two graphs to be matched, where each node is an ordered pair of nodes of the operand graphs. Contextual similarities between a pair of nodes are computed by accumulating weighted walks (normalized pairwise similarities) terminating at the corresponding paired node in TPG. Once the contextual similarities are obtained, we formulate subgraph matching as a node and edge selection problem in TPG. We use contextual similarities to construct an objective function and optimize it with a linear programming approach. Since random walk formulation through TPG takes into account higher order information, it is not a surprise that we obtain more reliable similarities and better discrimination among the nodes and edges. Experimental results shown on synthetic as well as real benchmarks illustrate that higher order contextual similarities add discriminating power and allow one to find approximate solutions to the subgraph matching problem.

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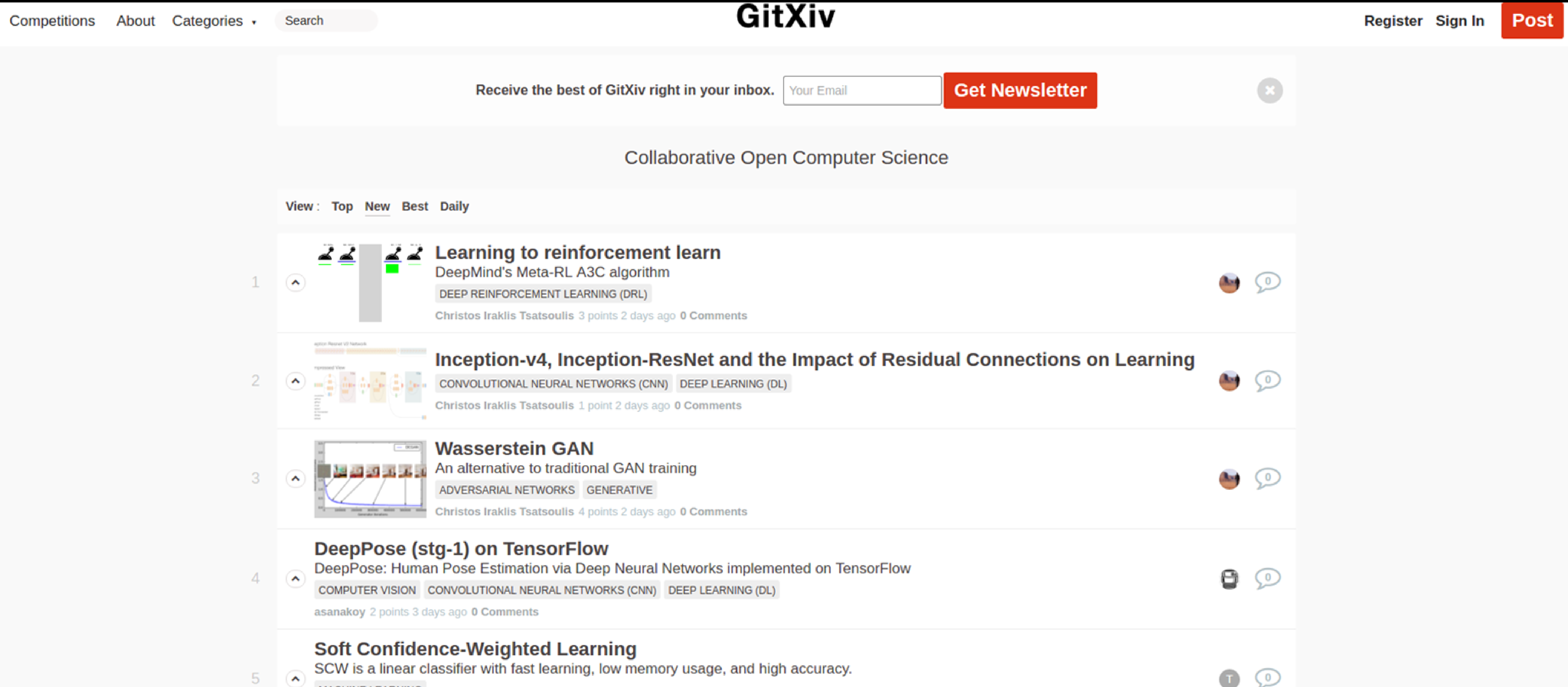

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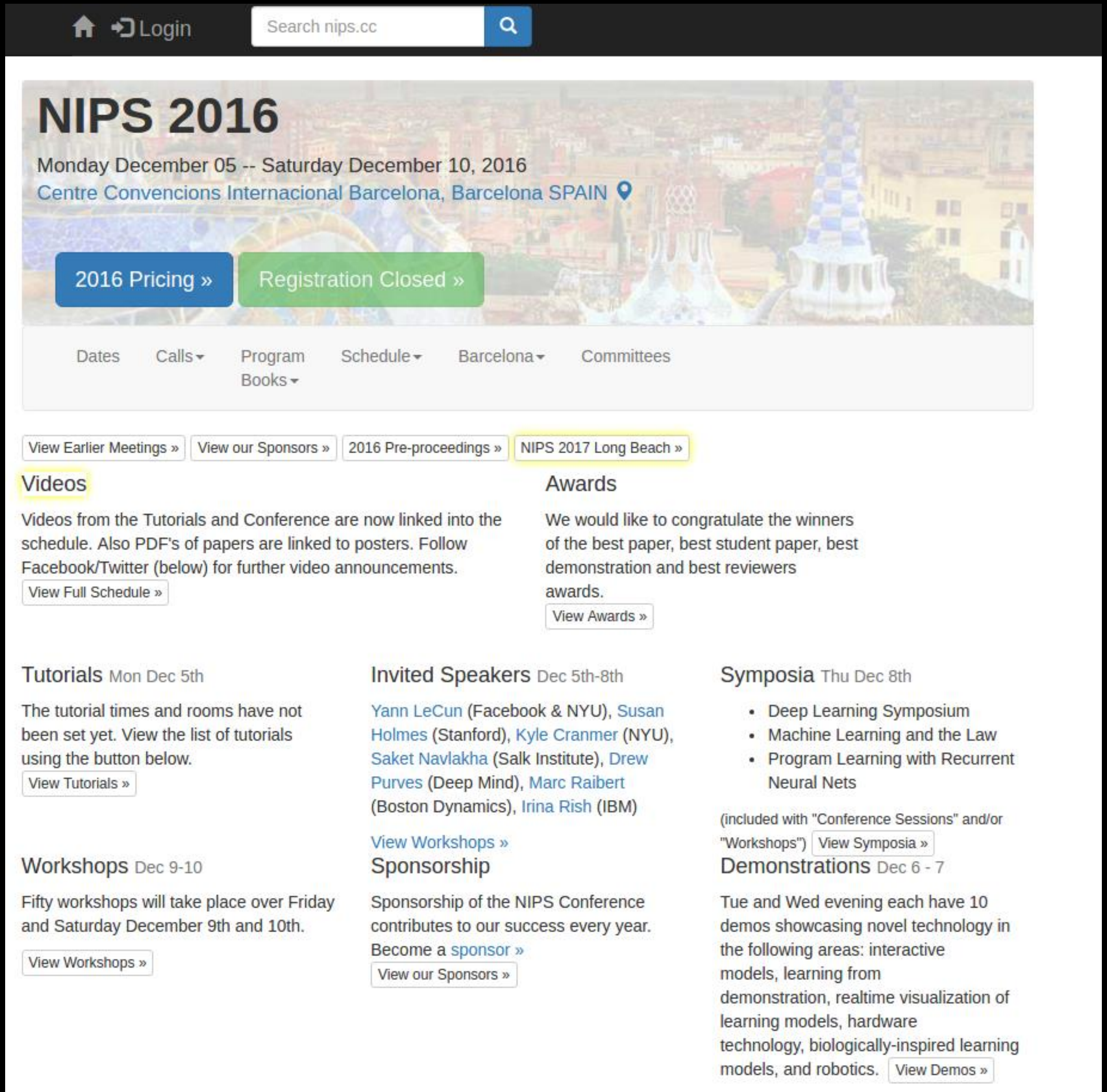

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Videos

Videos from the Tutorials and Conference are now linked into the schedule. Also PDF's of papers are linked to posters. Follow Facebook/Twitter (below) for further video announcements.

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Awards

We would like to congratulate the winners of the best paper, best student paper, best demonstration and best reviewers awards.

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Tutorials Mon Dec 5th

The tutorial times and rooms have not been set yet. View the list of tutorials using the button below.

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Invited Speakers Dec 5th-8th

Yann LeCun (Facebook & NYU), Susan Holmes (Stanford), Kyle Cranmer (NYU), Saket Navlakha (Salk Institute), Drew Purves (Deep Mind), Marc Raibert (Boston Dynamics), Irina Rish (IBM)

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Symposia Thu Dec 8th

- Deep Learning Symposium
- Machine Learning and the Law
- Program Learning with Recurrent Neural Nets

(included with "Conference Sessions" and/or "Workshops") View Symposia »

Workshops Dec 9-10

Fifty workshops will take place over Friday and Saturday December 9th and 10th.

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Demonstrations Dec 6 - 7

Tue and Wed evening each have 10 demos showcasing novel technology in the following areas: interactive models, learning from demonstration, realtime visualization of learning models, hardware technology, biologically-inspired learning models, and robotics. View Demos »

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The Department of Computer Science and Operations Research at Université de Montréal is seeking applications for a full-time tenure-track professor position at all ranks in areas related to machine learning and its applications (e.g., natural language, medicine, perception, recommendation systems, data mining). Application deadline is January 15 2017, and the expected starting date is June 1st 2017. For inquiries, contact Houari Sahraoui, Chair, at the address in the official posting.

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PhD Program in Machine Learning

The Ph.D. Program in Machine Learning is for students who are interested in research in Machine Learning and Computational Statistics. The program is operated jointly by faculty in the School of Computer Science and Department of Statistics.

Joint PhD Program in Statistics and Machine Learning

This PhD program differs from the Machine Learning PhD program in that it places significantly more emphasis on preparation in statistical theory and methodology. Similarly, this program differs from the Statistics PhD program in its emphasis on machine learning and computer science. The Joint Ph.D. Program in Machine Learning and Statistics is a new program aimed at preparing students for academic careers in both CS and Statistics departments at top universities.

Joint PhD Program in Machine Learning and Public Policy

The Joint Ph.D. Program in Machine Learning and Public Policy is a new program operated jointly by faculty in Machine Learning and the Heinz College (Schools of Public Policy, Information Systems, and Management). Students will gain the skills necessary to develop new state-of-the-art machine learning technologies and apply these successfully to real-world policy domains.

Joint PhD Program in Neural Computation and Machine Learning

This Joint PhD program trains students in the application of Machine Learning to Neuroscience by combining core elements of the ML PhD program and the Program in Neural Computation (PNC) offered by the Center for the Neural Basis of Cognition (CNBC).

Machine Learning Department | 5000 Forbes Avenue, Gates Hillman Center 8th Floor, Pittsburgh, PA 15213

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Thank you, Question?

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