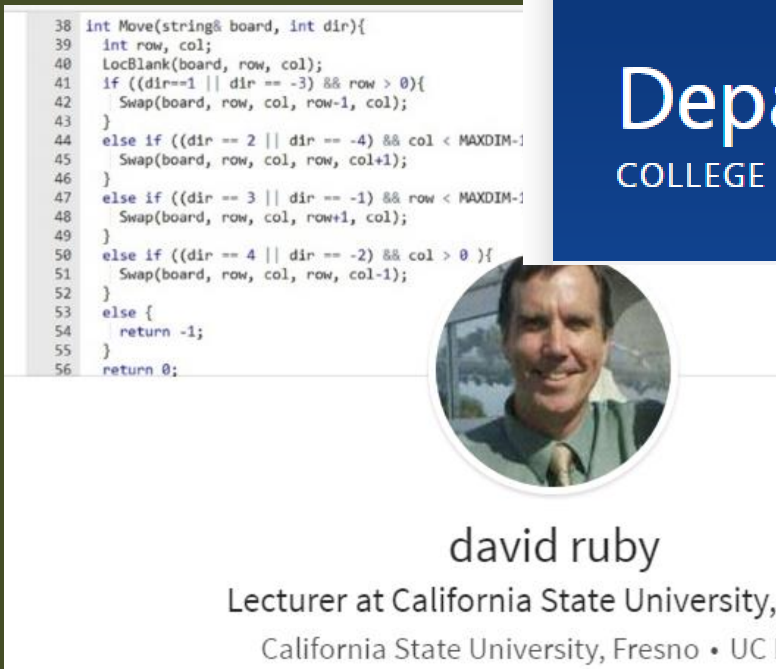
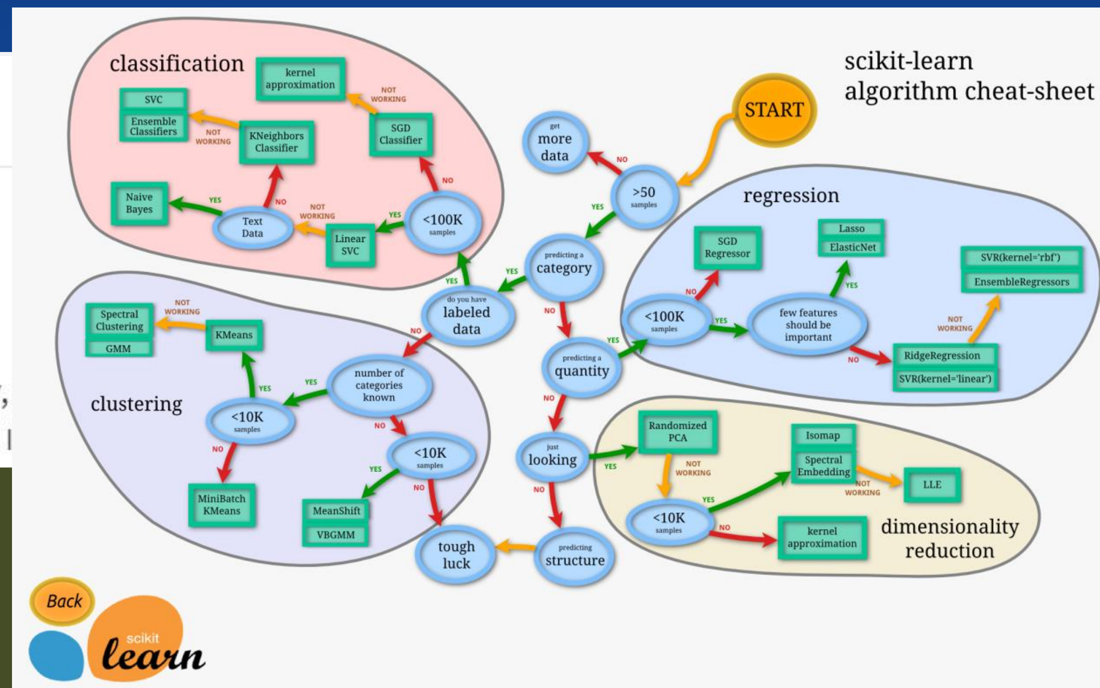
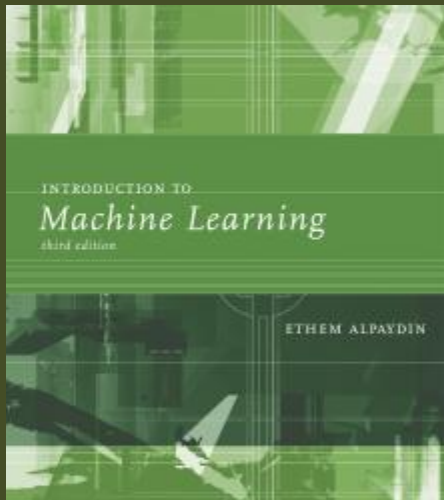




WELCOME:
MACHINE LEARNING

Spring, 2018



Primary Textbook:

INTRODUCTION TO MACHINE LEARNING

3RD EDITION

ETHEM ALPAYDIN

alpaydin@boun.edu.tr
http://www.cmpe.boun.edu.tr/~ethem/i2ml3e

Textbook Author: Ethem Alpaydin

Ethem ALPAYDIN

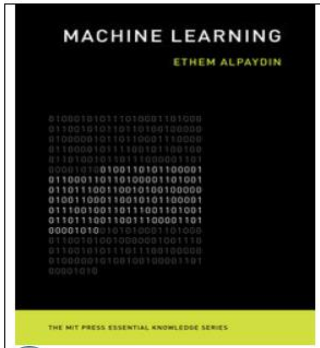
Türkçe

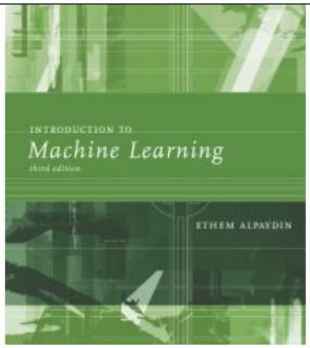
Professor in the
Department of Computer Engineering
Bogaziçi University

Member of The Science Academy, Turkey

Google Scholar, Semantic Scholar, DBLP, MS Academic Search, ACM Digital Library, Academia.edu, ResearchGate, LinkedIn.

Publications, Talks, Other Writing, Courses, Short Biography, Details





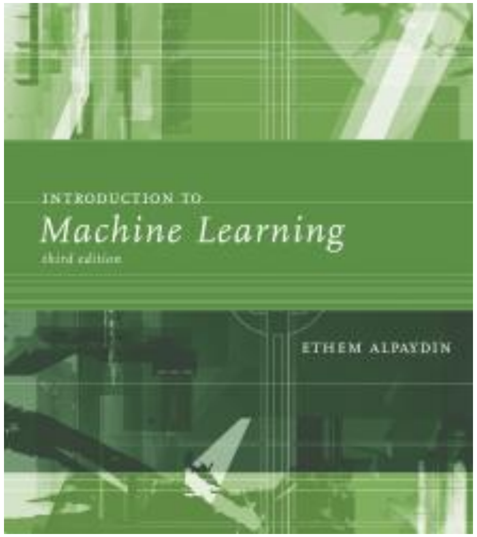
Ethem Alpaydin

+ Follow

Ethem ALPAYDIN is Professor in the Department of Computer Engineering, Bogazici University, Istanbul Turkey and is a member of the Science Academy, Istanbul. He received his PhD from the Ecole Polytechnique Fédérale de Lausanne, Switzerland in 1990 and was a postdoc at the International Computer Science Institute, Berkeley in 1991. He was a Fulbright scholar in 1997. He was a visiting researcher at MIT, USA in 1994, IDIAP, Switzerland in 1998 and TU Delft, The Netherlands in 2014

Textbook: Introduction To Machine Learning

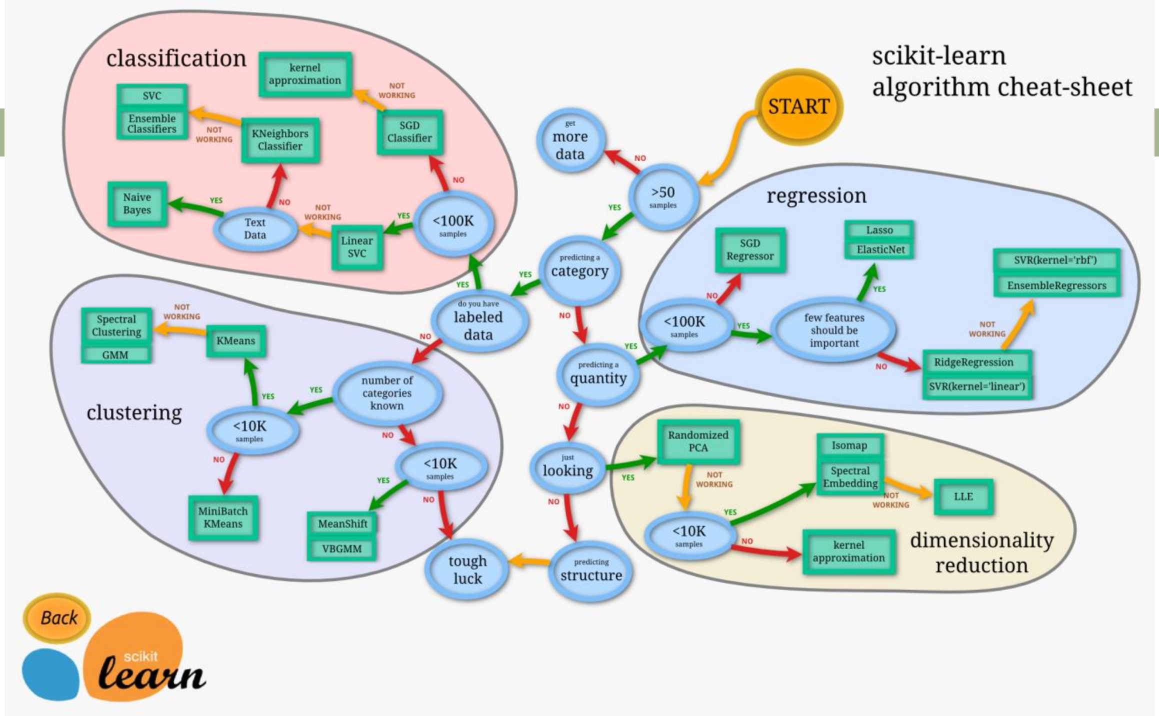
- Need an Academic Roadmap
  - What do Researchers in Field currently view component keys.
- Need References to Key Underlying Concepts
  - How are these key components derived.
- Need to avoid being swamped.
  - Too much technical details prevents progress.



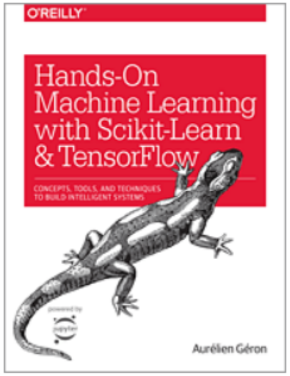
Machine Learning: Getting Going

- Theory alone is difficult to engage.
- New practioners need access routes.
- Gaining Intuition needs algorithm exploration.

Machine Learning Libraries



- Need to combine theory with practice.
- Will be using Scikit-Learn w/ Python
- Need Help Here…!



Hands-On Machine Learning with Scikit-Learn and TensorFlow

Concepts, Tools, and Techniques to Build Intelligent Systems

By Aurélien Géron

Publisher: O'Reilly Media
Release Date: March 2017
Pages: 576

Graphics in this book are printed in black and white.

Through a series of recent breakthroughs, deep learning has boosted the entire field of machine learning. Now, even programmers who know close to nothing about this technology can use simple, efficient tools to implement programs capable of learning from data. This practical book shows you how.

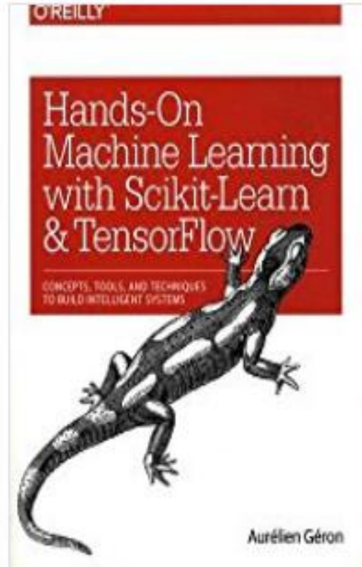
By using concrete examples, minimal theory, and two production-ready Python frameworks—scikit-learn and TensorFlow—author Aurélien Géron helps you gain an intuitive understanding of the concepts and tools for building intelligent systems. You'll learn a range of techniques, starting with simple linear regression and progressing to deep neural networks. With exercises in each chapter to help you apply what you've learned, all you need is programming experience to get started.

- Explore the machine learning landscape, particularly neural nets
- Use scikit-learn to track an example machine-learning project end-to-end
- Explore several training models, including support vector machines, decision trees, random forests, and ensemble methods
- Use the TensorFlow library to build and train neural nets
- Dive into neural net architectures, including convolutional nets, recurrent nets, and deep reinforcement learning
- Learn techniques for training and scaling deep neural nets
- Apply practical code examples without acquiring excessive machine learning theory or algorithm details

SECOND BOOK

Practical Handbook

Second Book: Author: Aurélien Geron



Aurélien Geron

ageron

Machine Learning consultant, former PM of YouTube video classification and founder & CTO of telco operator

Follow

Aurélien Géron

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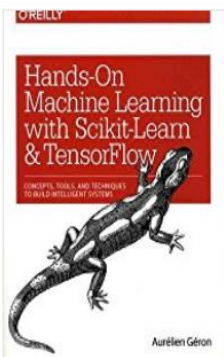

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Paperback

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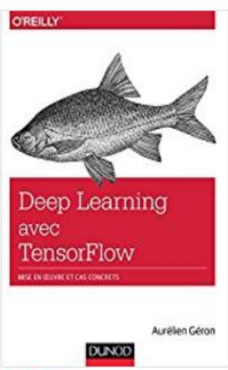

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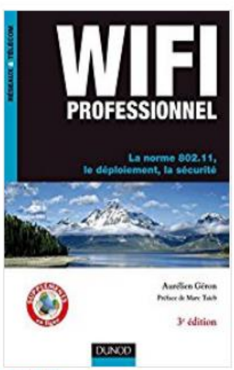

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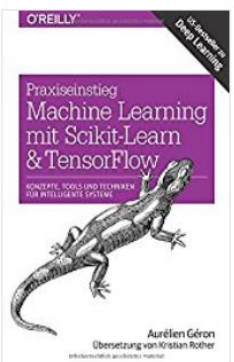


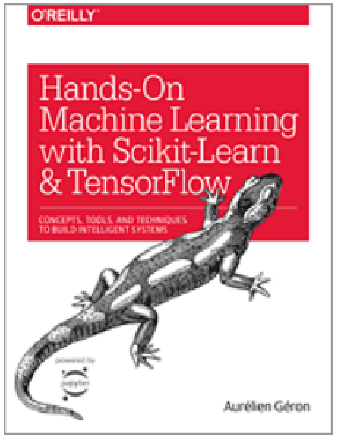
Paperback

Hands-On Machine Learning…

- We'll walk through second book along with theory material from Textbook.

Machine Learning Notebooks

This project aims at teaching you the fundamentals of Machine Learning in python. It contains the example code and solutions to the exercises in my O'Reilly book Hands-on Machine Learning with Scikit-Learn and TensorFlow:

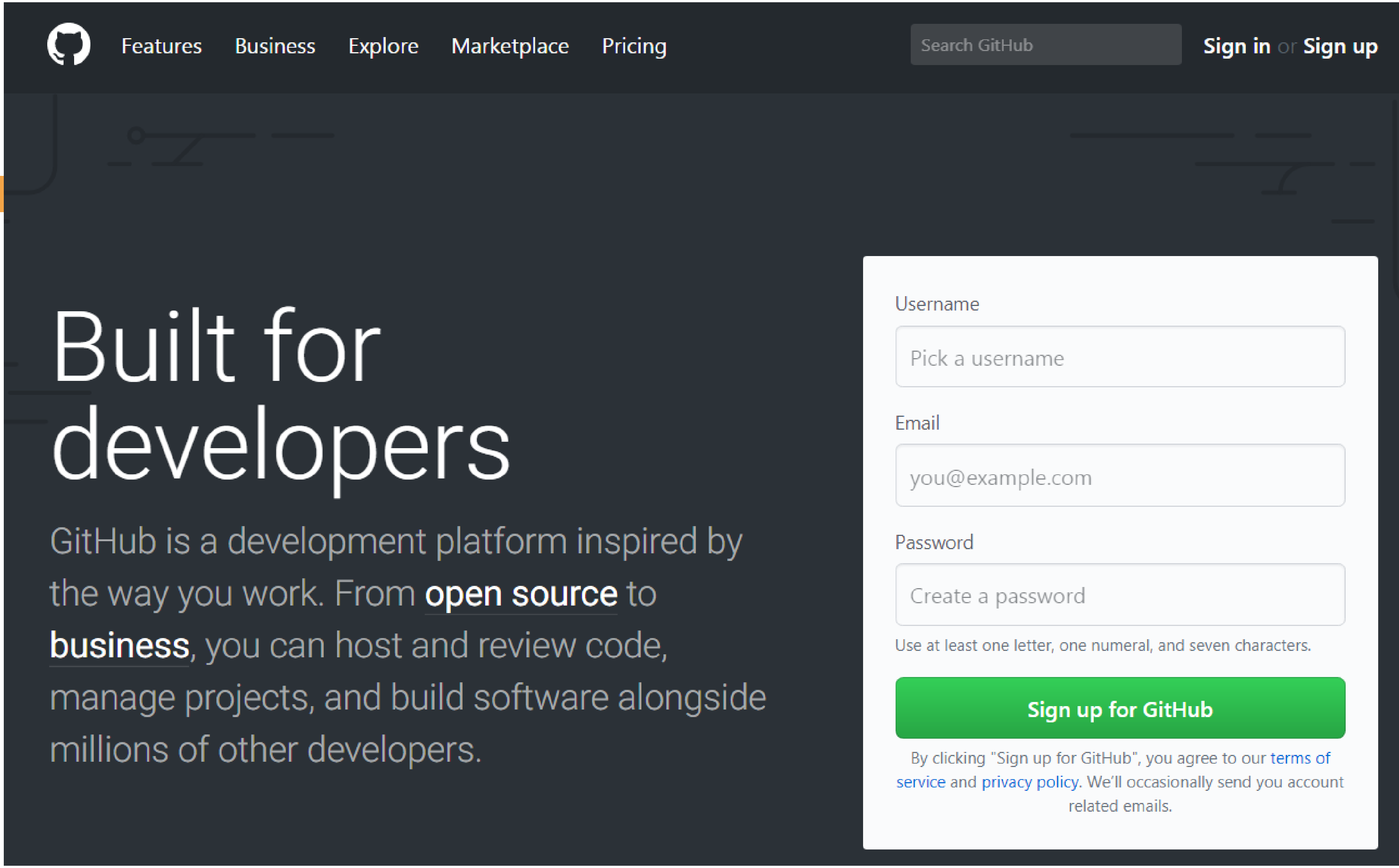


Simply open the Jupyter notebooks you are interested in:

- Using jupyter.org's notebook viewer
  - note: github.com's notebook viewer also works but it is slower and the math formulas are not displayed correctly,
- or by cloning this repository and running Jupyter locally. This option lets you play around with the code. In this case, follow the installation instructions below.

Machine Learning Practice

- Utilize Teams!
- Classes require computer
  - Computers used for quizzes and tests.
- Follow second book Python Configuration
- Explore Machine Learning with Python in Jupyter Notebooks on GitHub.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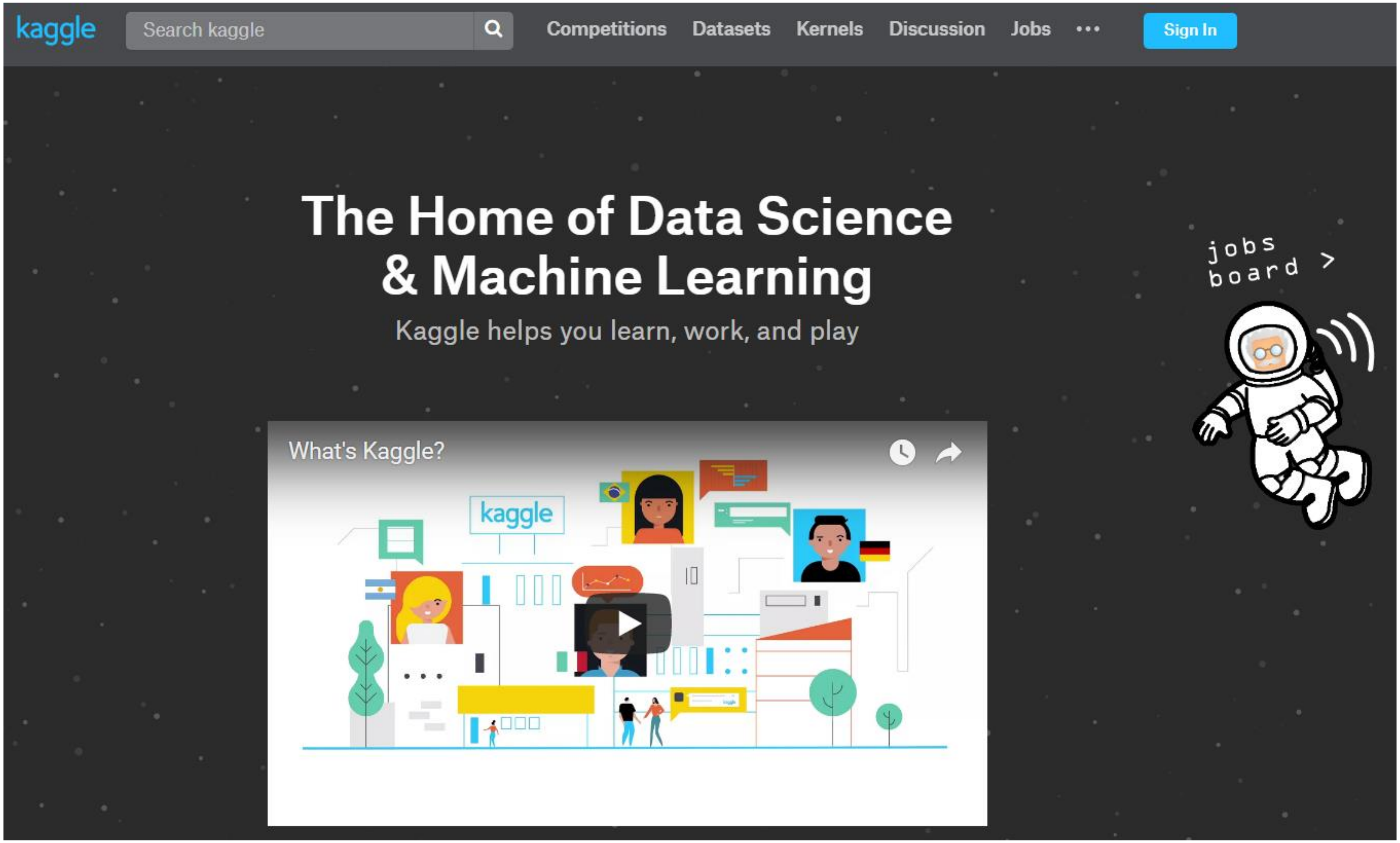
Pricing
Search GitHub
Sign in or Sign up
Built for developers
GitHub is a development platform inspired by the way you work. From open source to business, you can host and review code, manage projects, and build software alongside millions of other developers.
Username
Pick a username
Email
you@example.com
Password
Create a password
Use at least one letter, one numeral, and seven characters.
Sign up for GitHub
By clicking "Sign up for GitHub", you agree to our terms of service and privacy policy. We'll occasionally send you account related emails.

GitHub

- Everyone will use/create GitHub accounts.
- Teams will create Jupyter Notebooks to illustrate Machine Learning in Action.
- Datasets with Scikit Learn
- Datasets with Kaggle

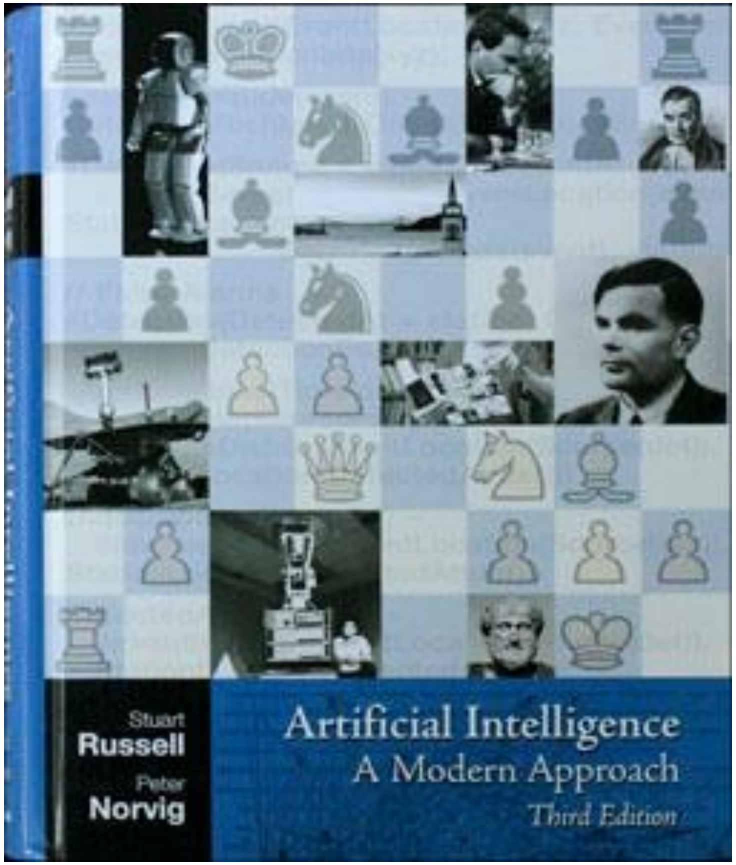
Kaggle

- Great resource for data science community



Additional Textbook:

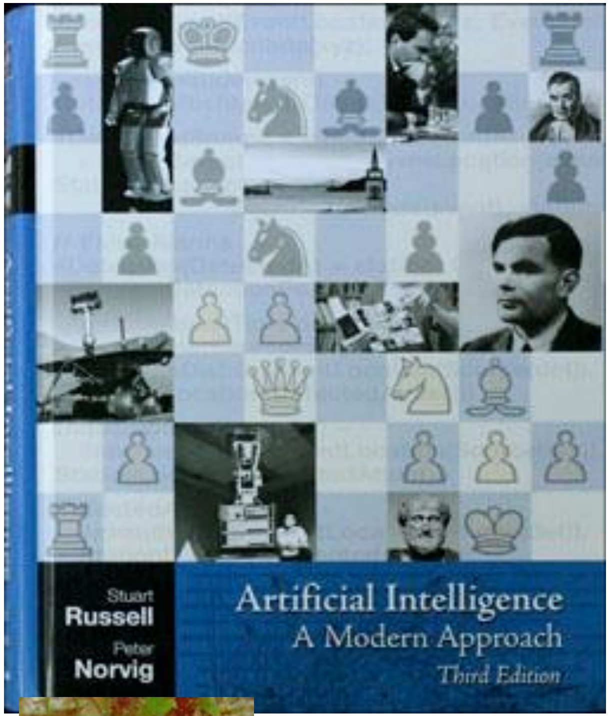
- Artificial Intelligence: A Modern Approach
  - Stuart Russell & Peter Norvig

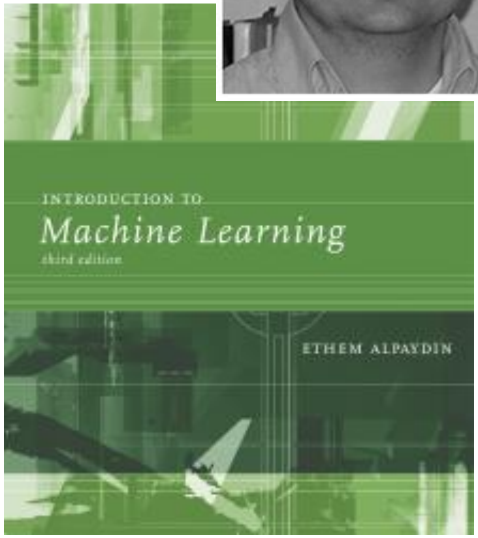


Artificial Intelligence: A Modern Approach

- Everyone should have a copy from 164
- Chapter 18: Machine Learning
- Chapter 20: Learning Probabilistic Models
- Chapter 21: Reinforcement Learning

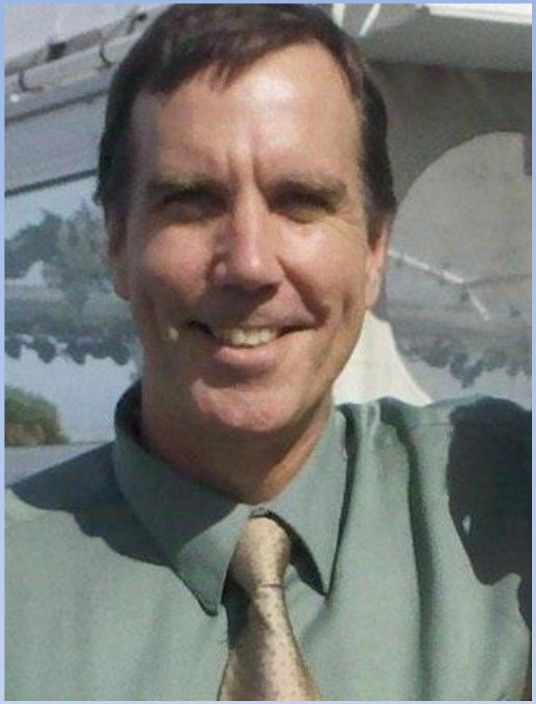
3 Sources --- 3 Perspectives





Grading:

- Particpation
  - Teams Formed
  - 1 team member must attend each class
  - Team reports in class
- Assignments
  - Juptyer Notebooks
  - Peer Reviews
- Quizzes
  - In Class – Computer Based
- Midterm
  - In Class – Computer Based
- Final
  - In Class – Computer Based



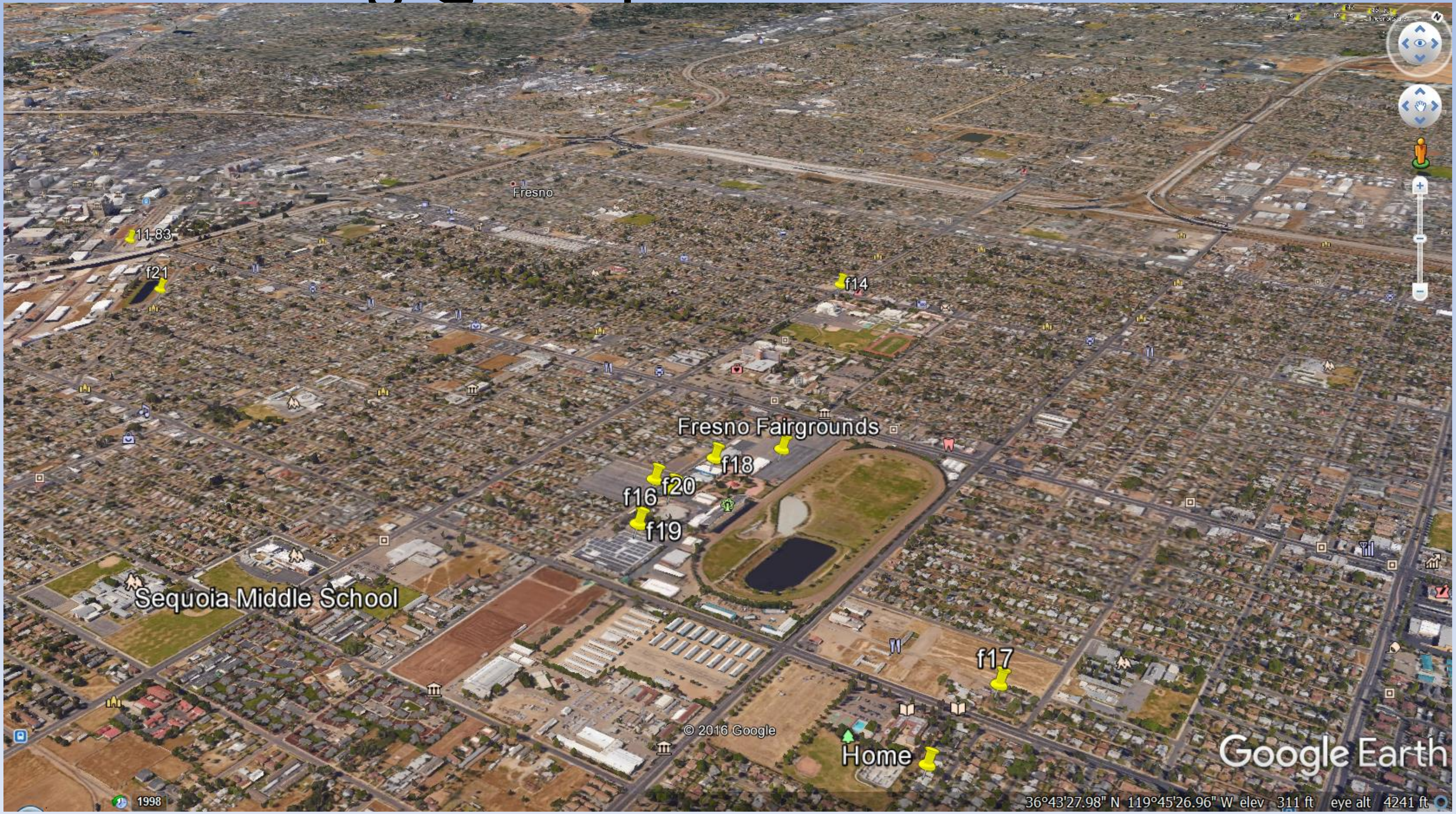
Class Instructor

- Office
  - Science II – 273
- Email:
  - druby@csufresno.edu

David Ruby

- First-Generation College Student
- How PhD?

Father Floyd Fresno Career Custodian Ending @ Sequoia Middle School

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Compute Science Focus: Jobs/Degrees

- Students want…
  - Jobs!
  - Advanced Degrees!!

- How???

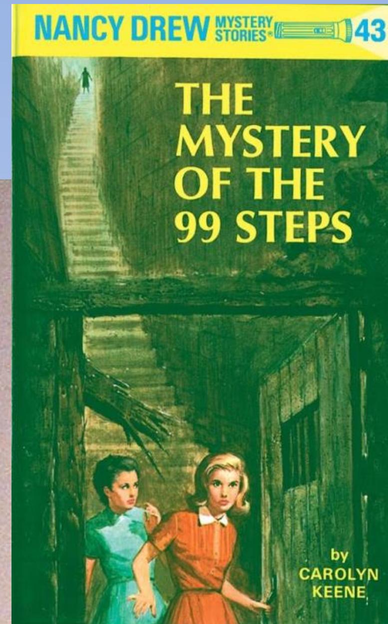
Dr. Joy Goto, Professor Biochemistry, Fresno State

- https://youtu.be/FXUiEPrK_II

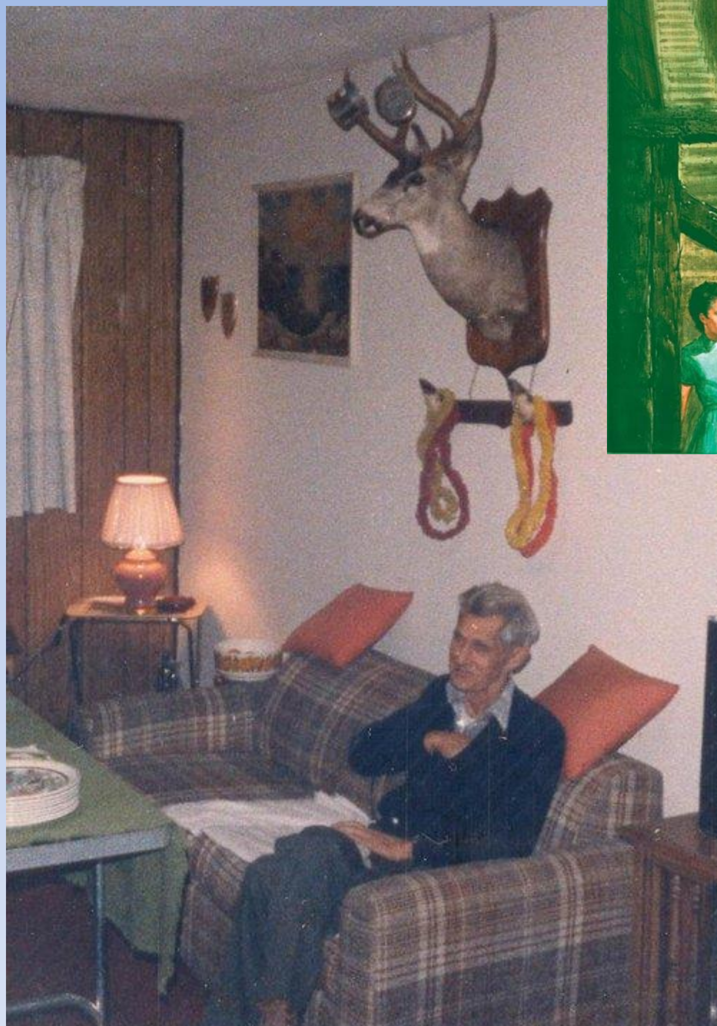
Dr. Joy Goto, Professor Biochemistry, Fresno State

- https://youtu.be/FXUiEPrK_II
- Engaging story of discovering joy in science growing up here in the central valley.

My Story



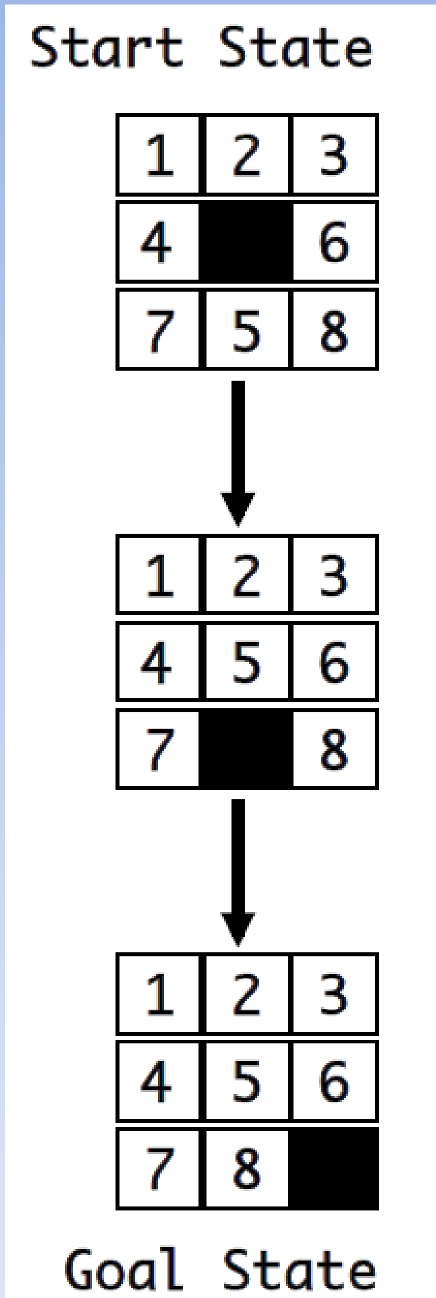
Interest
In
Puzzles



- Family Memories

Memories..
eXciting Puzzles !

- Home Hedges Maze Crawwwwwl !
- Also – First time w/ Sliding Tile Puzzle



Thesis: Tile-Sliding Puzzle

Artificial Intelligence

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1 contributor

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StepppingStone: An Empirical and Analytical Evaluation*

David Ruby and **Dennis Kibler**
Department of Information & Computer Science
University of California, Irvine
Irvine, CA 92717 U.S.A.
druby@ics.uci.edu

Abstract

Decomposing a difficult problem into simpler subproblems is a classic problem solving technique. Unfortunately, the most difficult subproblems can be as difficult, if not more difficult, than the original problem. This is not an obstacle to problem solving if the difficult subproblems recur in other problems. If the difficult subproblems recur often, then its solution need only be learned once and reused. SteppingStone is a learning problem solver that decomposes a problem into simple and difficult-but-recurring subproblems. It solves the

SteppingStone operates on problems defined with a state space representation consisting of a set of goals, a set of operators, and an initial state. The goal orderer takes as input a set of goals. It orders these goals so that the constrained search method will likely solve them. It does this by ordering them so as to reduce the likelihood of subgoal interactions using a domain independent heuristic we call *openness* [Ruby and Kibler, 1989]. It produces an ordered set of subgoals as output.

The constrained search component takes as input an

My Idea…

Memories are constructed.. Not stored complete!

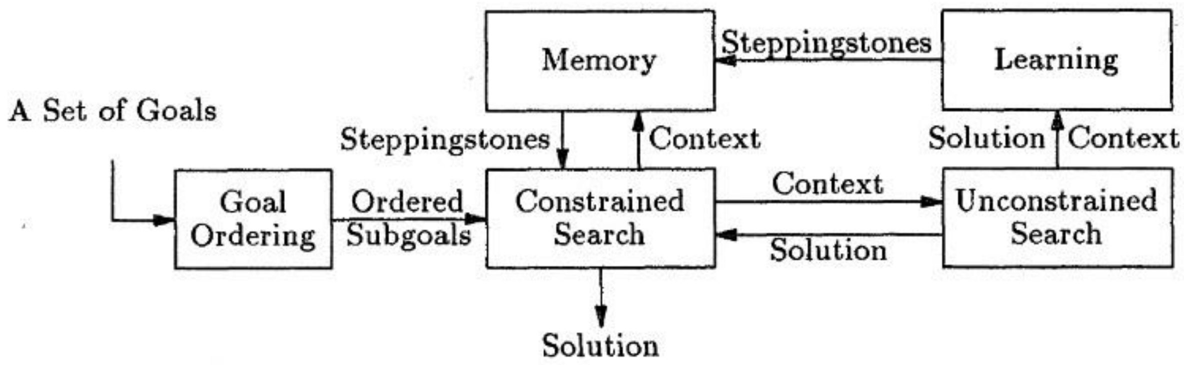


Figure 1: Overview of SteppingStone

the original impasse state.

When memory fails to return any useful steppingstones the constrained search component calls the unconstrained search component. The unconstrained search component takes as input a context, just as the memory component did. Unconstrained search relaxes the protection on the solved subgoals in its search for a solution. If it resolves the impasse, it returns the sequence of moves found to the constrained search component. The unconstrained search component also sends its impasse solution, along with the context, to the learner.

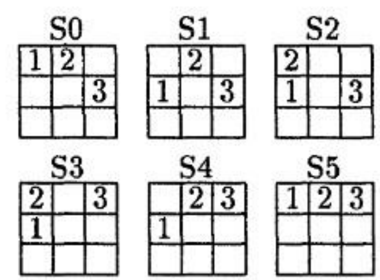
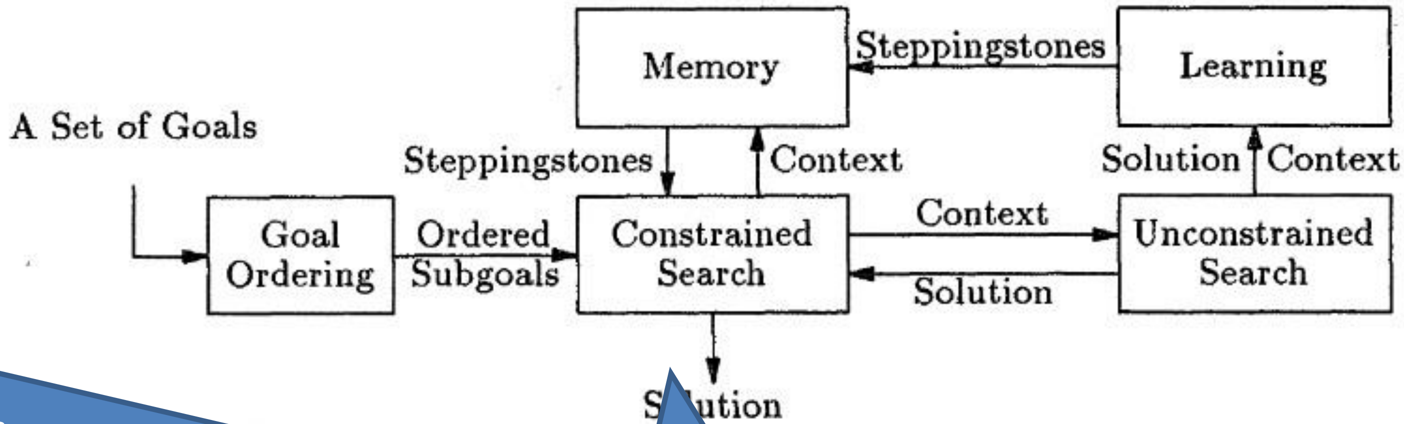


Figure 2: Steppingstones from Memory

Thesis: Tile Sliding Domain



1: Overv f SteppingStone

Memories have gaps!!!

When
stones the constra
constrained search compo
search component takes as input a con
memory component did. Unconstrained search re
the protection on the solved subgoals in its searc
a solution. If it resolves the impasse, it returns t
quence of moves found to the constrained search compo-
nent. The unconstrained search component also sends its impasse solution, along with the context, to the learner.

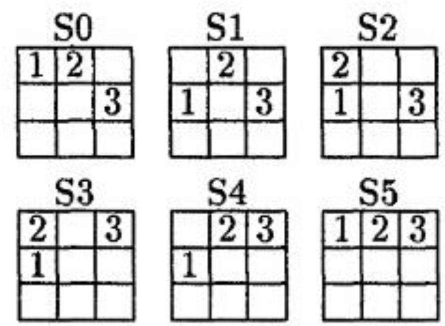
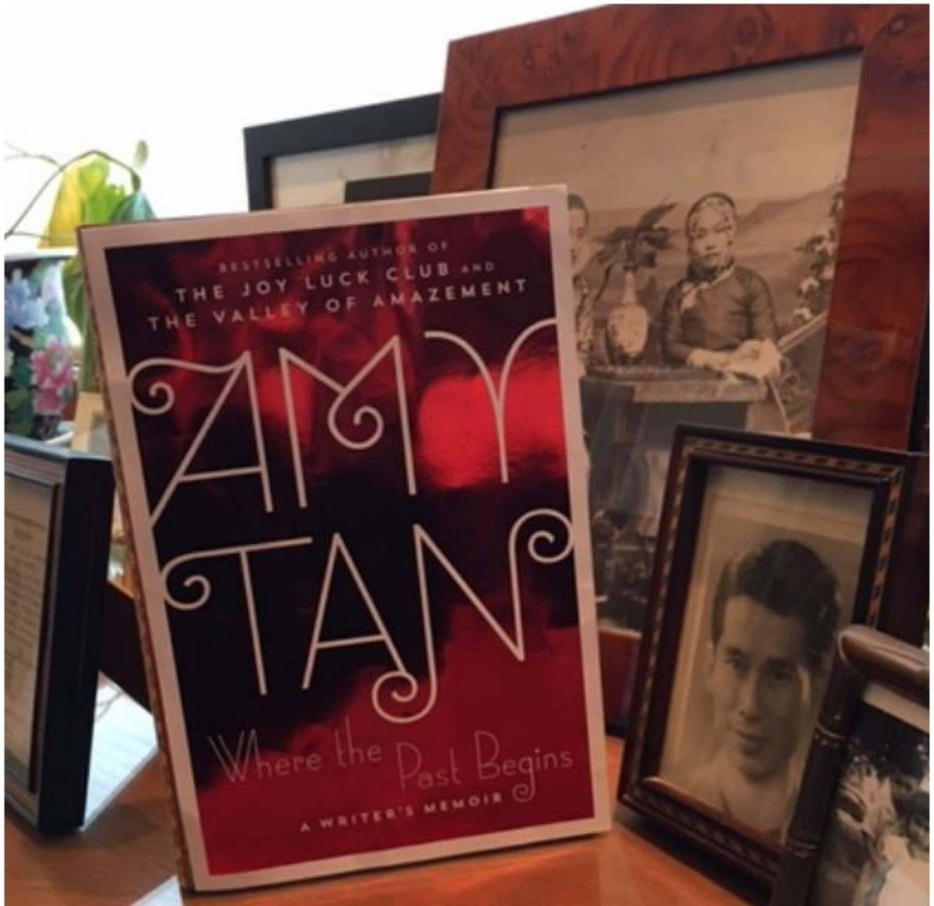
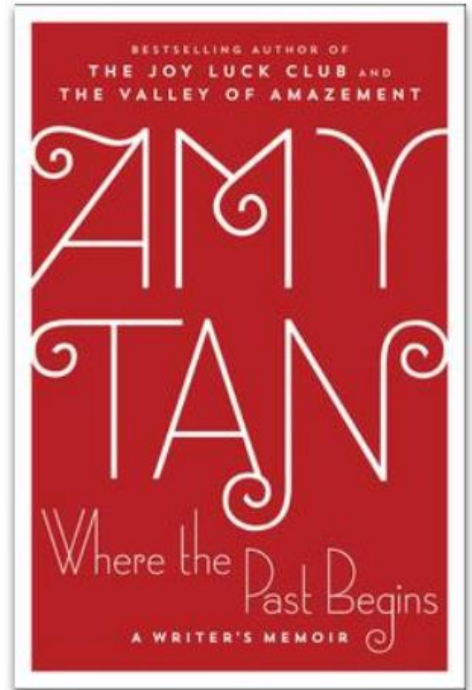


Figure 2: Steppingstones from Memory

Emotional Memory: Process of a Writer





coming

Oct 17, 2017

Pre-order

Malleable Memory (Gaps)
Learning & Memory w/ Elizabeth Loftus

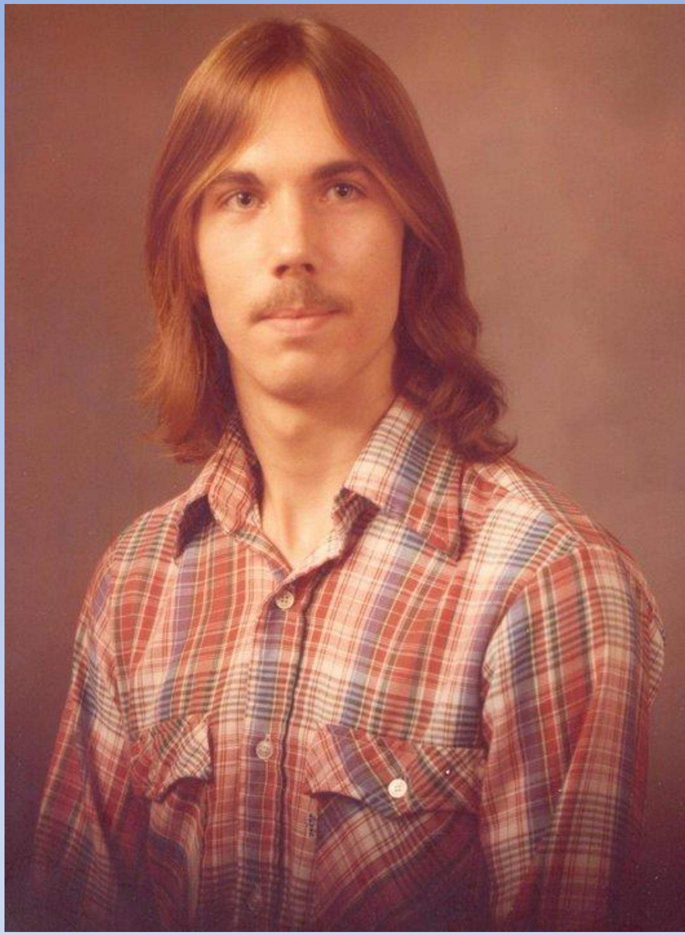

CORRUPTED MEMORY

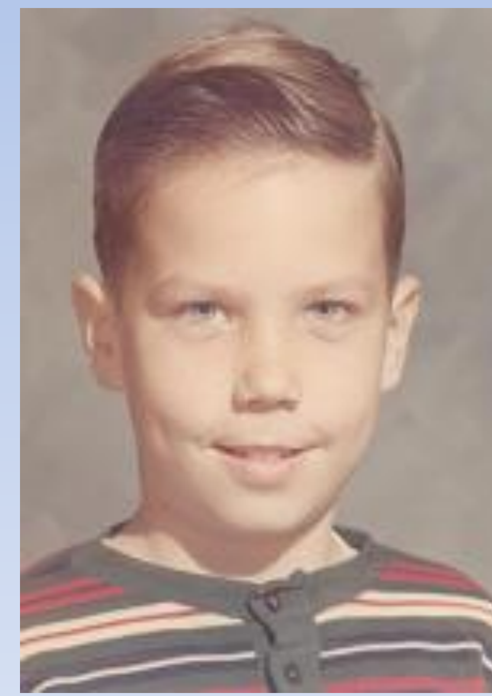
Elizabeth Loftus has spent decades exposing flaws in eyewitness testimony. Her ideas are gaining fresh traction in the US legal system.

BY MOHEB COSTANDI

Elizabeth Loftus is a cognitive psychologist at the University of California Irvine.

eXciting Mazes Memories!





- ME:
  - Do you remember the FUN maze?
- NEIGHBOR:
  - Do YOU remember this other HORRIBLE thing??
- ME:
  - Hmmm .. I guess not.
- Language influencing memory ??

Memories & Learning

JOURNAL OF VERBAL LEARNING AND VERBAL BEHAVIOR 13, 585–589 (1974)

Reconstruction of Automobile Destruction: An Example of the Interaction Between Language and Memory'

ELIZABETH F. LOFTUS AND JOHN C. PALMER

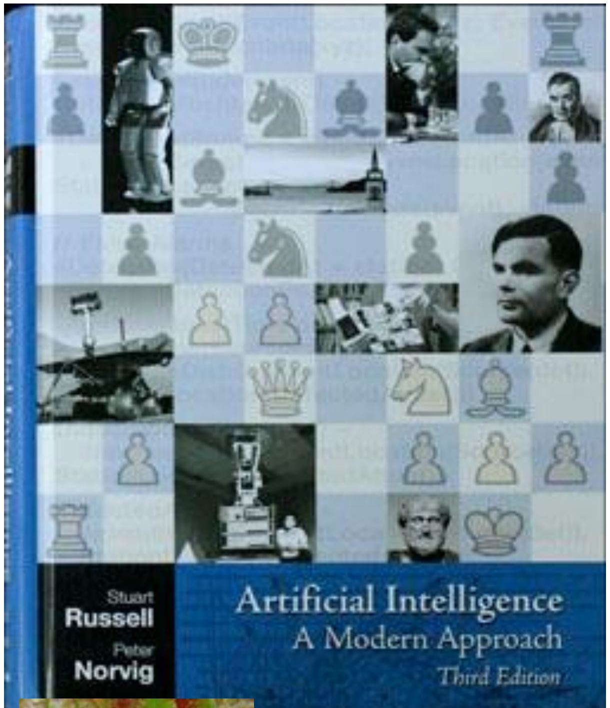
University of Washington

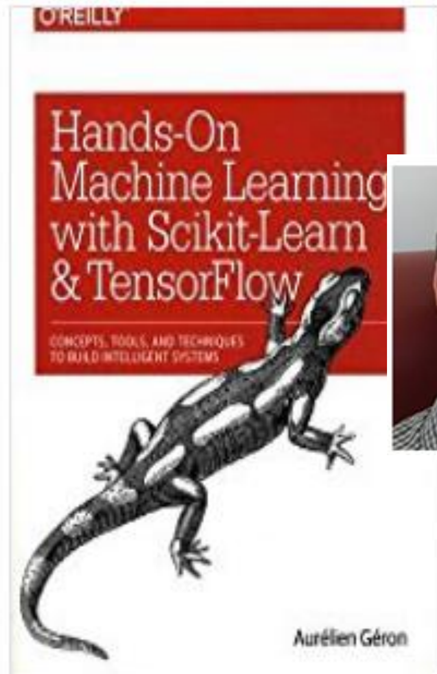
Two experiments are reported in which subjects viewed films of automobile accidents and then answered questions about events occurring in the films. The question, "About how fast were the cars going when they smashed into each other?" elicited higher estimates of speed than questions which used the verbs ***collided***, ***bumped***, ***contucted***, or ***hit*** in place of ***smashed***. On a retest one week later, those subjects who received the verb ***smashed*** were more likely to say "yes" to the question, "Did you see any broken glass?", even though broken glass was not present in the film. These results are consistent with the view that the questions asked subsequent to an event can cause a reconstruction in one's memory of that event.

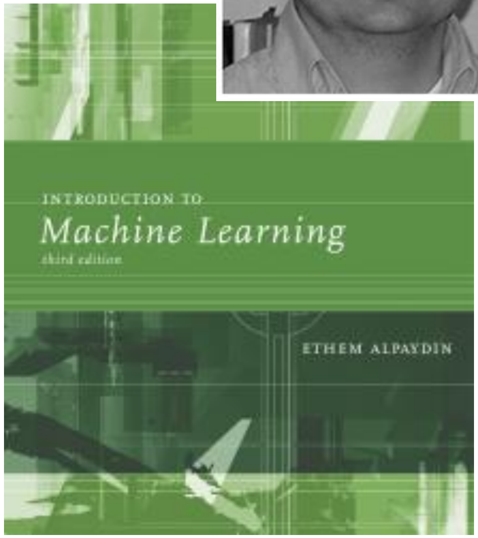
Computer Science / Memories

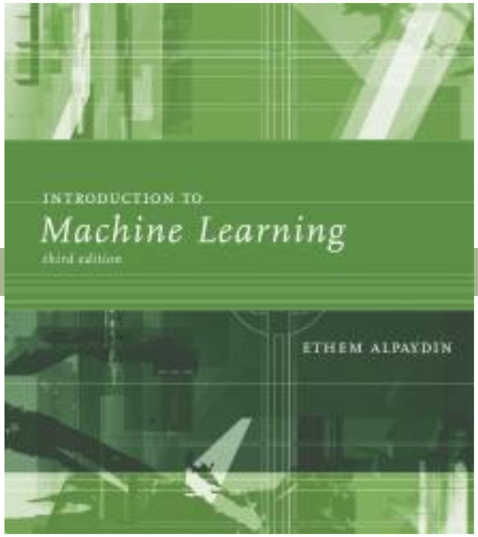
- Puzzles
- Abstractions
- Memories

3 Sources --- 3 Perspectives
Chapter Outlines





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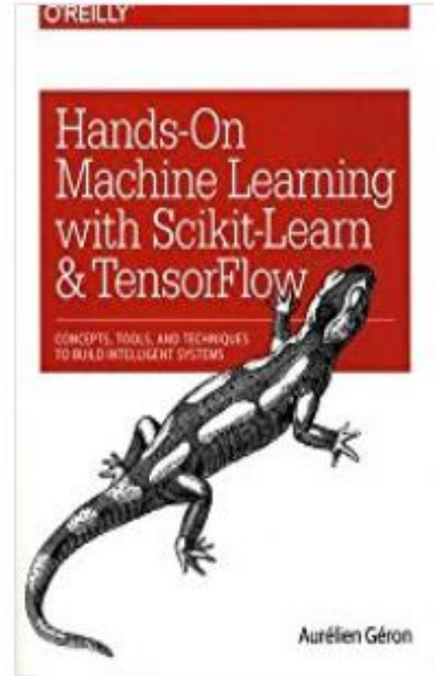
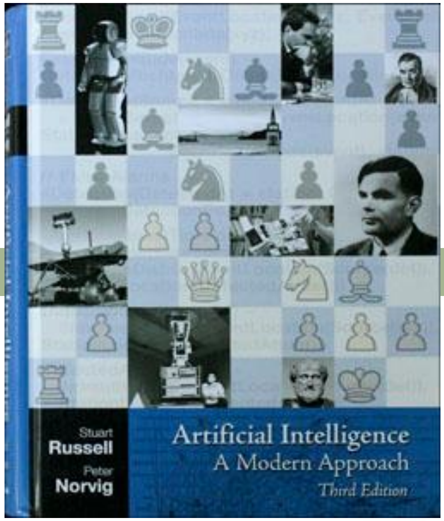
ETHEM ALPAYDIN

1. The Machine Learning Landscape

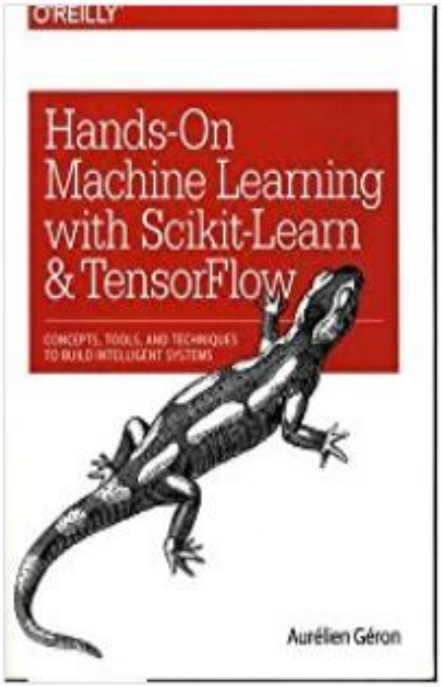
- What Is Machine Learning?
- Why Use Machine Learning?
- Types of Machine Learning Systems
  - Supervised/Unsupervised Learning
  - Batch and Online Learning
  - Instance-Based Versus Model-Based Learning
- Main Challenges of Machine Learning
  - Insufficient Quantity of Training Data
  - Nonrepresentative Training Data
  - Poor-Quality Data
  - Irrelevant Features
  - Overfitting the Training Data
  - Underfitting the Training Data
  - Stepping Back
- Testing and Validating
- Exercises

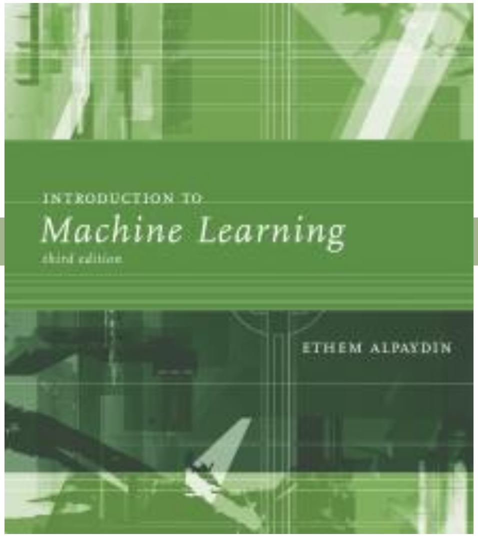



Stuart
Russell
Peter
Norvig
Artificial Intelligence
A Modern Approach
Third Edition

2. End-to-End Machine Learning Project

- Working with Real Data
- Look at the Big Picture
    - Frame the Problem
    - Select a Performance Measure
    - Check the Assumptions
- Get the Data
    - Create the Workspace
    - Download the Data
    - Take a Quick Look at the Data Structure
    - Create a Test Set
- Discover and Visualize the Data to Gain Insights
    - Visualizing Geographical Data
    - Looking for Correlations
    - Experimenting with Attribute Combinations
- Prepare the Data for Machine Learning Algorithms
    - Data Cleaning
    - Handling Text and Categorical Attributes
    - Custom Transformers
    - Feature Scaling
    - Transformation Pipelines

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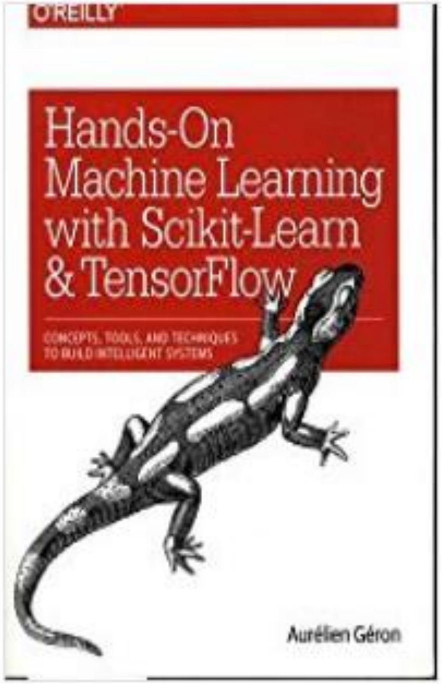
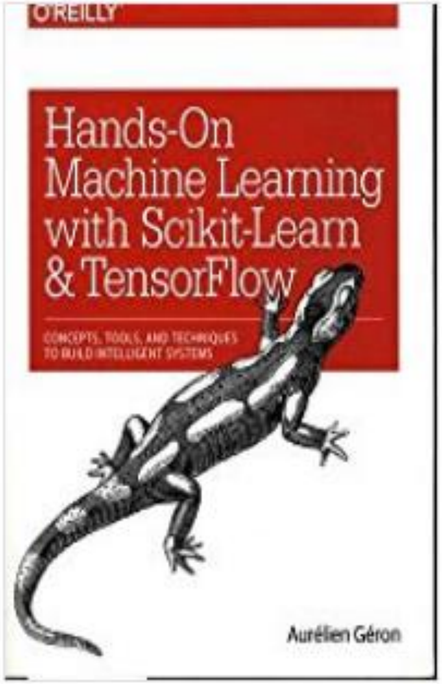
3. Classification

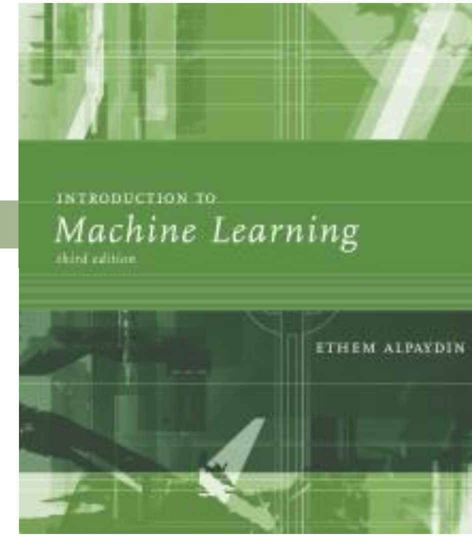
- MNIST
- Training a Binary Classifier
- Performance Measures
  - Measuring Accuracy Using Cross-Validation
  - Confusion Matrix
  - Precision and Recall
  - Precision/Recall Tradeoff
  - The ROC Curve
- Multiclass Classification
- Error Analysis
- Multilabel Classification
- Multioutput Classification
- Exercises



4. Training Models

- Linear Regression
  - The Normal Equation
  - Computational Complexity
- Gradient Descent
  - Batch Gradient Descent
  - Stochastic Gradient Descent
  - Mini-batch Gradient Descent
- Polynomial Regression
- Learning Curves
- Regularized Linear Models
  - Ridge Regression
  - Lasso Regression
  - Elastic Net
  - Early Stopping
- Logistic Regression
  - Estimating Probabilities
  - Training and Cost Function





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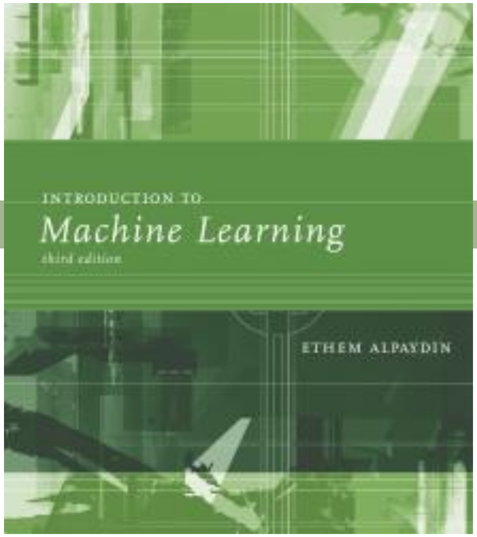
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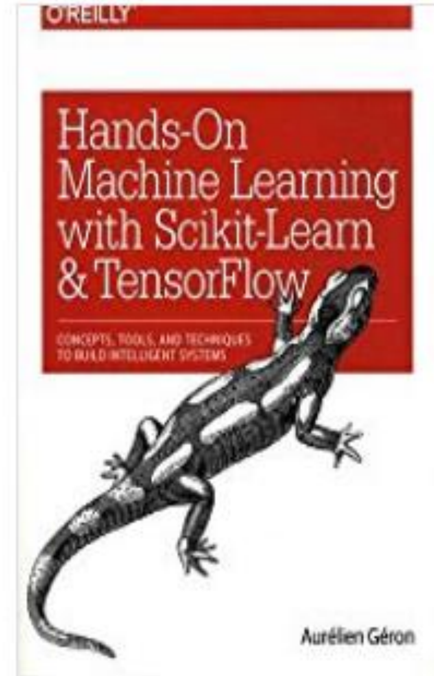


Chapter 6. Decision Trees

Like SVMs, *Decision Trees* are versatile Machine Learning algorithms that can perform both classification and regression tasks, and even multioutput tasks. They are very powerful algorithms, capable of fitting complex datasets. For example, in Chapter 2 you trained a `DecisionTreeRegressor` model on the California housing dataset, fitting it perfectly (actually overfitting it).

Decision Trees are also the fundamental components of Random Forests (see Chapter 7), which are among the most powerful Machine Learning algorithms available today.

In this chapter we will start by discussing how to train, visualize, and make predictions with Decision Trees. Then we will go through the CART training algorithm used by Scikit-Learn, and we will discuss how to regularize trees and use them for regression tasks. Finally, we will discuss some of the limitations of Decision Trees.

Titanic

Getting Started Prediction Competition

Titanic: Machine Learning from Disaster

Start here! Predict survival on the Titanic and get familiar with ML basics

Kaggle · 9,693 teams · 2 years to go

Overview Data Kernels Discussion Leaderboard Rules Team My Submissions **Submit Predictions**

Overview

- Description
- Evaluation
- Frequently Asked Questions
- Tutorials

Start here if...

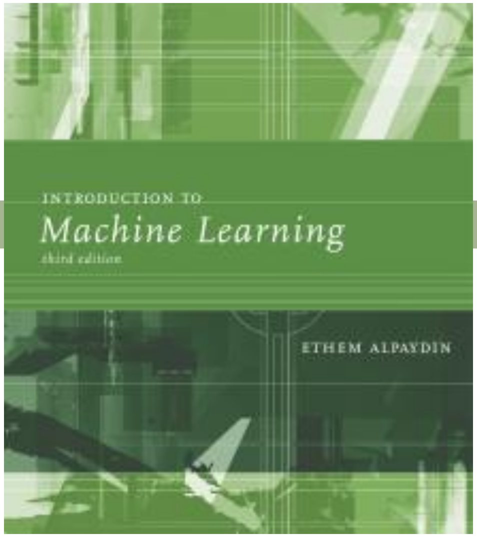
You're new to data science and machine learning, or looking for a simple intro to the Kaggle prediction competitions.

Competition Description

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

Midterm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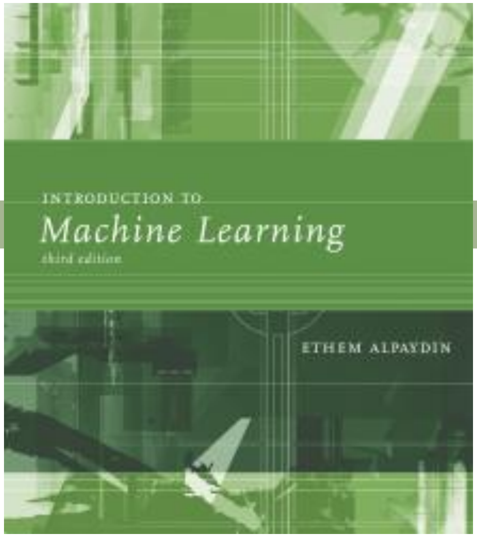
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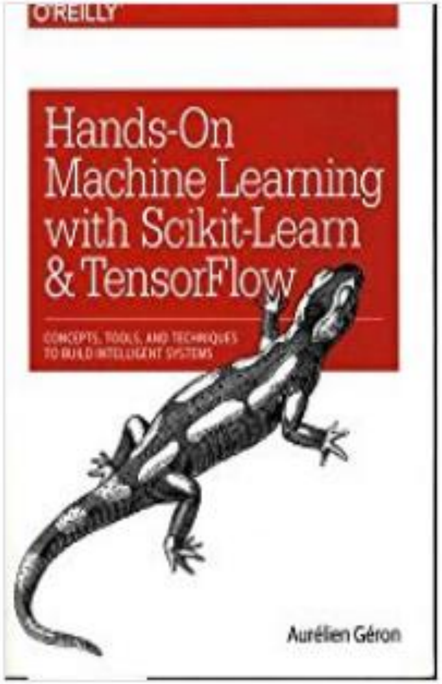
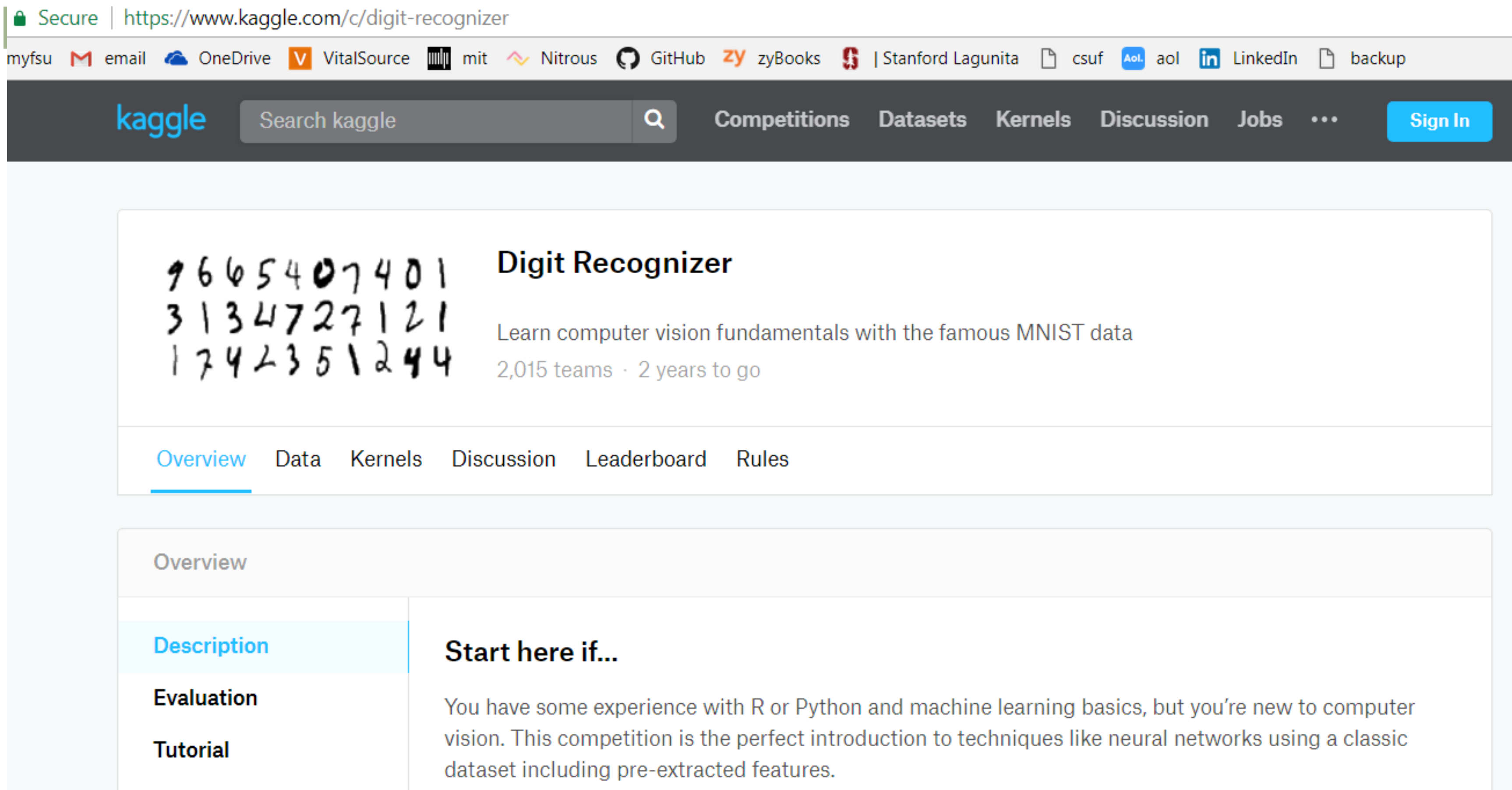
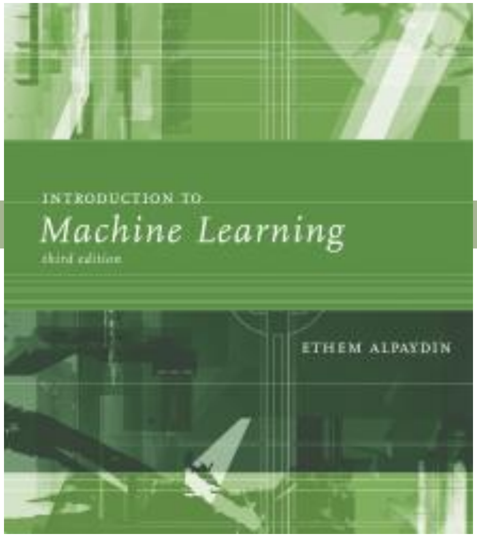


Chapter 8. Dimensionality Reduction

Many Machine Learning problems involve thousands or even millions of features for each training instance. Not only does this make training extremely slow, it can also make it much harder to find a good solution, as we will see. This problem is often referred to as the *curse of dimensionality*.

Kaggle MNIST

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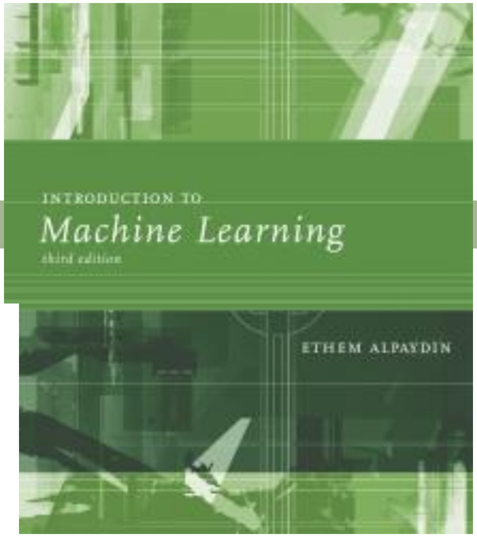
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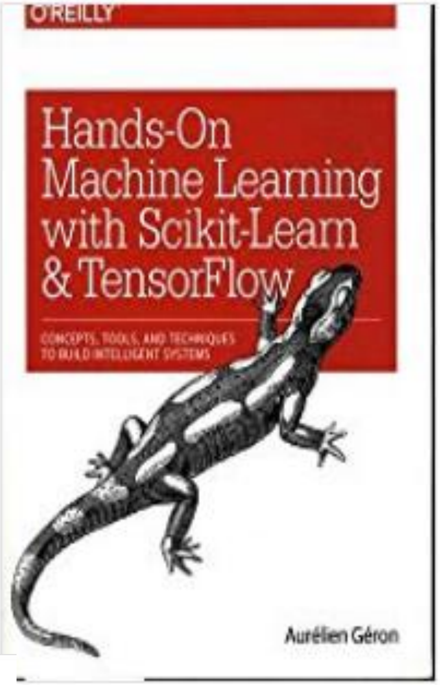
Geron, Chapter 5
R&N, Chapter 18



Chapter 5. Support Vector Machines

A *Support Vector Machine* (SVM) is a very powerful and versatile Machine Learning model, capable of performing linear or nonlinear classification, regression, and even outlier detection. It is one of the most popula models in Machine Learning, and anyone interested in Machine Learning should have it in their toolbox. SVM are particularly well suited for classification of complex but small- or medium-sized datasets.

This chapter will explain the core concepts of SVMs, how to use them, and how they work.

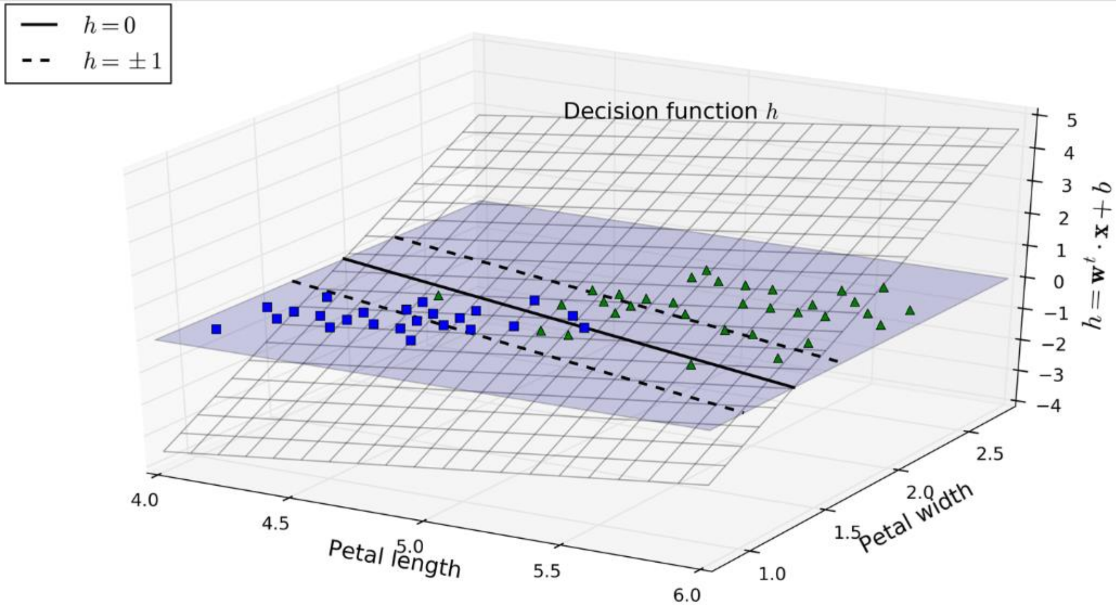
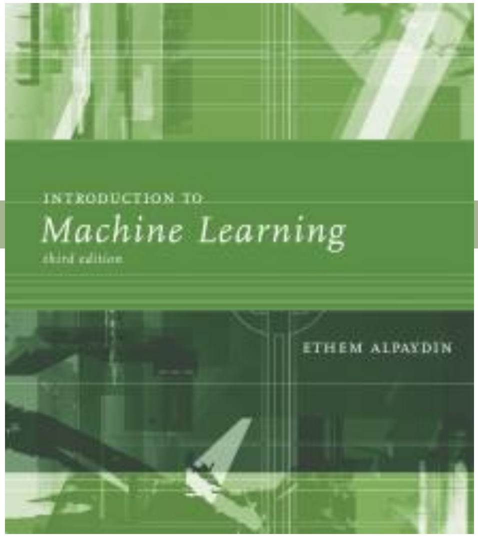
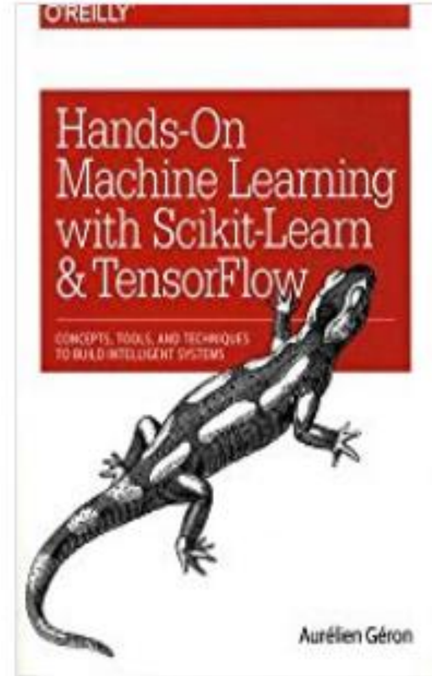


Figure 5-12. Decision function for the iris dataset

Alpaydin, Chapter 11
Neural Nets

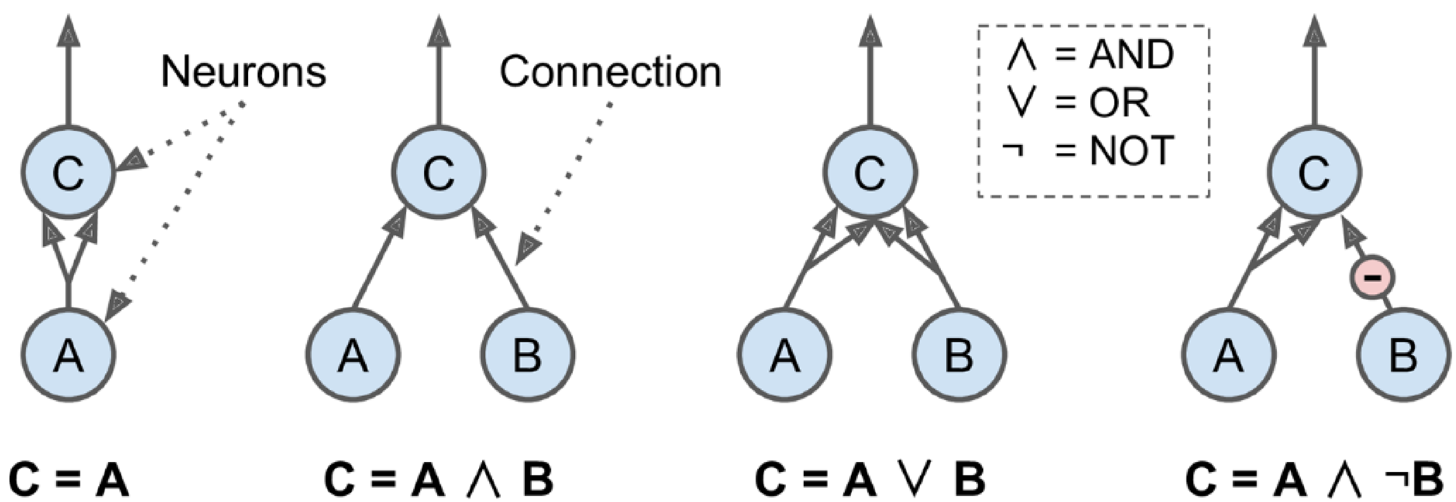


Geron, Chapter 10
R&N, Chapter 18

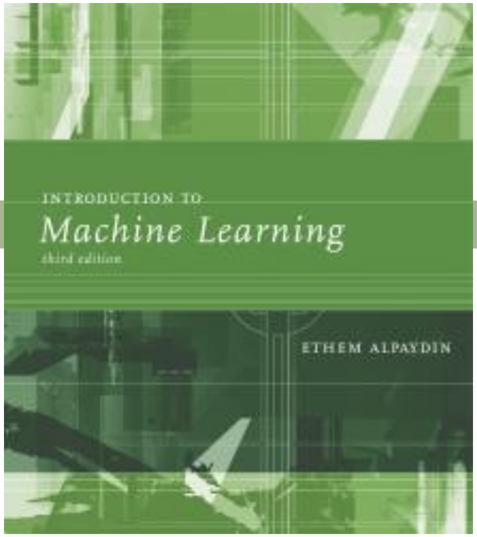


Chapter 10. Introduction to Artificial Neural Networks

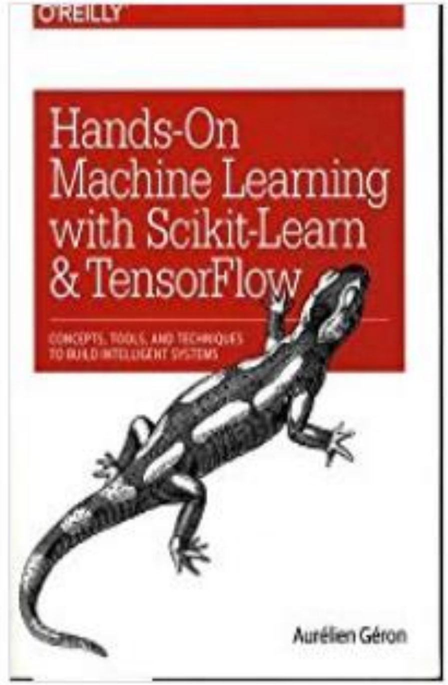
Birds inspired us to fly, burdock plants inspired velcro, and nature has inspired many other inventions. It seems only logical, then, to look at the brain's architecture for inspiration on how to build an intelligent machine. This is the key idea that inspired *artificial neural networks* (ANNs). However, although planes were inspired by birds, they don't have to flap their wings. Similarly, ANNs have gradually become quite different from their biological cousins. Some researchers even argue that we should drop the biological analogy altogether (e.g., by saying "units" rather than "neurons"), lest we restrict our creativity to biologically plausible systems. [1]



Alpaydin, Chapter 11
Neural Nets



Geron, Chapter 7
R&N, Chapter 18



Chapter 7. Ensemble Learning and Random Forests

Suppose you ask a complex question to thousands of random people, then aggregate their answers. In many cases you will find that this aggregated answer is better than an expert's answer. This is called the *wisdom of the crowd*. Similarly, if you aggregate the predictions of a group of predictors (such as classifiers or regressors), you will often get better predictions than with the best individual predictor. A group of predictors is called an *ensemble*; thus, this technique is called *Ensemble Learning*, and an Ensemble Learning algorithm is called an *Ensemble method*.

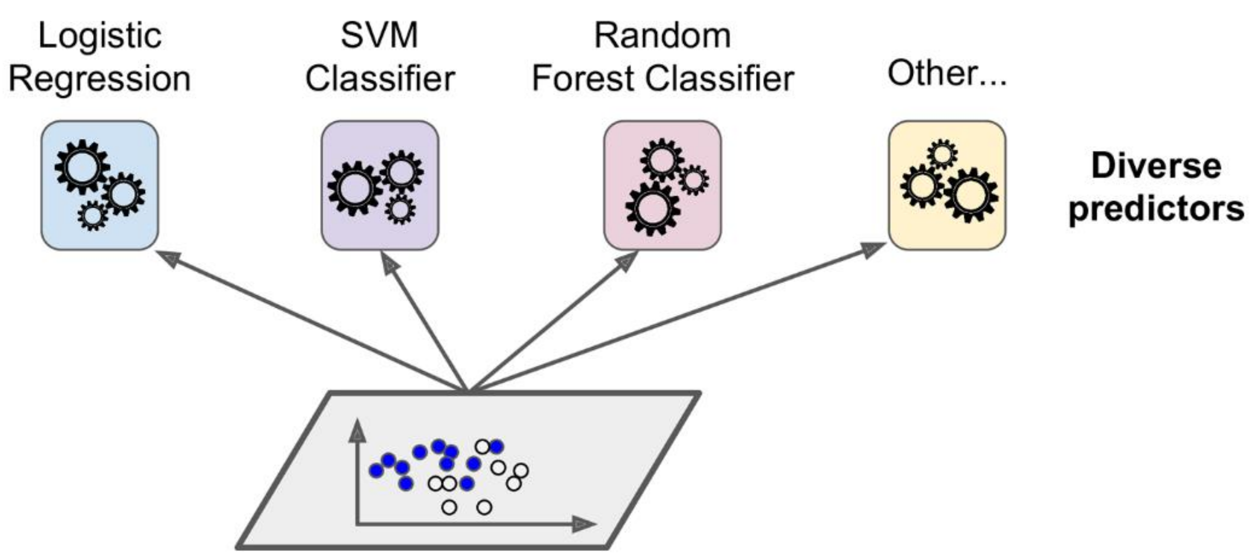


Figure 7-1. Training diverse classifiers

Final