Welcome to Data Bootcamp

Joseph Adler, Drew Conway, Jake Hofman, Hilary Mason

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Speakers

@jadler, @hmason, @drewconway, @jakehofman

Joseph Adler

LinkedIn

Joseph Adler has many years of experience in data mining and data analysis at companies including DoubleClick, American Express, and VeriSign. He graduated from MIT with an B.Sc. and M.Eng in Computer Science and Electrical Engineering. He is the inventor of several patents for computer security and cryptography, and the author of "Baseball Hacks" and "R in a Nutshell". Currently, he is a senior data scientist at LinkedIn.

Hilary Mason

bit.ly

Hilary is the lead scientist at bit.ly, where she is finding sense in vast data sets. She is a former computer science professor with a background in machine learning and data mining, has published numerous academic papers, and regularly releases code on her personal site, www.hilarymason.com. She has discovered two new species, loves to bake cookies, and asks way too many questions.

► Web site

Drew Conway

New York University

Drew Conway is a PhD student in political science at New York University. Drew studies terrorism and armed conflict; using tools from mathematics and computer science to gain a deeper understanding of these phenomena.

► Web site

Jake Hofman

Yahoo!

Jake Hofman is a member of the Human Social Dynamics group at Yahoo! Research. His work involves data-driven modeling of social data, focusing on applications of machine learning and statistical inference to large-scale data. He holds a B.S. in Electrical Engineering from Boston University and a Ph.D. in Physics from Columbia University.

Please *do* try this at home

All of the materials from today's tutorial are available on Github:

Clone the repository for data/code/slides

```
git clone https://github.com/drewconway/strata_bootcamp
```

Hacking

- Scripting: Python, Ruby, Perl, bash, ...
- Computing: R, SciPy/NumPy, MATLAB, ...
- Wrangling: sed, awk, grep, tr, wc, cut, sort, uniq, ...

```
$ tr , '\t' < data.csv > data.tsv
```

```
$ bzcat data.tsv.bz2 | awk -F'\t' 'NF != 16 {print}'
```

```
$ sed -e 's/<[^>]*>//g' < page.html > page.txt
```

Data-dependent products

Not Interested

Our best guess for Jake: **5 stars**

Average of 4,275,920 ratings: **3.8 stars**

The Big Lebowski

1998 R 117 minutes

Slacker Jeff "The Dude" Lebowski (Jeff Bridges) gets involved in a gargantuan mess of events when he's mistaken for another man named Lebowski, whose wife has been kidnapped and is being held for ransom. All the while, Dude's friend, Walter (John Goodman), stirs the pot. Brothers Joel Coen and Ethan Coen write and direct this cult comedy classic that also stars Steve Buscemi, Philip Seymour Hoffman, Julianne Moore and John Turturro.

Cast: Jeff Bridges, John Goodman, Philip Seymour Hoffman, Steve Buscemi, Julianne Moore, Tara Reid, Peter Stormare, David Huddleston, Philip Moon, Mark Pellegrino, Flea, Torsten Voges, Jimmie Dale Gilmore, Jack Kehler, John Turturro, James G. Hoosier, Richard Gant, Christian Clemenson, David Thewlis, Peter Siragusa, Sam Elliott, Ben Gazzara, Jon Polito, Asia Carrera, Paris Themmen

Director: Joel Coen

Genres: Comedy, Cult Comedies, Universal Studios Home Entertainment, Blu-ray

This movie is: Quirky, Witty

Format: DVD and streaming (Blu-ray availability date unknown) (HD available)

Play

Add to Instant Queue

Add to DVD Queue

Play Trailer

Recommended based on your interest in: Fargo, O Brother, Where Art Thou? and No Country for Old Men

Data-dependent products

- Effective/practical systems that learn from experience impact our daily lives, e.g.:
  - Recommendation systems
  - Spam detection
  - Optical character recognition
  - Face recognition
  - Fraud detection
  - Machine translation
  - ...

Black[1]-boxified?

Google code labs e.g. "ajax apis" or "open source" Search

Watch Google I/O keynotes live on May 19 and 20!

Google Prediction API (Labs) Home Docs FAQ Forum Terms

What is the Google Prediction API?

The Prediction API enables access to Google's machine learning algorithms to analyze your historic data and predict likely future outcomes. Upload your data to Google Storage for Developers, then use the Prediction API to make real-time decisions in your applications. The Prediction API implements supervised learning algorithms as a RESTful web service to let you leverage patterns in your data, providing more relevant information to your users. Run your predictions on Google's infrastructure and scale effortlessly as your data grows in size and complexity.

How do I start?

- Learn more about Google Prediction API.
- Request access.
- Try out the sample code.

Features

- Lightweight RESTful API
- Asynchronous training
- Automatically selects from several available machine learning techniques
- Supported inputs: numeric data or unstructured text
- Outputs hundreds of discrete categories
- Accessible from many platforms: Google App Engine, Apps Script (Google Spreadsheets), web & desktop apps, and command line

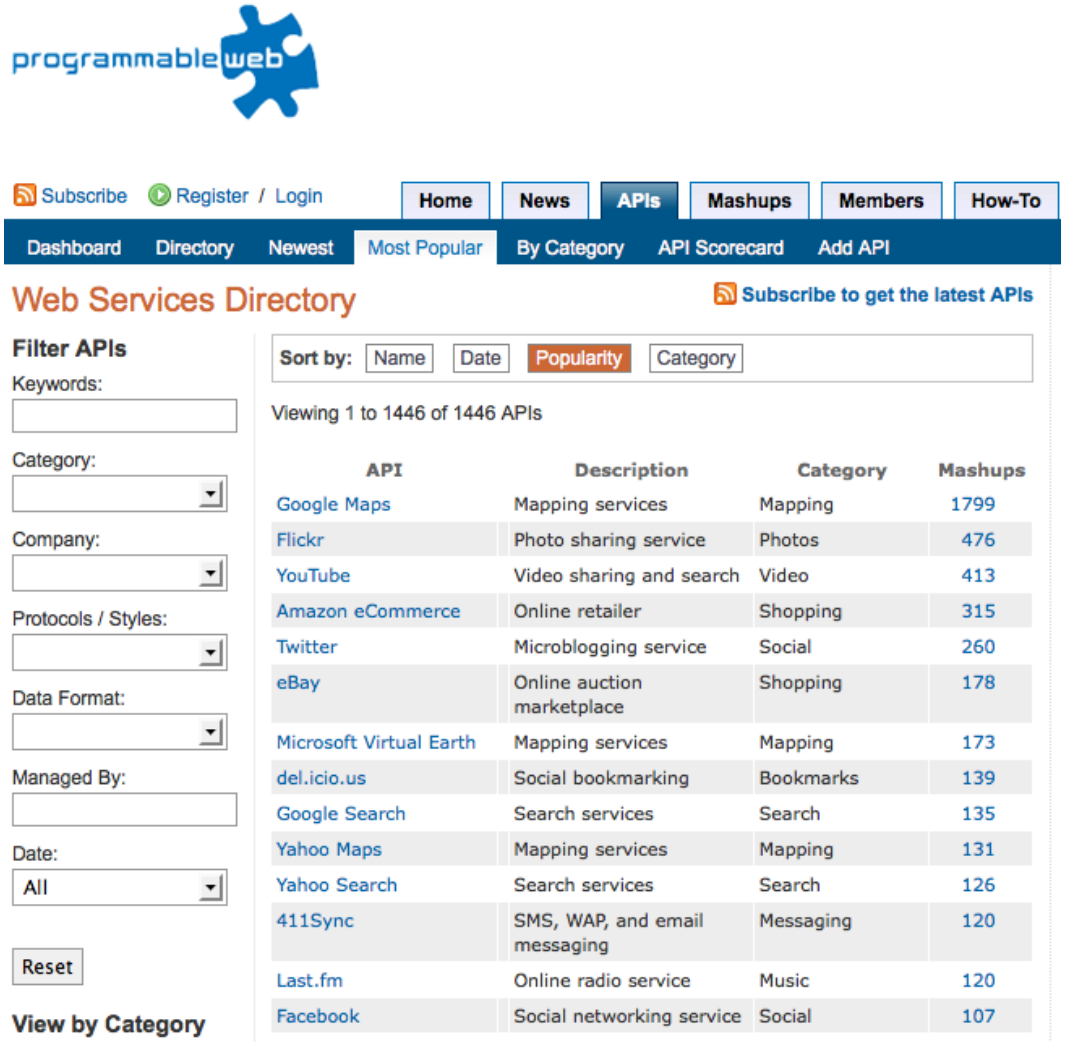
Uses

- Language identification
- Customer sentiment analysis
- Product recommendations & upsell opportunities
- Message routing decisions
- Diagnostics
- Document and email classification
- Suspicious activity identification
- Churn analysis
- And many more...

[1] s/black/blue/g

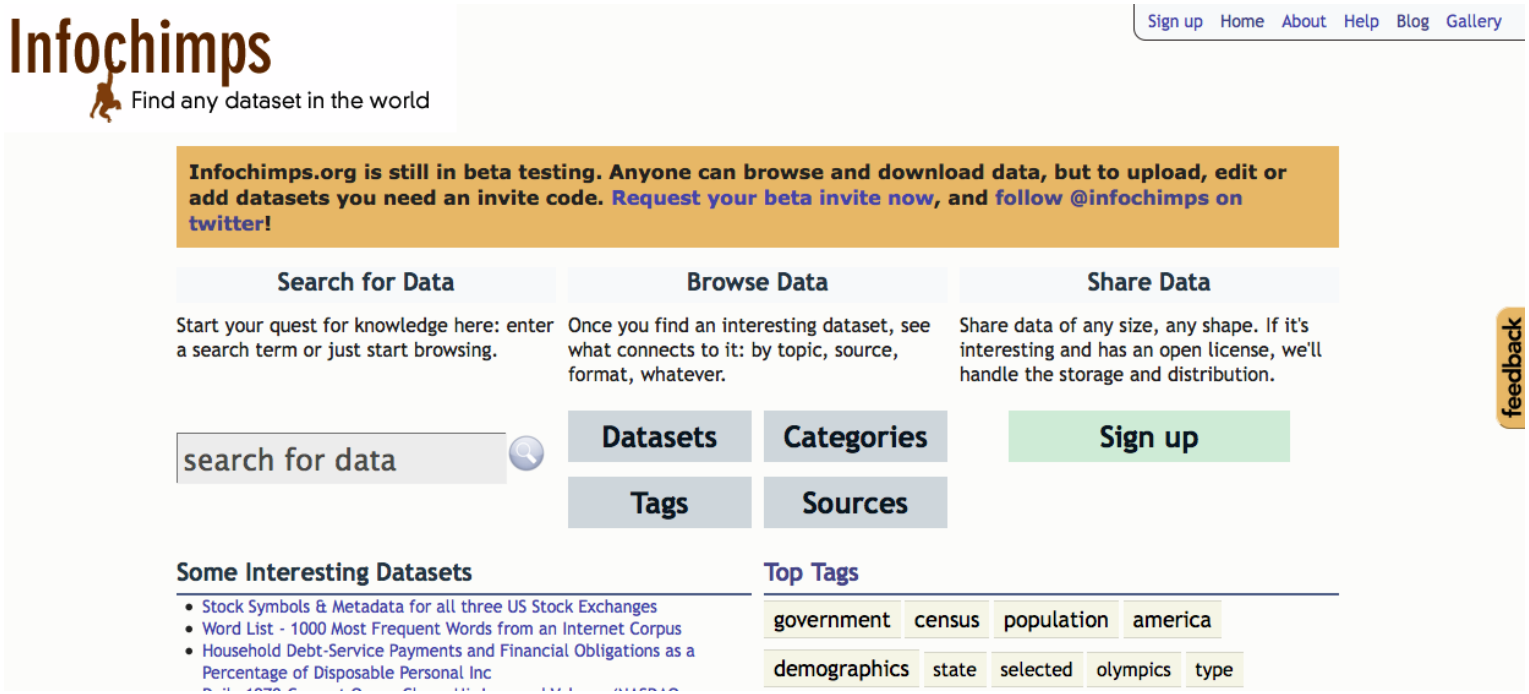
Got data?

- Web service APIs expose lots of data



Got data?

- Many free, public data sets available online



Roadmap?

Step 1: Have data

Step 2: ???

Step 3: Profit

Learning by example

Fwd: Yahoo! supercomputing cluster RFP - i have no idea. i have no idea. O

non urgent - whoops! yes that's what i meant, thanks for decoding my questi

SourceForge.net: variational bayes for network modularity - can i get admin

Byline - iPhone Apps, iPhone 3G apps and iPod touch Applications Gallery a

Laurence J. Peter: Facts are stubborn things, but statistics are more pliable.

Re: JAFOS 2008, Applied Math Session - yes. the listening post dude. On N

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Financial Aid Available: Find Funding for Your Education - Get the financial a
Find The Perfect School and Financal Aid for your College Degree - HI ! It ha
PHARMA_viagra_PHARMA_cialis - Wanted: web store with remedies. N

- How did you solve this problem?
- Can you make this process explicit (e.g. write code to do so)?

Learning by example

- We learn quickly from few, relatively unstructured examples ... but we don't understand *how* we accomplish this

Everything old is new again[2]

- Many fields ...
  - Statistics
  - Pattern recognition
  - Data mining
  - Machine learning
- ... similar goals
  - Extract and recognize patterns in data
  - Interpret or explain observations
  - Test validity of hypotheses
  - Efficiently search the space of hypotheses
  - Design efficient algorithms enabling machines to learn from data

[2] `http://cbcl.mit.edu/publications/theses/thesis-rifkin.pdf`

Statistics vs. machine learning[3]

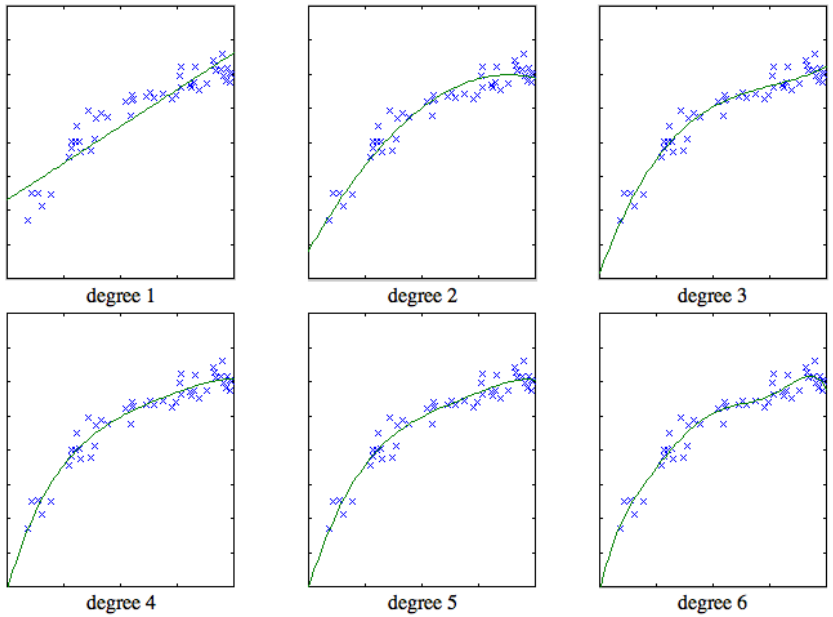
Glossary

Machine learning	Statistics
network, graphs	model
weights	parameters
learning	fitting
generalization	test set performance
supervised learning	regression/classification
unsupervised learning	density estimation, clustering
large grant = \$1,000,000	large grant= \$50,000
nice place to have a meeting: Snowbird, Utah, French Alps	nice place to have a meeting: Las Vegas in August

[3] http://anyall.org/blog/2008/12/statistics-vs-machine-learning-fight/

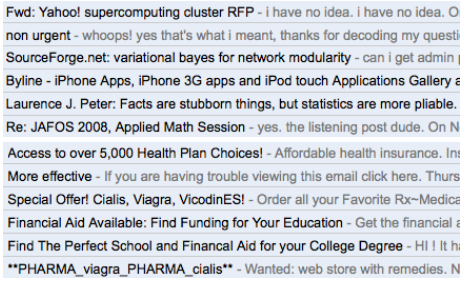
Philosophy

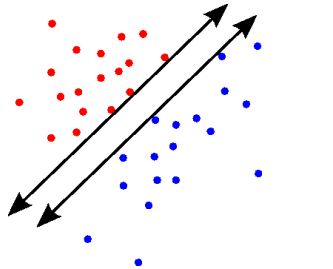
- We would like models that:
  - Provide predictive and explanatory power
  - Are complex enough to describe observed phenomena
  - Are simple enough to generalize to future observations

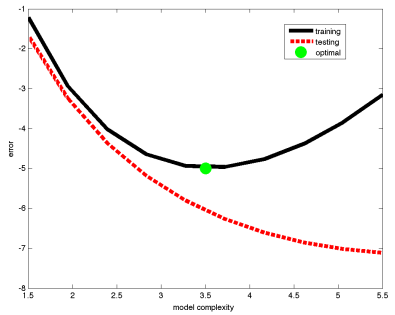


Roadmap, take 2[4]

1. Get data
2. Visualize/perform sanity checks
3. Clean/filter observations
4. Choose features to represent data
5. Specify model
6. Specify loss function
7. Develop algorithm to minimize loss
8. Choose performance measure
9. "Train" to minimize loss
10. "Test" to evaluate generalization

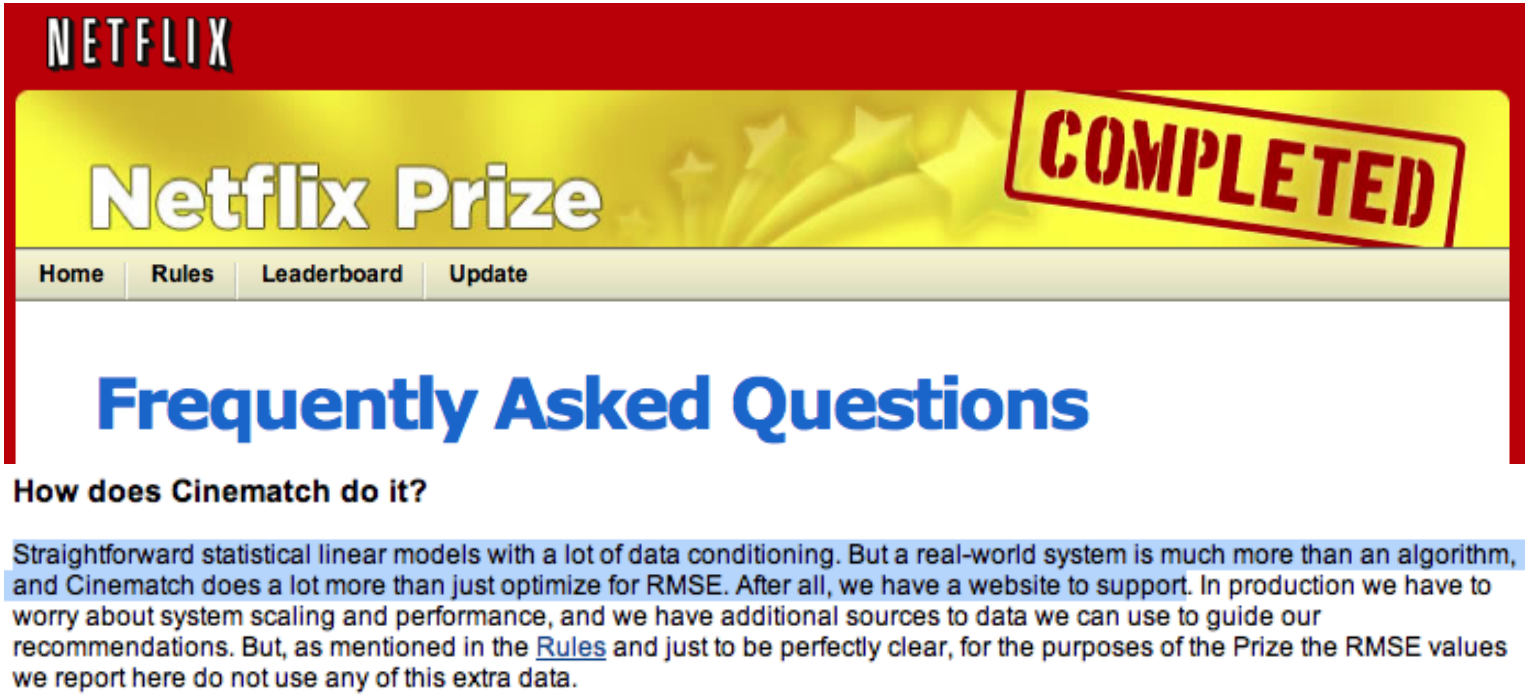






[4] http://www.dataists.com/2010/09/a-taxonomy-of-data-science/

Roadmap, take 3



Shipping = Feature

Add an asymmetric frequency feature $\mathbf{y}^{(3)}_{j,f_{ut}}$: **SBRAMF-UTB-UTF-MTF-ATF-MFF-AFF**

$$\widehat{r_{uit}} = \mu_i + \mu_u + \mu_{u,t} + \mu_{i,\mathrm{bin}(t)} + \left(\mathbf{p}^{(1)}_i + \mathbf{p}^{(2)}_{i,\mathrm{bin}(t)} + \mathbf{p}^{(3)}_{i,f_{ut}}\right)^T \left(\mathbf{q}^{(1)}_u + \mathbf{q}^{(2)}_{u,t} + \frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} \left(\mathbf{y}^{(1)}_j + \mathbf{y}^{(2)}_{j,\mathrm{bin}(t)} + \mathbf{y}^{(3)}_{j,f_{ut}}\right)\right) \tag{34}$$

Model extension (+)	epoch time	#epochs	probeRMSE, $k = 50$ features
SBRMF - SVD with biases	17[s]	69	0.9054
SBRAMF - asymmetric part	50[s]	30	0.8974
+UTB - user time bias	61[s]	50	0.8919
+UTF - user time feature	62[s]	38	0.8911
+MTF - movie time feature	74[s]	37	0.8908
+ATF - asymmetric time feature	74[s]	44	0.8905
+MFF - movie frequency feature	149[s]	46	0.8900
+AFF - asymmetric frequency feature	206[s]	45	0.8886 (0.8846 with $k = 1000$)

Themes

Data jeopardy

Regardless of scale, it's difficult to find the right questions to ask of the data

Themes

Data hacking

Cleaning and normalizing data is a substantial amount of the work (and likely impacts results)

Themes

Data hacking

The ability to iterate quickly, asking and answering many questions, is crucial

Themes

Data hacking

Hacks happen: sed/awk/grep are useful, and scale

Themes

Data "science"

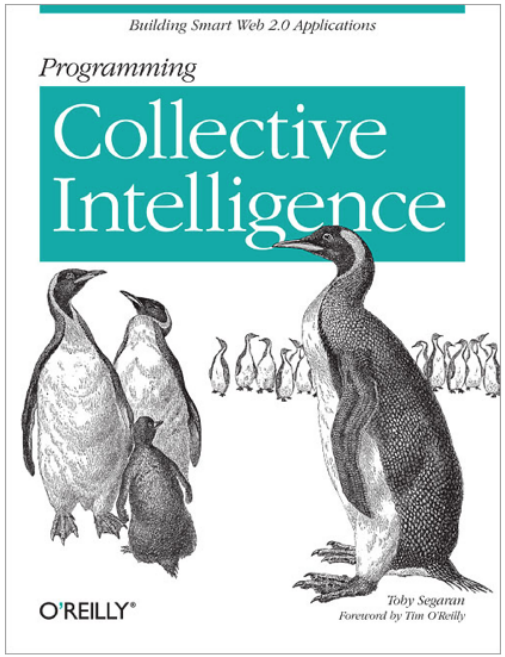
Simple methods (e.g., linear models) work surprisingly well, especially with lots of data

Themes

Data "science"

It's easy to cover your tracks—things are often much more complicated than they appear

References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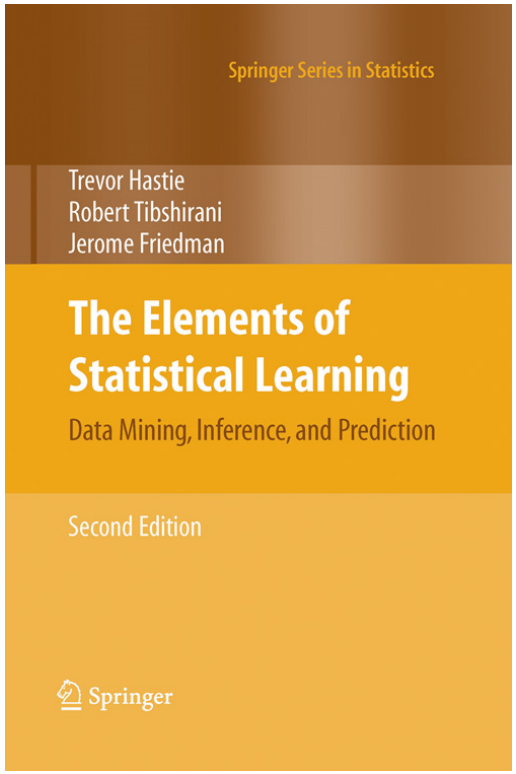
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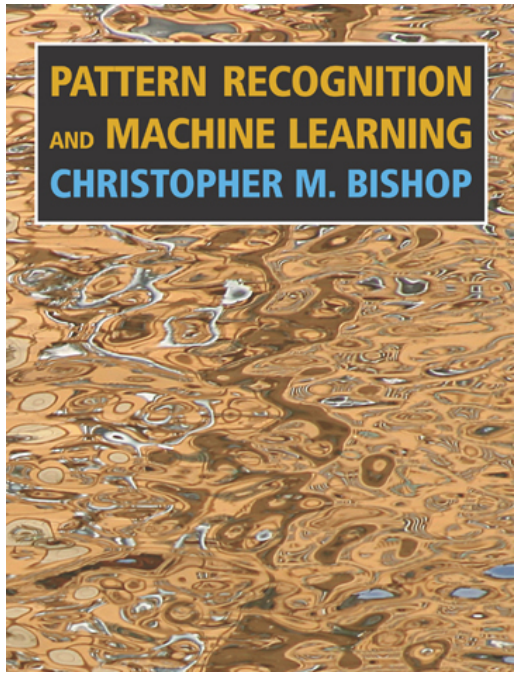
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