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Summarization

- i.e., ‘characterization’ or ‘generalization’
- maps data into subsets with associated simple descriptions
- extracts or derives representative information
- succinctly characterizes the contents

Example

- criteria used to compare universities by the U.S. News & World Report
- the average SAT or ACT score
- estimates the intellectual level of the student body

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Summarization Types

1. Computing the mean, variance, and other moments (e.g., skewness, kurtosis)
2. Extremes (min/max)
3. Estimating the number of distinct elements in a set
4. Counting the number of elements and finding frequently occuring ones
5. Calculating order statistics (e.g., median)

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Association Rules

- seek to uncover relationships among data
- association rules (AR) are models that identify specific types of data associations
- AR often used in retail sales to find items that are frequently purchased together
  - aka *market basket analysis*
- also used to predict the failure of telecommunication switches

Example

- grocery retailer to decide whether to put bread on sale
- retailer generates AR that show what products are often purchased with bread
  - 60% of the time pretzels are bought
  - 70% of the time jelly is also bought
- ∴, opt to place bread, pretzels, jelly in the same aisle near each other
- AR help determine which products are frequently bought together
  - used for effective advertising, marketing, and inventory control

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Association Rule Algorithms

1. A-priori
2. Eclat (Equivalence Class Transformation)
3. FP-growth (Frequent Pattern)

http://www.inquisitr.com/1106993/store-shelf-surveillance-cameras-may-be-coming-to-a-supermarket-near-you/

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Sequence Discovery (SD)

- used to find sequential patterns in data, based on a time sequence of actions
- unlike market basket analysis, which requires items be purchased at the same time, in SD the items are purchased over time in some order

Example

- webmaster analyzes web log to see how users access their webpages
- goal is to determine what sequence of pages are frequently accessed
- learns that 70% of users of page A follow one of these behavior patterns
  - <A,B,C>, <A,D,B,C>, <A,E,B,C>
- ∴, a link is added from page A to page C

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Sequence Discovery Algorithms

1. GSP (Generalized Sequential Pattern)
2. SPADE (Sequential Pattern Discovery using Equivalence Classes)
3. FreeSpan
4. PrefixSpan
5. MAPres

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Anomaly (or Outlier) Detection

- identify unusual data
- that might be interesting or
- errors that require further investigation

Example

- intrusion detection in networks
- discover consistent and useful patterns of system features that describe program and user behavior
- use relevant system features to compute classifiers that can recognize anomalies and known intrusions
- cs.columbia.edu/~wenke/papers/usenix/usenix.html

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Anomaly (or Outlier) Detection

- In data mining, **anomaly detection** (or **outlier detection**) is the identification of items, events or observations which **do not conform to an expected** pattern or other items in a dataset.[1]

- Typically the anomalous items will translate to some kind of problem, such as bank fraud, a structural defect, medical problems or errors in a text.

- Anomalies are also referred to as outliers, noise, deviations, and exceptions.[2]

https://en.wikipedia.org/wiki/Anomaly_detection

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Anomaly (or Outlier) Detection

- In the context of abuse and network intrusion detection, interesting objects are often **not *rare* objects**, but unexpected *bursts* in activity.

- This pattern does not adhere to the common statistical definition of an outlier as a rare object, and many outlier detection methods (in particular unsupervised methods) will fail on such data, unless it has been aggregated appropriately.

- Instead, a **cluster analysis algorithm** may be able to detect the microclusters formed formed by these patterns.[3]

https://en.wikipedia.org/wiki/Anomaly_detection

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Anomaly/Outlier Detection Algorithms

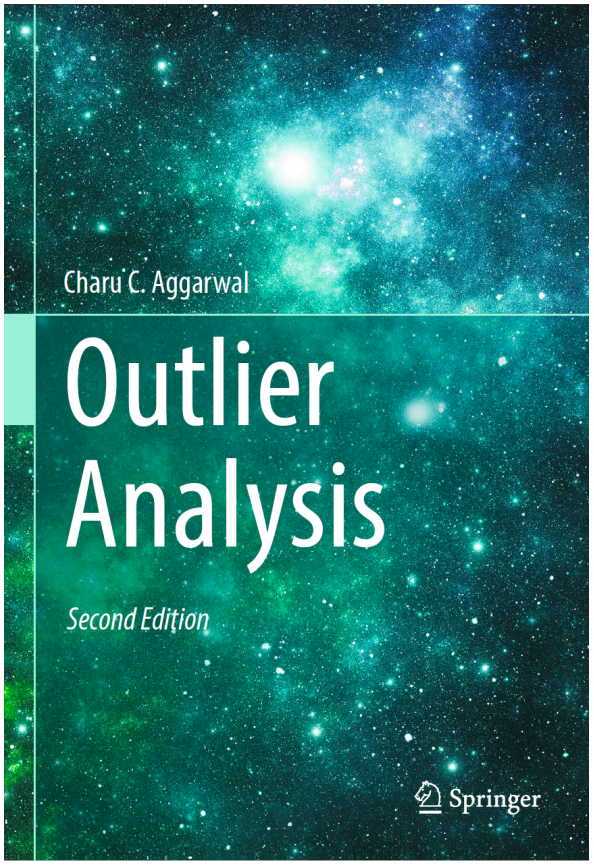


Table 1.1: Classification methods and their unsupervised analogs in outlier analysis

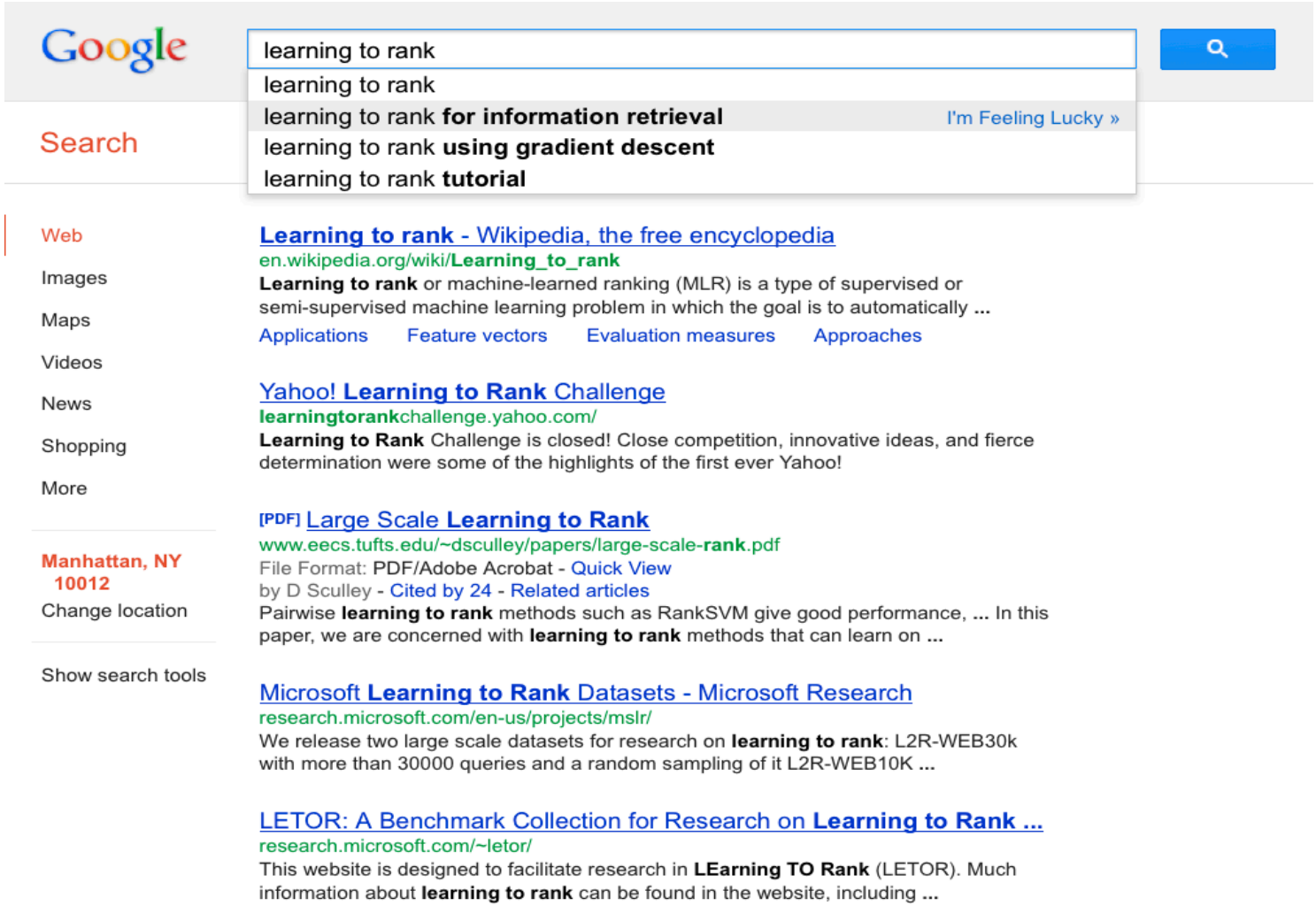
Supervised Model	Unsupervised Analog(s)	Type
k-nearest neighbor	k-NN distance, LOF, LOCI (Chapter 4)	Instance-based
Linear Regression	Principal Component Analysis (Chapter 3)	Explicit Generalization
Naive Bayes	Expectation-maximization (Chapter 2)	Explicit Generalization
Rocchio	Mahalanobis method (Chapter 3) Clustering (Chapter 4)	Explicit Generalization
Decision Trees Random Forests	Isolation Trees Isolation Forests (Chapters 5 and 6)	Explicit generalization
Rule-based	FP-Outlier (Chapter 8)	Explicit Generalization
Support-vector machines	One-class support-vector machines (Chapter 3)	Explicit generalization
Neural Networks	Replicator neural networks (Chapter 3)	Explicit generalization
Matrix factorization (incomplete data prediction)	Principal component analysis Matrix factorization (Chapter 3)	Explicit generalization

Ranking

comparing items

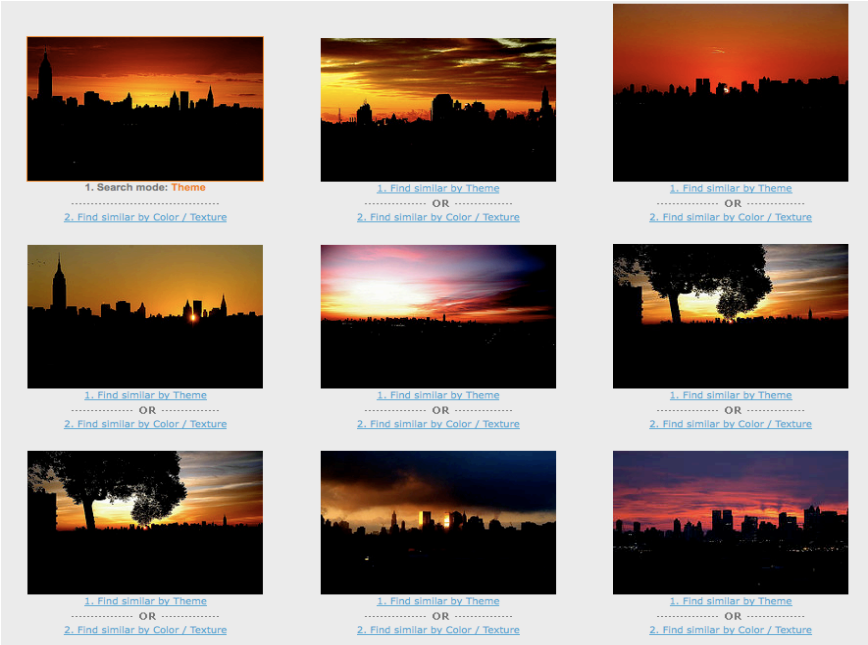
Due to Prof. David Sontag, NYU

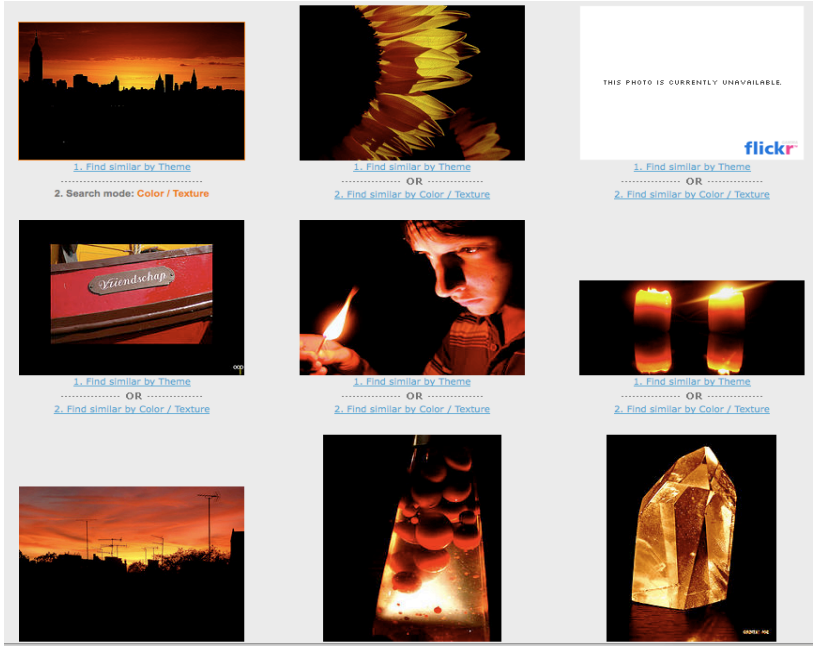
Web search



Due to Prof. David Sontag, NYU

Given image, find similar images





http://www.tiltomo.com/

Due to Prof. David Sontag, NYU

Collaborative Filtering

Due to Prof. David Sontag, NYU

Recommendation systems

Due to Prof. Sontag, NYU

Recommendation systems

Machine learning competition with a $1 million prize

Leaderboard

Display top 20 leaders.

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	The Ensemble	0.8553	10.10	2009-07-26 18:38:22
2	BellKor's Pragmatic Chaos	0.8554	10.09	2009-07-26 18:18:28
Grand Prize - RMSE <= 0.8563				
3	Grand Prize Team	0.8571	9.91	2009-07-24 13:07:49
4	Opera Solutions and Vandelay United	0.8573	9.89	2009-07-25 20:05:52
5	Vandelay Industries !	0.8579	9.83	2009-07-26 02:49:53
6	PragmaticTheory	0.8582	9.80	2009-07-12 15:09:53
7	BellKor in BigChaos	0.8590	9.71	2009-07-26 12:57:25
8	Dace	0.8603	9.58	2009-07-24 17:18:43
9	Opera Solutions	0.8611	9.49	2009-07-26 18:02:08
10	BellKor	0.8612	9.48	2009-07-26 17:19:11
11	BigChaos	0.8613	9.47	2009-06-23 23:06:52
12	Feeds2	0.8613	9.47	2009-07-24 20:06:46
Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8633	9.26	2009-07-21 02:04:40
14	Gravity	0.8634	9.25	2009-07-26 15:58:34
15	Ces	0.8642	9.17	2009-07-25 17:42:38
16	Invisible Ideas	0.8644	9.14	2009-07-20 03:26:12
17	Just a guy in a garage	0.8650	9.08	2009-07-22 14:10:42
18	Craig Carmichael	0.8656	9.02	2009-07-25 16:00:54
19	J Dennis Su	0.8658	9.00	2009-03-11 09:41:54
20	acmehill	0.8659	8.99	2009-04-16 06:29:35
Progress Prize 2007 - RMSE = 0.8712 - Winning Team: KorBell				
Cinematch score on quiz subset - RMSE = 0.9514				

Due to Prof. David Sontag, NYU

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Communities and Conferences

1. ACM SIGKDD (Know. Disc./DM)
2. ACM SIGMOD (Mgmt. of Data)
3. ACM CIKM (Info. Know. Mgmt.)
4. IEEE ICDE (Data Engineering)
5. VLDB (Very Large Data Bases)
6. ASA SLDM (Stat. Learning / Data Mining)
7. INFORMS Data Mining Section
8. SIAM Data Mining

KDD 2017

Halifax, Nova Scotia - Canada

August 13 - 17, 2017

KDD 2017 is a premier interdisciplinary conference bringing together researchers and practitioners from data science, data mining, knowledge discovery, large-scale data analytics, and big data.

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4. Real World Challenges

Social Implications, Data Mining in Practice, Challenges

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Social Implications of Data Mining

- data mining techniques are part of our everyday lives
- today we are routinely targeted with advertising
- data mining applications can derive information that was previously unknown
  - area code may correlate ethnicity
  - identify individuals using simple demographics
    - postal code, birthdate, gender

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- data mining applications can derive information that was previously unknown
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- data mining is used for fraud detection, identifying criminal suspects, predicting terrorists
  - aka profiling behaviors
- drawbacks
  - classification is imperfect
  - mistakes are made
- data mining techniques must be sensitive to privacy issues
  - i.e., not violate privacy directives

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Data Mining: In Practice

- human interaction
  - requires cooperation between data mining and domain-area experts
- generated models
  - overfitting
    - models generated do not fit future states; describe noise more so than relationships
  - coping with outliers
    - including outliers may present challenges to models

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Data Mining: In Practice

- human interaction
  - requires cooperation between data mining and domain-area experts
- generated models
  - overfitting
    - models generated do not fit future states; describe noise more so than relationships
  - coping with outliers
    - including outliers may present challenges to models
- interpretation of results
  - data mining output requires experts to interpret results
- visualization of results
  - helpful to communicate findings
- large datasets
  - sampling, parallelization helps
- high dimensionality
  - difficult to determine which attributes (dimensions) to use
  - apply dimensionality reduction methods

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Data Mining: In Practice

- multimedia data
  - present challenges to data mining algorithms
- missing data
  - can lead to invalid results
- irrelevant data
  - some attributes may be irrelevant
- noisy data
  - attributes might be invalid or incorrect; need to be resolved

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Data Mining: In Practice

- multimedia data
  - present challenges to data mining algorithms
- missing data
  - can lead to invalid results
- irrelevant data
  - some attributes may be irrelevant
- noisy data
  - attributes might be invalid or incorrect; need to be resolved
- changing data
  - datasets are not necessarily static; data mining must be rerun when there are updates
- integration
  - integration of data mining functions (e.g., into DBMS is desirable)
- disruptive
  - business practices may have to be modified to determine how to effectively use the information uncovered

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5. Ten DM Challenges (Among Others)

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C1. Curse of Dimensionality (COD)

Coined by R. Bellman (1961) in the context of control theory

- statistical inference increasingly more difficult as data becomes multivariate

In high dimensions …

- nearly all data sets are sparse
  - as the dimension increases the distance between points also increases

"*Statistical Data Mining*," David L. Banks, Wiley Interdisciplinary Reviews: Computational Statistics, 2, 9-25, doi: 10.102/wics.53

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In high dimensions …

- nearly all data sets are sparse
  - as the dimension increases the distance between points also increases
- number of possible models grows combinatorially fast
  - many more possible models

"*Statistical Data Mining*," David L. Banks, Wiley Interdisciplinary Reviews: Computational Statistics, 2, 9-25, doi: 10.102/wics.53

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C2. No Free Lunch (NFL) Theorem

A wide variety of techniques exist for modeling

- traditional statistical approaches, such as generalized linear models (GLMs) and linear discriminant analysis, to modern machine learning (ML) techniques, such as artificial neural networks (ANNs), support-vector machines (SVMs), Bayes (or belief) networks, and decision trees

Arising in Statistical Machine Learning the NFL Theorem states that …

- no technique will outperform all other techniques on all problems

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Arising in Statistical Machine Learning the NFL Theorem states that …

- no technique will outperform all other techniques on all problems
- any modeling effort should consider a range of techniques

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C3. Data Preparation

Critical modeling aspect is *data representation*

- transforms numbers/labels into a representation suitable for input to a model
- is the primary point where domain expertise can come into play

How to represent or encode an input variable in a model?

- number of calls per day a customer makes to an ISP

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How to represent or encode an input variable in a model?

- number of calls per day a customer makes to an ISP
  - a scalar (e.g., customer makes 5 calls, then the no. is 5).
  - use bins (e.g., 0-1, 2-5, 6-12, 12+) expressed as a binary vector
    - if customer made 5 or 20 calls, this is [0 1 0 0] or [0 0 0 1], respectively
  - many possible representations, which influences model accuracy

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Poor data preparation likely leads to inferior models

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C4. Model Selection

- There is a continuum of models from simple to complex
  - simple models capture the primary trends in a data set, but their simplicity may prevent them from capturing subtle patterns.
  - complex models capture subtle patterns, but they memorize training data quirks, instead of capturing patterns that will be useful for prediction.

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  - simple models capture the primary trends in a data set, but their simplicity may prevent them from capturing subtle patterns.
  - complex models capture subtle patterns, but they memorize training data quirks, instead of capturing patterns that will be useful for prediction.
- A key issue is *model selection*, picking the appropriate level of complexity for a model given data.
- Many methods exist for model selection
  - (e.g., cross validation, Bayesian averaging, ensembles, regularization)
- Rigorous model selection is important, otherwise the models will be far less accurate than they could be

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C5. Model Evaluation: Test Data

Once a model is built, the question arises: “Is it accurate?”

Unfortunately, modelers can inflate model accuracy estimates

Failing to use an independent test set.

- A set of training examples are used to construct the model.
- It is meaningless to assess the accuracy of the model using the training set, because one could always build a model that has extremely high accuracy on the training set.
- To obtain a fair estimate of performance, the model must be evaluated on examples that were not contained in the training set.
- To obtain independent training and test sets, the available data must be split into two nonoverlapping subsets, with the test set reserved only for evaluation.

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C6. Model Evaluation: Stationarity

Assuming stationarity of the test environment.

- For many difficult problems, a model built based on historical data will become a poorer and poorer predictor as time goes on, because the environment is *nonstationary* – the rules and behaviors of individuals change over time.

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C7. Model Evaluation: Filtering

Filtering data to bias results.

- In a large data set, one segment of the population may be easier to predict than another
  - For example, customers with low incomes are likely to be more cost sensitive, and hence, might reliably churn (i.e., customer turnover) when their bills rise above a certain amount.

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  - For example, customers with low incomes are likely to be more cost sensitive, and hence, might reliably churn (i.e., customer turnover) when their bills rise above a certain amount.
- If a model is trained and tested just on this segment of the population, it will be more accurate than a model that must handle the entire population.
- Selective filtering turns a hard problem into an easier problem.
  - For example, focusing on customers in the first three months of service, and assuming that performance on the broader customer base is comparable.

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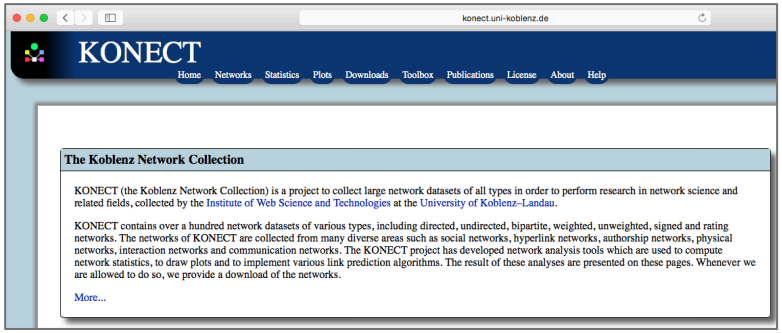
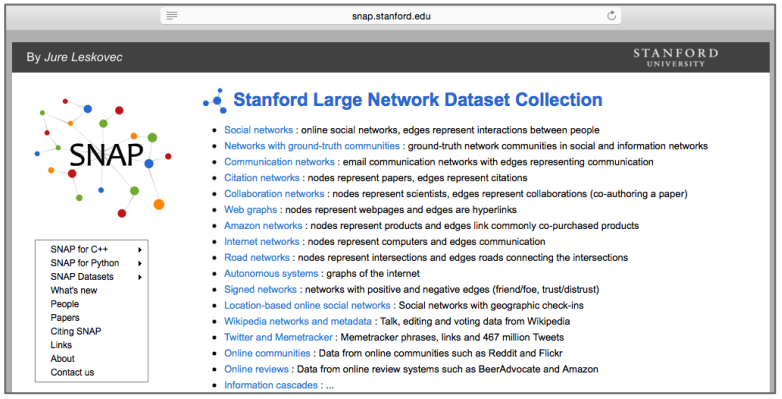
C8. Acquiring Data

- Although a great deal is said about the availability of data
- The truth is it isn't always easy to gain access to it for varying reasons
  - corporate confidentiality agreements (re: 3rd party data)
  - user privacy rights
  - conflicts of interest, such as in national security (in the defense domain)
  - global competitiveness
  - available for purchase only





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C9. Constraints & Discrepancies

Corporate/Operational Constraints

- managing time pressures/project schedule
- differences of opinion in the interpretation of results
- mitigation strategy
  - show consistency across many methods

Technological

- trustworthiness of the computing platform and the analytics
- incorrect usage of the tools
- mitigation strategy
  - “calibrate the instrument,” conduct experiments on known problems