CS145: INTRODUCTION TO DATA MINING

1: Introduction

Instructor: Yizhou Sun

yzsun@cs.ucla.edu

September 23, 2021

Join at

slido.com

#424 226

Course Information

- Course homepage:
  - https://github.com/yichousun/Fall2021_CS145_IntroDM
- Class Schedule
  - Slides
  - ...

- Prerequisites
  - You are expected to have background knowledge in data structures, algorithms, basic linear algebra, and basic statistics.
  - You will also need to be familiar with at least one programming language, and have programming experiences.

Meeting Time and Location

- When
  - Tuesdays & Thursdays, 10:00am-11:50am
- Where
  - WG Young Hall Room CS24

Instructor and TA Information

- Instructor: Yizhou Sun
  - Homepage: http://web.cs.ucla.edu/~yzsun/
  - Email: yzsun@cs.ucla.edu
  - Office: 3531F
  - Office hour: Mondays 2-3pm and Tuesdays 4:15-5:00pm
    - https://ucla.zoom.us/j/91640089211?pwd=dWdUaEJRMTQ0NEkwYTBoZG80N2lHdz09
    - Meeting ID: 916 4008 9211
    - Passcode: 667512

TAs

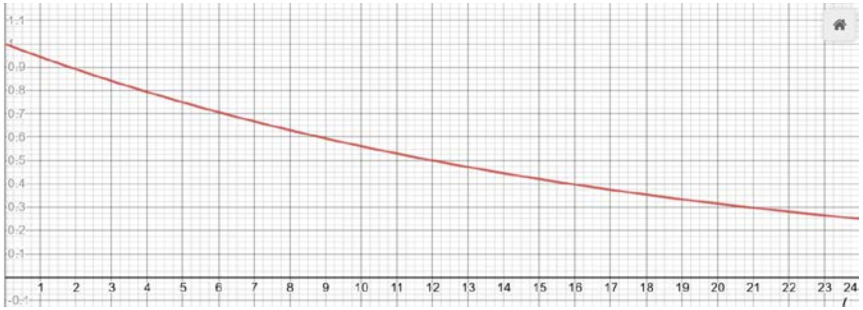
- Zongyue Qin (qinzongyuecs@ucla.edu)
  - office hours: Monday 9-11am @ BH 3551)
- Yewen Wang (wyw10804@gmail.com)
  - office hours: Wednesday 9-10am @ Boelter Hall 3551 Conference Room, 10-11am @ zoom
- Shichang Zhang (shichang@cs.ucla.edu)
  - office hours: Friday 10am-12pm @ BH 3551 Conference Room (May change to the TA office BH 3256 once it is open)

Grading

- Homework: 30%
- Midterm exam: 20%
- Final exam: 15%
- Course project: 25%
- Participation: 10%

Grading: Homework

- Homework: 30%
  - 6 assignments are expected
  - Deadline: 11:59pm of the indicated due date via *ccle* system
    - *Late submission policy:* get original score* $\mathbf{1}(t <= 24)e^{-(ln(2)/12)*t}$ if you are t hours late.



  - No copying or sharing of homework!
    - But you can discuss general challenges and ideas with others
    - *Suspicious cases will be reported to The Office of the Dean of Students*

Grading: Midterm and Final Exams

- Midterm exam (Nov. 4 in-class): 20%
  - 1 “Cheat” sheet is allowed
- Final exam (Dec. 9 3-5pm): 15%
  - Closed book exams
  - 2 “Cheat” sheets are allowed

Grading: Course Project

- Course project: 25%
  - Group project (3-4 people for one group)
  - Goal: Solve a given data mining problem
    - E.g., COVID-19 Prediction last year
    - Kaggle Competition style
  - You are expected to submit a project report and your code at the end of the quarter

Grading: Participation

- Participation (10%)
  - Quizzes
    - In-class quiz
  - In-class participation
  - Online participation (piazza)
    - piazza.com/ucla/fall2021/cs145

Textbook

- Recommended: Jiawei Han, Micheline Kamber, and Jian Pei. Data Mining: Concepts and Techniques, 3rd edition, Morgan Kaufmann, 2011
- References
  - "Data Mining: The Textbook" by Charu Aggarwal (http://www.charuaggarwal.net/Data-Mining.htm)
  - "Data Mining" by Pang-Ning Tan, Michael Steinbach, and Vipin Kumar (http://www-users.cs.umn.edu/~kumar/dmbook/index.php)
  - "Machine Learning" by Tom Mitchell (http://www.cs.cmu.edu/~tom/mlbook.html)
  - "Introduction to Machine Learning" by Ethem ALPAYDIN (http://www.cmpe.boun.edu.tr/~ethem/i2ml/)
  - "Pattern Classification" by Richard O. Duda, Peter E. Hart, David G. Stork (http://www.wiley.com/WileyCDA/WileyTitle/productCd-0471056693.html)
  - "The Elements of Statistical Learning: Data Mining, Inference, and Prediction" by Trevor Hastie, Robert Tibshirani, and Jerome Friedman (http://www-stat.stanford.edu/~tibs/ElemStatLearn/)
  - "Pattern Recognition and Machine Learning" by Christopher M. Bishop (http://research.microsoft.com/en-us/um/people/cmbishop/prml/)

Goals of the Course

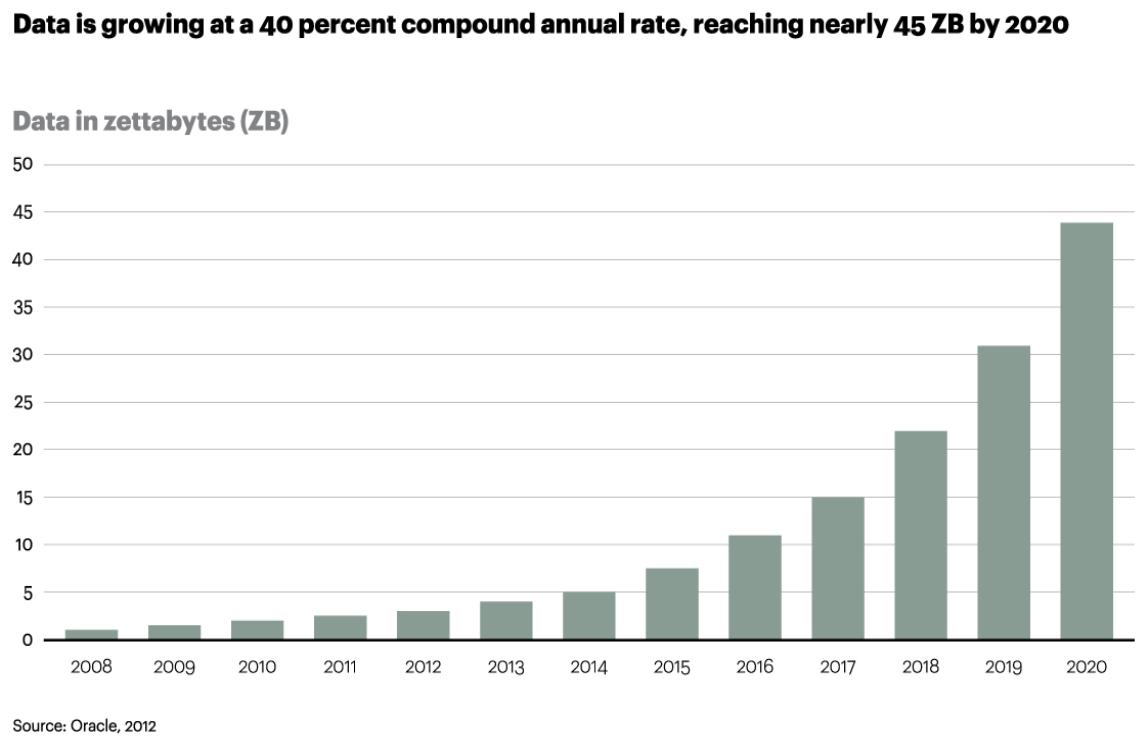
- Know what data mining is and learn the basic algorithms
- Know how to apply algorithms to real-world applications
- Provide a starting course for research in data mining

1. Introduction

- Why Data Mining?
- What Is Data Mining?
- A Multi-Dimensional View of Data Mining
  - What Kinds of Data Can Be Mined?
  - What Kinds of Patterns Can Be Mined?
  - What Kinds of Technologies Are Used?
  - What Kinds of Applications Are Targeted?
- Content covered by this course

Big Data

- 1 Zeta byte = 1 trillion Gigabytes.
- 5,200 GB of data for every person on Earth.



Example of Data Volumes

Unit	Value	Example
Kilobytes (KB)	1,000 bytes	a paragraph of a text document
Megabytes (MB)	1,000 Kilobytes	a small novel
Gigabytes (GB)	1,000 Megabytes	Beethoven's 5th Symphony
Terabytes (TB)	1,000 Gigabytes	all the X-rays in a large hospital
Petabytes (PB)	1,000 Terabytes	half the contents of all US academic research libraries
Exabytes (EB)	1,000 Petabytes	about one fifth of the words people have ever spoken
Zettabytes (ZB)	1,000 Exabytes	as much information as there are grains of sand on all the world's beaches
Yottabytes (YB)	1,000 Zettabytes	as much information as there are atoms in 7,000 human bodies

https://www.eecis.udel.edu/~amer/Table-Kilo-Mega-Giga---YottaBytes.html

Why Data Mining?

- The Explosive Growth of Data: from terabytes to petabytes
  - Data collection and data availability
    - Automated data collection tools, database systems, Web, computerized society
  - Major sources of abundant data
    - Business: Web, e-commerce, transactions, stocks, …
    - Science: Remote sensing, bioinformatics, scientific simulation, …
    - Society and everyone: news, digital cameras, YouTube, social media, mobile devices, …
- <u>We are drowning in data, but starving for knowledge!</u>
- "Necessity is the mother of invention"—Data mining—Automated analysis of massive data sets

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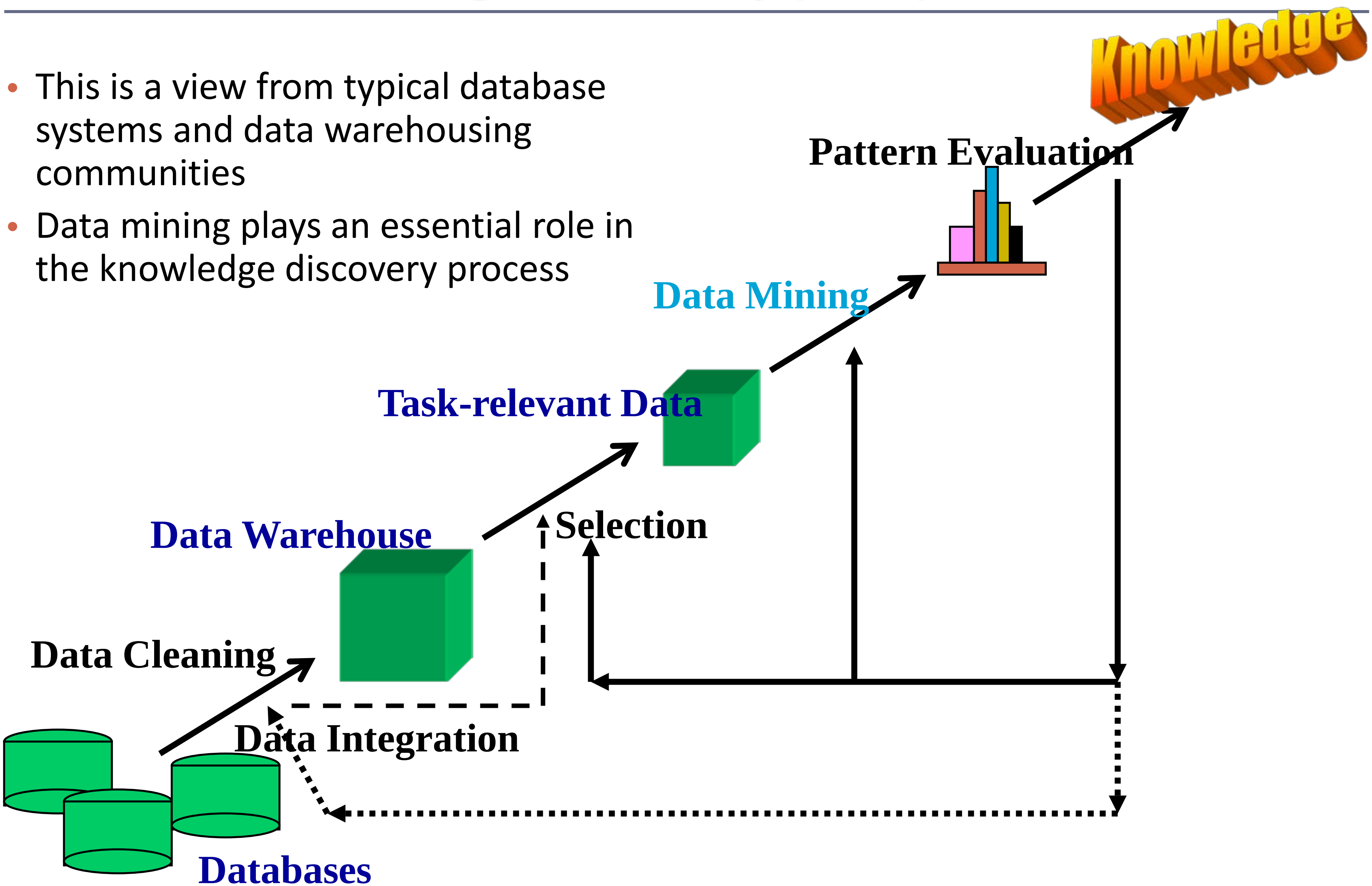
What Is Data Mining?

- Data mining (knowledge discovery from data)
  - Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data

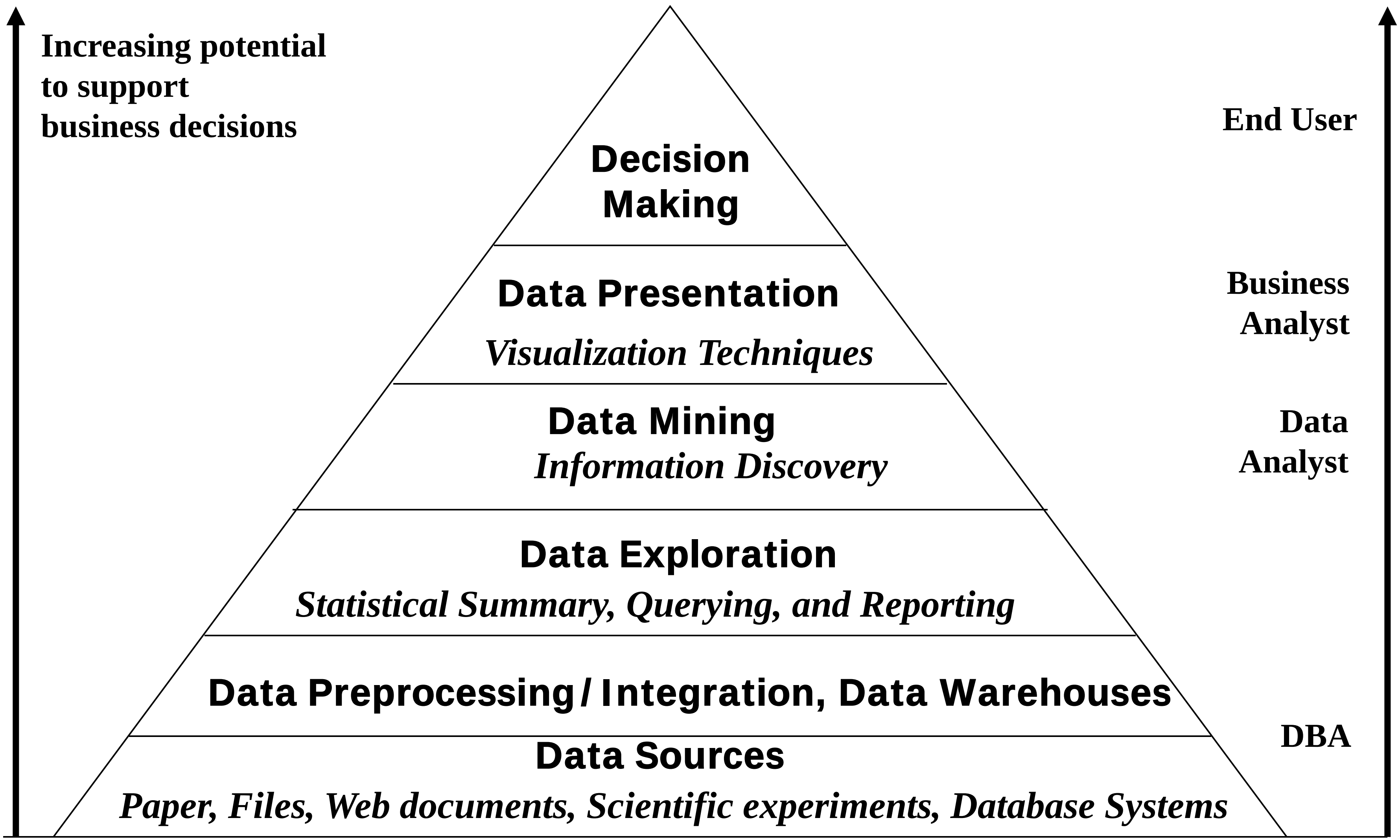
- Alternative names
  - Knowledge discovery (mining) in databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.

Knowledge Discovery (KDD) Process

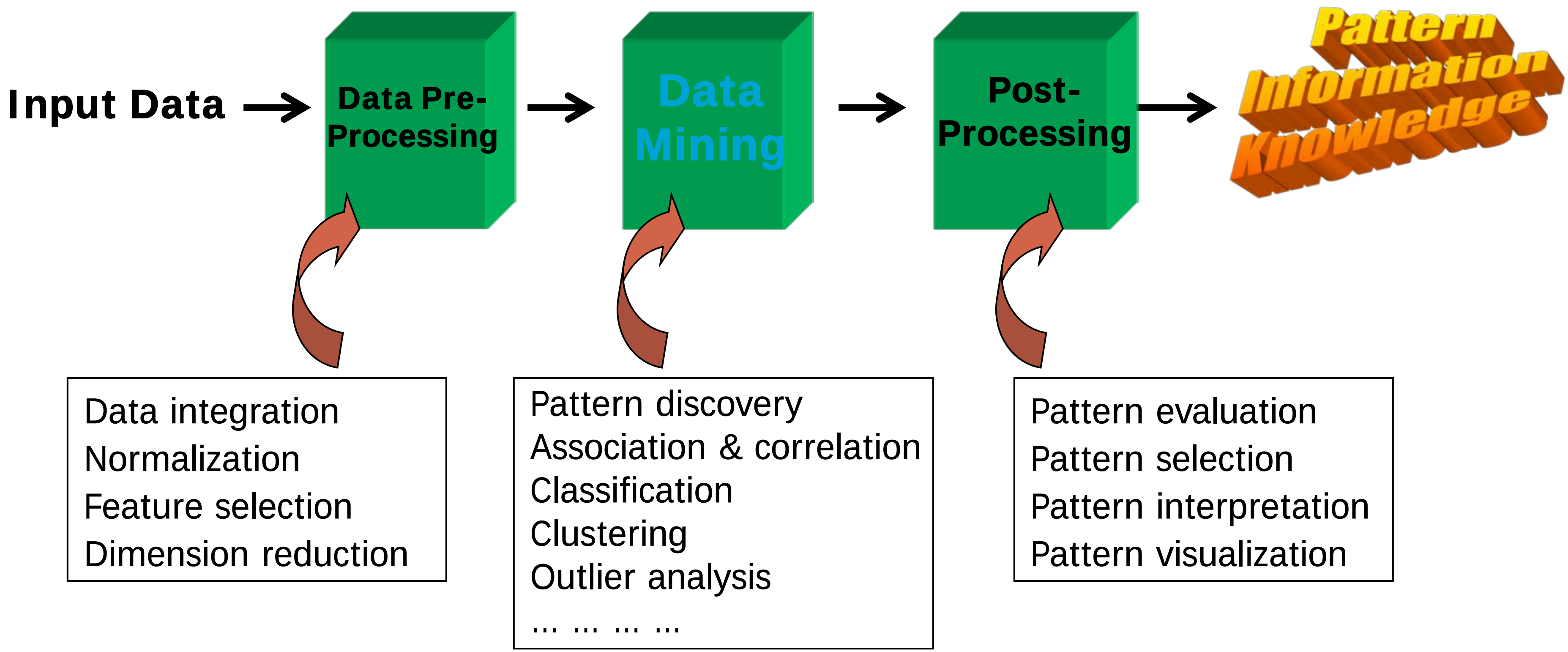
- This is a view from typical database systems and data warehousing communities
- Data mining plays an essential role in the knowledge discovery process



Data Mining in Business Intelligence



KDD Process: A Typical View from ML and Statistics



- This is a view from typical machine learning and statistics communities

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Multi-Dimensional View of Data Mining

- <u>**Data to be mined**</u>
  - Database data (extended-relational, object-oriented, heterogeneous, legacy), data warehouse, transactional data, stream, spatiotemporal, time-series, sequence, text and web, multi-media, graphs & social and information networks
- <u>**Knowledge to be mined (or: Data mining functions)**</u>
  - Characterization, discrimination, association, classification, clustering, trend/deviation, outlier analysis, etc.
  - Descriptive vs. predictive data mining
  - Multiple/integrated functions and mining at multiple levels
- <u>**Techniques utilized**</u>
  - Data-intensive, data warehouse (OLAP), machine learning, statistics, pattern recognition, visualization, high-performance, etc.
- <u>**Applications adapted**</u>
  - Retail, telecommunication, banking, fraud analysis, bio-data mining, stock market analysis, text mining, Web mining, etc.

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Vector/Tabular Data

	Sex	Race	Height	Income	Marital Status	Years of Educ.	Liberal-ness
R1001	M	1	70	50	1	12	1.73
R1002	M	2	72	100	2	20	4.53
R1003	F	1	55	250	1	16	2.99
R1004	M	2	65	20	2	16	1.13
R1005	F	1	60	10	3	12	3.81
R1006	M	1	68	30	1	9	4.76
R1007	F	5	66	25	2	21	2.01
R1008	F	4	61	43	1	18	1.27
R1009	M	1	69	67	1	12	3.25

Set Data

TID	*Items*
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Text Data

- “Text mining, also referred to as text data mining, roughly equivalent to text analytics, refers to the process of deriving high-quality information from text. High-quality information is typically derived through the devising of patterns and trends through means such as statistical pattern learning. Text mining usually involves the process of structuring the input text (usually parsing, along with the addition of some derived linguistic features and the removal of others, and subsequent insertion into a database), deriving patterns within the structured data, and finally evaluation and interpretation of the output. 'High quality' in text mining usually refers to some combination of relevance, novelty, and interestingness. Typical text mining tasks include text categorization, text clustering, concept/entity extraction, production of granular taxonomies, sentiment analysis, document summarization, and entity relation modeling (i.e., learning relations between named entities).” –from wiki

Text Data – Topic Modeling

Topics

```
gene      0.04
dna       0.02
genetic   0.01
...
```

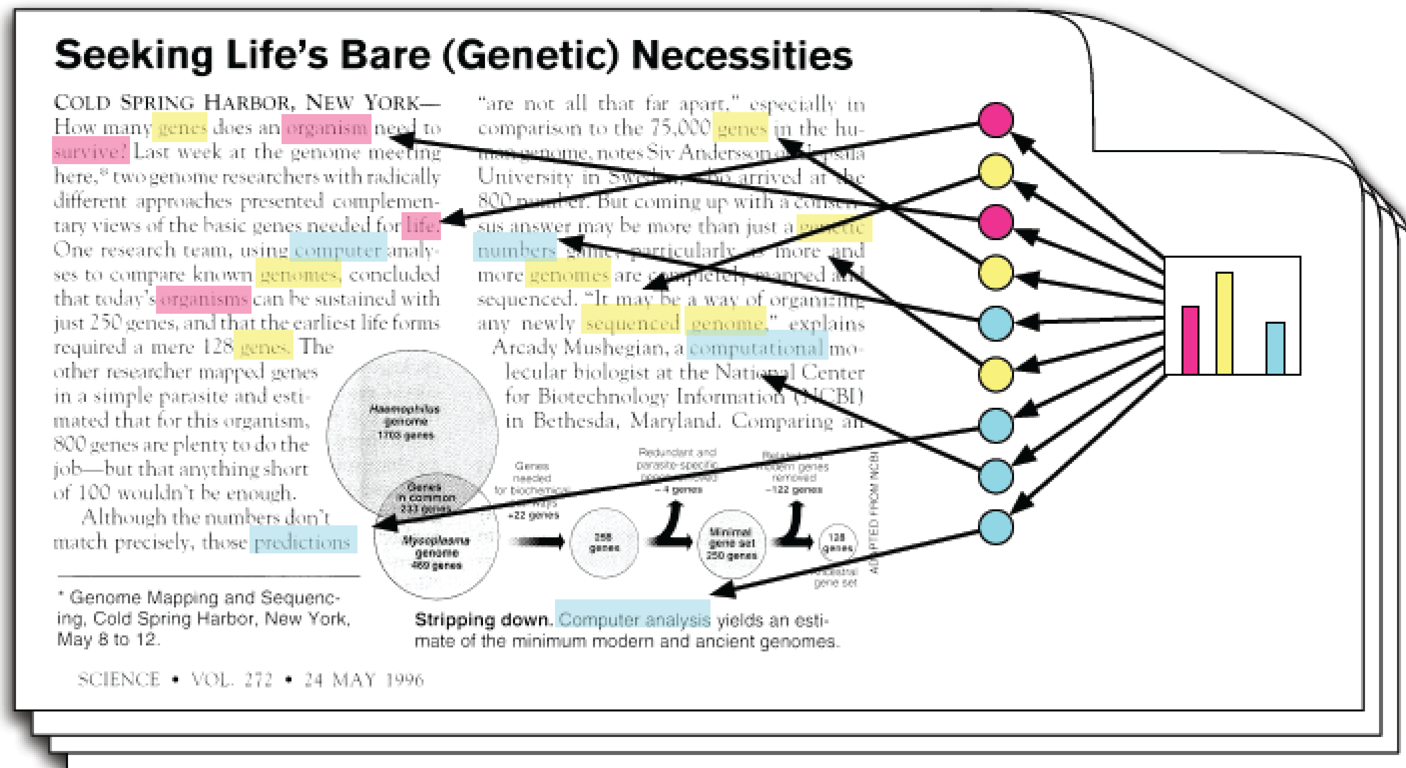
```
life      0.02
evolve    0.01
organism  0.01
...
```

```
brain     0.04
neuron    0.02
nerve     0.01
...
```

```
data      0.02
number    0.02
computer  0.01
...
```

Documents

Topic proportions and assignments



Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

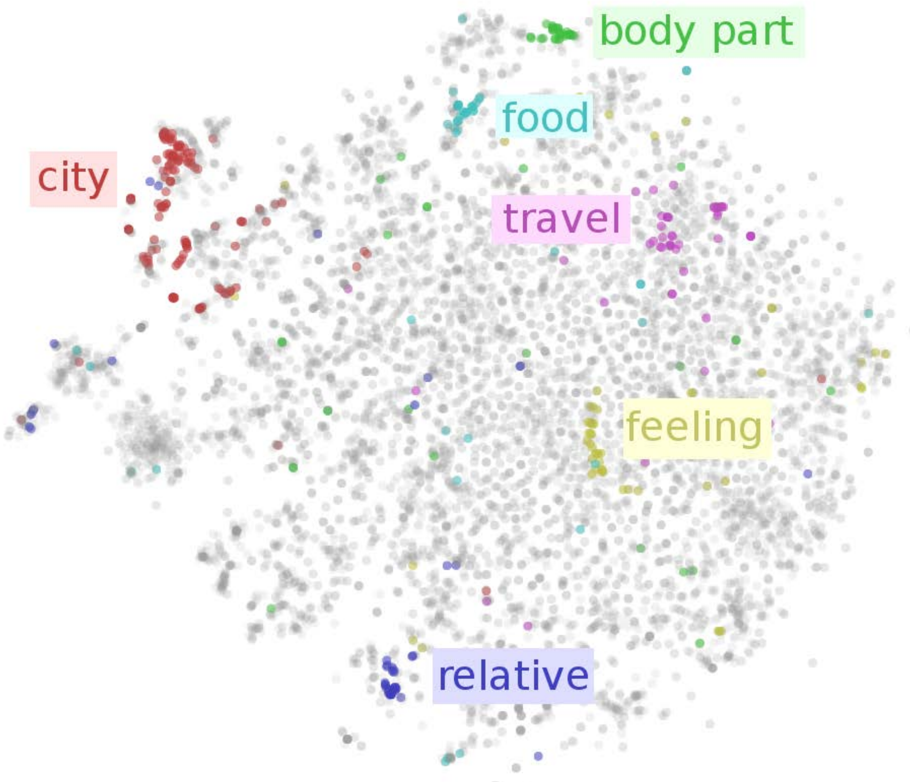
Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

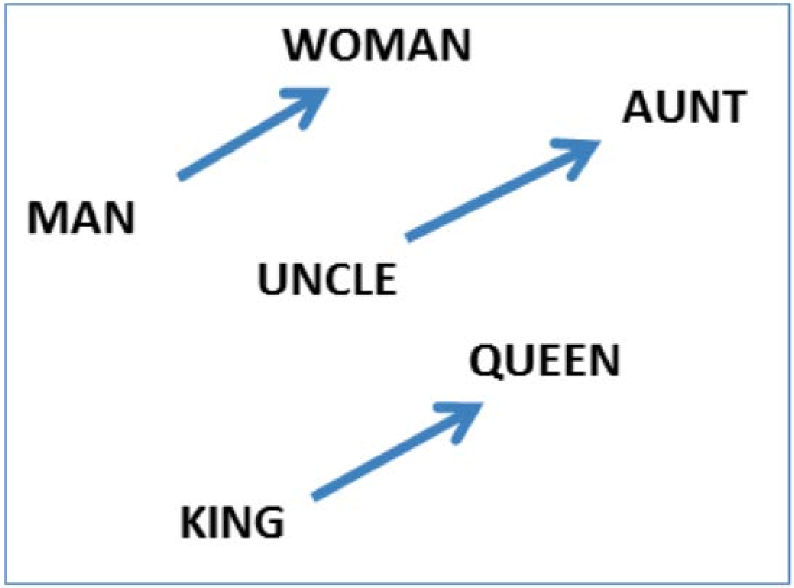
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

SCIENCE • VOL. 272 • 24 MAY 1996

Text Data – Word Embedding





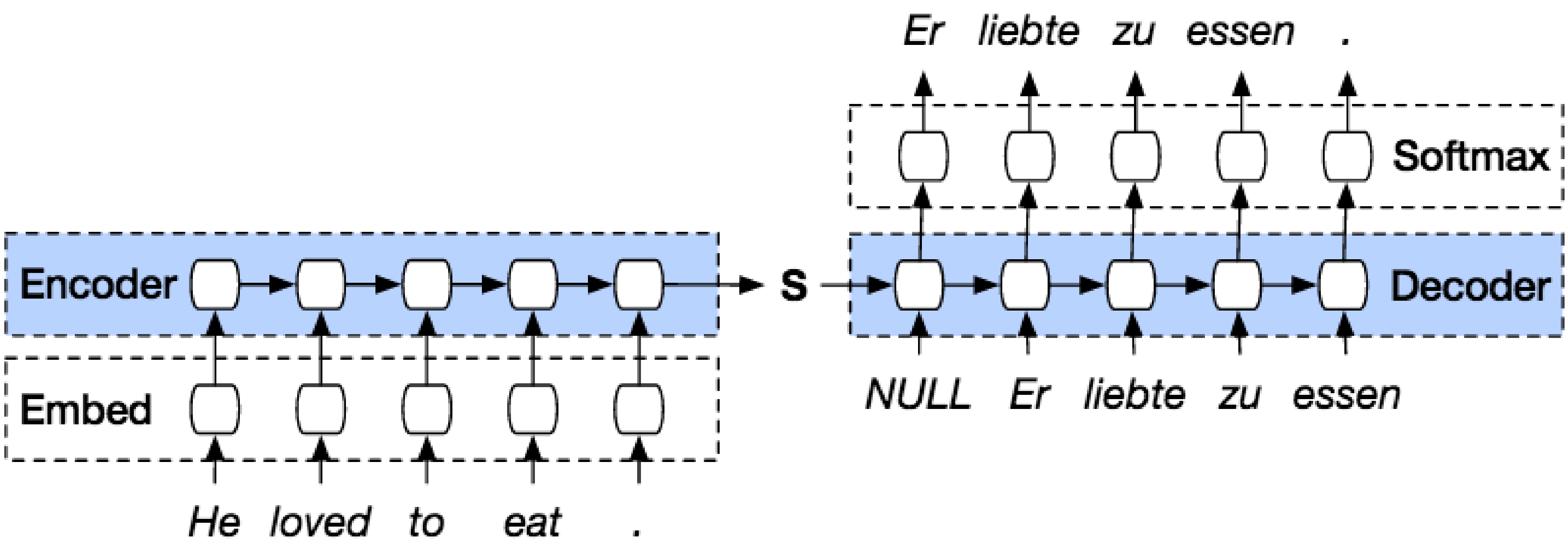
king - man + woman = queen

Sequence Data

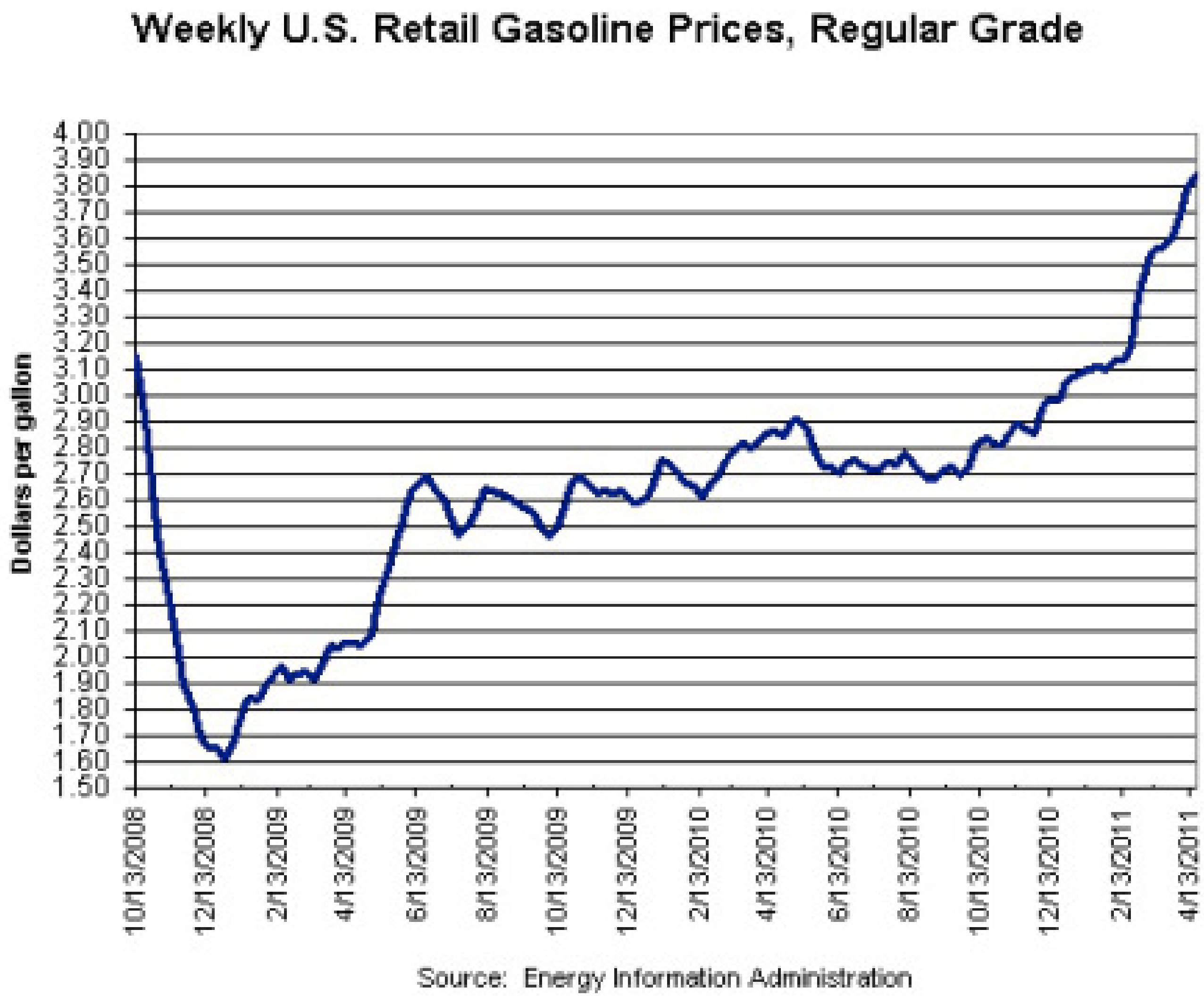
SYNTENIC ASSEMBLIES FOR CG15386

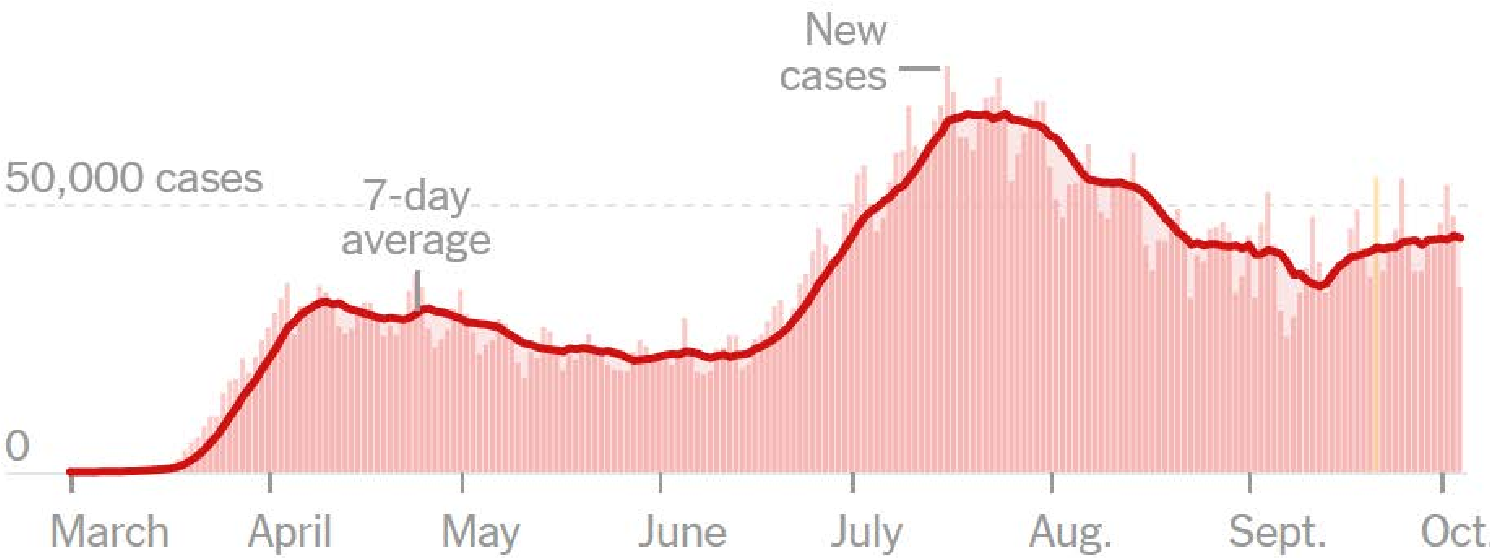
```
MD106   ATGCTTAGTAATCCCTACTTTAAGTCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG
NEWC    ATGCTTAGTAATCCTTACTTTAAATCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG
W501    ATGCTTAGTAATCCCTACTTTAAGTCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG
MD199   ATGCTTAGTAATCCCTACTTTAAGTCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG
C1674   ATGCTTAGTAATCCCTACTTTAAGTCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG
SIM4    ATGCTTAGTAATCCCTACTTTAAGTCCGTTTTGTGGCTGATTGGCTTCGGAGGAATGGG

MD106   CTACGGCCTAATGGTGCTAACAGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT
NEWC    CTACGGCCTAATGGTGCTAACCGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT
W501    CTACGGCCTAATGGTGCTAACCGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT
MD199   CTACGGCCTAATGGTGCTAACCGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT
C1674   CTACGGCCTAATGGTGCTAACCGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT
SIM4    CTACGGCCTAATGGTGCTAACCGAGCCGAACGTCGACAAAATAGAGCGCATCAAAGCCT

MD106   CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG
NEWC    CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG
W501    CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG
MD199   CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG
C1674   CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG
SIM4    CCGTTTCAAGTACCAAACTGAGTGCGGATGAGCAGCGAAAGGCTCTGTTTATGAAGAAG

MD106   CTGCAGGAGGCGTCCACCACCAGTGCCCCAATCTACAGGTCAGCGGCCGAGAAATAG
NEWC    CTGCAGGAGGCGTCCACCACCAGTGCCCCAATCTACAGGTCATCGGCCGAGAAATAG
W501    CTGCAGGAGGCGTCCACCACCACTGCCCCAATCTACAGGTCATCGGCCGAGAAATAG
MD199   CTGCAGGAGGCGTCCACCACCAGTGCCCCAATCTACAGGTCAGCGGCCGAGAAATAG
C1674   CTGCAGGAGGCGTCCACCACCAGTGCCCCAATCTACAGGTCAGCGGCCGAGAAATAG
SIM4    CTGCAGGAGGCGTCCACCACCAGTGCCCCAATCTACAGGTCAGCGGCCGAGAAATAG
```

Sequence Data – Seq2Seq



Time Series


Weekly U.S. Retail Gasoline Prices, Regular Grade
Dollars per gallon
4.00
3.90
3.80
3.70
3.60
3.50
3.40
3.30
3.20
3.10
3.00
2.90
2.80
2.70
2.60
2.50
2.40
2.30
2.20
2.10
2.00
1.90
1.80
1.70
1.60
1.50
10/13/2008
12/13/2008
2/13/2009
4/13/2009
6/13/2009
8/13/2009
10/13/2009
12/13/2009
2/13/2010
4/13/2010
6/13/2010
8/13/2010
10/13/2010
12/13/2010
2/13/2011
4/13/2011
Source: Energy Information Administration

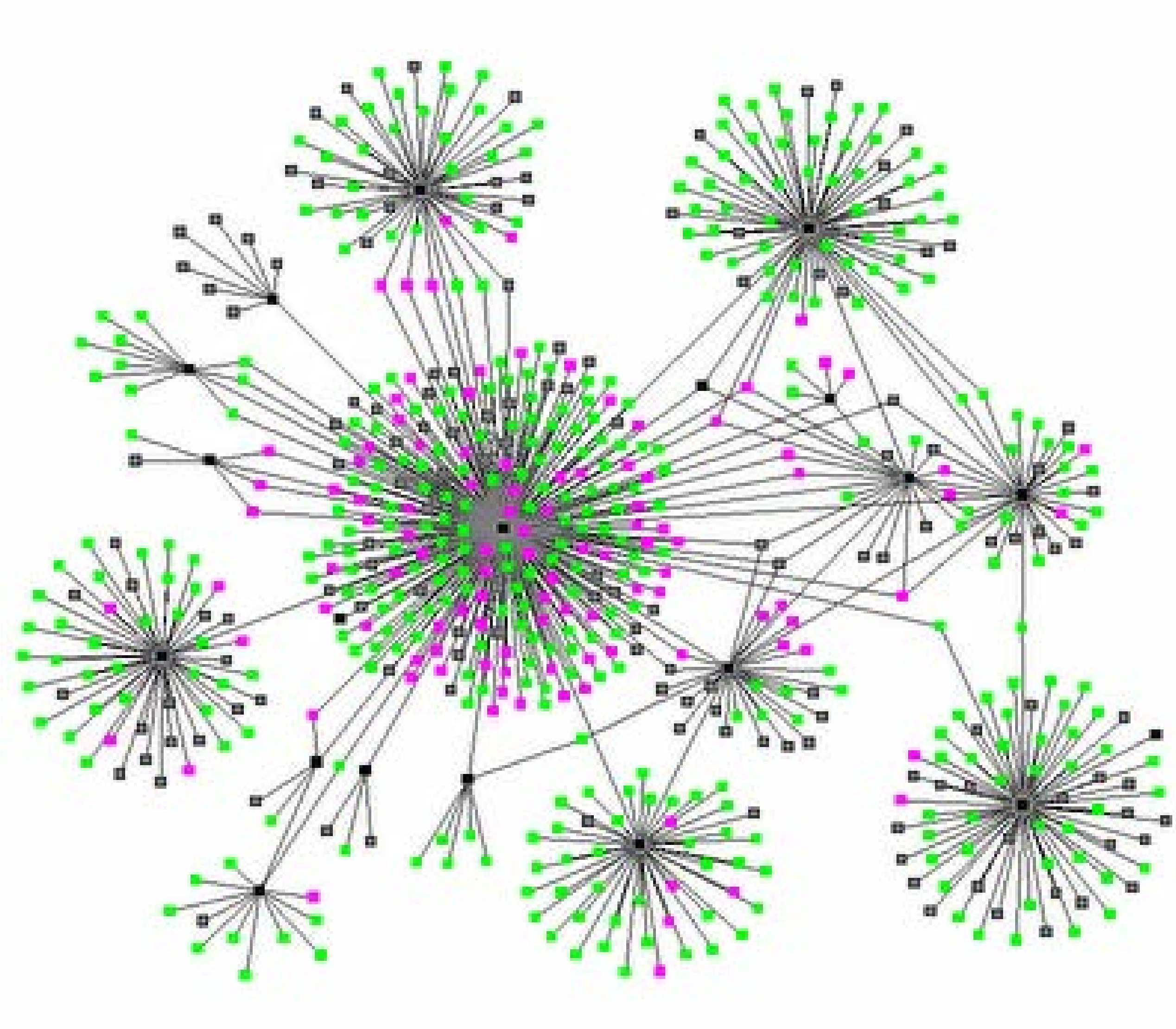


	TOTAL REPORTED	ON OCT. 4	14-DAY CHANGE
Cases	7.4 million+	34,491	+6% →
Deaths	209,603	332	–8% →

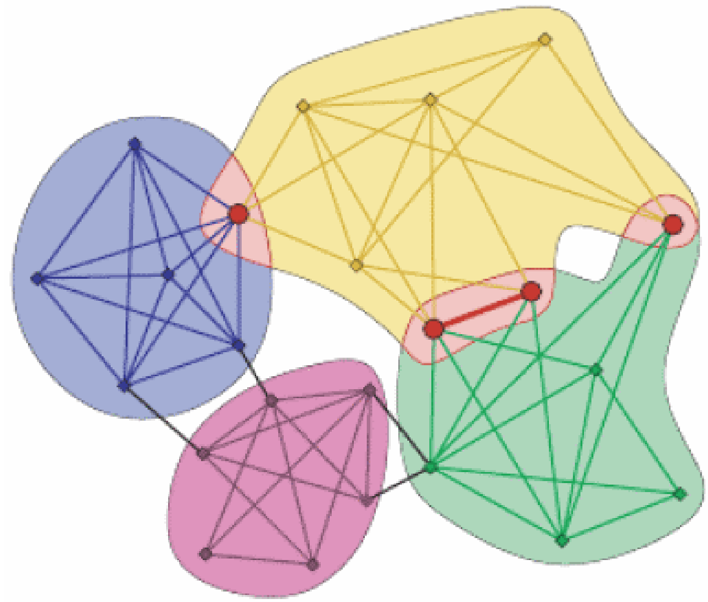
Day with data reporting anomaly.

Includes confirmed and probable cases where available. 14-day change trends use 7-day averages.

Graph / Network



Graph / Network – Community Detection



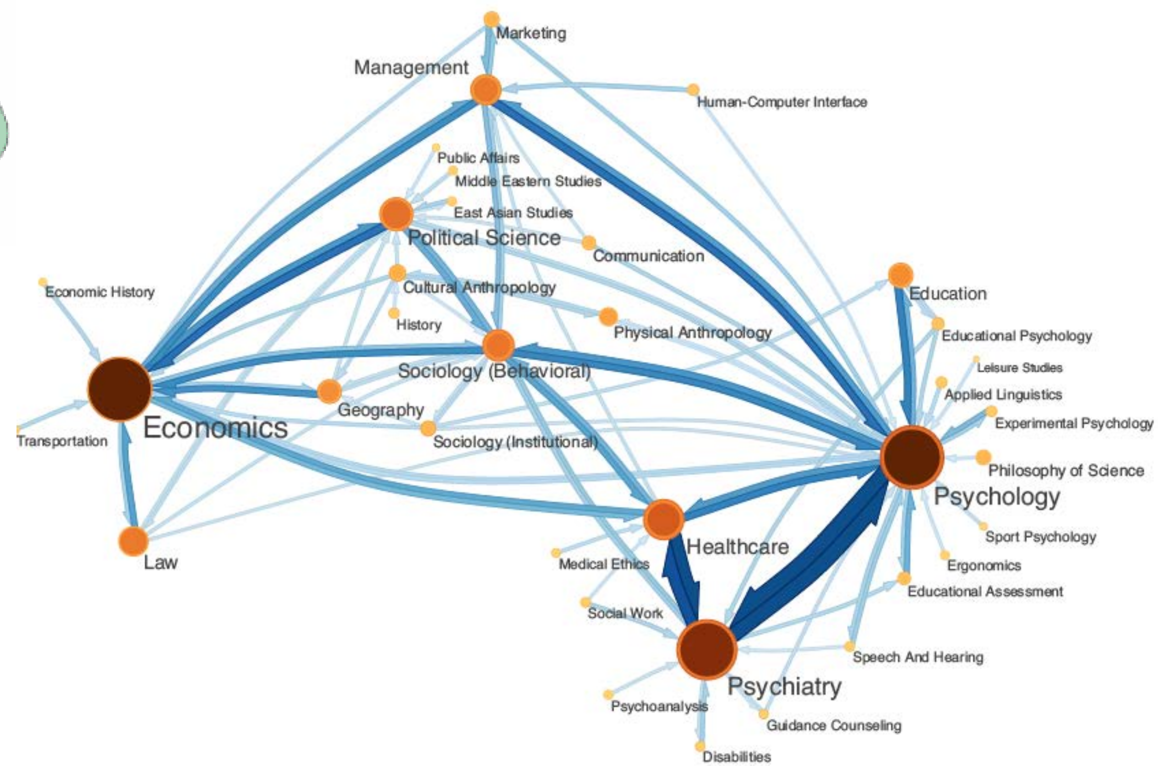


Image Data

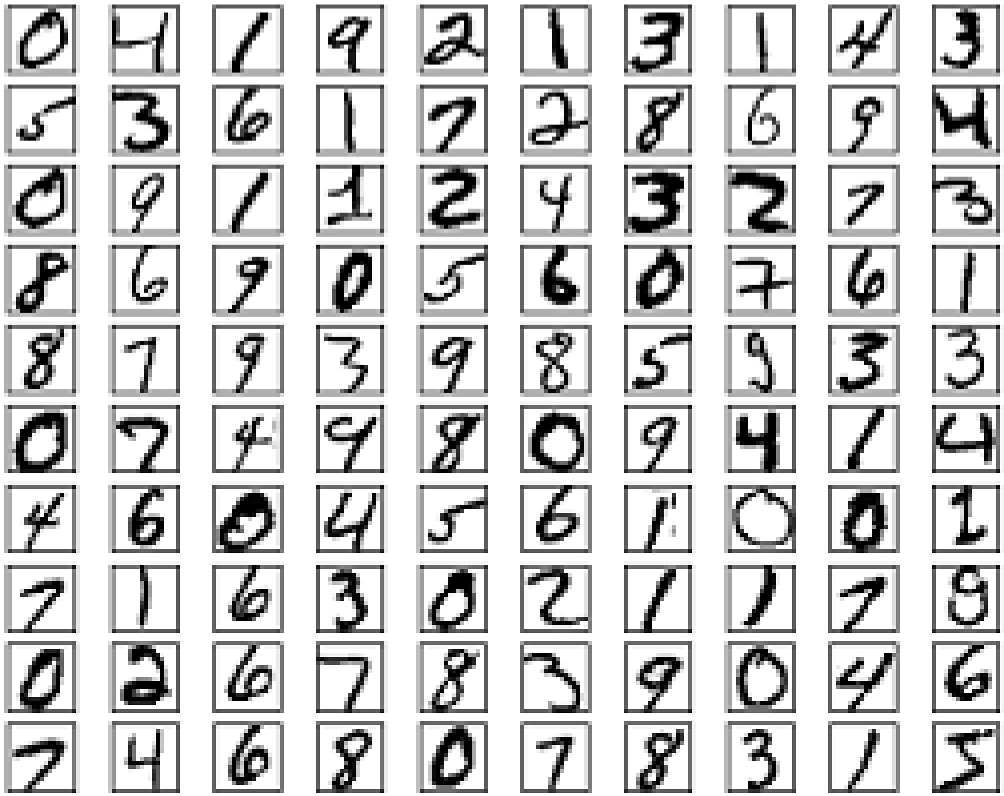


Image Data – Neural Style Transfer

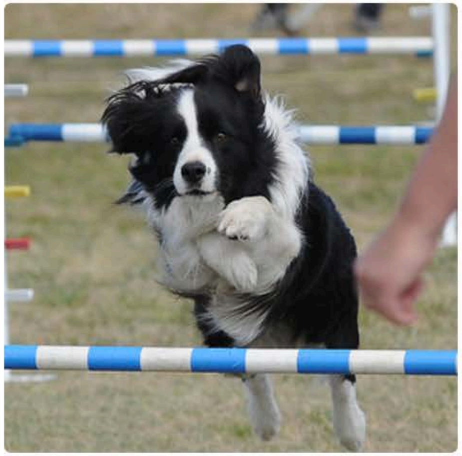
Image Data – Image Captioning

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"girl in pink dress is jumping in air."



"black and white dog jumps over bar."

"young girl in pink shirt is swinging on swing."

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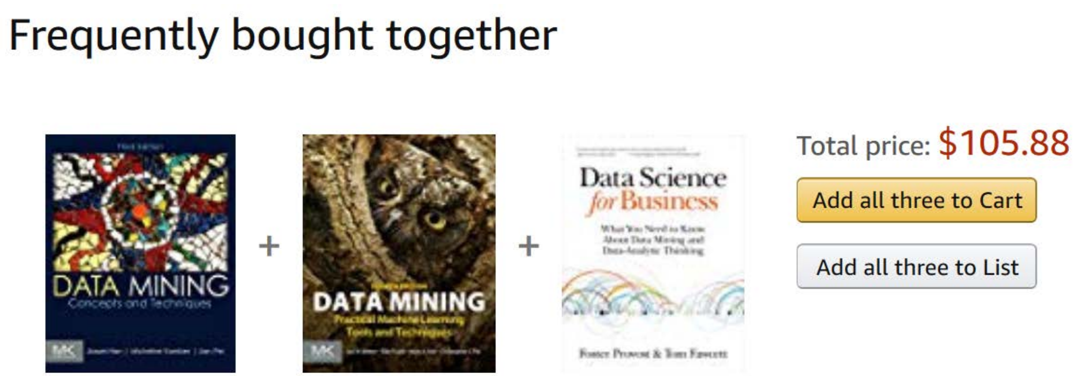
Data Mining Function: Association and Correlation Analysis

- Frequent patterns (or frequent itemsets)
  - What items are frequently purchased together in your Amazon transactions?



- Association, correlation vs. causality
  - A typical association rule
    - Diaper → Beer [0.5%, 75%] (support, confidence)

Data Mining Function: Classification

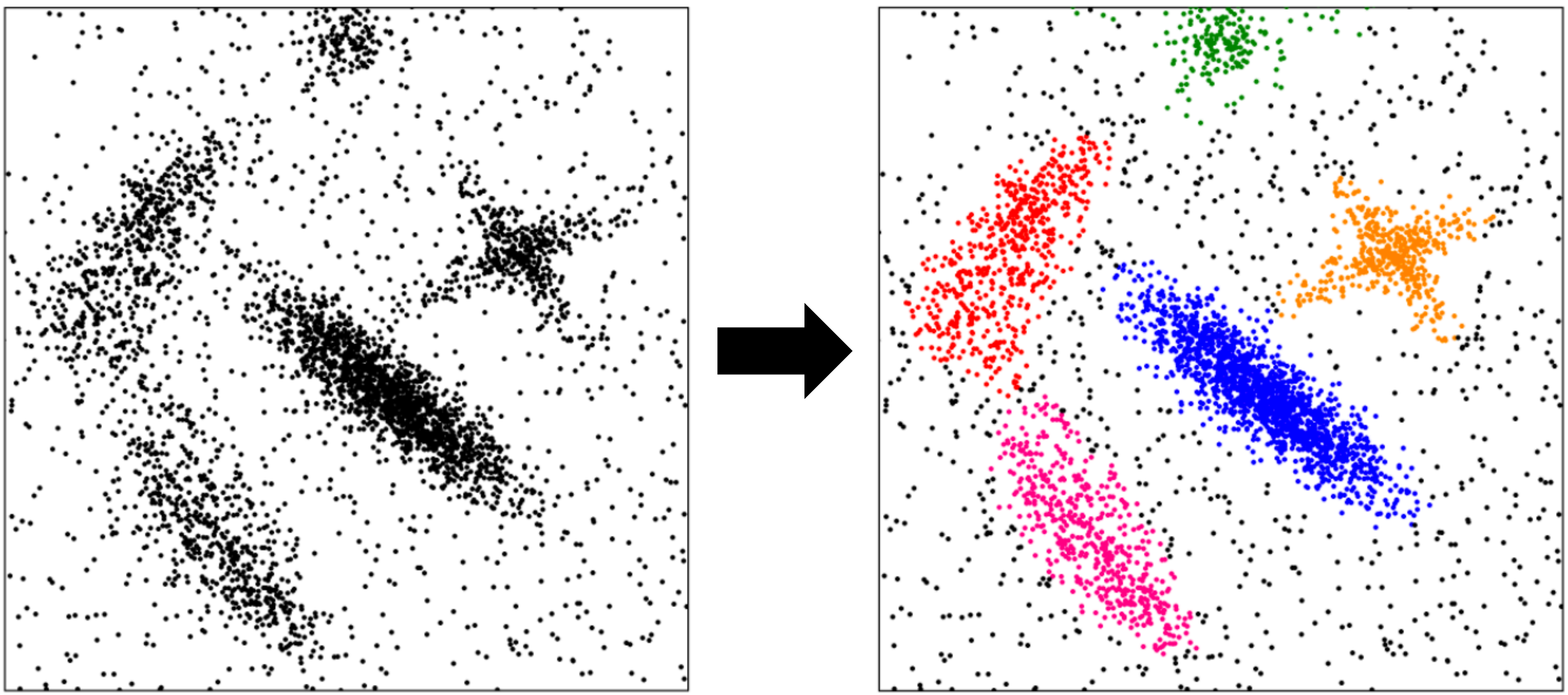
- Classification and label prediction
  - Construct models (functions) based on some training examples
  - Describe and distinguish classes or concepts for future prediction
    - E.g., classify countries based on (climate), or classify cars based on (gas mileage)
  - Predict some unknown class labels
- Typical methods
  - Decision trees, naïve Bayesian classification, support vector machines, neural networks, rule-based classification, pattern-based classification, logistic regression, ...
- Typical applications:
  - Credit card fraud detection, direct marketing, classifying stars, diseases, web-pages, ...

Image Classification Example

Data Mining Function: Cluster Analysis

- Unsupervised learning (i.e., Class label is unknown)
- Group data to form new categories (i.e., clusters), e.g., cluster houses to find distribution patterns
- Principle: Maximizing intra-class similarity & minimizing interclass similarity
- Many methods and applications

Clustering Example



Data Mining Functions: Others

- Prediction
- Similarity search
- Ranking
- Outlier detection
- …

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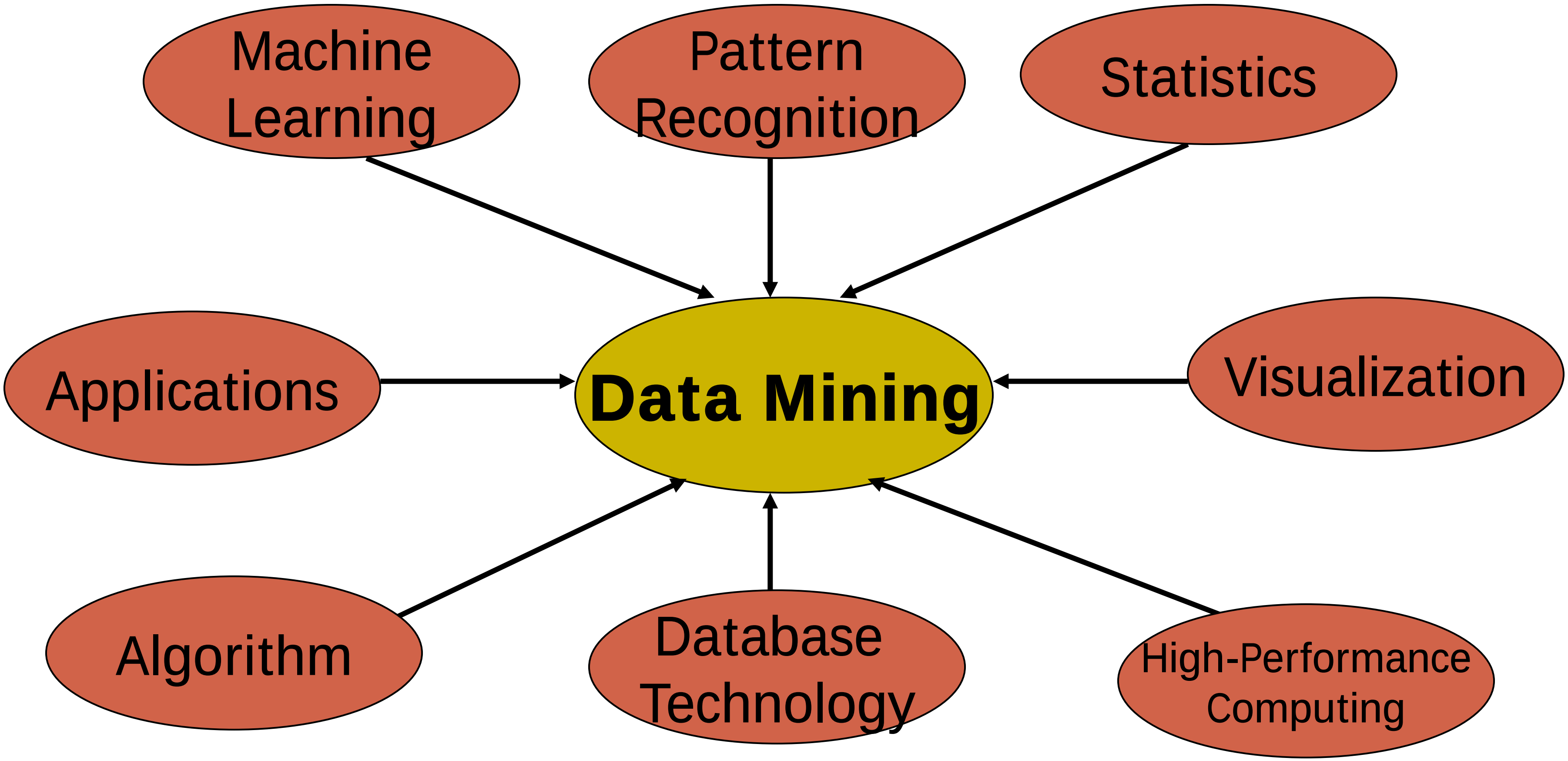
Data Mining: Confluence of Multiple Disciplines



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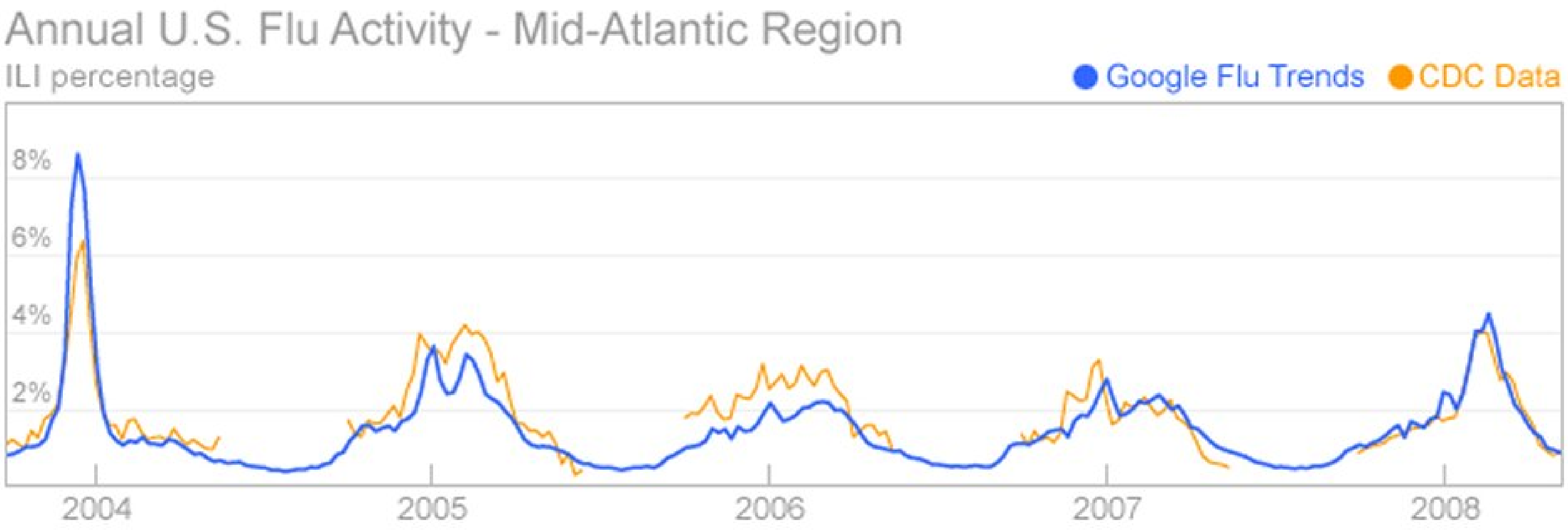
Applications of Data Mining

- Web page analysis: from web page classification, clustering to PageRank & HITS algorithms
- Collaborative analysis & recommender systems
- Basket data analysis to targeted marketing
- Biological and medical data analysis: classification, cluster analysis (microarray data analysis), biological sequence analysis, biological network analysis
- Data mining and software engineering (e.g., IEEE Computer, Aug. 2009 issue)
- Social media
- Game

Google Flu Trends

- https://www.youtube.com/watch?v=6111nS66Dpk



NetFlix Prize

- https://www.youtube.com/watch?v=4_e2sNYYfxA

NETFLIX

Netflix Prize

COMPLETED

Home | Rules | Leaderboard | Update

Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 **leaders.**

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07
12	BellKor	0.8624	9.46	2009-07-26 17:19:11

Facebook MyPersonality App

- https://www.youtube.com/watch?v=GOZArvMMHKs

Private traits and attributes are predictable from digital records of human behavior

Michal Kosinski[a,1], David Stillwell[a], and Thore Graepel[b]

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We show that easily accessible digital records of behavior, Facebook Likes, can be used to automatically and accurately predict a range of highly sensitive personal attributes including: sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender. The analysis presented is based on a dataset of over 58,000 volunteers who provided their Facebook Likes, detailed demographic profiles, and the results of several psychometric tests. The proposed model uses dimensionality reduction for preprocessing the Likes data, which are then entered into logistic/linear regression to predict individual psychodemographic profiles from Likes. The model correctly discriminates between homosexual and heterosexual men in 88% of cases, African Americans and Caucasian Americans in 95% of cases, and between Democrat and Republican in 85% of cases. For the personality trait "Openness," prediction accuracy is close to the test–retest accuracy of a standard personality test. We give examples of associations between attributes and Likes and discuss implications for online personalization

browsing logs (11–15). Similarly, it has been shown that personality can be predicted based on the contents of personal Web sites (16), music collections (17), properties of Facebook or Twitter profiles such as the number of friends or the density of friendship networks (18–21), or language used by their users (22). Furthermore, location within a friendship network at Facebook was shown to be predictive of sexual orientation (23).

This study demonstrates the degree to which relatively basic digital records of human behavior can be used to automatically and accurately estimate a wide range of personal attributes that people would typically assume to be private. The study is based on Facebook Likes, a mechanism used by Facebook users to express their positive association with (or "Like") online content, such as photos, friends' status updates, Facebook pages of products, sports, musicians, books, restaurants, or popular Web sites. Likes represent a very generic class of digital records, similar to Web search queries, Web browsing histories, and credit card purchases. For example, observing users' Likes related to music

1. Introduction

- Why Data Mining?
- What Is Data Mining?
- A Multi-Dimensional View of Data Mining
  - What Kinds of Data Can Be Mined?
  - What Kinds of Patterns Can Be Mined?
  - What Kinds of Technologies Are Used?
  - What Kinds of Applications Are Targeted?
- Content covered by this course

Course Content

- Functions to be covered
  - Prediction and classification
  - Clustering
  - Frequent pattern mining and association rules
  - Similarity search
- Data types to be covered
  - Vector/Tabular data
  - Set data
  - Sequential data
  - Time Series
  - Text data
  - Graph data

Where to Find References? DBLP, CiteSeer, Google

- Data mining and KDD (SIGKDD: CDROM)
  - Conferences: ACM-SIGKDD, IEEE-ICDM, SIAM-DM, PKDD, PAKDD, etc.
  - Journal: Data Mining and Knowledge Discovery, KDD Explorations, ACM TKDD
- Database systems (SIGMOD: ACM SIGMOD Anthology—CD ROM)
  - Conferences: ACM-SIGMOD, ACM-PODS, VLDB, IEEE-ICDE, EDBT, ICDT, DASFAA
  - Journals: IEEE-TKDE, ACM-TODS/TOIS, JIIS, J. ACM, VLDB J., Info. Sys., etc.
- AI & Machine Learning
  - Conferences: ICML, AAAI, IJCAI, COLT (Learning Theory), CVPR, NIPS, etc.
  - Journals: Machine Learning, Artificial Intelligence, Knowledge and Information Systems, IEEE-PAMI, etc.
- Web and IR
  - Conferences: SIGIR, WWW, WSDM, CIKM, etc.
  - Journals: WWW: Internet and Web Information Systems,
- Statistics
  - Conferences: Joint Stat. Meeting, etc.
  - Journals: Annals of statistics, etc.
- Visualization
  - Conference proceedings: CHI, ACM-SIGGraph, etc.
  - Journals: IEEE Trans. visualization and computer graphics, etc.

Recommended Reference Books

- E. Alpaydin. Introduction to Machine Learning, 2nd ed., MIT Press, 2011
- S. Chakrabarti. Mining the Web: Statistical Analysis of Hypertex and Semi-Structured Data. Morgan Kaufmann, 2002
- R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification, 2ed., Wiley-Interscience, 2000
- T. Dasu and T. Johnson. Exploratory Data Mining and Data Cleaning. John Wiley & Sons, 2003
- U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy. Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, 1996
- U. Fayyad, G. Grinstein, and A. Wierse, Information Visualization in Data Mining and Knowledge Discovery, Morgan Kaufmann, 2001
- J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques. Morgan Kaufmann, 3rd ed. , 2011
- T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed., Springer, 2009
- B. Liu, Web Data Mining, Springer 2006
- T. M. Mitchell, Machine Learning, McGraw Hill, 1997
- Y. Sun and J. Han, Mining Heterogeneous Information Networks, Morgan & Claypool, 2012
- P.-N. Tan, M. Steinbach and V. Kumar, Introduction to Data Mining, Wiley, 2005
- S. M. Weiss and N. Indurkhya, Predictive Data Mining, Morgan Kaufmann, 1998
- I. H. Witten and E. Frank, Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kaufmann, 2nd ed. 2005

Major Concepts Related to Probability and Statistics

- Elements of Probability
  - Sample space, event space, probability measure
  - Conditional probability
  - Independence, conditional independence
- Random variables
  - Cumulative distribution function, Probability mass function (for discrete random variable), Probability density function (for continuous random variable)
  - Expectation, variance
  - Some frequently used distributions
    - Discrete: Bernoulli, binomial, geometric, passion
    - Continuous: uniform, exponential, normal
- More random variables
  - Joint distribution, marginal distribution, joint and marginal probability mass function, joint and marginal density function
  - Chain rule
  - Bayes' rule
  - Independence
  - Expectation, conditional expectation, and covariance

Major Concepts in Linear Algebra

- Vectors
  - Addition, scalar multiplication, norm, dot product (inner product), projection, cosine similarity
- Matrices
  - Addition, scalar multiplication, matrix-matrix multiplication, trace, eigenvalues and eigenvectors

Optimization Related

- MLE and MAP Principle
- Gradient descent / stochastic gradient descent
- Newton's method
- Expectation-Maximum algorithm (EM)

Other Courses

- CS247: Advanced Data Mining
  - Focus on Text, Recommender Systems, and Networks/Graphs
  - Will be offered in Winter 2022
- CS249: Deep Graph Learning
  - Focus on Graph Mining and Learning
  - Will be offered in Spring 2022