What's it all about?

Most of these slides (used with permission) are based on the book:

Data Mining: Practical Machine Learning Tools and Techniques
by I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal

1

Chapter 1: What's it all about?

- Data mining and machine learning
- Simple examples: the weather problem and others
- Fielded applications
- The data mining process
- Machine learning and statistics
- Generalization as search
- Data mining and ethics

2

2

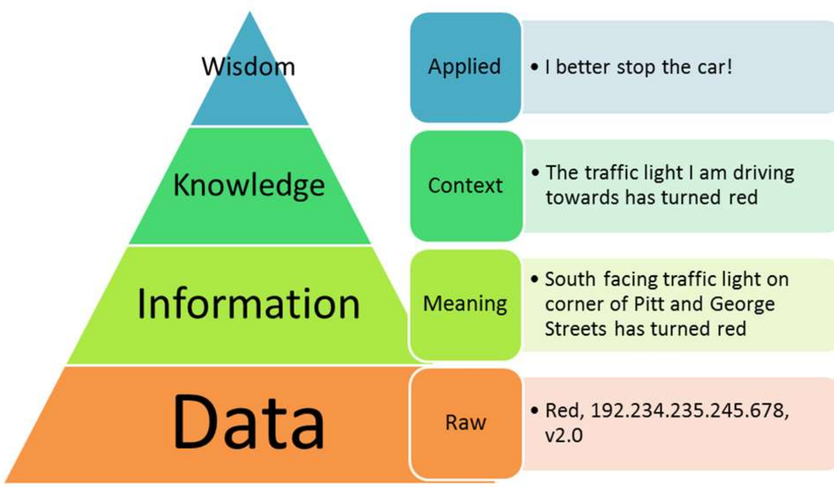
Information is crucial

- Example 1: *in vitro* fertilization
  - Given: embryos described by 60 features such as their morphology, oocyte, follicle and sperm sample
  - Problem: selection of embryos that will survive
  - Data: historical records of embryos and outcome
- Example 2: cow culling
  - Given: cows described by 700 features
  - Problem: selection of cows that should be culled
  - Data: historical records and farmers' decisions, age, health problems, fertility

3

3

Data – Information – Knowledge - Wisdom



4

From data to information

- Society produces huge amounts of data
  - Sources: business, science, medicine, economics, geography, environment, sports, …
- This data is a potentially valuable resource
- Raw data is useless: need techniques to automatically extract information from it
  - Data: recorded facts
  - Information: patterns underlying the data
- We are concerned with machine learning techniques for automatically finding patterns in data
- Patterns that are found may be represented as *structural descriptions* or as black-box models

5

5

Structural descriptions

- Example: if-then rules

```
If tear production rate = reduced
   then recommendation = none
Otherwise, if age = young and astigmatic = no
   then recommendation = soft
```

Age	Spectacle prescription	Astigmatism	Tear production rate	Recommended lenses
Young	Myope	No	Reduced	None
Young	Hypermetrope	No	Normal	Soft
Pre-presbyopic	Hypermetrope	No	Reduced	None
Presbyopic	Myope	Yes	Normal	Hard
…	…	…	…	…

6

6

Machine learning

- Definitions of "learning" from dictionary:

Definition	
To get knowledge of by study, experience, or being taught	Difficult to measure
To become aware by information or from observation **To commit to memory** **To be informed of, ascertain; to receive instruction**	Trivial for computers

- Operational definition:

Things learn when they change their behavior in a way that makes them perform better in the future. — Does a slipper learn?

7

7

Data mining

- Finding patterns in data that provide insight or enable fast and accurate decision making
- Strong, accurate patterns are needed to make decisions
  - Problem 1: most patterns are not interesting
  - Problem 2: patterns may be inexact (or spurious)
  - Problem 3: data may be garbled or missing
- Machine learning techniques identify patterns in data and provide many tools for data mining
- Of primary interest are machine learning techniques that provide structural descriptions

8

8

The weather problem

- Conditions for playing a certain game

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	Normal	False	Yes
…	…	…	…	…

- Apply the following classification rules in order

```
If outlook = sunny and humidity = high then play = no
If outlook = rainy and windy = true then play = no
If outlook = overcast then play = yes
If humidity = normal then play = yes
If none of the above then play = yes
```

9

9

Classification vs. association rules

- **Classification rule:**
  predicts value of a given attribute (the classification of an example)

```
If outlook = sunny and humidity = high
   then play = no
```

- **Association rule:**
  predicts value of arbitrary attribute (or combination)

```
If temperature = cool then humidity = normal
If humidity = normal and windy = false
   then play = yes
If outlook = sunny and play = no
   then humidity = high
If windy = false and play = no
   then outlook = sunny and humidity = high
```

10

10

Weather data with mixed attributes

- Some attributes have numeric values
- Mixed attributes problem

Outlook	Temperature	Humidity	Windy	Play
Sunny	85	85	False	No
Sunny	80	90	True	No
Overcast	83	86	False	Yes
Rainy	75	80	False	Yes
…	…	…	…	…

- Rules should also consider inequalities

```
If outlook = sunny and humidity > 83 then play = no
If outlook = rainy and windy = true then play = no
If outlook = overcast then play = yes
If humidity < 85 then play = yes
If none of the above then play = yes
```

11

11

The contact lenses data

Age	Spectacle prescription	Astigmatism	Tear production rate	Recommended lenses
Young	Myope	No	Reduced	None
Young	Myope	No	Normal	Soft
Young	Myope	Yes	Reduced	None
Young	Myope	Yes	Normal	Hard
Young	Hypermetrope	No	Reduced	None
Young	Hypermetrope	No	Normal	Soft
Young	Hypermetrope	Yes	Reduced	None
Young	Hypermetrope	Yes	Normal	hard
Pre-presbyopic	Myope	No	Reduced	None
Pre-presbyopic	Myope	No	Normal	Soft
Pre-presbyopic	Myope	Yes	Reduced	None
Pre-presbyopic	Myope	Yes	Normal	Hard
Pre-presbyopic	Hypermetrope	No	Reduced	None
Pre-presbyopic	Hypermetrope	No	Normal	Soft
Presbyopic	Hypermetrope	Yes	Normal	None

- Presbyopia: Long sightedness that accompanies the onset of middle age
- Myope: Short sightedness
- Hypermetrope: Long sightedness
- Astigmatism: Defect in the eye or lens

12

12

The contact lenses data

Age	Spectacle prescription	Astigmatism	Tear production rate	Recommended lenses
Young	Myope	No	Reduced	None
Young	Myope	No	Normal	Soft
Young	Myope	Yes	Reduced	None
Young	Myope	Yes	Normal	Hard
Young	Hypermetrope	No	Reduced	None
Young	Hypermetrope	No	Normal	Soft
Young	Hypermetrope	Yes	Reduced	None
Young	Hypermetrope	Yes	Normal	hard
Pre-presbyopic	Myope	No	Reduced	None
Pre-presbyopic	Myope	No	Normal	Soft
Pre-presbyopic	Myope	Yes	Reduced	None
Pre-presbyopic	Myope	Yes	Normal	Hard
Pre-presbyopic	Hypermetrope	No	Reduced	None
Pre-presbyopic	Hypermetrope	No	Normal	Soft
Pre-presbyopic	Hypermetrope	Yes	Reduced	None
Pre-presbyopic	Hypermetrope	Yes	Normal	None
Presbyopic	Myope	No	Reduced	None
Presbyopic	Myope	No	Normal	None
Presbyopic	Myope	Yes	Reduced	None
Presbyopic	Myope	Yes	Normal	Hard
Presbyopic	Hypermetrope	No	Reduced	None
Presbyopic	Hypermetrope	No	Normal	Soft
Presbyopic	Hypermetrope	Yes	Reduced	None
Presbyopic	Hypermetrope	Yes	Normal	None

13

13

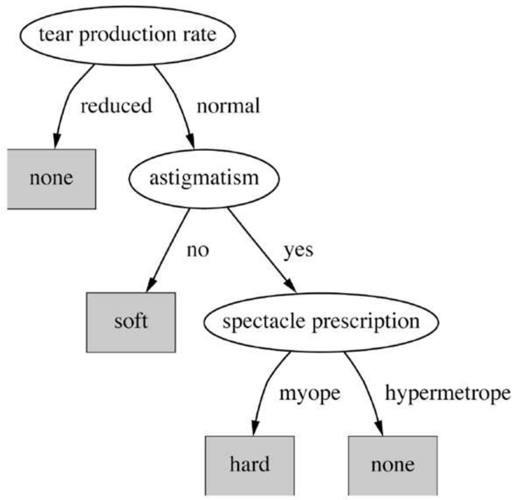
A complete and correct rule set

```
If tear production rate = reduced then recommendation = none
If age = young and astigmatic = no
   and tear production rate = normal then recommendation = soft
If age = pre-presbyopic and astigmatic = no
   and tear production rate = normal then recommendation = soft
If age = presbyopic and spectacle prescription = myope
   and astigmatic = no  then recommendation = none
If spectacle prescription = hypermetrope and astigmatic = no
   and tear production rate = normal then recommendation = soft
If spectacle prescription = myope and astigmatic = yes
   and tear production rate = normal then recommendation = hard
If age young and astigmatic = yes
   and tear production rate = normal then recommendation = hard
If age = pre-presbyopic
   and spectacle prescription = hypermetrope
   and astigmatic = yes then recommendation = none
If age = presbyopic and spectacle prescription = hypermetrope
   and astigmatic = yes then recommendation = none
```

14

14

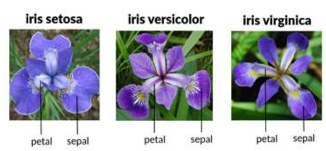
A decision tree for this problem



15

15

Classifying iris flowers



	Sepal length	Sepal width	Petal length	Petal width	Type
1	5.1	3.5	1.4	0.2	Iris setosa
2	4.9	3.0	1.4	0.2	Iris setosa
…					
51	7.0	3.2	4.7	1.4	Iris versicolor
52	6.4	3.2	4.5	1.5	Iris versicolor
…					
101	6.3	3.3	6.0	2.5	Iris virginica
102	5.8	2.7	5.1	1.9	Iris virginica
…					

```
If petal length < 2.45 then Iris setosa
If sepal width < 2.10 then Iris versicolor
...
```

16

16

Predicting CPU performance

- Example: 209 different computer configurations

	Cycle time (ns)	Main memory (Kb)		Cache (Kb)	Channels		Performance
	MYCT	MMIN	MMAX	CACH	CHMIN	CHMAX	PRP
1	125	256	6000	256	16	128	198
2	29	8000	32000	32	8	32	269
…							
208	480	512	8000	32	0	0	67
209	480	1000	4000	0	0	0	45

- Linear regression function

```
PRP = -55.9 + 0.0489 MYCT + 0.0153 MMIN + 0.0056 MMAX
      + 0.6410 CACH - 0.2700 CHMIN + 1.480 CHMAX
```

17

17

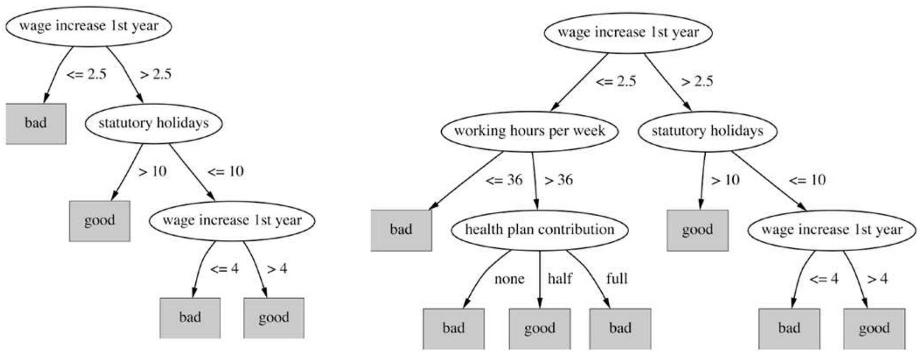
Data from labor negotiations

Attribute	Type	1	2	3	…	40
Duration	(Number of years)	1	2	3		2
Wage increase first year	Percentage	2%	4%	4.3%		4.5
Wage increase second year	Percentage	?	5%	4.4%		4.0
Wage increase third year	Percentage	?	?	?		?
Cost of living adjustment	{none,tcf,tc}	none	tcf	?		none
Working hours per week	(Number of hours)	28	35	38		40
Pension	{none,ret-allw, empl-cntr}	none	?	?		?
Standby pay	Percentage	?	13%	?		?
Shift-work supplement	Percentage	?	5%	4%		4
Education allowance	{yes,no}	yes	?	?		?
Statutory holidays	(Number of days)	11	15	12		12
Vacation	{below-avg,avg,gen}	avg	gen	gen		avg
Long-term disability assistance	{yes,no}	no	?	?		yes
Dental plan contribution	{none,half,full}	none	?	full		full
Bereavement assistance	{yes,no}	no	?	?		yes
Health plan contribution	{none,half,full}	none	?	full		half
Acceptability of contract	{good,bad}	bad	good	good		good

18

18

Decision trees for the labor data



- First tree is more intuitive
- Second tree is more accurate – but might be overfitted for training data
- First tree is obtained by pruning the second tree

19

19

Soybean classification

	Attribute	Number of values	Sample value
Environment	Time of occurrence	7	July
	Precipitation	3	Above normal
…			
Seed	Condition	2	Normal
	Mold growth	2	Absent
…			
Fruit	Condition of fruit pods	4	Normal
	Fruit spots	5	?
Leaf	Condition	2	Abnormal
	Leaf spot size	3	?
…			
Stem	Condition	2	Abnormal
	Stem lodging	2	Yes
…			
Root	Condition	3	Normal
Diagnosis		19	Diaporthe stem canker

20

20

The role of domain knowledge

```
If leaf condition is normal
   and stem condition is abnormal
   and stem cankers is below soil line
   and canker lesion color is brown
then
   diagnosis is rhizoctonia root rot
```

```
If leaf malformation is absent
   and stem condition is abnormal
   and stem cankers is below soil line
   and canker lesion color is brown
then
   diagnosis is rhizoctonia root rot
```

But in this domain, “leaf condition is normal” implies “leaf malformation is absent”!

On this dataset, computer generated rules performed well 97.5% of time compared to 72% as per expert derived rules

21

21

Fielded applications

- The result of learning—or the learning method itself—is deployed in practical applications
  - Processing loan applications
  - Screening images for oil slicks
  - Electricity supply forecasting
  - Diagnosis of machine faults
  - Marketing and sales
  - Separating crude oil and natural gas
  - Reducing banding in rotogravure printing
  - Finding appropriate technicians for telephone faults
  - Scientific applications: biology, astronomy, chemistry
  - Automatic selection of TV programs
  - Monitoring intensive care patients

22

22

Processing loan applications (American Express)

- Given: questionnaire with financial and personal information
- Question: should money be lent?
- Simple statistical method covers 90% of cases
- Borderline cases referred to loan officers
- But: 50% of accepted borderline cases defaulted!
- Solution: reject all borderline cases?
  - No! Borderline cases are most active customers

23

23

Enter machine learning

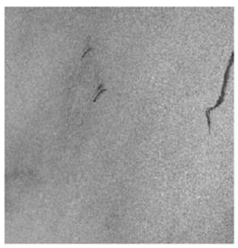
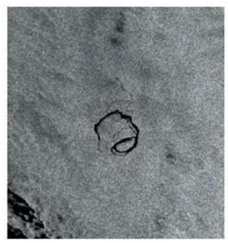
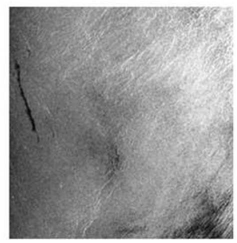
- 1000 training examples of borderline cases
- 20 attributes:
  - age
  - years with current employer
  - years at current address
  - years with the bank
  - other credit cards possessed,…
- Learned rules: correct on 70% of cases
  - human experts only 50%
- Rules could be used to explain decisions to customers

24

24

Screening images

- Given: radar satellite images of coastal waters
- Problem: detect oil slicks in those images
- Oil slicks appear as dark regions with changing size and shape
- Not easy: lookalike dark regions can be caused by weather conditions (e.g. high wind)
- Expensive process requiring highly trained personnel

25

25

Enter machine learning

- Extract dark regions from normalized image
- Attributes:
  - size of region
  - shape, area
  - intensity
  - sharpness and jaggedness of boundaries
  - proximity of other regions
  - info about background
- Constraints:
  - Few training examples—oil slicks are rare!
  - Unbalanced data: most dark regions aren’t slicks
  - Regions from same image form a batch
  - Requirement: adjustable false-alarm rate

26

26

Load forecasting

- Electricity supply companies need forecast of future demand for power
- Forecasts of min/max load for each hour => significant savings
- Given: manually constructed load model that assumes "normal" climatic conditions
- Problem: adjust for weather conditions
- Static model consist of:
  - base load for the year
  - load periodicity over the year
  - effect of holidays

27

27

Enter machine learning

- Predictions of manually created static model were corrected using "most similar" days
- Attributes:
  - temperature
  - humidity
  - wind speed
  - cloud cover readings
  - plus difference between actual load and predicted load
- Average difference among three "most similar" days added to static model
- Linear regression coefficients form attribute weights in similarity function
- Models provide quicker forecast – taking seconds rather than hours

28

28

Diagnosis of machine faults

- Diagnosis: classical domain of expert systems
- Given: Fourier analysis of vibrations measured at various points of a device's mounting
- Question: which fault is present?
- Preventative maintenance of electromechanical motors and generators
- Information very noisy
- So far: diagnosis by expert/hand-crafted rules

29

29

Enter machine learning

- Available: 600 faults with expert's diagnosis
- ~300 unsatisfactory, rest used for training
- Attributes augmented by intermediate concepts that embodied causal domain knowledge
- Expert not satisfied with initial rules because they did not relate to his domain knowledge
- Further background knowledge resulted in more complex rules that were satisfactory
- Learned rules outperformed hand-crafted ones

30

30

Marketing and sales I

- Companies precisely record massive amounts of marketing and sales data
- Applications:
  - Customer loyalty:
    identifying customers that are likely to defect by detecting changes in their behavior
    (e.g. banks/phone companies)
  - Special offers:
    identifying profitable customers
    (e.g. reliable owners of credit cards that need extra money during the holiday season)

31

31

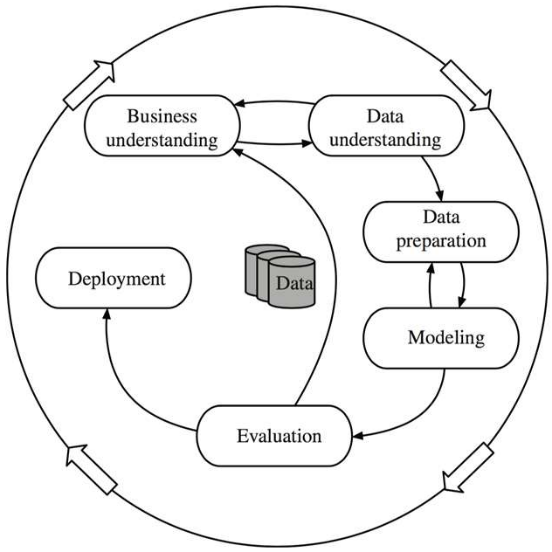
Marketing and sales II

- Market basket analysis
  - Association techniques find groups of items that tend to occur together in a transaction
    (used to analyze checkout data)
- Historical analysis of purchasing patterns
- Identifying prospective customers
  - Focusing promotional mailouts
    (targeted campaigns are cheaper than mass-marketed ones)

32

32

The data mining process



33

33

Machine learning and statistics

- Historical difference (grossly oversimplified):
  - Statistics: testing hypotheses
  - Machine learning: finding the right hypothesis
- But: huge overlap due to multiple works in different places
  - Decision trees (C4.5 and CART)
  - Nearest-neighbor methods
- Today: perspectives have converged
  - Most machine learning algorithms employ statistical techniques

34

34

Generalization as search

- Inductive learning: find a concept description that fits the data
  - learner discovers rules by observing examples
- Example: rule sets as description language
  - Enormous, but finite, search space
- Simple solution:
  - enumerate the concept space
  - eliminate descriptions that do not fit examples
  - surviving descriptions contain target concept

35

35

Enumerating the concept space

- Search space for weather problem
  - 4 x 4 x 3 x 3 x 2 = 288 possible combinations
  - With 14 rules => 2.7×10^{34} possible rule sets
- Other practical problems:
  - More than one description may survive
  - No description may survive
    - Language is unable to describe target concept
    - *or* data contains noise
- Another view of generalization as search:
  hill-climbing in description space according to pre-specified matching criterion
  - Many practical algorithms use heuristic search that cannot guarantee to find the optimum solution

36

36

Bias

- Bias: show inclination or prejudice for or against someone or something
- Important decisions in learning systems:
  - Concept description language
  - Order in which the space is searched
  - Way that overfitting to the particular training data is avoided
- These form the "bias" of the search:
  - Language bias
  - Search bias
  - Overfitting-avoidance bias

37

37

Language bias

- Important question:
  - is language universal
    or does it restrict what can be learned?
- Universal language can express arbitrary subsets of examples
- If language includes logical *or* ("disjunction"), it is universal
- Example: rule sets
- Domain knowledge can be used to exclude some concept descriptions *a priori* from the search

38

38

Search bias

- Search heuristic
  - "Greedy" search: performing the best single step
  - "Beam search": keeping several alternatives
  - …
- Direction of search
  - *General-to-specific*
    - E.g. specializing a rule by adding conditions
  - *Specific-to-general*
    - E.g. generalizing an individual instance into a rule

39

39

Overfitting-avoidance bias

- Can be seen as a form of search bias
- Modified evaluation criterion
  - E.g., balancing simplicity and number of errors
- Modified search strategy
  - E.g., pruning (simplifying a description)
    - Pre-pruning: stops at a simple description before search proceeds to an overly complex one
    - Post-pruning: generates a complex description first and simplifies it afterwards

40

40

Data mining and ethics I

- Ethical issues arise in practical applications
- Anonymizing data is difficult
  - 85% of Americans can be identified from just zip code, birth date and sex
- Data mining often used to discriminate
  - E.g., loan applications: using some information (e.g., sex, religion, race) is unethical
- Ethical situation depends on application
  - E.g., same information ok in medical application
- Attributes may contain problematic information
  - E.g., area code may correlate with race

41

41

Data mining and ethics II

- Important questions:
  - Who is permitted access to the data?
  - For what purpose was the data collected?
  - What kind of conclusions can be legitimately drawn from it?
- Caveats must be attached to results
- Purely statistical arguments are never sufficient!
- Are resources put to good use?

42

42