Data Mining
Part 1

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Data Mining
Practical Machine Learning Tools and Techniques

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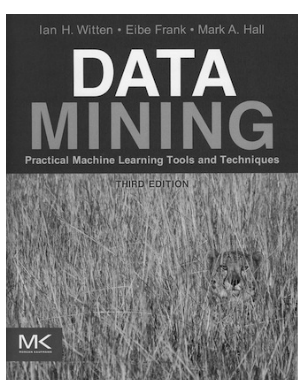


What's it all about?

Data vs information

Data mining and machine learning

Structural descriptions

- Rules: classification and association
- Decision trees

Datasets

- Weather, contact lens, CPU performance, labor negotiation data, soybean classification

Fielded applications

- Loan applications, screening images, load forecasting, machine fault diagnosis, market basket analysis

Generalization as search

Data mining and ethics

Data vs. information

Society produces huge amounts of data

- Sources: business, science, medicine, economics, geography, environment, sports, …

Potentially valuable resource

Raw data is useless: need techniques to automatically extract information from it

- Data: recorded facts
- Information: patterns underlying the data

Information is crucial

Example 1: *in vitro* fertilization

- Given: embryos described by 60 features
- 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

Data mining

Extracting

- implicit,
- previously unknown,
- potentially useful

information from data

Needed: programs that detect patterns and regularities in the data

Strong patterns $\Rightarrow$ good predictions

- 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

Algorithms for acquiring structural descriptions from examples

Structural descriptions represent patterns explicitly

- Can be used to predict outcome in new situation
- Can be used to understand and explain how prediction is derived (*may be even more important*)

Methods originate from artificial intelligence, statistics, and research on databases

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
…	…	…	…	…

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
…	…	…	…	…

```
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
```


Ross Quinlan

Machine learning researcher from 1970’s

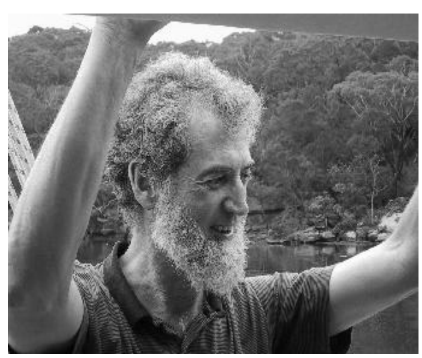
University of Sydney, Australia

1986 “Induction of decision trees” *ML Journal*

1993 *C4.5: Programs for machine learning*. Morgan Kaufmann

199? Started

RULEQUEST RESEARCH
data mining tools



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
```


Weather data with mixed attributes

Some attributes have numeric values

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
…	…	…	…	…

```
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
```

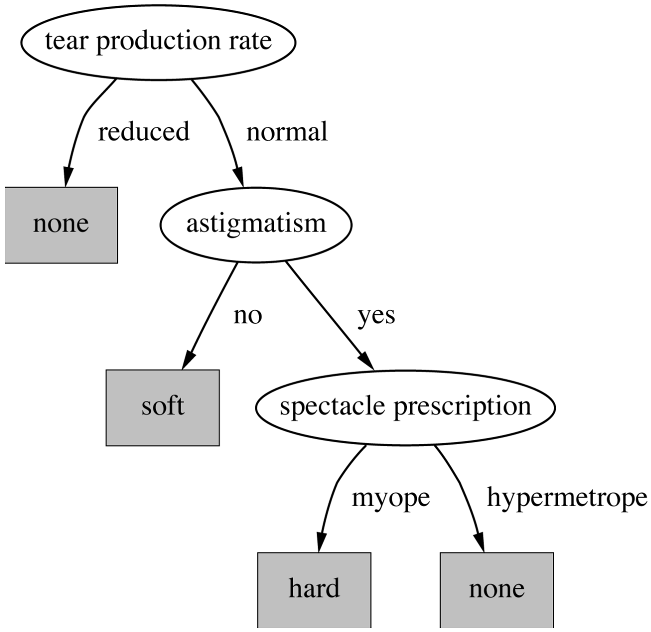
The contact lenses data

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

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
```

A decision tree for this problem



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
...
```

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

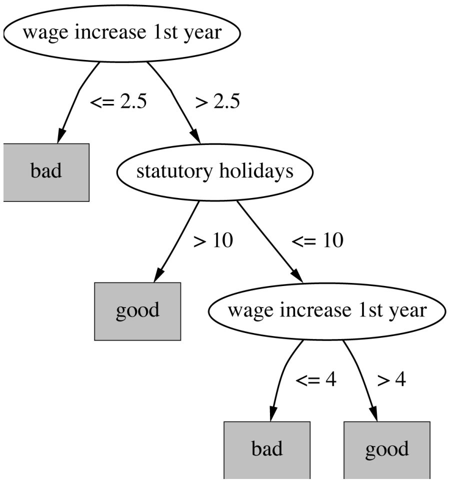
Linear regression function

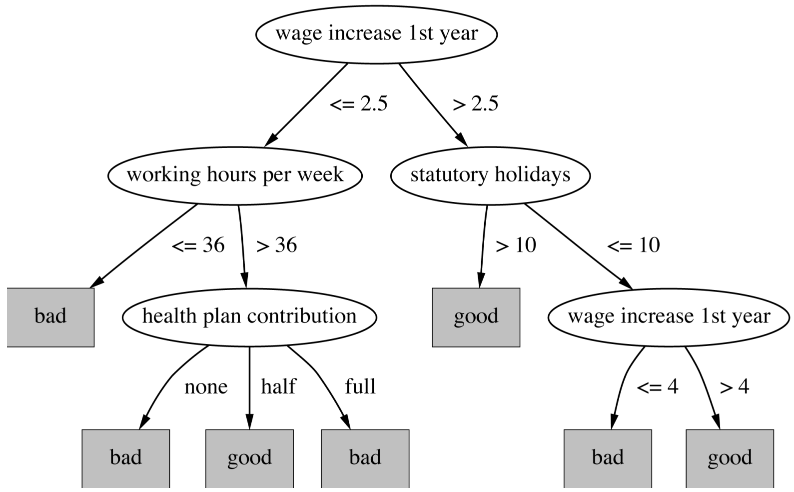
```
PRP = -55.9 + 0.0489 MYCT + 0.0153 MMIN + 0.0056 MMAX
      + 0.6410 CACH - 0.2700 CHMIN + 1.480 CHMAX
```


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}	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

Decision trees for the labor data





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

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”!

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

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

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

Screening images

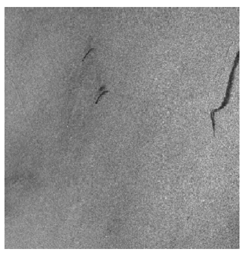
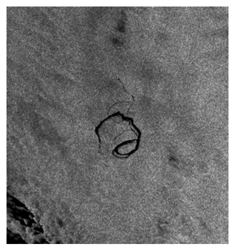
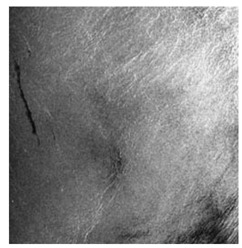
Given: radar satellite images of coastal waters

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

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

Load forecasting

Electricity supply companies need forecast of future demand for power

Forecasts of min/max load for each hour
$\Rightarrow$ 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

Enter machine learning

Prediction corrected using “most similar” days

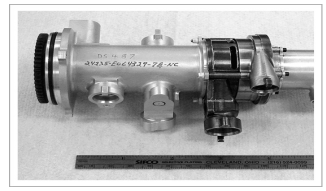
Attributes:

- 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

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

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

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)

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)

Machine learning and statistics

Historical difference (grossly oversimplified):

- Statistics: testing hypotheses
- Machine learning: finding the right hypothesis

But: huge overlap

- Decision trees (C4.5 and CART)
- Nearest-neighbor methods

Today: perspectives have converged

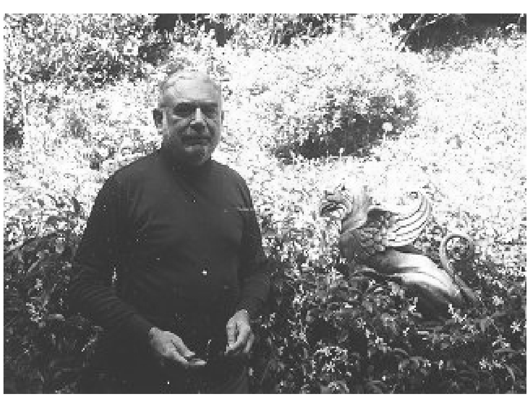
- Most ML algorithms employ statistical techniques

Statisticians

Sir Ronald Aylmer Fisher

Born: 17 Feb 1890 London, England
Died: 29 July 1962 Adelaide, Australia

Numerous distinguished contributions to developing the theory and application of statistics for making quantitative a vast field of biology



Leo Breiman

Developed decision trees

1984 Classification and Regression Trees. Wadsworth.

Generalization as search

Inductive learning: find a concept description that fits the data

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

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

- Most practical algorithms use heuristic search that cannot guarantee to find the optimum solution

Bias

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

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

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

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

Data mining and ethics I

Ethical issues arise in practical applications

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

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?