Machine Learning Techniques for Data Mining

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PART I

What’s it all about?

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

- Extraction of implicit, previously unknown, and potentially useful information from data
- Needed: programs that detect patterns and regularities in the data
- Strong patterns can be used to make predictions
  - Problem 1: most patterns are not interesting
  - Problem 2: patterns may be inexact (or even completely spurious) if data is garbled or missing

Machine learning techniques

- Technical basis for data mining: 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 (maybe even more important)
- Methods originate from artificial intelligence, statistics, and research on databases

Structural descriptions

- For 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
...	...	...	...	...

Can machines really learn?

- Definitions of “learning” from dictionary:

  To get knowledge of by study, experience, or being taught
  To become aware by information or from observation
  } Difficult to measure

  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?

- Does learning imply intention?

The weather problem

- Conditions for playing an unspecified 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
```

Classification vs. association rules

- Classification rule: predicts value of pre-specified attribute (the classification of an example)

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

- Associations rule: predicts value of arbitrary attribute or combination of attributes

```
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

- Two attributes with 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
```

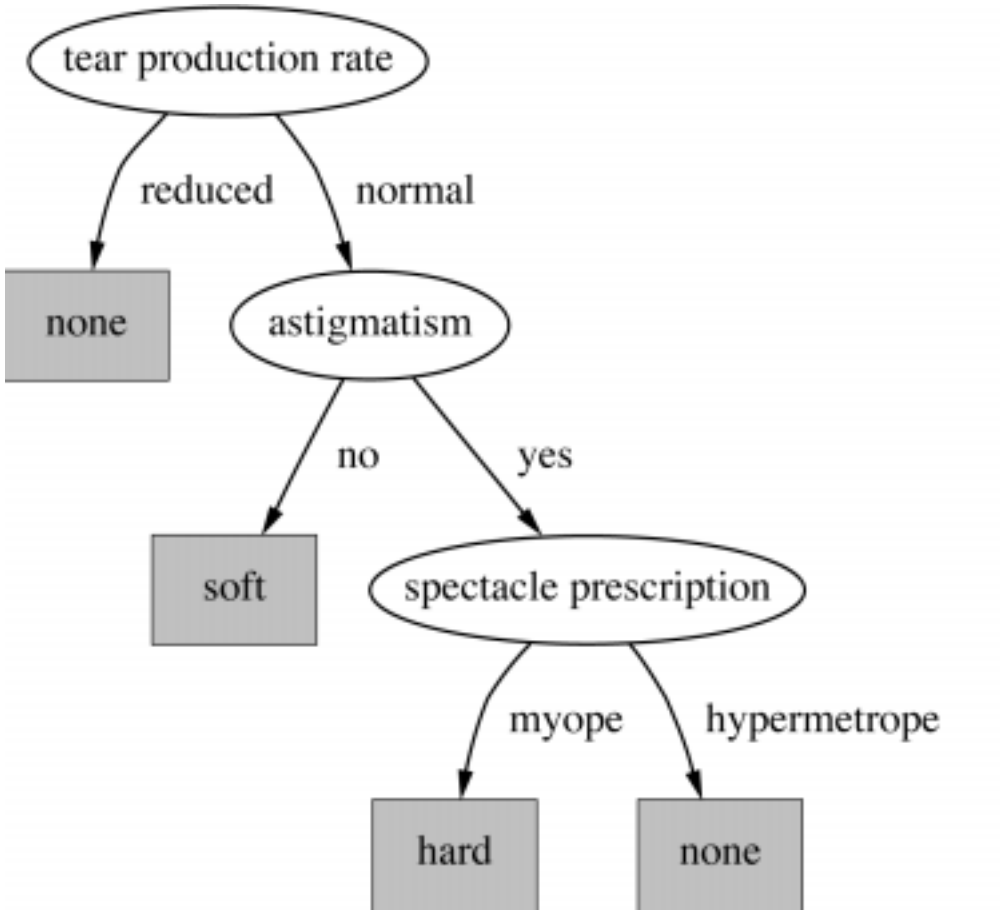
The contact lenses data

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

- Examples: 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

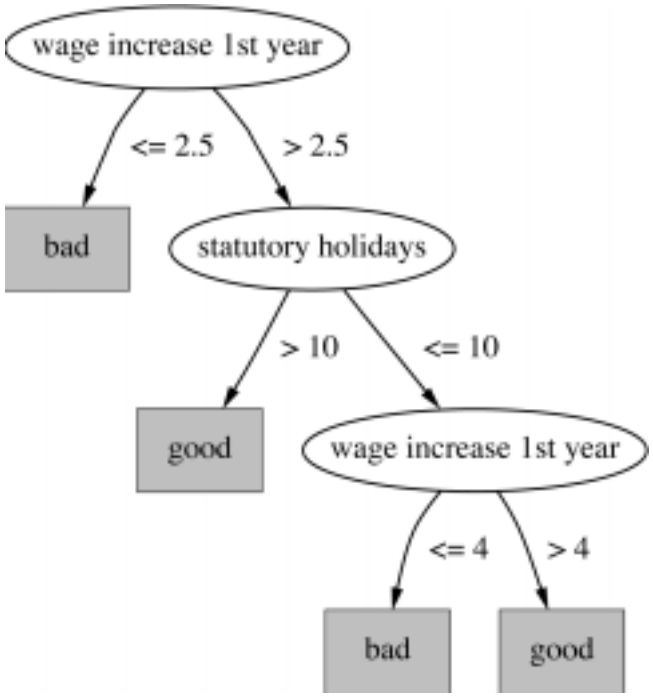
- Linear regression function

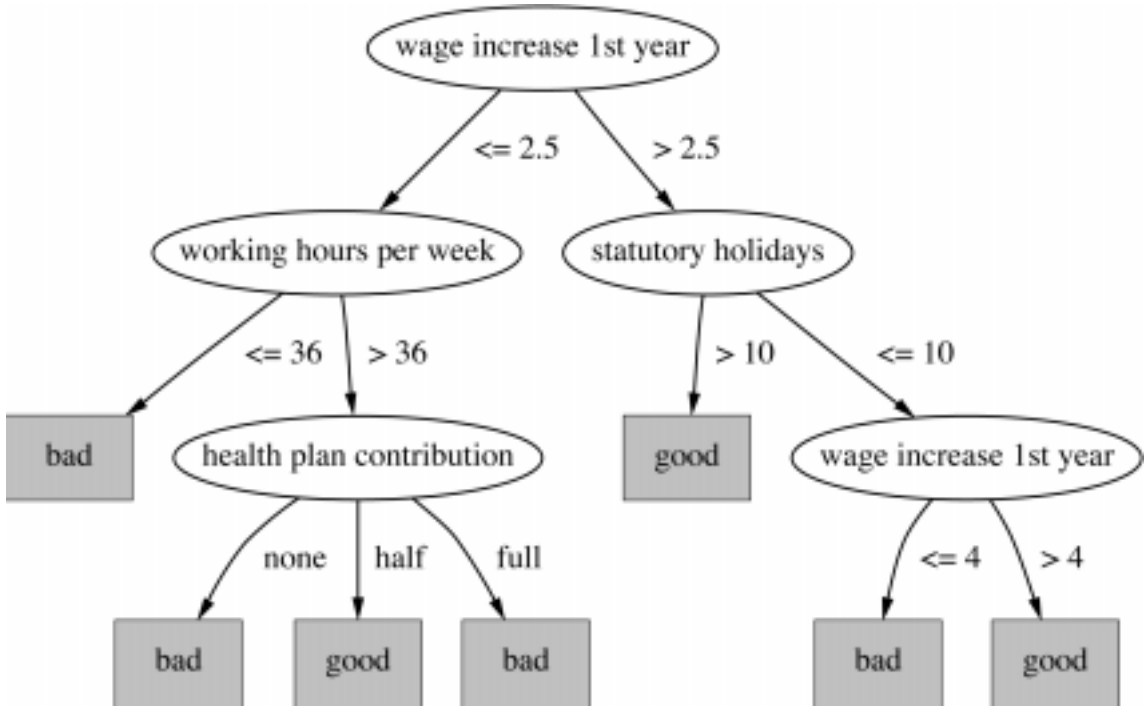
```
PRP = -55.9 + 0.0489 MYCT + 0.0153 MMIN + 0.0056 MMAX
      + 0.6410 CACH - 0.2700 CHMIN + 1.480 CHMAX
```

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-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

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	?
Leaves	Condition	2	Abnormal
	Leaf spot size	3	?
…			
Stem	Condition	2	Abnormal
	Stem lodging	2	Yes
…			
Roots	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
```

Fielded applications

- Where the result of learning or the learning method itself is deployed in practical applications
  - Reducing delays in rotogravure printing
  - Autoclave layout for aircraft parts
  - Automatic classification of sky objects
  - Predicting pilot bids
  - Automated completion of repetitive forms
  - Text retrieval
  - …

Processing loan applications

- Given: questionnaire with financial and personal information
- Problem: should money be lend?
- 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 predicted 2/3 of borderline cases correctly!
- Also: company liked rules because they could be used to explain decisions to customers

Screening images

- Given: radar satellite images of coastal waters
- Problem: detecting 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

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

Load forecasting

- Electricity supply companies require forecast of future demand for power
- Accurate forecasts of minimum and maximum load for each hour result in significant savings
- Given: manually constructed static load model that assumes “normal” climatic conditions
- Problem: adjusting 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, and cloud cover readings, along with difference between actual load and predicted load
- Average difference among three most similar days added to static model
- Coefficients of linear regression 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
- Problem: 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, the rest used for training
- Attributes were augmented by intermediate concepts that embodied causal domain knowledge
- Expert was 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
- Possible 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 to find groups of items that tend to occur together in a transaction (mainly 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

- Difference historically (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

Generalization as search

- Inductive learning: finding a concept description that fits the data
- Example: rule sets as description language
  - Enormous, but finite, search space
- Simple solution: enumerating the concept space, eliminating 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 rules
  - No more than 14 rules: 2.7×10^{24} possible rule sets
- Possible remedy: candidate-elimination algorithm
- Other practical problems:
  - More than one description may survive
  - No description may survive
    - Language may not be able to describe target concept
    - Data may contain noise

The version space

- Space of consistent concept descriptions
- Completely determined by two sets
  - *L*: most specific descriptions that cover all positive examples and no negative ones
  - *G*: most general descriptions that do not cover any negative examples and all positive ones
- Only *L* and *G* need to be maintained and updated
- But: still computationally very expensive
- And: does not solve other practical problems

Version space example

- Given: red or green cows or chicken

L={} *G*={<*,*>}

<green,cow>: positive

L={<green,cow>} *G*={<*,*>}

<red,chicken>: negative

L={<green,cow>} *G*={<green,*>,<*,cow>}

<green, chicken>: positive

L={<green,*>} *G*={<green,*>}

Candidate-elimination algorithm

```
Initialize L and G
For each example e:
  If e is positive:
    Delete all elements from G that do not cover e
    For each element r in L that does not cover e:
      Replace r by all of its most specific generalizations that cover e
        and that are more specific than some element in G
    Remove elements from L that are more general than some other element in L
  If e is negative:
    Delete all elements from L that cover e
    For each element r in G that covers e:
      Replace r by all of its most general specializations that do not cover e
        and that are more general than some element in L
    Remove elements from G that are more specific than some other element in G
```

Bias

- The most important decisions in learning systems:
  - The concept description language
  - The order in which the space is searched
  - The way that overfitting to the particular training data is avoided
- These properties form the “bias” of the search:
  - Language bias
  - Search bias
  - Overfitting-avoidance bias

Language bias

- Most important question: is language universal or does it restrict what can be learned?
- Universal language can express arbitrary subsets of examples
- If language can represent statements involving logical *or* (“disjunctions”) 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

- Many 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 in practical applications:
  - 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?