

Input: concepts, instances, attributes

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

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Input: concepts, instances, attributes

- Components of the input for learning
- What's a concept?
 - Classification, association, clustering, numeric prediction
- What's in an example?
 - Relations, flat files
- What's in an attribute?
 - Nominal, ordinal, interval, ratio
- Preparing the input
 - ARFF, sparse data, attributes, missing and inaccurate values, unbalanced data, getting to know your data

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Components of the input

- Concepts: kinds of things that can be learned
 - Aim: intelligible and operational concept description
- Instances: the individual, independent examples of a concept to be learned
 - More complicated forms of input with dependencies between examples are possible
- Attributes: measuring aspects of an instance
 - We will focus on nominal and numeric ones

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What's a concept?

- Concept: thing to be learned
- Concept description: output of learning scheme
- Styles of learning:
 - Classification learning:
predicting a discrete class
 - Association learning:
detecting associations between features
 - Clustering:
grouping similar instances into clusters
 - Numeric prediction:
predicting a numeric quantity

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Classification learning

- Example problems: weather data, contact lenses, irises, labor negotiations
- Classification learning is *supervised*
 - Scheme is provided with actual outcome
- Outcome is called the *class* of the example
- Measure success on fresh data for which class labels are known (*test data*)
- In practice success is often measured subjectively

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Association learning

- Can be applied if no class is specified and any kind of structure is considered “interesting”
- Difference to classification learning:
 - Can predict any attribute’s value, not just the class, and more than one attribute’s value at a time
 - Hence: far more association rules than classification rules
 - Thus: constraints are necessary, such as minimum coverage and minimum accuracy

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Clustering

- Finding groups of items that are similar
- Clustering is *unsupervised*
 - The class of an example is not known
- Success often measured subjectively

	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
...					

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Numeric prediction

- Variant of classification learning where “class” is numeric (also called “regression”)
- Learning is supervised
 - Scheme is being provided with target value
- Measure success on test data

Outlook	Temperature	Humidity	Windy	Play-time
Sunny	Hot	High	False	5
Sunny	Hot	High	True	0
Overcast	Hot	High	False	55
Rainy	Mild	Normal	False	40
...

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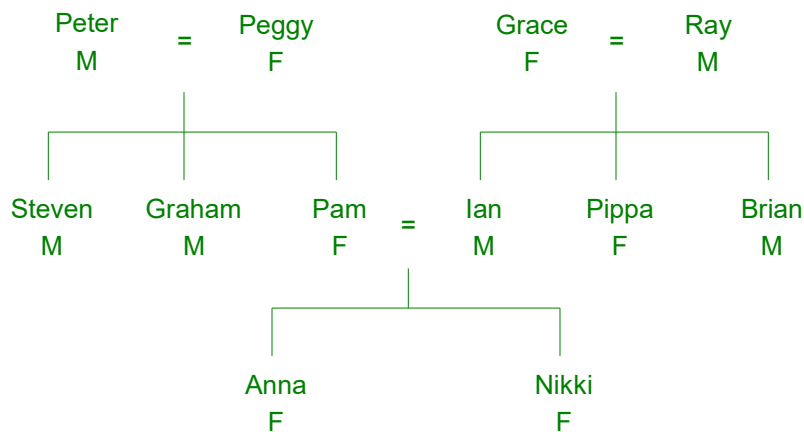
What's in an example?

- Instance: specific type of example
 - Thing to be classified, associated, or clustered
 - Individual, independent example of target concept
 - Characterized by a predetermined set of attributes
- Input to learning scheme: set of instances/dataset
 - Represented as a single relation/flat file
- Rather restricted form of input
 - No relationships between objects
- Most common form in practical data mining

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Example of relations: A family tree



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Family tree represented as a table

Name	Gender	Parent1	parent2
Peter	Male	?	?
Peggy	Female	?	?
Steven	Male	Peter	Peggy
Graham	Male	Peter	Peggy
Pam	Female	Peter	Peggy
Ian	Male	Grace	Ray
Pippa	Female	Grace	Ray
Brian	Male	Grace	Ray
Anna	Female	Pam	Ian
Nikki	Female	Pam	Ian

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The “sister-of” relation

First person	Second person	Sister of?
Peter	Peggy	No
Peter	Steven	No
...
Steven	Peter	No
Steven	Graham	No
Steven	Pam	Yes
...
Ian	Pippa	Yes
...
Anna	Nikki	Yes
...
Nikki	Anna	yes

First person	Second person	Sister of?
Steven	Pam	Yes
Graham	Pam	Yes
Ian	Pippa	Yes
Brian	Pippa	Yes
Anna	Nikki	Yes
Nikki	Anna	Yes
<i>All the rest</i>		No

Closed-world assumption

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A full representation in one table

First person				Second person				Sister of?
Name	Gender	Parent1	Parent2	Name	Gender	Parent1	Parent2	
Steven	Male	Peter	Peggy	Pam	Female	Peter	Peggy	Yes
Graham	Male	Peter	Peggy	Pam	Female	Peter	Peggy	Yes
Ian	Male	Grace	Ray	Pippa	Female	Grace	Ray	Yes
Brian	Male	Grace	Ray	Pippa	Female	Grace	Ray	Yes
Anna	Female	Pam	Ian	Nikki	Female	Pam	Ian	Yes
Nikki	Female	Pam	Ian	Anna	Female	Pam	Ian	Yes
<i>All the rest</i>								No

**If second person's gender = female
and first person's parent = second person's parent
then sister-of = yes**

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The "ancestor-of" relation

First person				Second person				Ancestor of?
Name	Gender	Parent1	Parent2	Name	Gender	Parent1	Parent2	
Peter	Male	?	?	Steven	Male	Peter	Peggy	Yes
Peter	Male	?	?	Pam	Female	Peter	Peggy	Yes
Peter	Male	?	?	Anna	Female	Pam	Ian	Yes
Peter	Male	?	?	Nikki	Female	Pam	Ian	Yes
Pam	Female	Peter	Peggy	Nikki	Female	Pam	Ian	Yes
Grace	Female	?	?	Ian	Male	Grace	Ray	Yes
Grace	Female	?	?	Nikki	Female	Pam	Ian	Yes
<i>Other positive examples here</i>								Yes
<i>All the rest</i>								No

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Recursion

- Infinite relations require recursion

```
If person1 is a parent of person2
then person1 is an ancestor of person2
```

```
If person1 is a parent of person2
and person2 is an ancestor of person3
then person1 is an ancestor of person3
```

- Appropriate techniques are known as “inductive logic programming” (ILP) methods
 - Example ILP method: Quinlan’s FOIL rule learner
 - Problems: (a) noise and (b) computational complexity

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Multi-instance concepts

- Each individual example comprises a bag (aka *multi-set*) of instances
 - All instances are described by the same attributes
 - One or more instances within an example may be responsible for the example's classification
- Goal of learning is still to produce a concept description
- Important real-world applications
 - Prominent examples are drug activity prediction and image classification
 - A drug can be viewed as bag of different geometric arrangements of the drug molecule
 - An image can be represented as a bag of image components (e.g. the target class might be "beach", where the image contains both "sand" and "water")
 - A set (bag) of keychains is positive if it contains proper key



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What's in an attribute?

- Each instance is described by a fixed predefined set of features, its “attributes”
- But: number of attributes may vary in practice
- Different instances have different features (e.g. number of wheels is relevant for cars but not for ships)
 - Possible solution: “irrelevant value” flag
- Related problem: existence of an attribute may depend of value of another one (e.g. name of spouse depends on married/unmarried attribute)
- Possible attribute types (“levels of measurement”):
 - *Nominal, ordinal, interval and ratio*

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Nominal levels of measurement

- Also known as categorical, enumerated or discrete
- Values are distinct symbols
 - Values themselves serve only as labels or names
 - *Nominal* comes from the Latin word for name
- Example: attribute “outlook” from weather data
 - Values: “sunny”, “overcast”, and “rainy”
- No relation is implied among nominal values (no ordering or distance measure)
- Only equality tests can be performed

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Ordinal levels of measurement

- Impose order on values
- But: no distance between values defined
- Example:
attribute “temperature” in weather data
 - Values: “hot” > “mild” > “cool”
- Note: addition and subtraction don’t make sense
- Example rule:
temperature < hot \Rightarrow play = yes
- Distinction between nominal and ordinal not always clear (e.g., attribute “outlook” – sunny -> overcast -> rainy)

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Interval quantities

- Interval quantities are not only ordered but measured in fixed and equal units
- Example 1: attribute “temperature” expressed in degrees Fahrenheit
- Example 2: attribute “year”
- Difference of two values makes sense (e.g. difference in temperature values)
- Sum or product doesn’t make sense (e.g. sum of years 1935 and 1949)
 - Zero point is not defined! (When exactly was year 0?)

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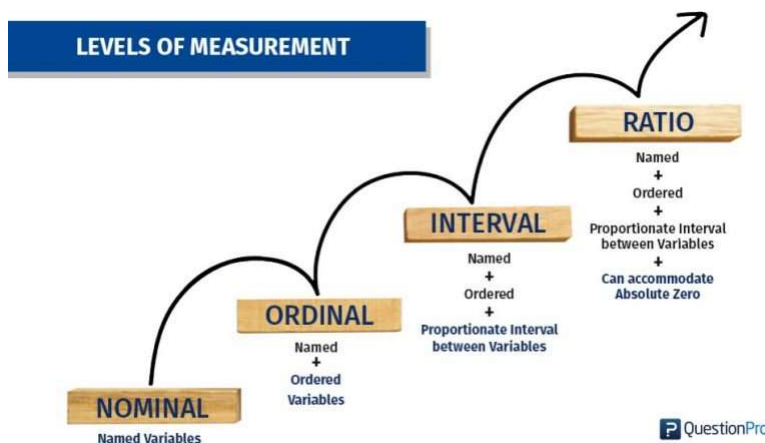
Ratio quantities

- Ratio quantities are ones for which the measurement scheme defines a zero point
- Example: attribute “distance”
 - Distance between an object and itself is zero
- Ratio quantities are treated as real numbers
 - All mathematical operations are allowed
 - E.g. multiply distance by 3
- But: is there an “inherently” defined zero point?
 - Answer depends on scientific knowledge (e.g., Fahrenheit knew no lower limit to temperature)
 - Years since a big bang is a ratio quantity

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An illustration



- Interval scale example: Celsius/Fahrenheit temperature scale
- Ratio scale has true zero value, negative values are not possible. E.g. person’s height, weight

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Further illustration

Offers:	Nominal	Ordinal	Interval	Ratio
The sequence of variables is established	-	Yes	Yes	Yes
Mode	Yes	Yes	Yes	Yes
Median	-	Yes	Yes	Yes
Mean	-	-	Yes	Yes
Difference between variables can be evaluated	-	-	Yes	Yes
Addition and Subtraction of variables	-	-	Yes	Yes
Multiplication and Division of variables	-	-	-	Yes
Absolute zero	-	-	-	Yes

- Ref: <https://www.questionpro.com/blog/nominal-ordinal-interval-ratio/>

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Attribute types used in practice

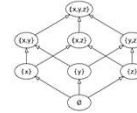
- Many data mining schemes accommodate just two levels of measurement: nominal and ordinal
- Others deal exclusively with ratio quantities
- Nominal attributes are also called “categorical”, “enumerated”, or “discrete”
 - But: “enumerated” and “discrete” imply order
- Special case: dichotomy (“boolean” attribute)
- Ordinal attributes are sometimes coded as “numeric” or “continuous”
 - But: “continuous” implies mathematical continuity

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Metadata

- Information about the data that encodes background knowledge
- In theory this information can be used to restrict the search space of the learning algorithm
- Examples:
 - Dimensional considerations
(i.e., expressions must be dimensionally correct)
In general, the dimension of any physical quantity can be written as $L^a M^b T^c I^d \Theta^e N^f J^g$ for some powers $a, b, c, d, e, f, a, b, c, d, e, f,$ and g .
 - Circular orderings
(e.g., degrees in compass, day such as next day, previous day..)
 - Partial orderings
(e.g., generalization/specialization relations)
POSET
- Data mining schemes usually don't take metadata in account



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Preparing the input

- Denormalization (combining multiple table data in one) is not the only issue when data is prepared for learning
- Problem: different data sources (e.g., sales department, customer billing department, ...)
 - Differences: styles of record keeping, coding conventions, time periods, data aggregation, primary keys, types of errors
 - Data must be assembled, integrated, cleaned up
 - “Data warehouse”: consistent point of access
- External data may be required (“overlay data” – e.g. demographic data is required for marketing and sales applications)
- Critical: type and level of data aggregation (e.g. aggregated phone call data is required to analyze customer behavior)

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The ARFF data format

```
%  
% ARFF file for weather data with some numeric features  
%  
@relation weather  
  
@attribute outlook {sunny, overcast, rainy}  
@attribute temperature numeric  
@attribute humidity numeric  
@attribute windy {true, false}  
@attribute play? {yes, no}  
  
@data  
sunny, 85, 85, false, no  
sunny, 80, 90, true, no  
overcast, 83, 86, false, yes  
...
```

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Additional attribute types

- ARFF data format also supports *string* attributes:

```
@attribute description string
```

- Similar to nominal attributes but list of values is not pre-specified

- Additionally, it supports *date* attributes:

```
@attribute today date
```

- Uses the ISO-8601 combined date and time format *yyyy-MM-dd-THH:mm:ss*

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Relational attributes

- Relational attributes allow multi-instance problems to be represented in ARFF format
 - Each value of a relational attribute is a *separate* bag of instances, but each bag has the same attributes

```
@attribute bag relational
@attribute outlook { sunny, overcast, rainy }
@attribute temperature numeric
@attribute humidity numeric
@attribute windy { true, false }
@end bag
```

- Nested attribute block gives the structure of the referenced instances

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Multi-instance ARFF

```
%
% Multiple instance ARFF file for the weather data
%
@relation weather

@attribute bag_ID { 1, 2, 3, 4, 5, 6, 7 }
@attribute bag relational
@attribute outlook {sunny, overcast, rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {true, false}
@attribute play? {yes, no}
@end bag

@data
1, "sunny, 85, 85, false\nsunny, 80, 90, true", no
2, "overcast, 83, 86, false\nrainy, 70, 96, false", yes
...
```

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Sparse data

- In some applications most attribute values are zero and storage requirements can be reduced
 - E.g.: word counts in a text categorization problem
- ARFF supports sparse data storage

```
0, 26, 0, 0, 0, 0, 63, 0, 0, 0, "class A"  
0, 0, 0, 42, 0, 0, 0, 0, 0, 0, "class B"
```

```
{1 26, 6 63, 10 "class A"}  
{3 42, 10 "class B"}
```

- Some learning algorithms work very efficiently with sparse data (e.g. sparse multinomial logistic regression, Extreme Learning Machines (ELM) which are a type of neural network)

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Attribute types

- Interpretation of attribute types in an ARFF file depends on the learning scheme that is applied
 - Numeric attributes are interpreted as
 - ordinal scales if less-than and greater-than are used
 - ratio scales if distance calculations are performed (normalization/standardization may be required)
 - Note also that some instance-based schemes define a distance between nominal values (0 if values are equal, 1 otherwise)
- Background knowledge may be required for correct interpretation of data
 - E.g., consider integers in some given data file: nominal, ordinal, or ratio scale?

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Nominal vs. ordinal

- Attribute “age” nominal

```
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
```

- Attribute “age” ordinal
(e.g. “young” < “pre-presbyopic” < “presbyopic”)

```
If age ≤ pre-presbyopic and astigmatic = no  
and tear production rate = normal  
then recommendation = soft
```

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Missing values

- Missing values are frequently indicated by out-of-range entries for an attribute
 - There are different types of missing values: unknown, unrecorded, irrelevant
 - Reasons:
 - malfunctioning equipment
 - changes in experimental design
 - collation of different datasets
 - measurement not possible
- Missing value may have significance in itself (e.g., missing test in a medical examination)
 - Most schemes assume that is not the case and “missing” may need to be coded as an additional, separate attribute value

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Inaccurate values

- Reason: data has not been collected for mining it
- Result: errors and omissions that affect the accuracy of data mining
- These errors may not affect the original purpose of the data (e.g., age of customer)
- Typographical errors in nominal attributes \Rightarrow values need to be checked for consistency
- Typographical and measurement errors in numeric attributes \Rightarrow outliers need to be identified
- Errors may be deliberate (e.g., wrong zip codes)
- Other problems: duplicates, stale data

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Unbalanced data

- Unbalanced data is a well-known problem in classification problems
 - One class is often far more prevalent than the rest
 - Example: detecting a rare disease
- Main problem: simply predicting the majority class yields high accuracy but is not useful
 - Predicting that no patient has the rare disease gives high classification accuracy
- Unbalanced data requires techniques that can deal with unequal misclassification costs
 - Misclassifying an afflicted patient may be much more costly than misclassifying a healthy one

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Getting to know your data

- Simple visualization tools are very useful
 - Nominal attributes: histograms (Is the distribution consistent with background knowledge?)
 - Numeric attributes: graphs (Any obvious outliers?)
- 2-D and 3-D plots show dependencies
- May need to consult domain experts
- Too much data to inspect manually? Take a sample!

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Questions?

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