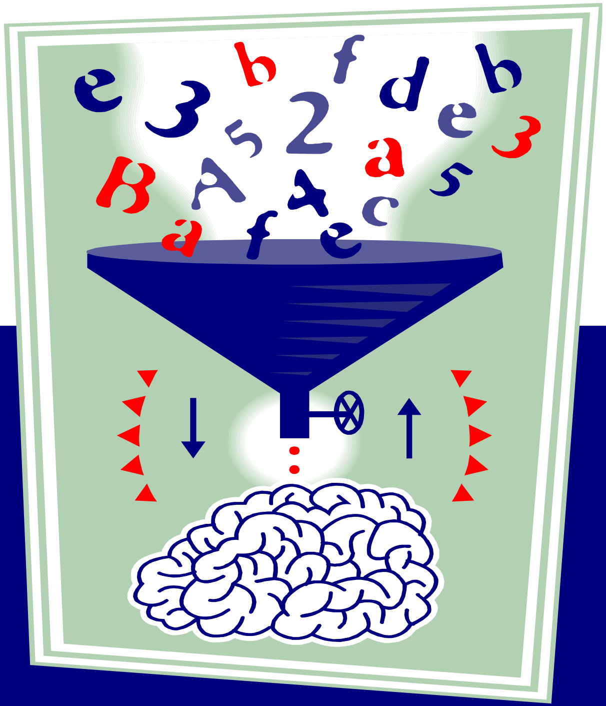
Data Preparation for Knowledge Discovery



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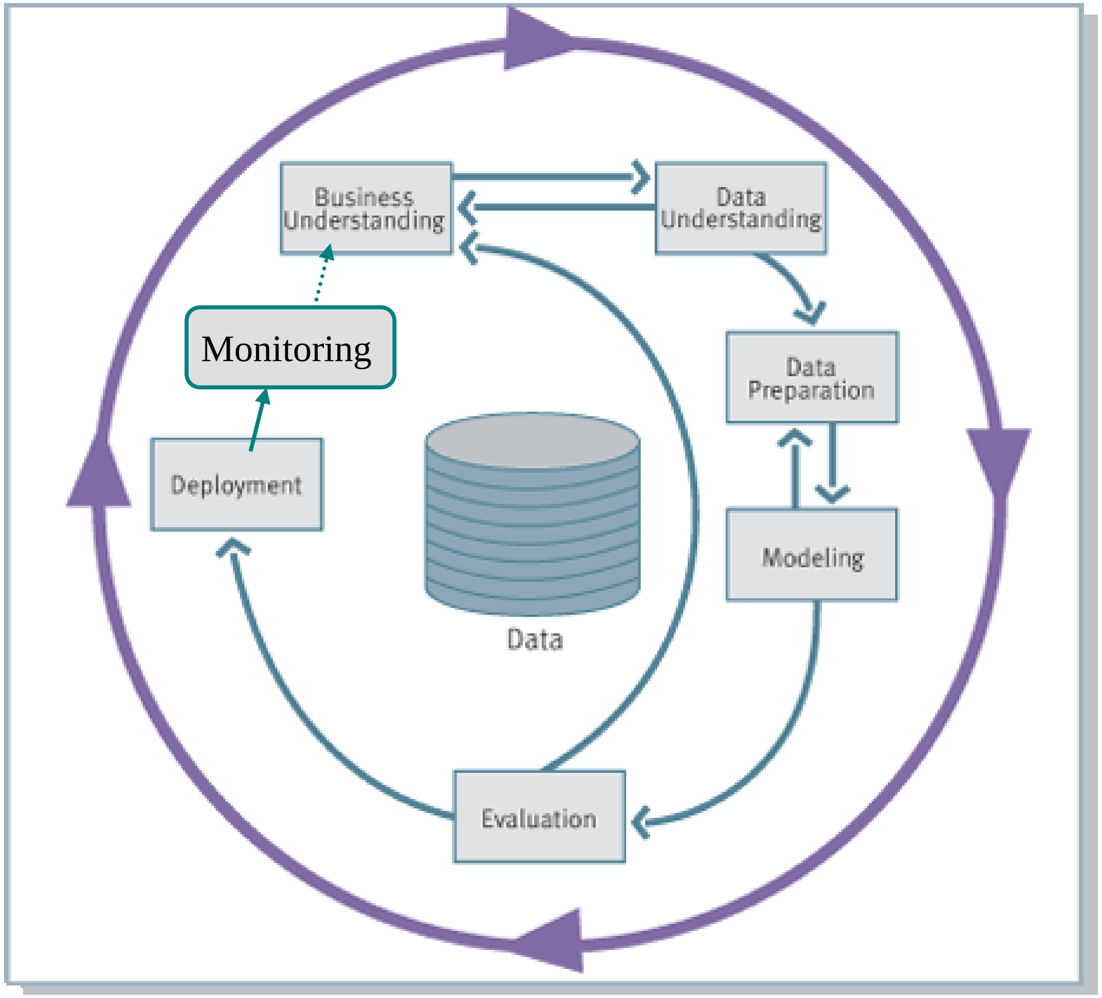
Introduction to Machine Learning and Data Mining

Lecture #6

Outline: Data Preparation

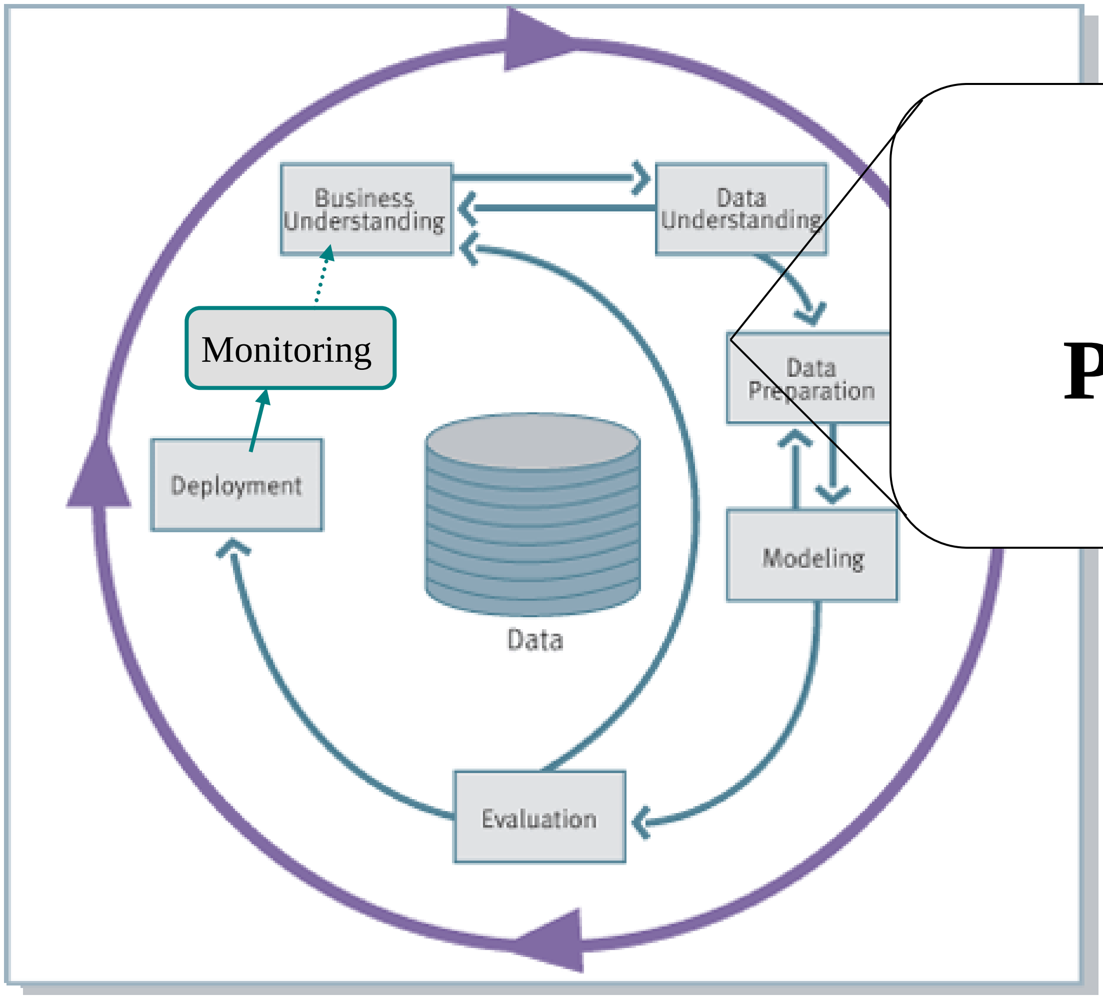
- Data Understanding
- Data Cleaning
  - Metadata
  - Missing Values
  - Unified Date Format
  - Nominal to Numeric
  - Discretization
- Field Selection and “False Predictors”
- Unbalanced Target Distribution

Knowledge Discovery Process flow, according to CRISP-DM



see https://www.datascience-pm.com/crisp-dm-2/ for more information

Knowledge Discovery Process, in practice



Data Preparation

Data Preparation estimated to take 80-90% of the time and effort

Data Understanding: Relevance

- What data is available for the task?
- Is this data relevant?
- Is additional relevant data available?
- How much historical data is available?
- Who is the data expert ?

Data Understanding: Quantity

- Number of instances (records)
  - *Rule of thumb: 5,000 or more desired*
  - if less, results are less reliable; use special methods (boosting, …)
- Number of attributes (fields)
  - *Rule of thumb: for each field, 10 or more instances*
  - If more fields, use feature reduction and selection
- Number of targets
  - *Rule of thumb: >100 for each class*
  - if very unbalanced, use stratified sampling

Data Cleaning Steps

- Data acquisition and metadata
- Missing values
- Unified date format
- Converting nominal to numeric
- Discretization of numeric data
- Data validation and statistics

Data Cleaning: Acquisition

- Data can be in DBMS
  - ODBC, JDBC protocols
- Data in a flat file
  - Fixed-column format
  - Delimited format: tab, comma “,” , other
  - E.g. C4.5 and Weka “arff” use comma-delimited data
  - Attention: Convert field delimiters inside strings
- Verify the number of fields before and after

Data Cleaning: Example

- **Original data (fixed column format)**

000000000130.06.19971979-10-3080145722   #000310 111000301.01.000100000000004
0000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.0000
00000000000. 000000000000000.000000000000000.0000000……
000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.00
0000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.0000
00000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000
000000000.000000000000000.000000000000000.000000000000000.00 000000000300.00 000000000300.00

- **Clean data**

0000000001,199706,1979.833,8014,5722   ,   ,#000310 ….
,111,03,000101,0,04,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0300,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0300,0300.00

Data Cleaning: Metadata

- **Field types:**
  - **binary, nominal (categorical), ordinal, numeric, …**
  - **For nominal fields: tables translating codes to full descriptions**
- **Field role:**
  - input : inputs for modeling
  - target : output
  - id/auxiliary : keep, but not use for modeling
  - ignore : don't use for modeling
  - weight : instance weight
  - …
- **Field descriptions**

Data Cleaning: Reformatting

Convert data to a standard format (e.g. arff or csv)

- Missing values
- Unified date format
- Binning of numeric data
- Fix errors and outliers
- Convert nominal fields whose values have order to numeric.
  - ***Q: Why?***

Data Cleaning: Reformatting, 2

Convert nominal fields whose values have order to numeric to be able to use “>” and “<“ comparisons on these fields.

Data Cleaning: Missing Values

- Missing data can appear in several forms:
  - <empty field> "0" "." "999" "NA" …
- Standardize missing value code(s)
- ***Q: How can we deal with missing values?***

Data Cleaning: Missing Values, 2

- Dealing with missing values:
  - ignore records with missing values
  - treat missing value as a separate value
  - Imputation:
    fill in with mean, median or mode values
  - let the DM algorithm deal with it

Data Cleaning: Unified Date Format

- We want to transform all dates to the same format internally
- Some systems accept dates in many formats
  - e.g. “Sep 24, 2003” , 9/24/03, 24.09.03, etc
  - dates are transformed internally to a standard value
- Frequently, just the year (YYYY) is sufficient
- For more details, we may need the month, the day, the hour, etc
- Representing date as YYYYMM or YYYYMMDD can be OK, but has problems
- ***Q: What are the problems with YYYYMMDD dates?***

Data Cleaning: Unified Date Format, 2

- Problems with YYYYMMDD dates:
  - YYYYMMDD does not preserve intervals:
  - 20040201 – 20040131

    !=

    20040131 – 20040130
  - This can introduce bias into models

Unified Date Format Options

- To preserve intervals, we can use
  - Unix system date:
    Number of seconds since 1970
  - Number of days since Jan 1, 1960 (SAS)
- Problem:
  - values are non-obvious
  - don't help intuition and knowledge discovery
  - harder to verify, easier to make an error

KSP Date Format

$$\text{KSP Date} = \text{YYYY} + \frac{\text{days\_starting\_Jan\_1} - 0.5}{365 + \text{1\_if\_leap\_year}}$$

- Preserves intervals (almost)
- The year and quarter are obvious
  - Sep 24, 2003 is 2003 + (267-0.5)/365= 2003.7301 (round to 4 digits)
- Consistent with date starting at noon
- Can be extended to include time

Y2K issues: 2 digit Year

- 2-digit year in old data – legacy of Y2K
- E.g. **Q: Year 02 – is it 1902 or 2002 ?**
  - A: Depends on context (e.g. child birthday or year of house construction)
  - Typical approach: CUTOFF year, e.g. 30
  - if YY < CUTOFF , then 20YY, else 19YY

Conversion: Nominal to Numeric

- Some tools can deal with nominal values internally
- Other methods (neural nets, regression, nearest neighbor) require only numeric inputs
- To use nominal fields in such methods need to convert them to a numeric value
  - **Q: Why not ignore nominal fields altogether?**
  - A: They may contain valuable information
- Different strategies for binary, ordered, multi-valued nominal fields

Conversion

- How would you convert binary fields to numeric?
  - E.g. Gender=M, F
- How would you convert ordered attributes to numeric?
  - E.g. Grades

Conversion: Binary to Numeric

- Binary fields
  - E.g. Gender=M, F
- Convert to Field_0_1 with 0, 1 values
  - e.g. Gender = M → Gender_0_1 = 0
    Gender = F → Gender_0_1 = 1

Conversion: Ordered to Numeric

- Ordered attributes (e.g. Grade) can be converted to numbers preserving *natural* order, e.g.
  - A → 4.0
  - A- → 3.7
  - B+ → 3.3
  - B → 3.0
- **Q: Why is it important to preserve *natural* order?**

Conversion: Ordered to Numeric, 2

Natural order allows meaningful comparisons, e.g. Grade > 3.5

Conversion: Nominal, Few Values

- Multi-valued, unordered attributes with small (*rule of thumb < 20*) no. of values
  - e.g. Color=Red, Orange, Yellow, …, Violet
  - for each value *v* create a binary “flag” variable C_*v*, which is 1 if Color=*v*, 0 otherwise

ID	Color	…
371	red	
433	yellow	

→

ID	C_red	C_orange	C_yellow	…
371	1	0	0	
433	0	0	1	

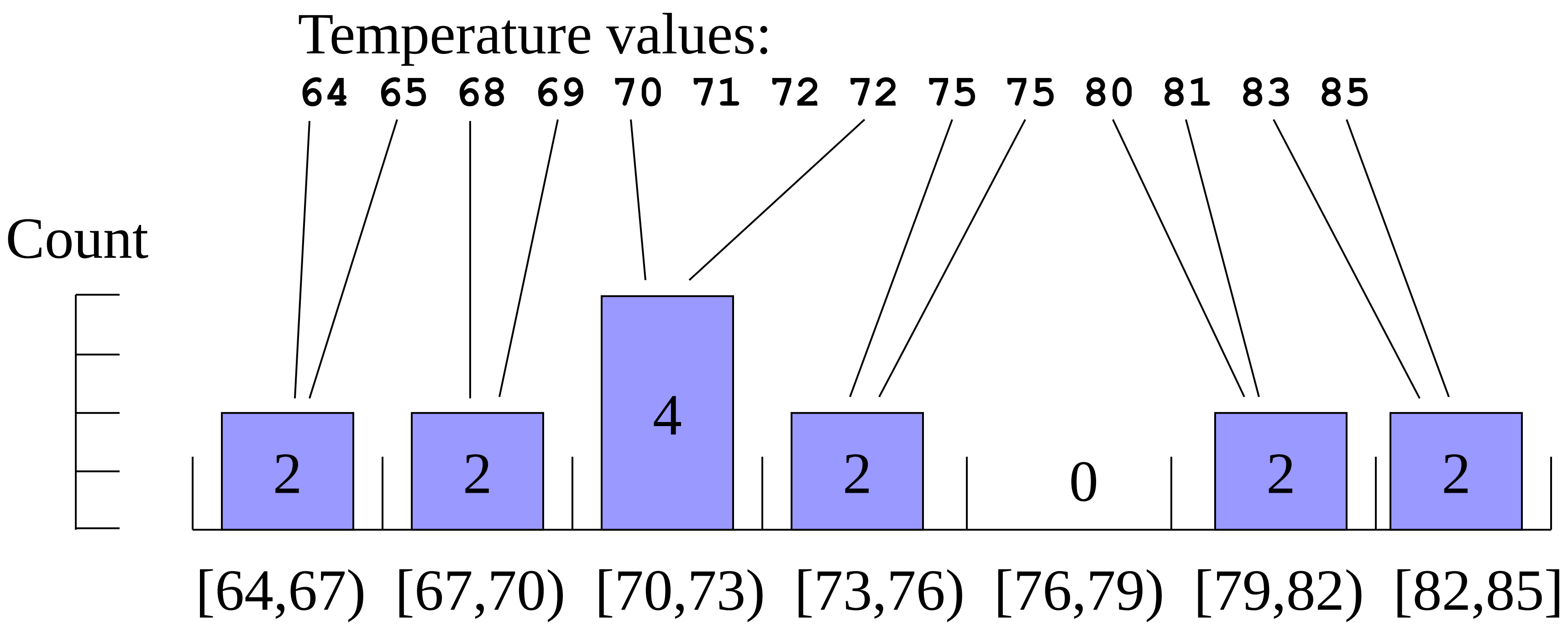
Conversion: Nominal, Many Values

- Examples:
  - US State Code (50 values)
  - Profession Code (7,000 values, but only few frequent)
- **Q: How to deal with such fields?**
- A: Ignore ID-like fields whose values are unique for each record
- For other fields, group values “naturally”:
  - e.g. 50 US States → 3 or 5 regions
  - Profession – select most frequent ones, group the rest
- Create binary flag-fields for selected values

Data Cleaning: Discretization

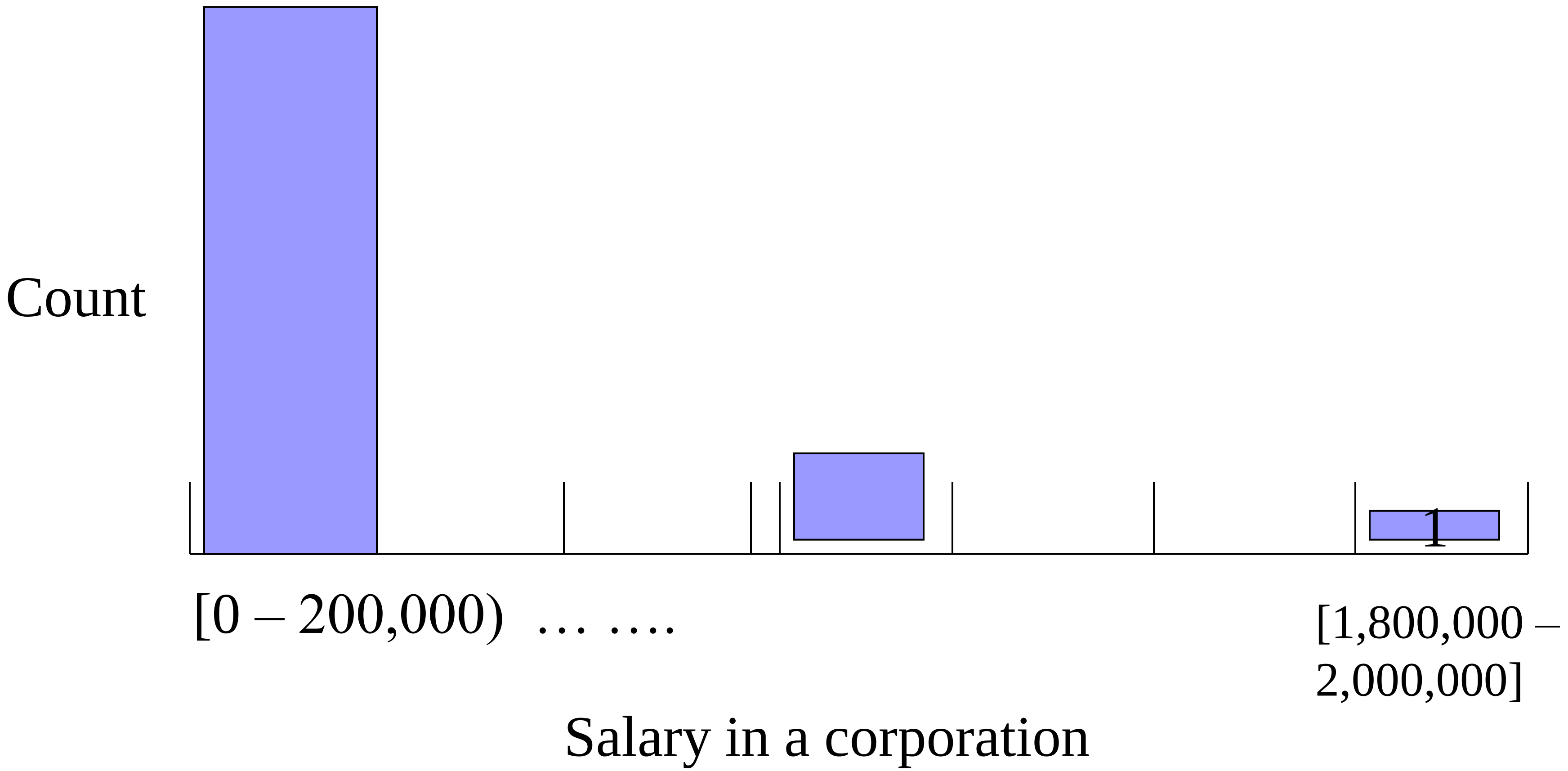
- Some methods require discrete values, e.g. most versions of Naïve Bayes, …
- Discretization is very useful for generating a summary of data
- Also called “binning”

Discretization: Equal-width

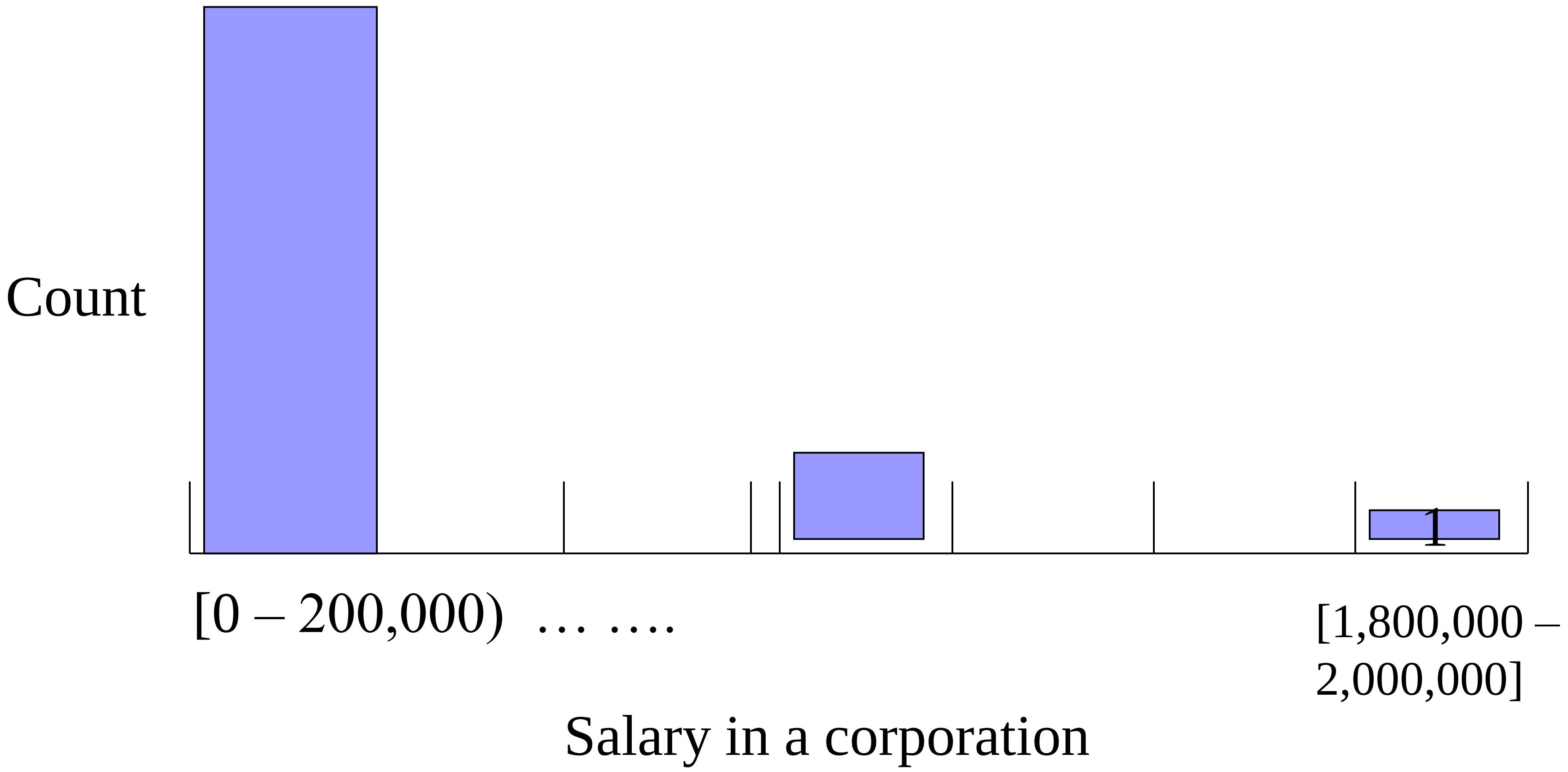


Equal Width, bins Low <= value < High

Discretization:
Equal-width may produce clumping



Equal-width problems

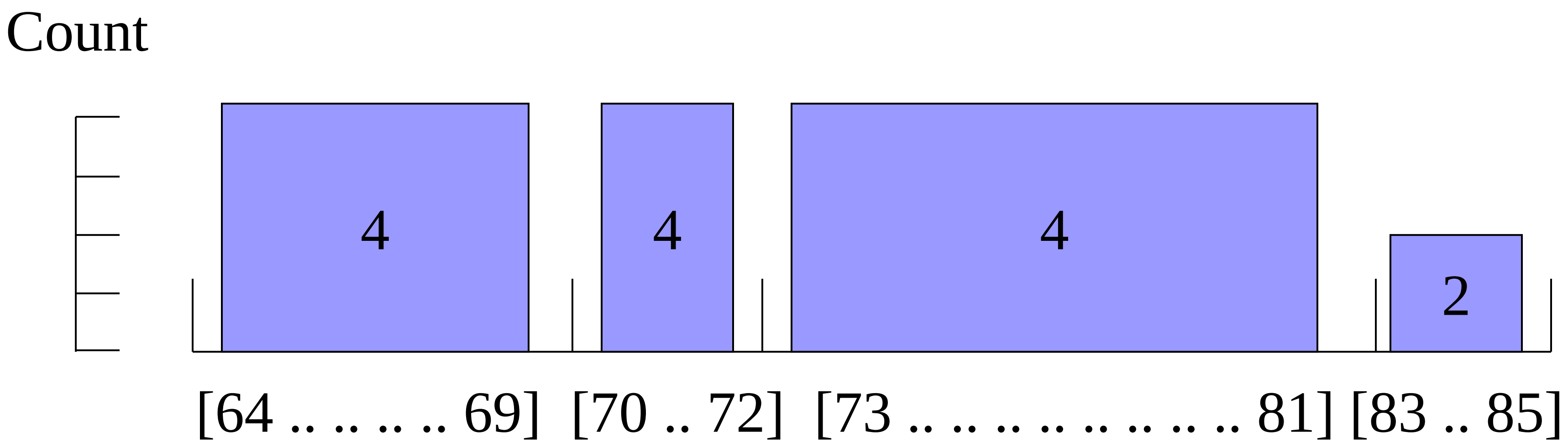


What can we do to get a more even distribution?

Discretization: Equal-height

Temperature values:

`64 65 68 69 70 71 72 72 75 75 80 81 83 85`



Equal Height = 4, except for the last bin

Discretization: Equal-height advantages

- Generally preferred because avoids clumping
- In practice, “almost-equal” height binning is used which avoids clumping and gives more intuitive breakpoints
- Additional considerations:
  - don’t split frequent values across bins
  - create separate bins for special values (e.g. 0)
  - readable breakpoints (e.g. round breakpoints)

Discretization

How else can we discretize?

What is another method from the literature?

Discretization: Class Dependent

min of 3 values per bucket

64	**65**	**68**	**69**	**70**	**71**	**72**	**72**	**75**	**75**	**80**	**81**	**83**	**85**
Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No

64 85

Discretization considerations

- Equal Width is simplest, good for many classes
  - can fail miserably for unequal distributions
- Equal Height gives better results
- Class-dependent can be better for classification
  - Note: decision trees build discretization on the fly
  - Naïve Bayes requires initial discretization
- Many other methods exist …

Outliers and Errors

- Outliers are values thought to be out of range.
- Approaches:
  - do nothing
  - enforce upper and lower bounds
  - let binning handle the problem

Examine Data Statistics

```
*****************      Field 9:  MILES_ACCUMULATED

Total entries = 865636 (23809 different values).  Contains non-numeric values.    Missing
data indicated by "" (and possibly others).

Numeric items = 165161,  high = 418187.000,  low = -95050.000
       mean = 4194.557,  std = 10505.109,  skew =    7.000

Most frequent entries:

       Value   Total
            :        700474 ( 80.9%)
           0:        32748 (  3.8%)
           1:        416 (  0.0%)
           2:        337 (  0.0%)
          10:        321 (  0.0%)
           8:        284 (  0.0%)
           5:        269 (  0.0%)
           6:        267 (  0.0%)
          12:        262 (  0.0%)
           7:        246 (  0.0%)
           4:        237 (  0.0%)
```

Data Cleaning: Field Selection

First: Remove fields with no or little variability

- Examine the number of distinct field values
  - *Rule of thumb: remove a field where almost all values are the same (e.g. null), except possibly in minp % or less of all records.*
  - *minp* could be 0.5% or more generally less than 5% of the number of targets of the smallest class

False Predictors or Information "Leakers"

- False predictors are fields correlated to target behavior, which describe events that happen at the same time or *after* the target behavior
- If databases don't have the event dates, a false predictor will appear as a good predictor
- Example: Service cancellation date is a leaker when predicting attriters.
- **Q: Give another example of a false predictor**

False Predictor Example

Q: What is a false predictor for a student's likelihood of passing a course?

A: The student's final grade.

False Predictors: Find "suspects"

- Build an initial decision-tree model
- Consider very strongly predictive fields as "suspects"
  - strongly predictive – if a field by itself provides close to 100% accuracy, at the top or a branch below
- Verify "suspects" using domain knowledge or with a domain expert
- Remove false predictors and build an initial model

(Almost) Automated False Predictor Detection

- For each field
  - Build 1-field decision trees for each field
  - (or compute correlation with the target field)
- Rank all suspects by 1-field prediction accuracy (or correlation)
- Remove suspects whose accuracy is close to 100% (Note: the threshold is domain dependent)
- Verify top “suspects” with domain expert

Selecting Most Relevant Fields

- If there are too many fields, select a subset that is most relevant.
- Can select top N fields using 1-field predictive accuracy as computed earlier.
- What is good N?
  - Rule of thumb -- keep top 50 fields

Field Reduction Improves Classification

- most learning algorithms look for non-linear combinations of fields -- can easily find many spurious combinations given small # of records and large # of fields
- Classification accuracy improves if we first reduce number of fields
- Multi-class heuristic: select equal # of fields from each class

Derived Variables

- Better to have a fair modeling method and good variables, than to have the best modeling method and poor variables.
- Insurance Example: People are eligible for pension withdrawal at age 59 ½.
  Create it as a separate Boolean variable!
- *Advanced methods exists for automatically examining variable combinations, but it is very computationally expensive!

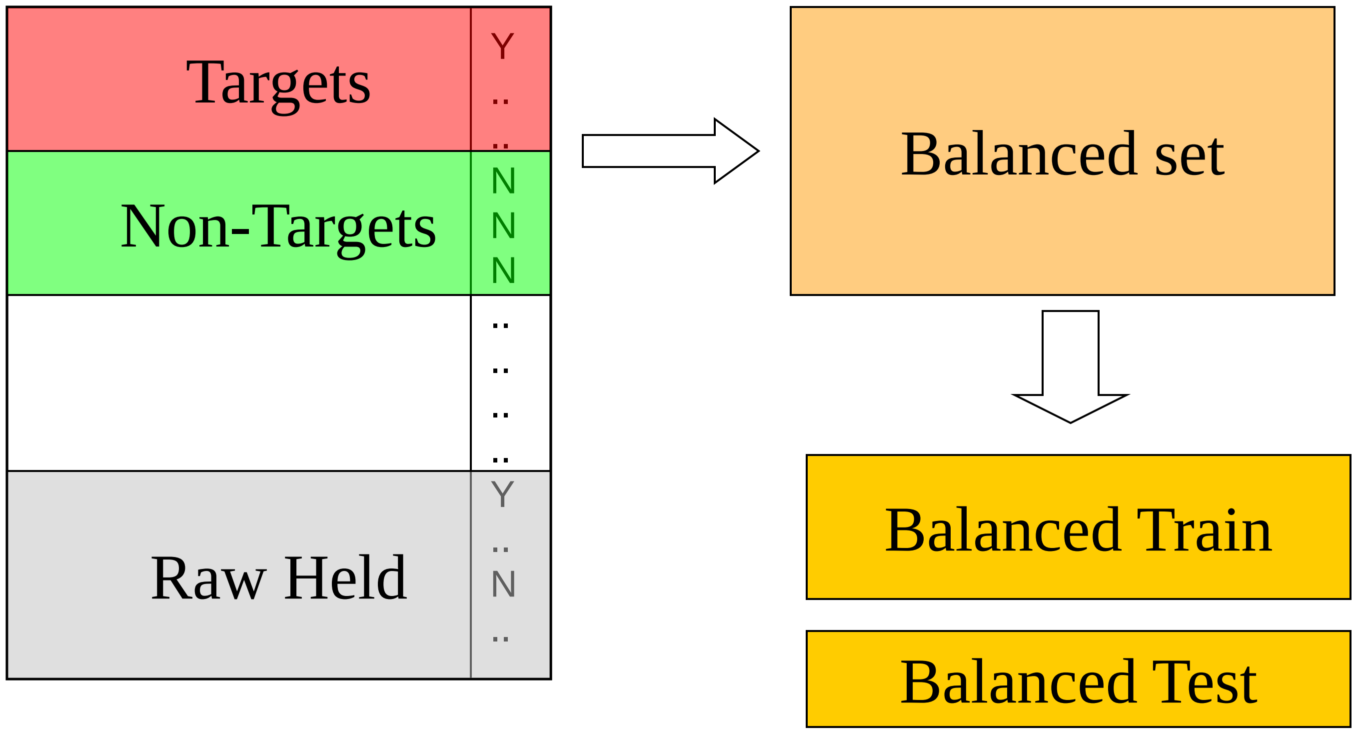
Unbalanced Target Distribution

- Sometimes, classes have very unequal frequency
  - Attrition prediction: 97% stay, 3% attrite (in a month)
  - medical diagnosis: 90% healthy, 10% disease
  - eCommerce: 99% don’t buy, 1% buy
  - Security: >99.99% of Americans are not terrorists
- Similar situation with multiple classes
- Majority class classifier can be 97% correct, but useless

Handling Unbalanced Data

- With two classes: let positive targets be a minority
- Separate raw held-aside set (e.g. 30% of data) and raw train
  - put aside raw held-aside and don't use it till the final model
- Select remaining positive targets (e.g. 70% of all targets) from raw train
- Join with equal number of negative targets from raw train, and randomly sort it.
- Separate randomized balanced set into balanced train and balanced test

Building Balanced Train Sets



Learning with Unbalanced Data

- Build models on balanced train/test sets
- Estimate the final results (lift curve) on the raw held set

- Can generalize “balancing” to multiple classes
  - stratified sampling
  - Ensure that each class is represented with approximately equal proportions in train and test

Data Preparation Key Ideas

- Use meta-data
- Inspect data for anomalies and errors
- Eliminate “false predictors”
- Optionally:
  - reduce the number of fields
  - “balance” the data
- Plan for verification – verify the results after each step

Summary

Good data preparation is key to producing valid and reliable models