Data Wrangling and Data Analysis

Data Preparation (2)

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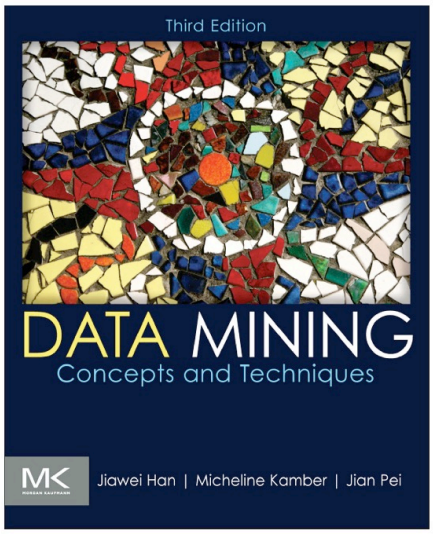
Reading Material for Today

- Data Mining: Concepts and Techniques Book

  Chapter 3.3 - 3.5



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2023-2024 ADSM electives

Don’t forget to send in the pre-enrolment form.
Deadline: October 2.

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- Assignment 2 is available
- Social event tomorrow
- Tomorrow’s lab is a revision
- Guest lecture tomorrow

DATA DRINKS

LOCATION: THE VAGANT BUILDING

DATE: TUESDAY SEPTEMBER 26 (17:00 - 20:00)

Come by for a drink and a piece of pizza, chat with your peers and compete against them at table football!

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Topics for Today

- Data transformation
- Data Integration
- Data reduction
- Data discretization

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Data Transformation

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Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods for data transformation
  - Smoothing: Remove noise from data
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Aggregation: Summarization, data cube construction

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Data Transformation (Cont.)

- Methods for data transformation
  - Normalization: Scaled to fall within a smaller, specified range
    - Min-max normalization
    - Z-score normalization
    - Normalization by decimal scaling
  - Data reformatting:
    - E.g. Jack Wilsher ➔ Wilsher, J.
  - Use the same unit:
    - Records in inches and cm
    - Records with prices in Euros and Dollars

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Data Normalization (Standardization)

The goal of standardization or normalization is to make an entire set of values have a particular property.

Data Normalization – Min-Max Normalization

- Transform the data from a given range with $[min_A, max_A]$ to a new interval $[new\_min_A, new\_max_A]$ for a given attribute A :

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

where v is the current value of attribute A.

Data Normalization – Min-Max Normalization

- Example:

  Suppose that the minimum and the maximum in the attribute income are €12,000 and €98,000, respectively

  We would like to map the income into the interval $[0,1]$

  Using min-max normalization, a value of €73,600 for income is transformed into:

$$\frac{73{,}600 - 12{,}000}{98{,}000 - 12{,}000}(1.0 - 0.0) + 0.0 = 0.716$$


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Data Normalization – Z-Score Normalization

- Transform the data by converting the values to a common scale with an average of zero and a standard deviation of one.
- A value, v, of attribute A is normalized to v' by computing:

$$v' = \frac{v - \bar{A}}{\sigma_A}$$

where $\bar{A}$ and σ_A are the mean and standard deviation of attribute A, respectively.


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Data Normalization – Z-Score Normalization

- Example:
  - Suppose that the mean and standard deviation of the values for the feature income are 54,000 and 16,000, respectively. With z-score normalization, a value of €73,600 for income is transformed to:

$$\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$$


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Data Normalization – Decimal Scaling Normalization

- Transform the data by moving the decimal points of values of attribute A.
- The number of decimal points moved depends on the maximum absolute value of A.
- A value v of A is normalized to v' by computing: $v' = \frac{v}{10^j}$ where j is the smallest integer such that $\max(|v'|) < 1$


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Data Normalization – Decimal Scaling Normalization

- Example:
  - Suppose that the recorded values of A range from −986 to 917.
  - The maximum absolute value of A is 986.
  - To normalize by decimal scaling, we divide each value by 1,000 (i.e., $j = 3$) so that −986 normalizes to −0.986 and 917 normalizes to 0.917

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Data Transformation (Cont.)

- Exercise
  - Use flash fill of Microsoft Excel to convert set of names from the format Family_name, First_name middle_initial. to First_name Family_name
    - E.g. Wilsher, John K. to John Wilsher

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Data Integration (Revisited)

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Data Integration

- Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-No
  - Integrate metadata from different sources
- Entity identification problem:
  - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
  - For the same real-world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units

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Handling Redundancy when Integrating Data

- Handling data redundancy is an important task of the data integration
- Duplicate records can be identified by applying entity resolution techniques
- Redundant attributes can be detected by correlation and covariance analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining quality


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Entity Resolution

Problem of identifying and linking/grouping different representations of the same real-world object.

Examples:

- Different ways of addressing (names, email addresses, FaceBook accounts) the same person in text.
- Web pages with differing descriptions of the same business.
- Different photos of the same object.
- …


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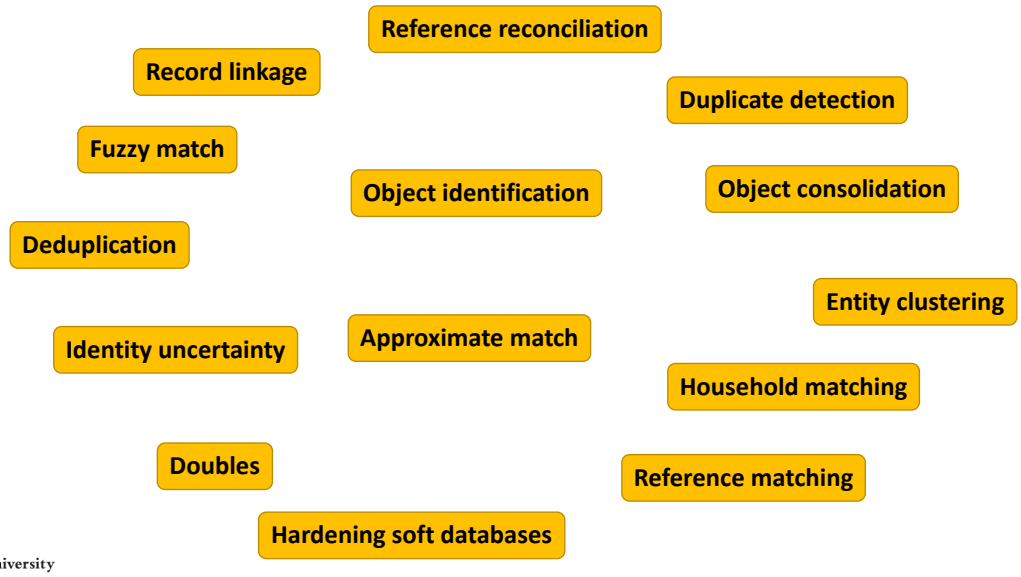
Ironically, Entity Resolution has Many Duplicate Names



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Entity Resolution – Normalization

- Schema Normalization
  - Schema matching: e.g., Contact No. vs. Phone
  - Compound attributes: e.g., address vs. (street, city, zip)
- Data Normalization
  - Capitalization, white-space normalization
  - Correcting typos, replacing abbreviations, variations, nick names
    - Usually done by employing dictionaries

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Entity Resolution – Matching Features

- Given two records, compute a vector of similarity scores for corresponding features
- E.g., to match two bibliographical references, compute:
  - First author match score
  - Title match score
  - Venue match score
  - Year match score
  - …
- Score can be Boolean (match/mismatch) or a continuous value based on specific similarity measure (distance function).


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Entity Resolution – Similarity Measures

- Atomic similarity measures
  - Difference between numerical values
  - Jaro for comparing names
  - Edit distance for typos
  - Phonetic-based
    - Soundex
- Set similarity
  - Jaccard similarity
- Vector-based
  - Cosine similarity


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Entity Resolution – Issues

- Similarity measures has different scales
  - How to combine the different values to compare the tuples
- Pairwise similarity between records is expensive
  - Takes $O(n^2)$
- Blocking to reduce the quadratic time complexity
  - Divide the records into blocks
  - Perform pairwise comparison between records within the same block only
  - When $\#blocks = k$ and block size $\approx (n/k)$, the time complexity $O(k(n/k)^2)$

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Data Reduction

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Data Reduction

- **Data reduction**: obtain a reduced representation of the dataset
  - Much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction?
  - A dataset could be extremely large – Complex data analysis may take a very long time to run on the complete dataset.
- Data reduction strategies
  - Dimensionality reduction, e.g., remove unimportant attributes
    - Principal Components Analysis (PCA)
    - Singular Value Decomposition (SVD)
    - Feature subset selection, feature creation

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Dimensionality Reduction

- Curse of dimensionality
  - When dimensionality increases, data becomes increasingly sparse
  - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
  - The possible combinations of subspaces will grow exponentially
- Dimensionality reduction
  - Avoid the curse of dimensionality
  - Help eliminate irrelevant features and reduce noise
  - Reduce time and space required in data mining
  - Allow easier visualization

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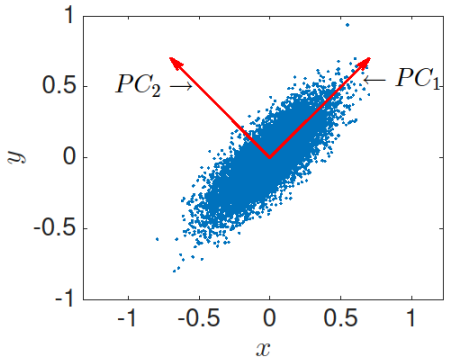
Principal Component Analysis (PCA)

- Find a projection that captures the largest amount of variation in data
- The original data are projected onto a much smaller space, resulting in dimensionality reduction.
- We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space



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Principal Component Analysis (Steps)

- Given: N data vectors from d-dimensions, find $k \leq d$ principal components that can accurately represent the data
  - Normalize input data: each attribute falls within the same range
  - Compute k orthonormal (unit) vectors, i.e., principal components
  - Each input data (vector) is a linear combination of the k principal component vectors
  - The principal components are sorted in order of decreasing "significance" or strength
  - The components are sorted
    - Reduce the data dimensionality by eliminating the weak components
    - Weak components have low variance
    - We can reconstruct a good approximation of the original data using strong components
- Works for numeric data only

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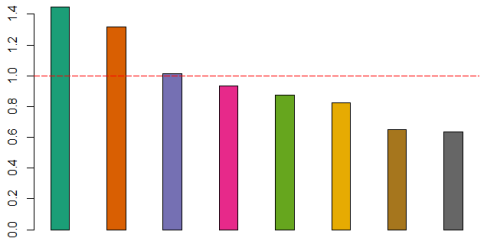
PCA for Dimensionality Reduction

- Can ignore the components of lesser significance.



- You lose some information, but if the eigenvalues are small, it is not much
  - d dimensions in original data
  - calculate d eigenvectors and eigenvalues
  - choose only the first k eigenvectors, based on their eigenvalues (eigenvectors with eigenvalues greater than 1 are considered important)
  - final data set has only k dimensions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Attribute Subset Selection for Data Reduction

- Another way to reduce dimensionality of data
- Redundant attributes
  - Duplicate much or all of the information contained in one or more other attributes
  - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
  - Contain no information that is useful for the data mining task at hand
  - E.g., students' ID is often irrelevant to the task of predicting students' GPA


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Model-Based Data Reduction

- Linear regression
  - Data modeled to fit a straight line
  - Often uses the least-square method to fit the line
- Multiple regression
  - Allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- Log-linear model
  - Approximate data by a function whose logarithm is linear


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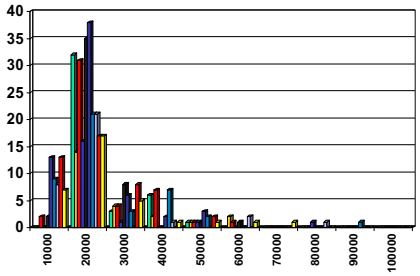
Histograms for Data Reduction

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
  - Equal-width: equal bucket range
  - Equal-frequency (or equal-depth)

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Clustering-Based Data Reduction

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is "smeared"
- There are many choices of clustering definitions and clustering algorithms
- Clustering will be studied in more details in weeks 7 & 8


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Sampling-Based Data Reduction

- Sampling: obtaining a small sample s to represent the whole data set N
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
  - Develop adaptive sampling methods, e.g., stratified sampling
- Note: Sampling may not reduce database I/Os (page at a time)


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Types of Sampling

- Simple random sampling
  - There is an equal probability of selecting any particular item
- Sampling without replacement
  - Once an object is selected, it is removed from the population
- Sampling with replacement
  - A selected object is not removed from the population
- Stratified sampling:
  - Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
  - Used in conjunction with skewed data

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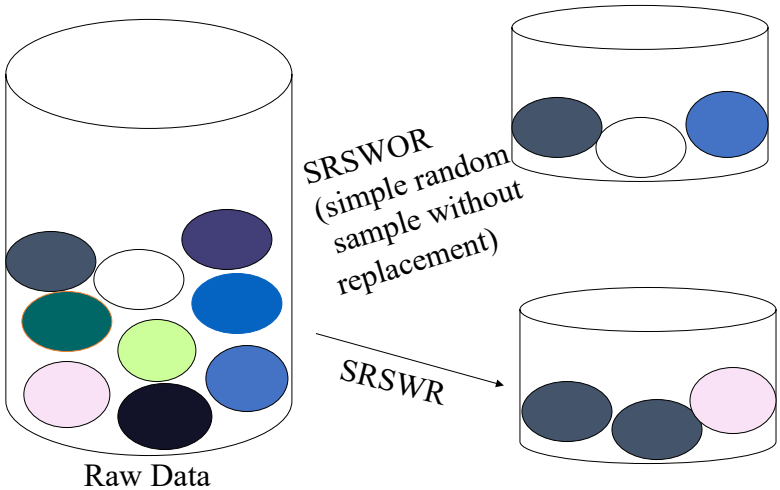
Sampling – with or without Replacement



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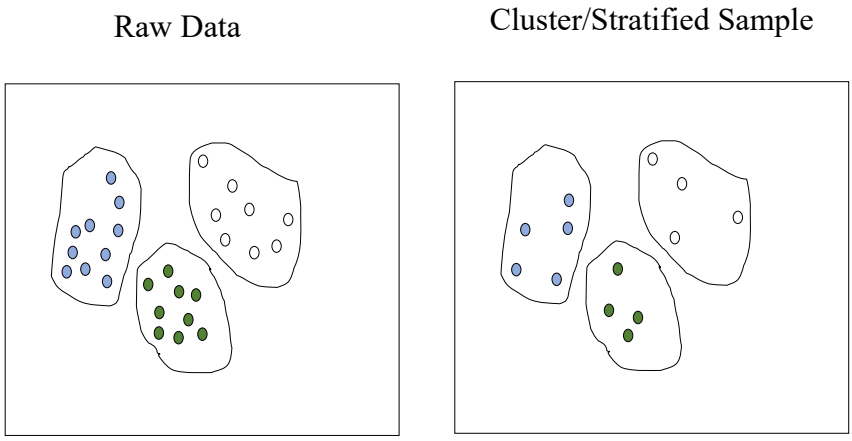
Sampling – Cluster or Stratified Sampling



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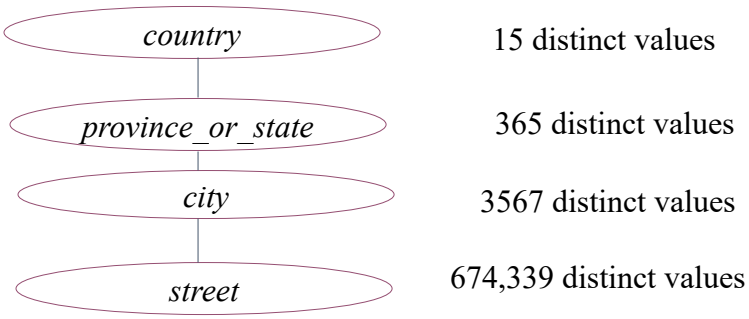
Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy



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Wrap-Up

Summarize what you learned today in 2-minutes

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Data Discretization

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Data Discretization

- Three types of attributes
  - Nominal: values from an unordered set, e.g., color, profession
  - Ordinal: values from an ordered set, e.g., military or academic rank
  - Numeric: real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
  - Interval labels can be used to replace actual data values
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)

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Discretization Methods

- Typical methods: All the methods can be applied recursively
  - Binning – Histograms
  - Clustering
  - Classification (e.g. Decision-trees)
  - Correlation

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Discretization Methods – Binning

- Equal-width (distance) partitioning
  - Divides the range into N intervals of equal size: uniform grid
  - If *A* and *B* are the smallest and largest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
  - The most straightforward, but outliers may dominate presentation
  - Skewed data is not handled well

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Discretization Methods – Binning (Cont.)

- Equal-depth (frequency) partitioning
  - Divides the range into *N* intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky

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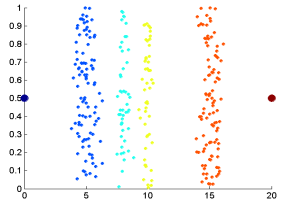
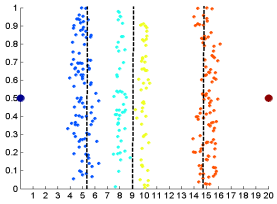
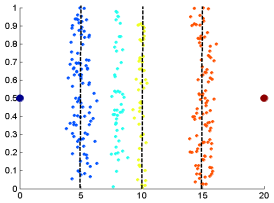
Discretization Methods – Binning (Cont.)



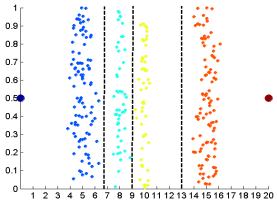
Data



Equal frequency (binning)



Equal width (binning)



Clustering-based discretization leads to better results (for this dataset)

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Discretization Methods – Classification & Correlation

- Classification (e.g., decision tree analysis)
  - Supervised: Given class labels, e.g., cancerous vs. benign
  - Using entropy to determine split point (discretization point)
  - Top-down, recursive split
  - Details to be covered later during the course
- Correlation analysis
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes) to merge
  - Merge performed recursively, until a predefined stopping condition is satisfied

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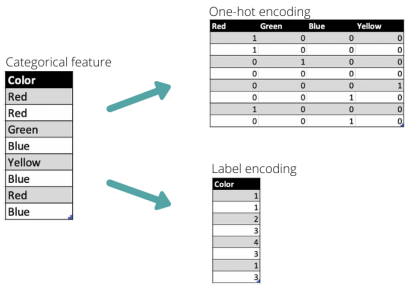
Other Data Preparation Techniques



- Transforming categorical data into numerical data (See the Figure)
  - Label encoding
  - One-hot encoding
- Data Enrichment
  - Augmentation
  - Join & Union
- Data Validation
  - Check Permitted Characters
  - Find Type-Mismatched Data

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