BITS Pilani
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MACHINE LEARNING

Session 2
(3rd August,2025)

Course Plan

M1	Introduction
M2	Machine learning Workflow
M3	Linear Models for Regression
M4	Linear Models for Classification
M5	Decision Tree
M6	Instance Based Learning
M7	Support Vector Machine
M8	Bayesian Learning
M9	Ensemble Learning
M10	Unsupervised Learning
M11	Machine Learning Model Evaluation/Comparison

Agenda

- Role of Data
- Data Preprocessing / wrangling
- Data skewness removal (sampling)
- Model Training ***(will be covered in subsequent modules)***
- Model Testing and performance metrics ***(will be covered in subsequent modules)***

ML in a Nutshell

- Tens of thousands of machine learning algorithms
  - Hundreds new every year
- Every ML algorithm has three components
  - **Data Representation**
  - **Parameter Optimization**
  - **Model Evaluation, Selection**

ML in Practice

Loop

- Understand domain, prior knowledge, and goals
- Data integration, selection, cleaning, pre-processing, etc.
- Learn optimal parameter of the models
- Interpret results
- Consolidate and deploy discovered knowledge

Definition of Data

- Collection of ***data objects*** and their ***attributes***
- An ***attribute*** is a property or characteristic of an object
  - Examples: eye color of a person, temperature, etc.
  - *aka* variable, field, characteristic, dimension, or feature
- A collection of attributes describe an ***object***
  - Object is also known as record, point, case, sample, entity, or instance

Attributes

Objects

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Types of Attributes

- There are different types of attributes
  - Nominal
    - Examples: ID numbers, zip codes
  - Ordinal
    - Examples: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height {tall, medium, short}
  - Interval
    - Examples: calendar dates, temperatures in Celsius or Fahrenheit.
  - Ratio
    - Examples: temperature in Kelvin, length, counts, elapsed time (e.g., time to run a race)

Properties of Attribute Values

- The type of an attribute depends on which of the following properties/operations it possesses:
  - Distinctness: $= \ \neq$
  - Order: $< \ >$
  - Differences are meaningful : $+ \ -$
  - Ratios are meaningful $* \ /$
  - Nominal attribute: distinctness
  - Ordinal attribute: distinctness & order
  - Interval attribute: distinctness, order & meaningful differences
  - Ratio attribute: all 4 properties/operations

Difference Between Ratio and Interval

- Is it physically meaningful to say that a temperature of 10 ° is twice that of 5° on
  - the Celsius scale?
  - the Fahrenheit scale?
  - the Kelvin scale?
- Consider measuring the height above average
  - If Bill's height is three inches above average and Bob's height is six inches above average, then would we say that Bob is twice as tall as Bill?
  - Is this situation analogous to that of temperature?

	Attribute Type	Description	Examples	Operations
Categorical Qualitative	Nominal	Nominal attribute values only distinguish. (=, ≠)	zip codes, employee ID numbers, eye color, sex: {*male*, *female*}	mode, entropy, contingency correlation, $\chi 2$ test
	Ordinal	Ordinal attribute values also order objects. (<, >)	hardness of minerals, {*good*, *better*, *best*}, grades, street numbers	median, percentiles, rank correlation, run tests, sign tests
Numeric Quantitative	Interval	For interval attributes, differences between values are meaningful. (+, -)	calendar dates, temperature in Celsius or Fahrenheit	mean, standard deviation, Pearson's correlation, *t* and *F* tests
	Ratio	For ratio variables, both differences and ratios are meaningful. (*, /)	temperature in Kelvin, monetary quantities, counts, age, mass, length, current	geometric mean, harmonic mean, percent variation

This categorization of attributes is due to S. S. Stevens

	Attribute Type	Transformation	Comments
Categorical Qualitative	Nominal	Any permutation of values	If all employee ID numbers were reassigned, would it make any difference?
	Ordinal	An order preserving change of values, i.e., *new_value = f(old_value)* where *f* is a monotonic function	An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}.
Numeric Quantitative	Interval	*new_value = a * old_value + b* where a and b are constants	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
	Ratio	*new_value = a * old_value*	Length can be measured in meters or feet.

This categorization of attributes is due to S. S. Stevens

Discrete and Continuous Attributes

- **Discrete Attribute**
  - Has only a finite or countably infinite set of values
  - Examples: zip codes, counts, or the set of words in a collection of documents
  - Often represented as integer variables.
  - Note: binary attributes are a special case of discrete attributes
- **Continuous Attribute**
  - Has real numbers as attribute values
  - Examples: temperature, height, or weight.
  - Practically, real values can only be measured and represented using a finite number of digits.
  - Continuous attributes are typically represented as floating-point variables.

Important Characteristics of Data

- Dimensionality (number of attributes)
    - High dimensional data brings a number of challenges
- Sparsity
    - Only presence counts
- Resolution
    - Patterns depend on the scale
- Size
    - Type of analysis may depend on size of data

Data Types

- Relational/Object
- Transactional Data
- Document Data
- Web & Social Network Data
- Spatial Data
- Time Series
- Sequence Data

Discrete Numeric

Asymmetric Binary

Ordinal

Continuous Numeric

Symmetric Binary

	ServiceRating	IsPriority Customer	CardType	Credit Score	isMultipleAccount Holder
Jack	5	Yes	Platinum	7.5	Yes
Jill	2	Yes	Gold	8.2	No
John	9	No	Gold	7	Yes

Data Types

- Relational/Object
- Transactional Data
- Document Data
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- Spatial Data
- Time Series
- Sequence Data

	Purchase 1	Purchase 2	......	...	......
Jack	Paper, Pen, Medicine	Milk, Bread, Egg, Milk			
Jill	Rice, Medicine, Vegetable, Milk	Rice, Egg, Vegetable, Milk			
John	Bread, Jam, Butter , Jam	Milk, Bread, Pasta, Medicine			

	Items Bought
Transaction 1	Paper, Pen, Medicine
Transaction 2	Rice, Medicine, Vegetable, Milk
Transaction 3	Milk, Bread, Egg, Milk
Transaction 4	Bread, Jam, Butter , Jam

Data Types

- Relational/Object
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	Trend	Data	Story	Mining	Cloth
Document 1	5	10	4	8	0
Document 2	5	5	8	0	7
Document 3	2	8	2	4	0

Data Types

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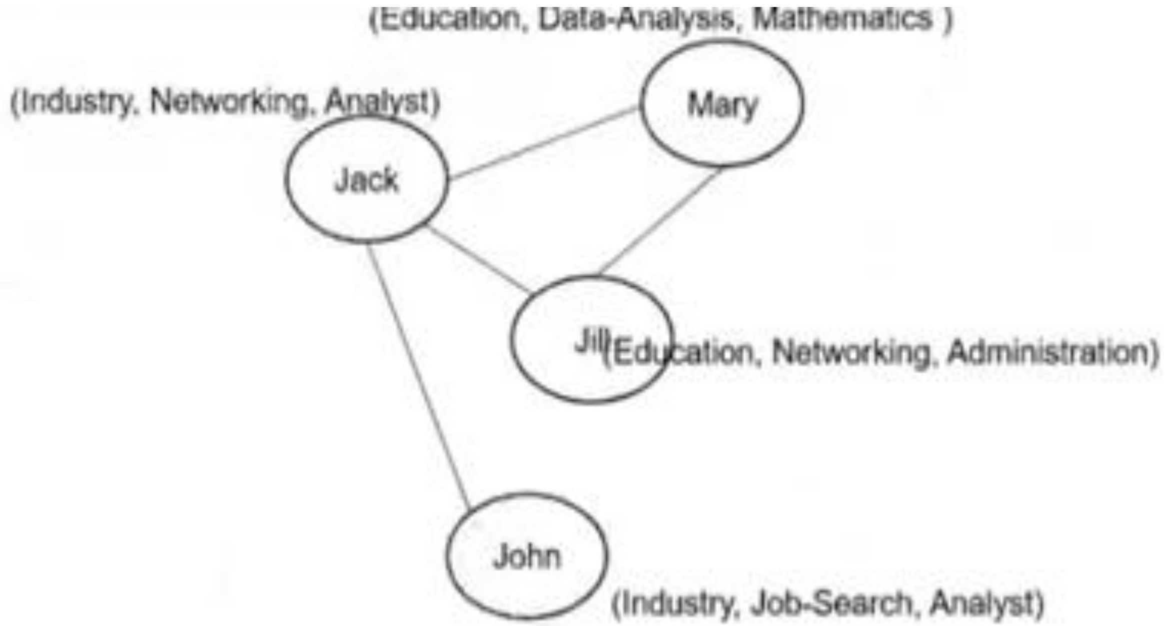

Categorical Nominal

	Work-Field	Purpose of Connect	Domain of work	No.of. Connections	Link to parent	…
John	Industry	Job-Search	Analyst	1	Jack	
Mary	Education	Data-Analysis	Mathematics	2	Jack, Jill	

Data Types

- Relational/Object
- Transactional Data
- Document Data
- Web & Social Network Data
- Spatial Data
- Time Series
- Sequence Data

User	Call Type	Call Duration	Time Stamp	Tower Cell ID	Latitude	Longitude
9341959679262440000	Voice	10	2019-11-20 14:15 :01	123456	12.97	77.58
9341959679262440000	Text	0	2019-11-19 11:10 :09	123456	12.73	77.82
9221959659362440000	Voice	10	2019-11-20 14:15 :01	324576	19.07	72.87

Data Types

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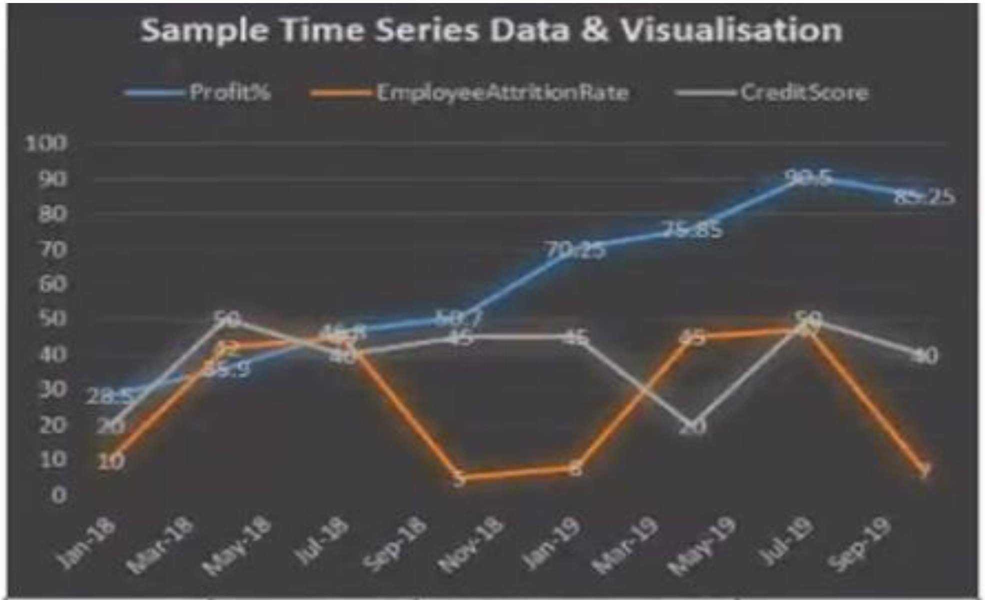

	Profit%	EmployeeAttrition Rate	CreditScore
Jan 18	28.5	10	20
April 18	35.9	42	50
July 18	46.8	45	40
Oct 18	50.7	5	45
Jan 19	70.25	8	45
April 19	75.85	45	20
July 19	90.5	47	50

Data Types

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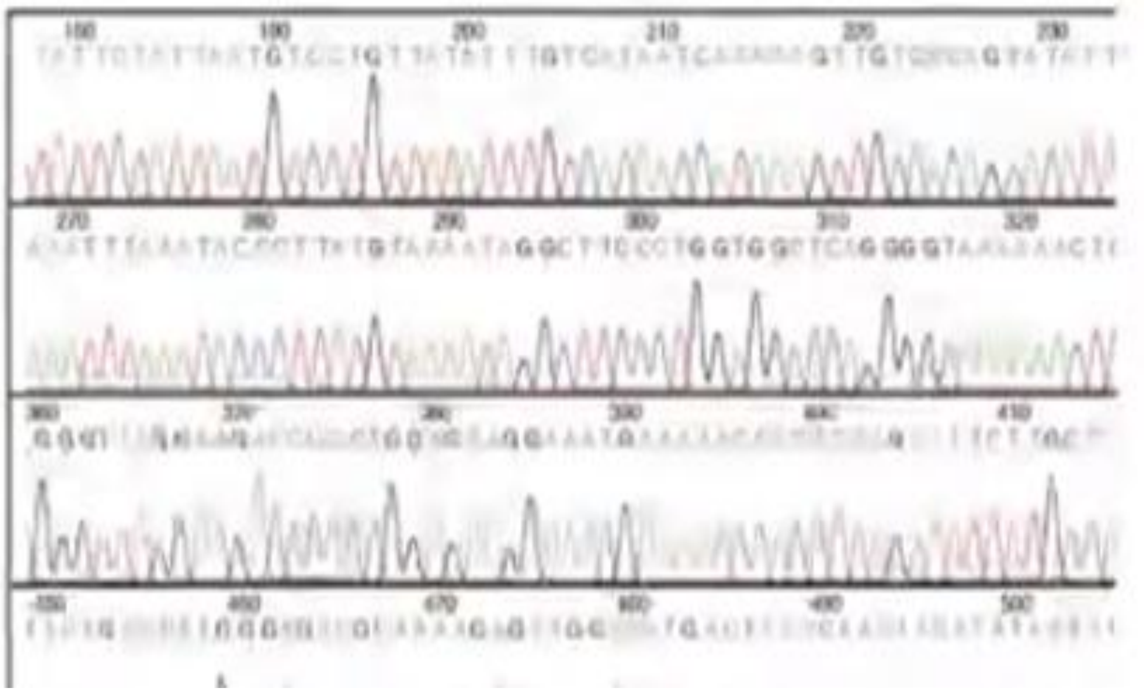


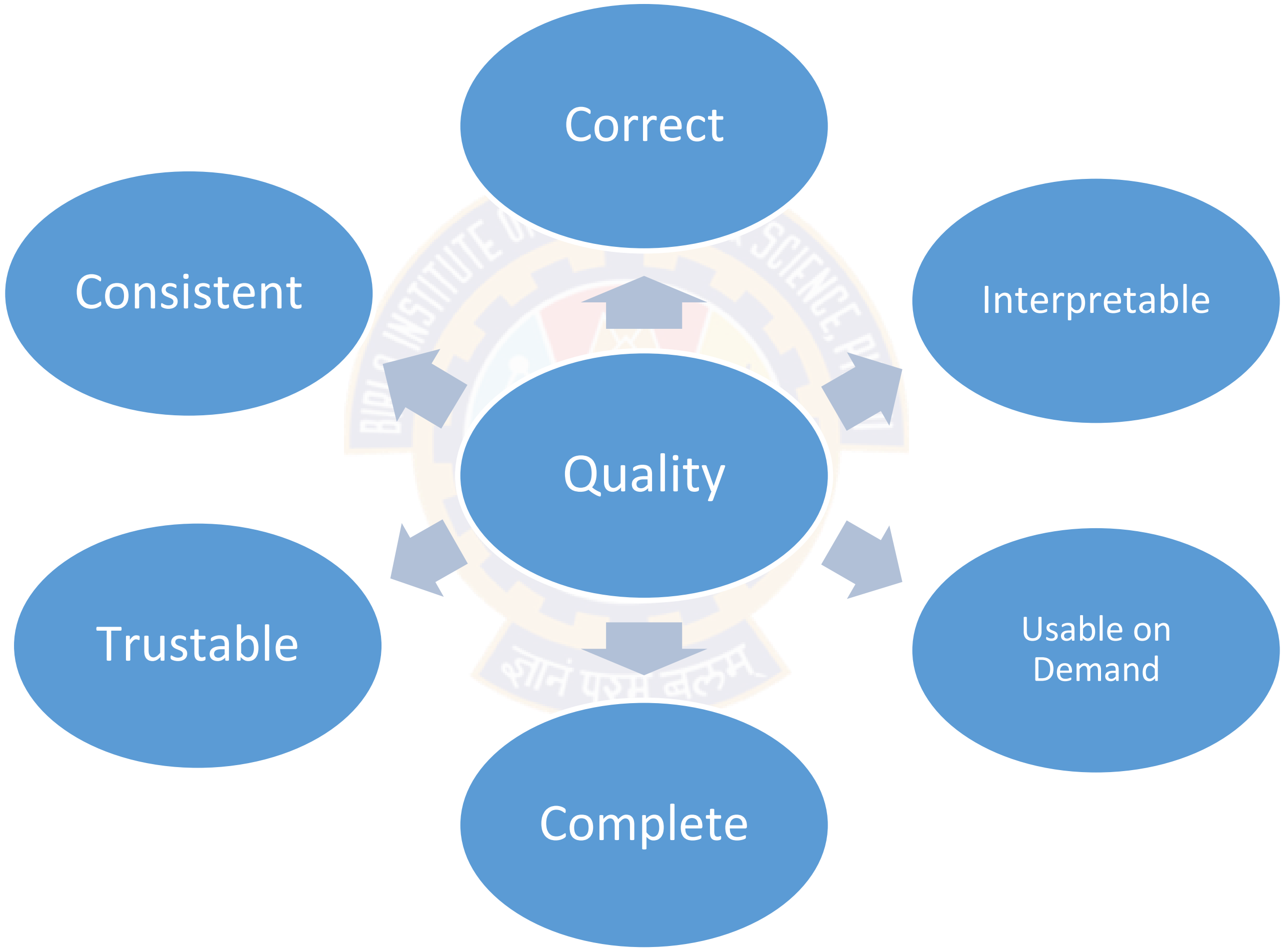
Case Study – 1

Identify the Data Types and attribute types

A bank wishes to analyze its customer base for targeted marketing and needs to segment the customers based on its account information with its branch. Post analysis it might be interested to target potential customers of high income level possessing Titanium card types.

Name	Gender	Service Rating	Is Priority Customer?	Card Type	Credit Score	Is Multiple Account Holder	Income Level	Region
Jack	Male	5	Yes	Platinum	7.5	Yes	Upper	BGLR
Jill	Female	2	Yes	Gold	8.2	No	Middle	DELHI
John	Male	9	No	Gold	7	Yes	Lower	BGLR
Mary	Male	6	No	Gold	6.0	No	Lower	BGLR

Data Quality



Data Quality

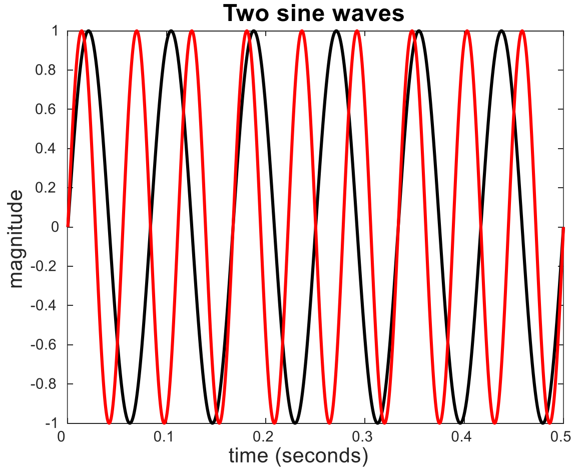
- Poor data quality negatively affects many data processing efforts

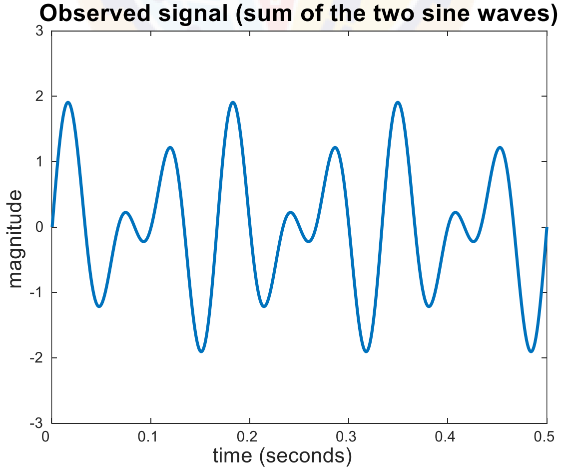
- ML example: a classification model for detecting people who are loan risks is built using poor data
  - Some credit-worthy candidates are denied loans
  - More loans are given to individuals that default

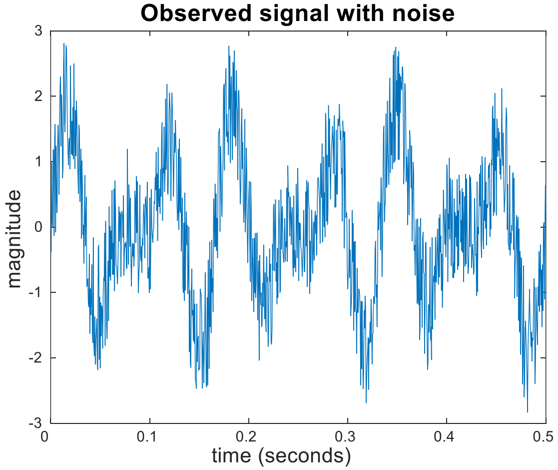
- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?
- Examples of data quality problems:
  - Noise and outliers
  - Wrong data
  - Fake data
  - Missing values
  - Duplicate data

Noise

- For objects, noise is an extraneous object
- For attributes, noise refers to modification of original values
  - Examples: distortion of a person's voice when talking on a poor phone and "snow" on television screen
  - The figures below show two sine waves of the same magnitude and different frequencies, the waves combined, and the two sine waves with random noise
    - The magnitude and shape of the original signal is distorted

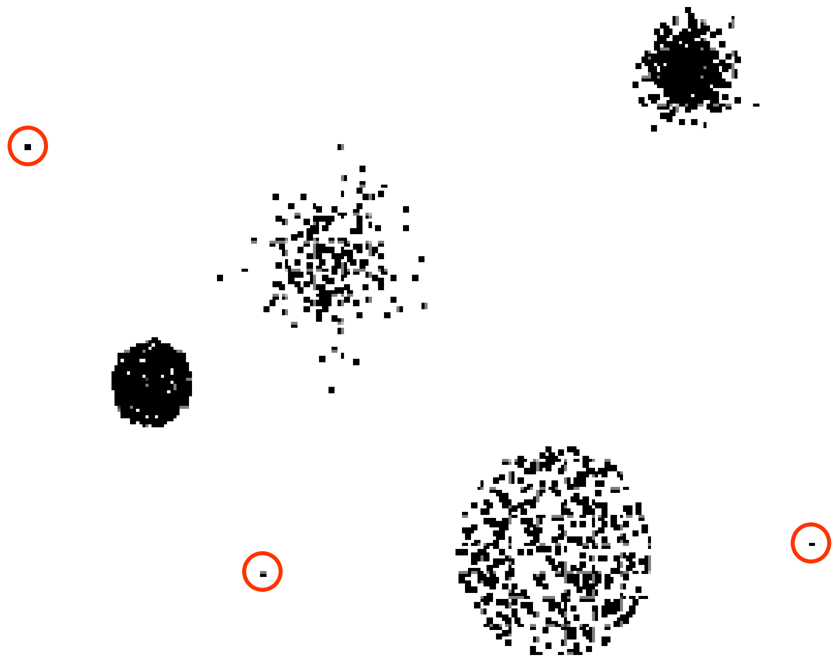






Outliers

- *Outliers* are data objects with characteristics that are considerably different than most of the other data objects in the data set
  - Case 1: Outliers are noise that interferes with data analysis
  - Case 2: Outliers are the goal of our analysis
    - Credit card fraud
    - Intrusion detection



Missing Values

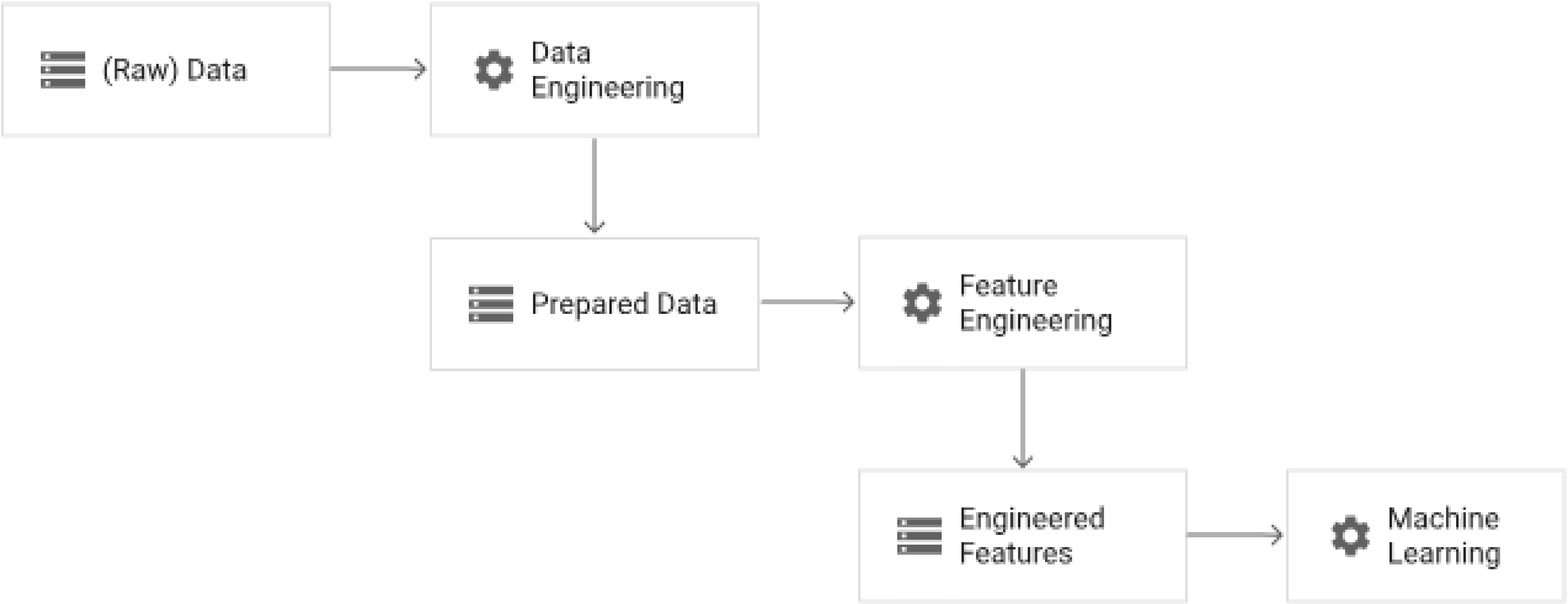
- Reasons for missing values
  - Information is not collected
    - (e.g., people decline to give their age and weight)
  - Attributes may not be applicable to all cases
    - (e.g., annual income is not applicable to children)
- Handling missing values
  - Eliminate data objects or variables
  - Estimate missing values
    - Example: time series of temperature
    - Example: census results
  - Ignore the missing value during analysis

Duplicate Data

- Data set may include data objects that are duplicates, or almost duplicates of one another
  - Major issue when merging data from heterogeneous sources
- Examples:
  - Same person with multiple email addresses
- Data cleaning
  - Process of dealing with duplicate data issues

Preprocessing

- Preprocessing the data for ML involves both data engineering and feature engineering
- Data engineering : process of converting raw data into prepared data.
- Feature engineering : tunes the prepared data to create the features that are expected by the ML model



https://www.tensorflow.org/tfx/guide/tft_bestpractices

Case study

•*BITS WILP is in collaboration with multiple IT companies interested to upskill and level skill their employee through inducting them in tailored Mtech AIML program. Over a year of successful completion , the student are yet to complete another one semester and enroll in Dissertation to complete the program with certification. Students of similar academic background irrespective of the time of enrollment, seems to score more or less in same range in every semester*. ***Accounting department requires to complete few academic year closure documentation for which , they would have to bill the collaborative organization based on the prospective no. of students who might be eligible for project semester***. *As of current semester the students have completed their exams but the process is pending for grading. As Data analyst help accounts team to get necessary information with the given available data across all the collaborative program.*

AttributesOfInterest
Name Gender Age DataOfBirth Organisation JobTitle NatureOfJob EntranceScore EligibilityScore PreviousDegree WILPBatch Section ISM MFML ACI ML NLP ……….

Challenge 1 : Insufficient Training Data.
Idea : Trade-off algorithm vs Data readiness

Data Pre-processing

- Data Aggregation
- Data cleansing
- Instances selection and partitioning
- Feature tuning

Aggregation

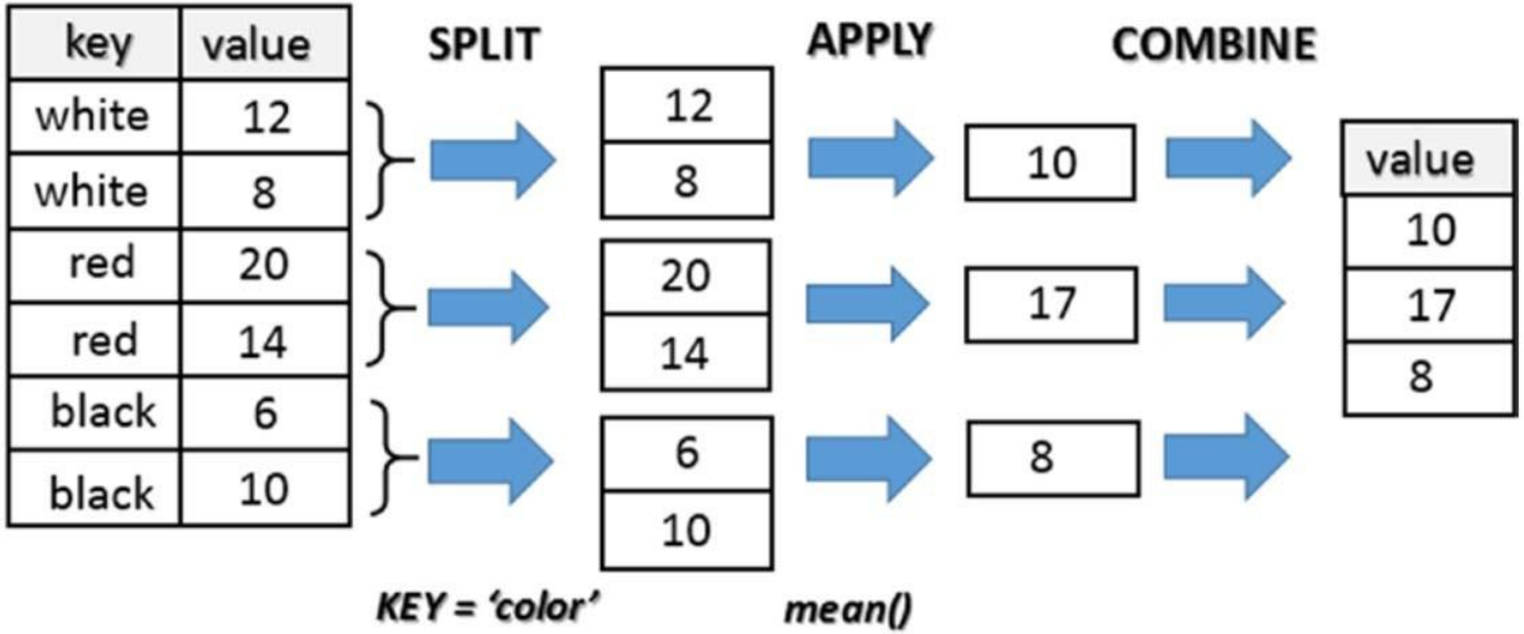
- Combining two or more attributes (or objects) into a single attribute (or object)
- Purpose
  - Data reduction -reduce the number of attributes or objects
  - Change of scale
    - Cities aggregated into regions, states, countries, etc.
    - Days aggregated into weeks, months, or years
  - More "stable" data - aggregated data tends to have less variability

Table 2.4. Data set containing information about customer purchases.

Transaction ID	Item	Store Location	Date	Price	...
⋮	⋮	⋮	⋮	⋮	
101123	Watch	Chicago	09/06/04	\$25.99	...
101123	Battery	Chicago	09/06/04	\$5.99	...
101124	Shoes	Minneapolis	09/06/04	\$75.00	...
⋮	⋮	⋮	⋮	⋮	

Data Aggregation

Python Group By Example



Source: Python for Data Analytics by Fabio Nelli

Data cleansing

- Removing or correcting records of corrupted or invalid values from raw data
  - NOISY: containing noise, errors, or outliers .
    - e.g., Salary="−10" (an error)
  - INCONSISTENT: containing discrepancies in codes or names, e.g.,
    - Age="42", Birthday="03/07/2010"
    - Was rating "1, 2, 3", now rating "A, B, C"
    - discrepancy between duplicate records
  - INTENTIONAL (e.g., disguised missing data)
    - Jan. 1 as everyone's birthday
- Removing records that are missing a large number of columns
- Duplicate data

Data cleansing

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	10000K	Yes
6	No	NULL	60K	No
7	Yes	Divorced	220K	NULL
8	No	Single	85K	Yes
9	No	Married	90K	No
9	No	Single	90K	No

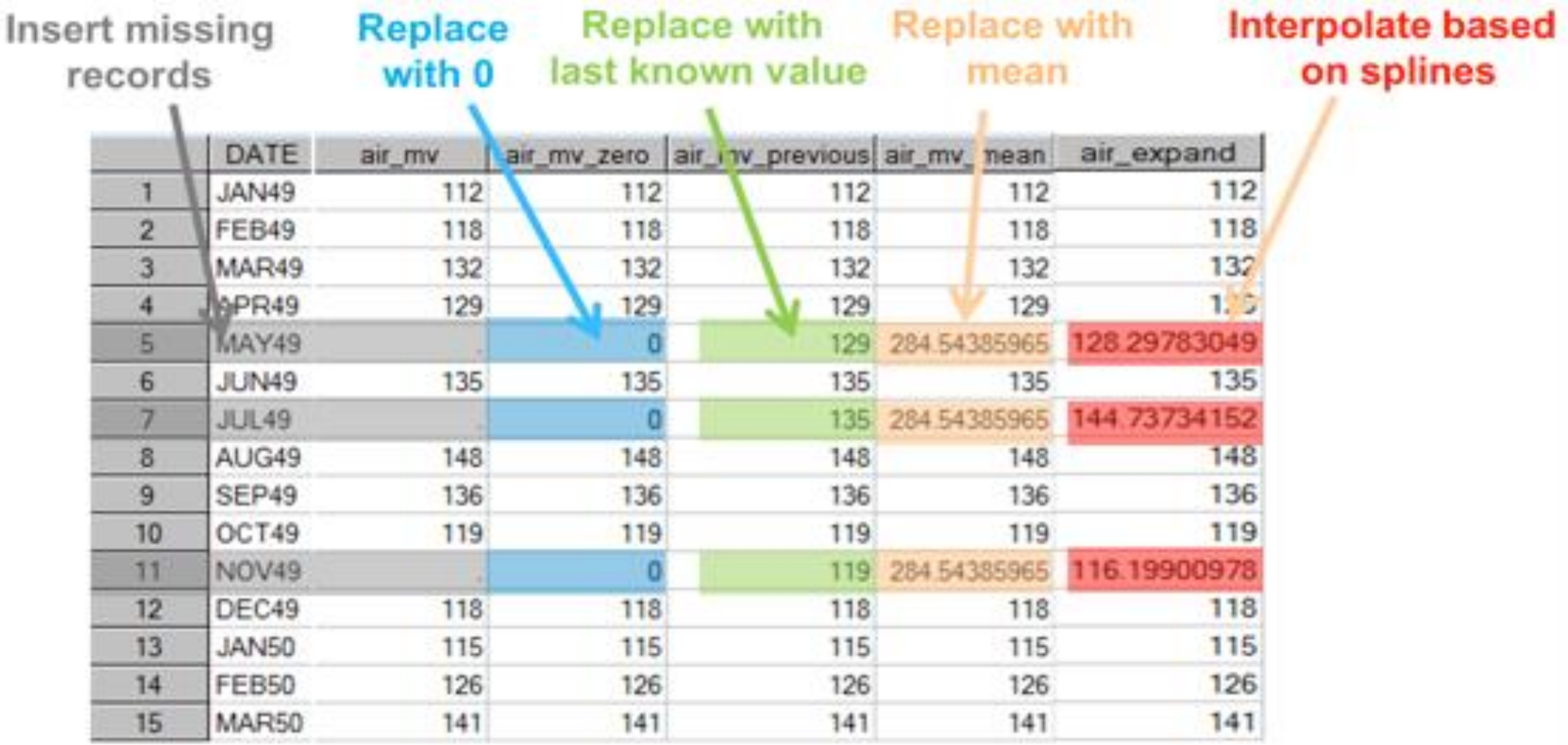
A mistake or a millionaire?

Missing values

Inconsistent duplicate entries

Data cleansing

Imputing Missing values



	DATE	air_mv	air_mv_zero	air_mv_previous	air_mv_mean	air_expand
1	JAN49	112	112	112	112	112
2	FEB49	118	118	118	118	118
3	MAR49	132	132	132	132	132
4	APR49	129	129	129	129	[illegible]
5	MAY49	.	0	129	284.54385965	128.29783049
6	JUN49	135	135	135	135	135
7	JUL49	.	0	135	284.54385965	144.73734152
8	AUG49	148	148	148	148	148
9	SEP49	136	136	136	136	136
10	OCT49	119	119	119	119	119
11	NOV49	.	0	119	284.54385965	116.19900978
12	DEC49	118	118	118	118	118
13	JAN50	115	115	115	115	115
14	FEB50	126	126	126	126	126
15	MAR50	141	141	141	141	141

Data cleansing

Handling outliers (univariate)

- IQR
  - Outliers are usually, a value higher/lower than 1.5 x IQR
- Z-score method (3 sigma)

Data cleansing

Handling outliers (univariate) using IQR

❖ **Interquartile Range (IQR)**:
- IQR = Q3 - Q1 (where Q1 is the 25th percentile and Q3 is the 75th percentile)

❖ **Outlier Detection**:
- **Lower Bound**: Q1 - 1.5 * IQR
- **Upper Bound**: Q3 + 1.5 * IQR

❖ **Example**:
- If Q1 = 10 and Q3 = 20, then IQR = 10
- Lower Bound = 10 - 1.5 * 10 = -5
- Upper Bound = 20 + 1.5 * 10 = 35
- Data points < -5 or > 35 are outliers

Exercise

- **Find the outlier in the following data using Inter-Quartile Range.**

- Data = 10,2, 11, 15,11,14,13,17,12,22,14,11.

1. Sort :10, 11, 11, 11, 12, 12, 13, 14, 14, 15, 17, 22
2. Median: (12+13)/2=12.5=Q2
3. Q1=11(25^{th} percentile)
4. Q3=14.5(75^{th} percentile)
5. IQR=Q3-Q1=3.5
6. Min=Q1-1.5IQR=5.75
7. Max=Q3+1.5IQR=19.75

- Outlier=22

Quartile Formula

The Quartile Formula For Q1 $= \frac{1}{4}(n+1)^{th}$ term

The Quartile Formula For Q3 $= \frac{3}{4}(n+1)^{th}$ term

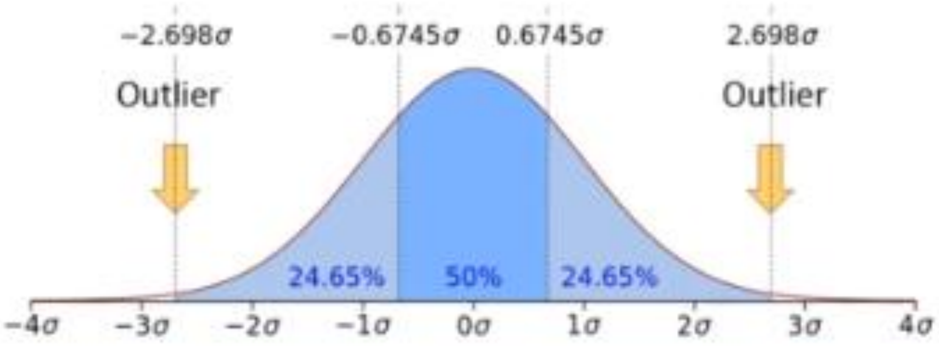
The Quartile Formula For Q2 $=$ Q3 – Q1 (Equivalent to Median)

Data cleansing

Handling outliers (univariate) using 3 sigma

- **3 Sigma Rule**: Based on the properties of a normal distribution
  - **Mean (μ) and **Standard Deviation (σ)**

  - **99% of the observations of a variable following a normal distribution lie within mean +/- 3 X standard deviation**



- **Outlier Detection**:
  - **Lower Bound**: $\mu - 3\sigma$
  - **Upper Bound**: $\mu + 3\sigma$
- **Example Calculation**:
  - If $\mu=50$ and $\sigma=5$, then:
    - Lower Bound = 50 - 3 * 5 = 35
    - Upper Bound = 50 + 3 * 5 = 65
  - Data points < 35 or > 65 are outliers

Instances selection and partitioning

training, evaluation (validation), test sets

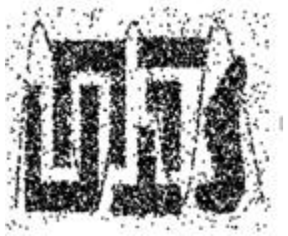
Challenge 2 : Non-representative Training Data .

Idea : Training Data be representative of the new cases we want to generalize

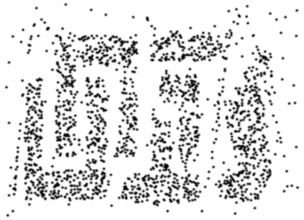
- Small sample size leads to sampling noise. Increase sampling size.
- If sampling process is flawed, even large sample size can lead to sampling bias

The key principle for effective sampling is the following:

- Using a sample will work almost as well as using the entire data set, if the sample is representative
- A sample is representative if it has approximately the same properties (of interest) as the original set of data



8000 points



2000 Points

500 Points

Instances selection and partitioning

training, evaluation (validation), test sets

- Sampling is the main technique employed for data reduction.
  - It is often used for both the preliminary investigation of the data and the final data analysis.

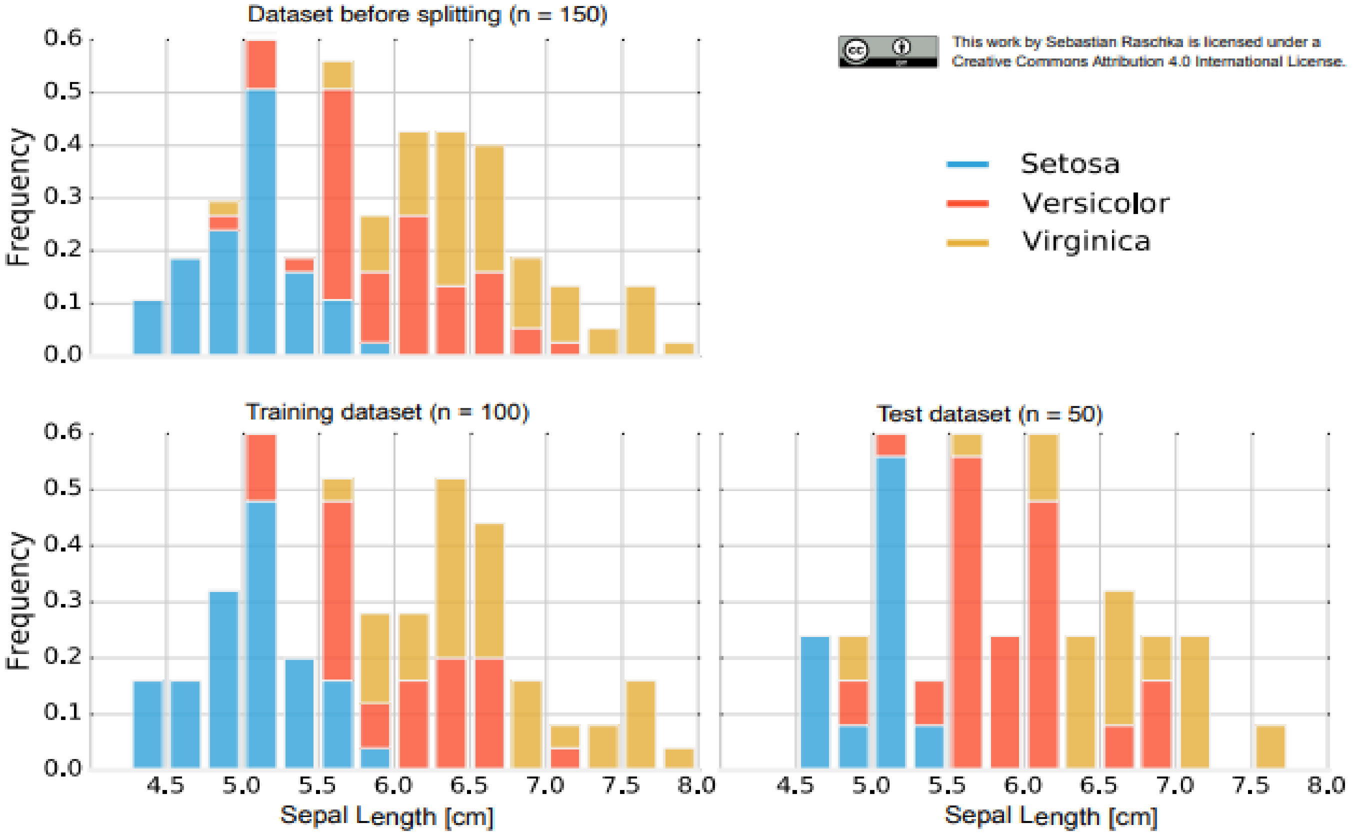
- Statisticians often sample because obtaining the entire set of data of interest is too expensive or time consuming.

- Sampling is typically used in data mining because processing the entire set of data of interest is too expensive or time consuming.

Instances selection and partitioning

Sampling

Issues with Subsampling (Independence Violation)



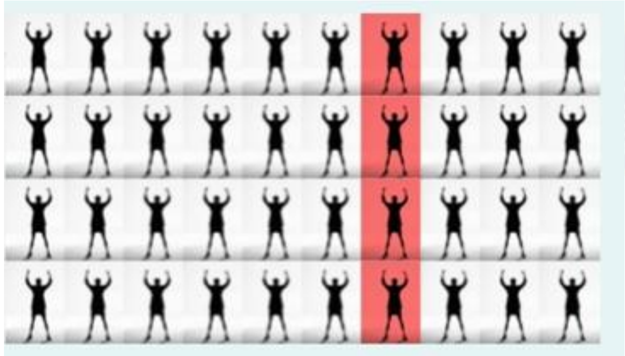
IRIS Dataset of Flowers
50 Setosa,
50 Versicolor,
50 Virginica

- **Random subsampling can assign 2/3 (100) to training set and 1/3 (50) to the test set**
- **Training set → 38 x Setosa, 28 x Versicolor, 34 x Virginica**
- **Test set → 12 x Setosa, 22 x Versicolor, 16 x Virginica**

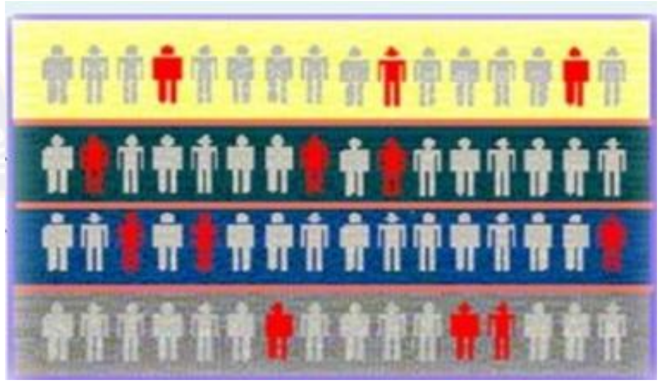
Instances selection and partitioning

Sampling - Frequently Used

Simple Random Type



Stratified Sampling Type



Clustered Sampling Type

Instances selection and partitioning

Sampling - Imbalanced Training Set

- **Scenario** : Building Classifiers with Imbalanced Training Set
- Modify the distribution of training data so that rare class is well-represented in training set
  - Under sample the majority class
  - Over sample the rare class

Feature tuning Feature Scaling

To map the continuous values from one range to target range to easily compare and fit in apt distribution to enable statistical processing

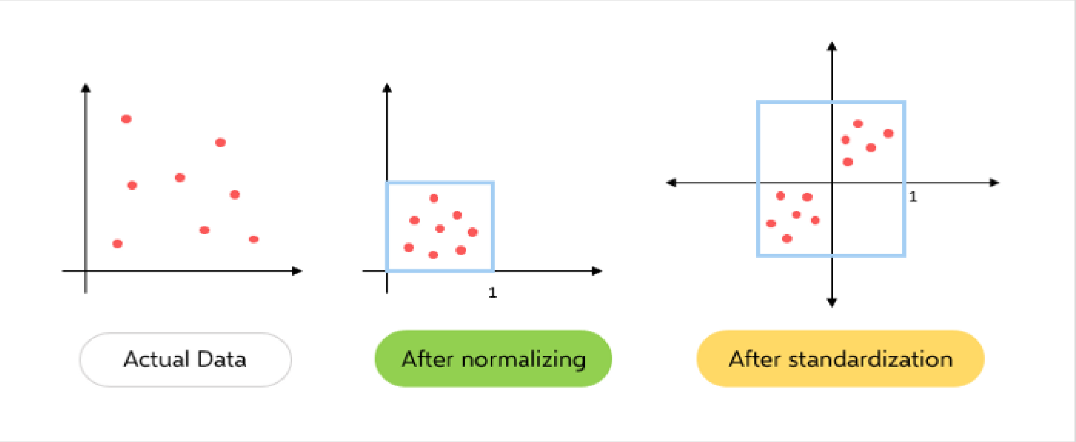
Feature scaling

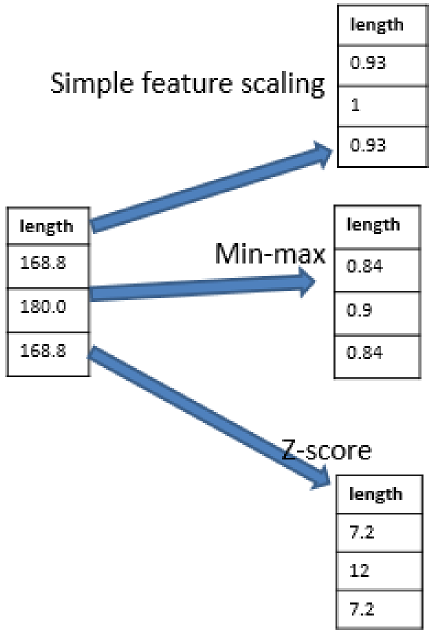
Normalization

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Standardization

$$X' = \frac{\text{X} - \text{Mean}}{\text{Standard deviation}}$$





Note: Scaling the target values is generally not required

Feature tuning

Feature Scaling - Normalization Vs Standardization

- Normalization
  - when approximate upper and lower bounds on data is known
  - When data is approximately uniformly distributed across that range. E.g age. Not to be used on skewed attribute e.g. income
  - when the algorithms do not make assumptions about the data distribution e.g. (KNN,NN)
  - scales in a range of [0,1] or [-1,1]
- Standardization
  - used when algorithms make assumptions about the data distribution (Gaussian distribution)
  - not bounded by range
  - less affected by outliers

Note:

- Fit the scalers to the training data only
- Use them to transform the training set and the test set

Feature tuning

Feature Scaling - Normalization Vs Standardization

- **Min-max normalization**: to [new_min$_A$, new_max$_A$]

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

  - Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to

$$\frac{73{,}600 - 12{,}000}{98{,}000 - 12{,}000}(1.0 - 0) + 0 = 0.716$$

- **Z-score normalization/Standardization** (μ: mean, σ: standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

  - Ex. Let μ = 54,000, σ = 16,000. Then $\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$

- **Normalization by decimal scaling** $v' = \frac{v}{10^j}$ Where j is the smallest integer such that Max(|ν'|) < 1

Feature Engineering

- Feature engineering needed for coming up with a good set of features - Irrelevant Features
- Feature extraction
  - Dimensionality reduction
- Feature selection
  - more useful features to train on among existing features.
- Feature Construction
  - Combine existing features to produce a more useful one
- Feature Transformation

Case study

Input:

WILP student details enrolled in Mtech AIML program.

Analysis:

Predict the GPA of the AIML students in Semester3 to estimate the no. of students who might enroll in dissertation

Observation:

Students with similar educational background tend to perform same in the exams

AttributesOfInterest
Name Gender Age DataOfBirth Organisation JobTitle NatureOfJob EntranceScore EligibilityScore PreviousDegree WILPBatch Section ISM MFML ACI ML NLP ……….

Feature Engineering - Extraction
Curse of Dimensionality

- Reducing the number of features by creating lower-dimension
- When dimensionality increases, data becomes increasingly sparse in the space that it occupies
- Solution : Dimensionality Reduction techniques: e.g Principal Components Analysis (PCA)

AttributesOfInterest
Name Gender Age DataOfBirth Organisation JobTitle NatureOfJob EntranceScore EligibilityScore PreviousDegree WILPBatch Section ISM MFML ACI ML NLP ……….

Feature Engineering - Selection

- Selecting a subset of the input features for training the model

  Handle Redundant features

  Remove Irrelevant feature

  dropping features (missing a large number of value)

dataframe= *dataframe*.drop([‘*COLNAME-1*',‘*COLNAME-2*'],axis=1)

AttributesOfInterest
~~Name~~ ~~Gender~~ ~~Age~~ ~~DataOfBirth~~ ~~Organisation~~ ~~JobTitle~~ ~~NatureOfJob~~ ~~EntranceScore~~ ~~EligibilityScore~~ PreviousDegree ~~WILPBatch~~ ~~Section~~ ISM MFML ACI ML NLP ……….

Feature Engineering - construction

- Creating new features by using techniques
  - Polynomial expansion (by using univariate mathematical functions)
  - Feature crossing (to capture feature interactions)
  - Features can also be constructed by using business logic from the domain of the ML use case.

Feature Engineering - Transform

AttributesOfInterest
PreviousDegree SEM-1-Total SEM-2-Total SEM-3-Total CGPA isEligibleForDissertation

AttributesOfInterest
PreviousDegree SEM-1-GPA SEM-2-GPA SEM-3-GPA CGPA isEligibleForDissertation

AttributesOfInterest
PreviousDegree S1-isComplete S2-isComplete S3-isComplete CGPA isEligibleForDissertation

Feature Engineering - Transform

Encoding Numerical Features

- **Discretization** : Convert continuous attribute into a discrete attribute
  - Naive Bayes, decision trees and their ensembles including Random forest, Minimum distance classifiers or KNN prefer discrete features.
  - Also known as binning' or 'bucketing'
  - To handle outliers.
  - To improve the value spread i.e., spread of data
- Discretization involves converting the raw values of a numeric attribute (e.g., age) into
  - interval labels (e.g., 0–10, 11–20, etc.) OR
  - conceptual labels (e.g., youth, adult, senior)

Feature Engineering - Transform

Encoding Numerical Features

Simple Discretization: Binning

- Equal-width (distance) partitioning
  - Divides the range into *N* intervals of equal size: uniform grid
  - if *A* and *B* are the lowest and highest 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
- Equal-depth (frequency) partitioning
  - Divides the range into N intervals, each containing approximately same number of samples
  - Good data scaling

Feature Engineering - Transform

Encoding Categorical Features

- Binarization maps a categorical attribute into one or more binary variables - One Hot/ Dummy Encoding

Car	Fuel
A	Gas
B	Diesel
C	Gas
D	gas

Car	Fuel		Gas	Diesel
A	Gas	….	1	0
B	Diesel	….	0	1
C	Gas	….	1	0
D	gas	….	1	0

- Categorical features to a numeric representation - Label Encoding

Fuel
Gas
Diesel
Gas
gas

Fuel
1
2
1
3

Problem Type 3

Pre-Processing

- A marketing domain has launched their APP products tailored for different categories of students population in a city to get feedback. The focus group has given following feedback. How do you propose to ready the data for analysis?

Features liked	Features to improve	Do you have similar app?	How much do you pay for existing app per month?	Rate game (1-10)	Rate social media connect (1-5)	Shopping facility (1-10)	How would you recommend this to a friend	Education
Graphics	Usability	No	$35	8	5	4	High	School
Interactive	More features		Rs.500	8	3	6	Low	College
Graphics		Yes	Rs.250	7	5	6	Medium	School
Cheap	Creativity	Yes	$20	7	5	8	High	College

Question : Identify the basic preprocessing & data cleaning required for this case

Challenges of Machine Learning

- Training Data
  - Insufficient
  - Non representative
- Model Selection
  - Overfitting
  - Underfitting
- Validation and Testing

IMPORTANT NOTE TO THE STUDENTS:

More on this slide will be discussed by faculty only in later modules 4,5,6…. On appropriate sections

Few Terminologies

(To interpret the jargons in the prescribed text book)

Terminologies

- **Training example.** An example of the form $\langle \mathbf{x}, f(\mathbf{x}) \rangle$.
- **Target function (target concept).** The true function f.
- **Hypothesis**. A proposed function h believed to be similar to f.
- **Concept**. A boolean function. Examples for which $f(\mathbf{x}) = 1$ are called **positive examples** or **positive instances** of the concept. Examples for which $f(\mathbf{x}) = 0$ are called **negative examples** or **negative instances.**
- **Classifier**. A discrete-valued function. The possible values $f(\mathbf{x}) \in \{1, \ldots, K\}$ are called the **classes** or **class labels**.
- **Hypothesis Space**. The space of all hypotheses that can, in principle, be output by a learning algorithm.
- **Version Space**. The space of all hypotheses in the hypothesis space that have not yet been ruled out by a training example.

Amount taken	Period	Credit Score	Defaulter
40 lakhs	5 years	1000	No
10 Lakhs	5 months	550	YES
80 Lakhs	3 years	950	No
20 Lakhs	4 years	1500	No

Inductive Learning Hypothesis

- **Any hypothesis found to approximate the target function well over a sufficiently large set of training examples will also approximate the target function well over other unobserved examples**

- **Inductive learning** or "**Prediction**":
  - **Given** examples of a function *(X, F(X))*
  - **Predict** function *F(X)* for new examples *X*
- Classification

  F(X) = Discrete

- Regression

  F(X) = Continuous

- Probability estimation

  F(X) = Probability*(X):*

Inductive Learning Hypothesis

- Target Concept
- Discrete : $f(x) \in \{Yes, No, Maybe\}$
- Continuous : $f(x) \in [20-100]$
- Probability Estimation : $f(x) \in [0-1]$

Sky	**AirTemp**	**Humidity**	**Wind**	**Water**	**Forecast**	***EnjoySport?***
Sunny	Warm	Normal	Strong	Warm	Same	Yes
Sunny	Warm	High	Strong	Warm	Same	Yes
Rainy	Cold	High	Strong	Warm	Change	No
Sunny	Warm	High	Strong	Cool	Change	Yes

Inductive Learning Hypothesis

- Target Concept
- Discrete : $f(x) \in \{Yes, No, Maybe\}$
- Continuous : $f(x) \in [20\text{-}100]$
- Probability Estimation : $f(x) \in [0\text{-}1]$

Sky	AirTemp	Altitude	Wind	Water	Forecast	Humidity
Sunny	Warm	Normal	Strong	Warm	Same	60
Sunny	Warm	High	Strong	Warm	Same	75
Rainy	Cold	High	Strong	Warm	Change	70
Sunny	Warm	High	Strong	Cool	Change	45

Inductive Learning Hypothesis

- Target Concept
- Discrete : $f(x) \in \{Yes, No, Maybe\}$
- Continuous : $f(x) \in [20\text{-}100]$
- Probability Estimation : $f(x) \in [0\text{-}1]$

Sky	**AirTemp**	**Humidity**	**Wind**	**Water**	**Forecast**	***P(EnjoySport =Yes)***
Sunny	Warm	Normal	Strong	Warm	Same	0.95
Sunny	Warm	High	Strong	Warm	Same	0.7
Rainy	Cold	High	Strong	Warm	Change	0.5
Sunny	Warm	High	Strong	Cool	Change	0.6

Hypothesis

Example	*Sky*	*AirTemp*	*Humidity*	*Wind*	*Water*	*Forecast*	*EnjoySport*
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

- **One possible hypothesis** (?, ***Cold,*** High, ?, ?, ?)
- The most **general hypothesis**-that every day is a positive example-(?, ?, ?, ?, ?, ?)
- The most **specific possible hypothesis**-that no day is a positive example **(ϕ, ϕ, ϕ, ϕ, ϕ, ϕ)**

Thank you