CS5805 : Machine Learning I
Lecture #3

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COLLEGE OF ENGINEERING
COMPUTER SCIENCE
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- Data mining is part of statistics, engineering, optimization, and computer science.
- We start our data mining process by creating a Dataset, describing an aspect of the real world.

Data objects

record, *point*, *vector*, *pattern*, *event*, *case*, *sample*, *instance*, *observation* or *entity*.

Attributes

variable, *field*, *feature* or *dimension*.

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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

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  - A collection of attributes describe an Object.

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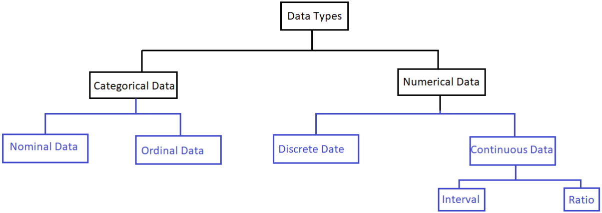
Type of Attributes

Categorical

- Categorical data is a type of data than can be stored into groups or categories with the aid of names or labels. It is also known as qualitative data.

Numerical



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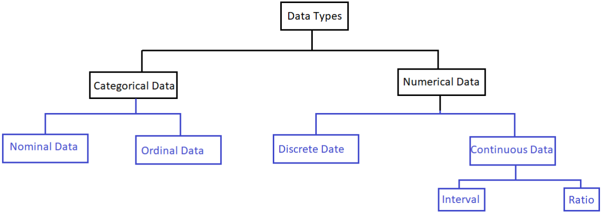

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- Three common types of mean calculations are

1-Arithmetic mean

2-Geometric mean

3-Harmonic mean

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- Python function from Numpy package : np.mean()

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- This information can be summarized in a table called Confusion matrix. Let consider a binary classification:

		Predicted CLass	
		Class=1	Class=0
Actual Class	Class=1	f_{11}	f_{10}
	Class=0	f_{01}	f_{00}

Accuracy

$$Accuracy = \frac{f_{11} + f_{00}}{f_{11} + f_{10} + f_{01} + f_{00}}$$

Error rate

$$Error\ rate = \frac{f_{10} + f_{01}}{f_{11} + f_{10} + f_{01} + f_{00}}$$

Confusion Matrix

		Test result	
		Sick (positive)	Healthy (negative)
Actual	Sick	T.P	F.N
	Healthy	F.P	T.N

Sensitivity (Recall, Hit rate, true positive rate)

Number of correct positive predictions divided by the total number of positives.

$$TPR = \frac{T.P}{T.P + F.N}$$

Specificity (selectivity, true negative rate)

Number of correct negative predictions divided by the total number of negatives.

$$TNR = \frac{T.N}{T.N + F.P}$$

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- Sometimes we are looking for high Precision but sometimes looking for high Recall.

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- This means False Positive should be low and **Precision High**.

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- F1 score gives the same weightage to recall and precision.

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- Curse of dimensionality is a problem that occurs when data has **too many features**.

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- Dimensionality of a dataset is the **number of attributes** that the objects possess in the dataset.
- Each feature adds an extra dimension to our model.
- Analyzing data with a small number of dimensions tends to be qualitatively different from analyzing moderate or high-dimensions.
- Curse of dimensionality is a problem that occurs when data has **too many features**.
    - Over-fitting our model - results in poor performance.
- Because of above issue, dimensionality reduction is an important motivation in preprocessing.

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Types of Dataset

Record Data

- Data Matrix

Graph

Ordered Data

Types of Dataset

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- Temporal Data
- Sequential Data
- Generic Sequential Data

Record Data

- Data that consists of a collection of records, each of which consists of a fixed set of attributes.

	total_bill	tip	sex	smoker	day	time	size
0	16.99000	1.01000	Female	No	Sun	Dinner	2
1	10.34000	1.66000	Male	No	Sun	Dinner	3
2	21.01000	3.50000	Male	No	Sun	Dinner	3
3	23.68000	3.31000	Male	No	Sun	Dinner	2
4	24.59000	3.61000	Female	No	Sun	Dinner	4
5	25.29000	4.71000	Male	No	Sun	Dinner	4
6	8.77000	2.00000	Male	No	Sun	Dinner	2
7	26.88000	3.12000	Male	No	Sun	Dinner	4
8	15.04000	1.96000	Male	No	Sun	Dinner	2
9	14.78000	3.23000	Male	No	Sun	Dinner	2
10	10.27000	1.71000	Male	No	Sun	Dinner	2
11	35.26000	5.00000	Female	No	Sun	Dinner	4
12	15.42000	1.57000	Male	No	Sun	Dinner	2
13	18.43000	3.00000	Male	No	Sun	Dinner	4

Data Matrix

- Data objects with only numeric attributes can be represented by *mxn* matrix, where there are *m* rows, one for each object, and *n* columns one for each attribute.

Projection of x Load	Projection of y load	Distance	Load	Thickness
10.23	5.27	15.22	2.7	1.2
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- The data objects can be thought of as points in a multi-dimensional space where each dimension represents a distinct attribute.

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Document Data

- Each document becomes a 'term' vector.

	team	coach	pla y	ball	score	game	wi n	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

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Transaction Data

- A special type of record data where each record (transaction) involves a set of items.

TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

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Graph Data

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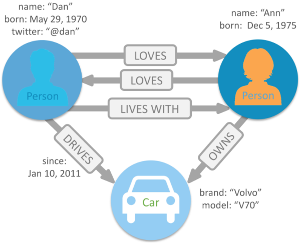

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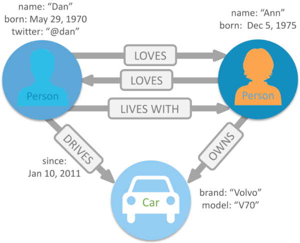

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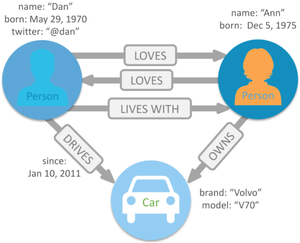

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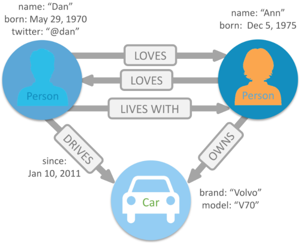

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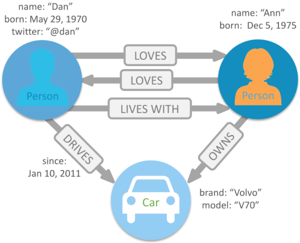
- E.g, social network, payment networks, road networks,..



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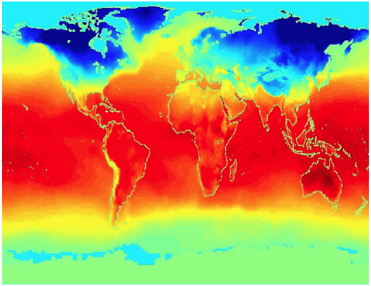

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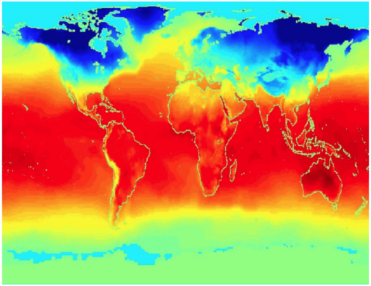

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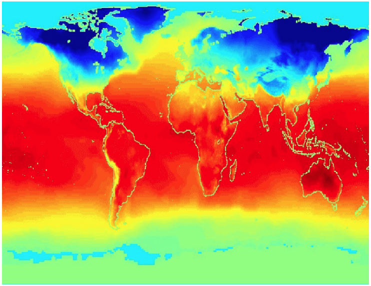

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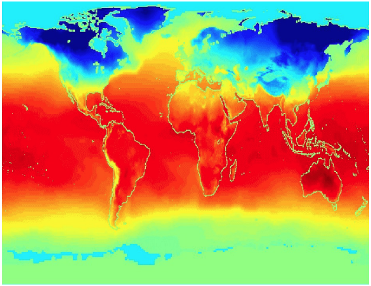
- E.g, Average monthly temperature of land & ocean.



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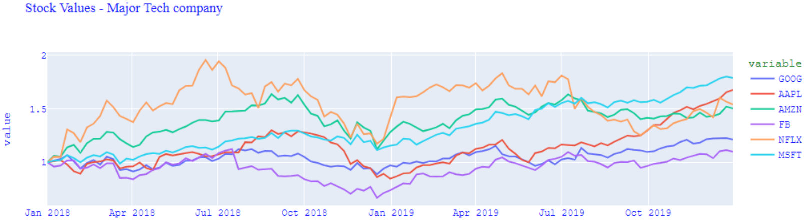

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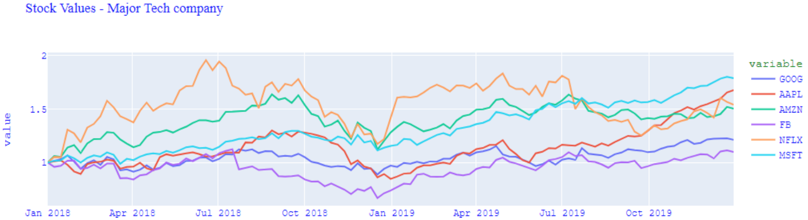

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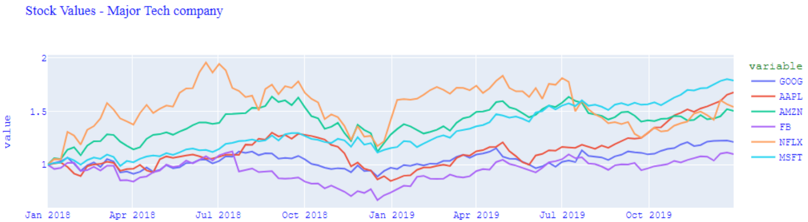

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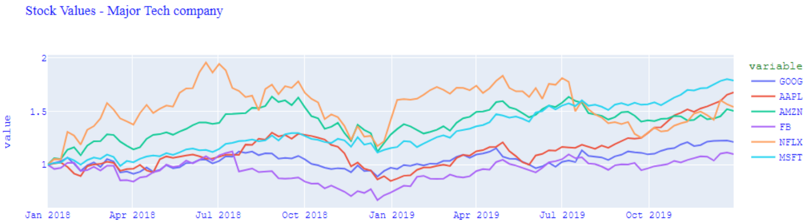

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  - **inplace**: If True, do operation and return None.

Sample Dataframe-Python

- Detecting missing values using df.isna()

```
import pandas as pd
import numpy as np

data = {"Product_Name":["Mouse", "Monitor", "CPU", "Speakers","Headset"],
        "Unit_Price":[200, 5000.235, 10000.550,  250.50, None],
        "No_Of_Units":[5, 10, 20,  8, pd.NaT],
        "Available_Quantity":[6,5,5, pd.NaT,np.NaN],
        "Remarks":[np.NaN,pd.NaT,pd.NaT,pd.NaT,pd.NaT]
       }
df = pd.DataFrame(data)

print(df.isna().sum())

df_copy1 = df.copy()
df_copy2 = df.copy()
df_copy3 = df.copy()

df_copy1.dropna(axis=1,inplace=True)
df_copy2.dropna(how='any',axis=1,inplace=True)
df_copy3.dropna(how='all',axis=1,inplace=True)
```

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- DataFrame.fillna() is used to fill missing values using the specified method.
- DataFrame.replace(): can be used for replacement.

Sample Dataframe-Python

- Replacing missing values with specified integer.

```
# importing libraries
import pandas as pd
import numpy as np

nums = {'Set_of_Numbers': [2, 3, 5, 7, 11, 13,
                           np.nan, 19, 23, np.nan]}

# Create the dataframe
df1 = pd.DataFrame(nums, columns=['Set_of_Numbers'])
df2 = df1.copy()
# Apply the function
df2['Set_of_Numbers'] = df1['Set_of_Numbers'].fillna(0)

# print the DataFrame
print(df2)
```

Sample Dataframe-Python

- Replacing missing values mean and mode.

```
# importing pandas module
import pandas as pd

# making data frame from csv file
nba = pd.read_csv("C:\GW\Time series Analysis\dataset/nba.csv")
# check if missing value exists
print(nba.isna().sum())
# replacing na values in college with No college
nba["College"].fillna("No College", inplace = True)

# replacing missing values of 'College' feature
# with the mode of the same feature
nba["College"].fillna(nba["College"].mode()[0], inplace = True)

# replacing missing values of the 'Salary' with the mean value
# of the column
nba["Salary"].fillna(nba["Salary"].mean(), inplace = True)
```

Backward fill-Python

- Replacing missing values with backward fill option Dataframe.bfill().

```
import pandas as pd

# Creating a dataframe with "na" values.

df1 = pd.DataFrame({"A": [None, 1, 2, 3, None, None],
                    "B": [11, 5, None, None, None, 8],
                    "C": [None, 5, 10, 11, None, 8]})
df2 = df1.copy()
df3 = df1.copy()
# Filling missing values backward across row
df2.bfill(axis ='rows', inplace=True)
# Filling missing values backward across column
df3.bfill(axis ='columns', inplace=True)
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df3 = df1.copy()
# Filling missing values backward across row
df2.bfill(axis ='rows', inplace=True)
# Filling missing values backward across column
df3.bfill(axis ='columns', inplace=True)
```

Forward fill-Python

- Replacing missing values with forward fill option Dataframe.ffill().

```
# importing pandas as pd
import pandas as pd

# Creating the dataframe
df = pd.DataFrame({"A": [5, 3, None, 4],
                   "B": [None, 2, 4, 3],
                   "C": [4, 3, 8, 5],
                   "D": [5, 4, 2, None]})
df1 = df.copy()
df2 = df.copy()
# applying ffill() method to fill the missing values-row
df1.ffill(axis = 0, inplace=True)
# applying ffill() method to fill the missing values-column
df2 = df2.ffill(axis = 1)
```

Forward fill-Python

- Replacing missing values with forward fill option Dataframe.ffill().
- When ffill() is applied across the index, any missing value is filled based on the corresponding value in the previous row.

```
# importing pandas as pd
import pandas as pd

# Creating the dataframe
df = pd.DataFrame({"A": [5, 3, None, 4],
                   "B": [None, 2, 4, 3],
                   "C": [4, 3, 8, 5],
                   "D": [5, 4, 2, None]})
df1 = df.copy()
df2 = df.copy()
# applying ffill() method to fill the missing values-row
df1.ffill(axis = 0, inplace=True)
# applying ffill() method to fill the missing values-column
df2 = df2.ffill(axis = 1)
```

Forward fill-Python

- Replacing missing values with forward fill option Dataframe.ffill().
- When ffill() is applied across the index, any missing value is filled based on the corresponding value in the previous row.
- When ffill() is applied across the column axis, missing values are filled by the value in previous column in the same row.

```python
# importing pandas as pd
import pandas as pd

# Creating the dataframe
df = pd.DataFrame({"A": [5, 3, None, 4],
                   "B": [None, 2, 4, 3],
                   "C": [4, 3, 8, 5],
                   "D": [5, 4, 2, None]})
df1 = df.copy()
df2 = df.copy()
# applying ffill() method to fill the missing values-row
df1.ffill(axis = 0, inplace=True)
# applying ffill() method to fill the missing values-column
df2 = df2.ffill(axis = 1)
```

Forward & Backward fill-Python

- Forward and Backward fill can be applied using Dataframe.fillna() with method parameters to be set as:

```
import pandas as pd

# Creating a dataframe with "na" values.

df1 = pd.DataFrame({"A": [None, 1, 2, 3, None, None],
                    "B": [11, 5, None, None, None, 8],
                    "C": [None, 5, 10, 11, None, 8]})
df2 = df1.copy()
df3 = df1.copy()
df4 = df1.copy()
df5 = df1.copy()
# Filling missing values backward across row
df2.fillna(axis ='rows', method = 'bfill',inplace=True)
df3.fillna(axis ='columns', method = 'bfill',inplace=True)
# Filling missing values forward across column
df4.fillna(axis ='rows', method = 'ffill',inplace=True)
df5.fillna(axis ='columns', method = 'ffill',inplace=True)
```

Forward & Backward fill-Python

- Forward and Backward fill can be applied using Dataframe.fillna() with method parameters to be set as:
  - 'bfill/'backfill'

```
import pandas as pd

# Creating a dataframe with "na" values.

df1 = pd.DataFrame({"A": [None, 1, 2, 3, None, None],
                    "B": [11, 5, None, None, None, 8],
                    "C": [None, 5, 10, 11, None, 8]})
df2 = df1.copy()
df3 = df1.copy()
df4 = df1.copy()
df5 = df1.copy()
# Filling missing values backward across row
df2.fillna(axis ='rows', method = 'bfill',inplace=True)
df3.fillna(axis ='columns', method = 'bfill',inplace=True)
# Filling missing values forward across column
df4.fillna(axis ='rows', method = 'ffill',inplace=True)
df5.fillna(axis ='columns', method = 'ffill',inplace=True)
```

Forward & Backward fill-Python

- Forward and Backward fill can be applied using Dataframe.fillna() with method parameters to be set as:
  - 'bfill/'backfill'
  - 'ffill'/'pad'

```
import pandas as pd

# Creating a dataframe with "na" values.

df1 = pd.DataFrame({"A": [None, 1, 2, 3, None, None],
                    "B": [11, 5, None, None, None, 8],
                    "C": [None, 5, 10, 11, None, 8]})
df2 = df1.copy()
df3 = df1.copy()
df4 = df1.copy()
df5 = df1.copy()
# Filling missing values backward across row
df2.fillna(axis ='rows', method = 'bfill',inplace=True)
df3.fillna(axis ='columns', method = 'bfill',inplace=True)
# Filling missing values forward across column
df4.fillna(axis ='rows', method = 'ffill',inplace=True)
df5.fillna(axis ='columns', method = 'ffill',inplace=True)
```