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Data Science
(Level-I)

Ajeet K. Jain, M. Narsimlu
(ML TEAM)- SONET, KMIT, Hyderabad

Session – 30

This session deals with

Data Science Project Life cycle

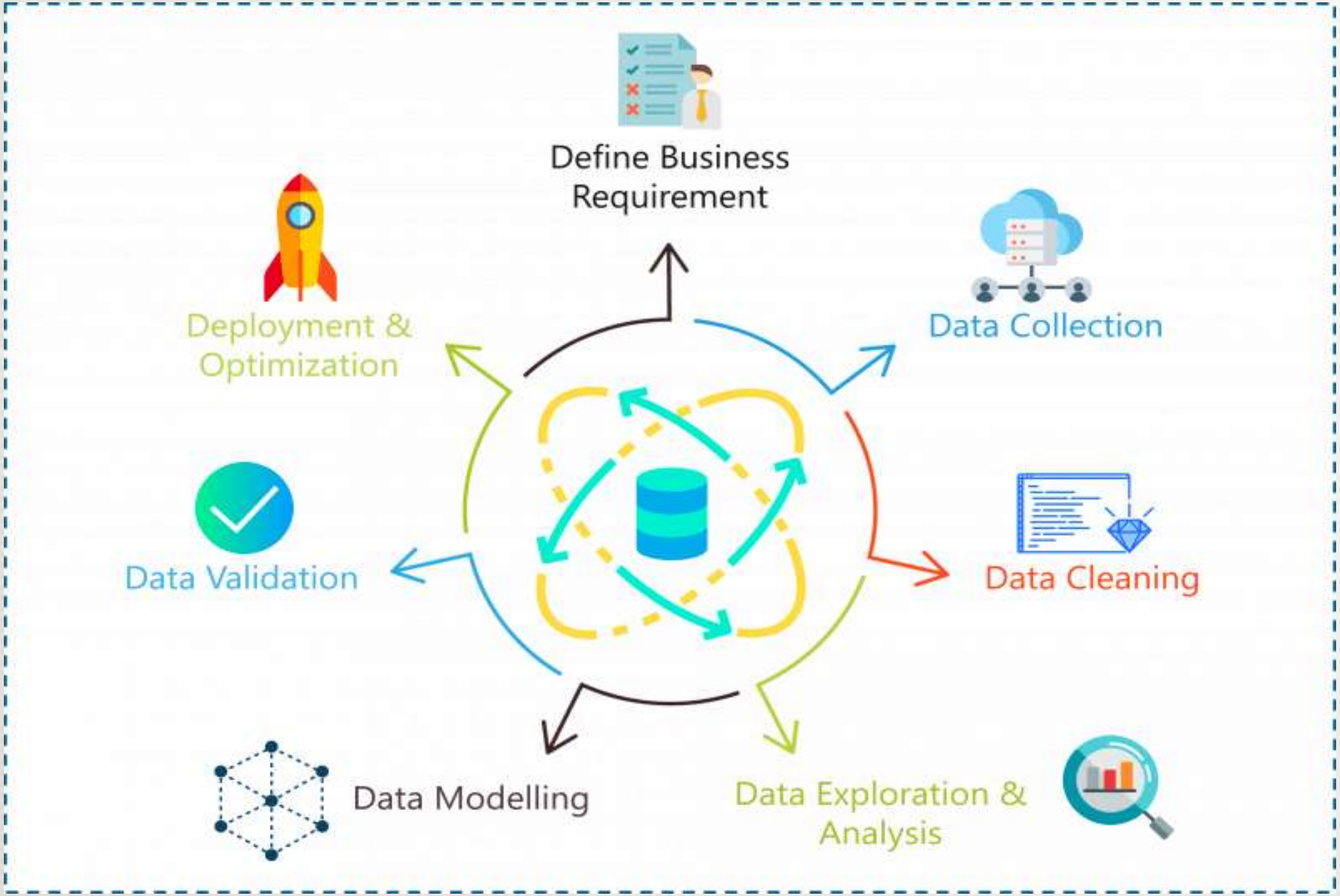
Introduction to Case Study

Data Science-Project Life Cycle

A business problem statement in Data Science can be solved by following the phases

1. Define Problem Statement/ Business Requirement
2. Data Collection
3. Data Cleaning /preparation
4. Data Exploration & Analysis
5. Data Modelling
6. Deployment & Optimization

Project Life Cycle -Architecture



Case Study -01

Problem statement

- Subsidy Inc. delivers subsidies to individuals based on their income
- Accurate income data is one of the hardest piece of data to obtain across the world
- Subsidy Inc. has obtained a large data set of authenticated data on individual income, demographic parameters, and a few financial parameters
- Subsidy Inc. wishes us to :

  Develop an income classifier system for individuals

<u>The Objective is to:</u>

Simplify the data system by reducing the number of variables to be studied, without sacrificing too much of accuracy. Such a system would help Subsidy Inc. in planning subsidy outlay, monitoring and preventing misuse.

Required modules

```python
#To visualize the data
import seaborn as sns
#To work with dataframes
import pandas as pd
#To perform numerical operations
import numpy as np
#To partition the data
from sklearn.model_selection import train_test_split
#importing the library for logistic regression
from sklearn.linear_model import LogisticRegression
#importing performance metrics
from sklearn.metrics import accuracy_score,confusion_matrix
```

Data Description

```python
#importing data
data_income=pd.read_csv("income.csv")
#create a copy of original data
df_income=data_income.copy()
print(df_income.describe())
```

Numerical Data Description

	age	capitalgain	capitalloss	hoursperweek
count	31978.000000	31978.000000	31978.000000	31978.000000
mean	38.579023	1064.360623	86.739352	40.417850
std	13.662085	7298.596271	401.594301	12.345285
min	17.000000	0.000000	0.000000	1.000000
25%	28.000000	0.000000	0.000000	40.000000
50%	37.000000	0.000000	0.000000	40.000000
75%	48.000000	0.000000	0.000000	45.000000
max	90.000000	99999.000000	4356.000000	99.000000

Information about Data Set

```
#importing data
data_income=pd.read_csv("income.csv")
#create a copy of original data
df_income=data_income.copy()
print(df_income.info())
```

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Output

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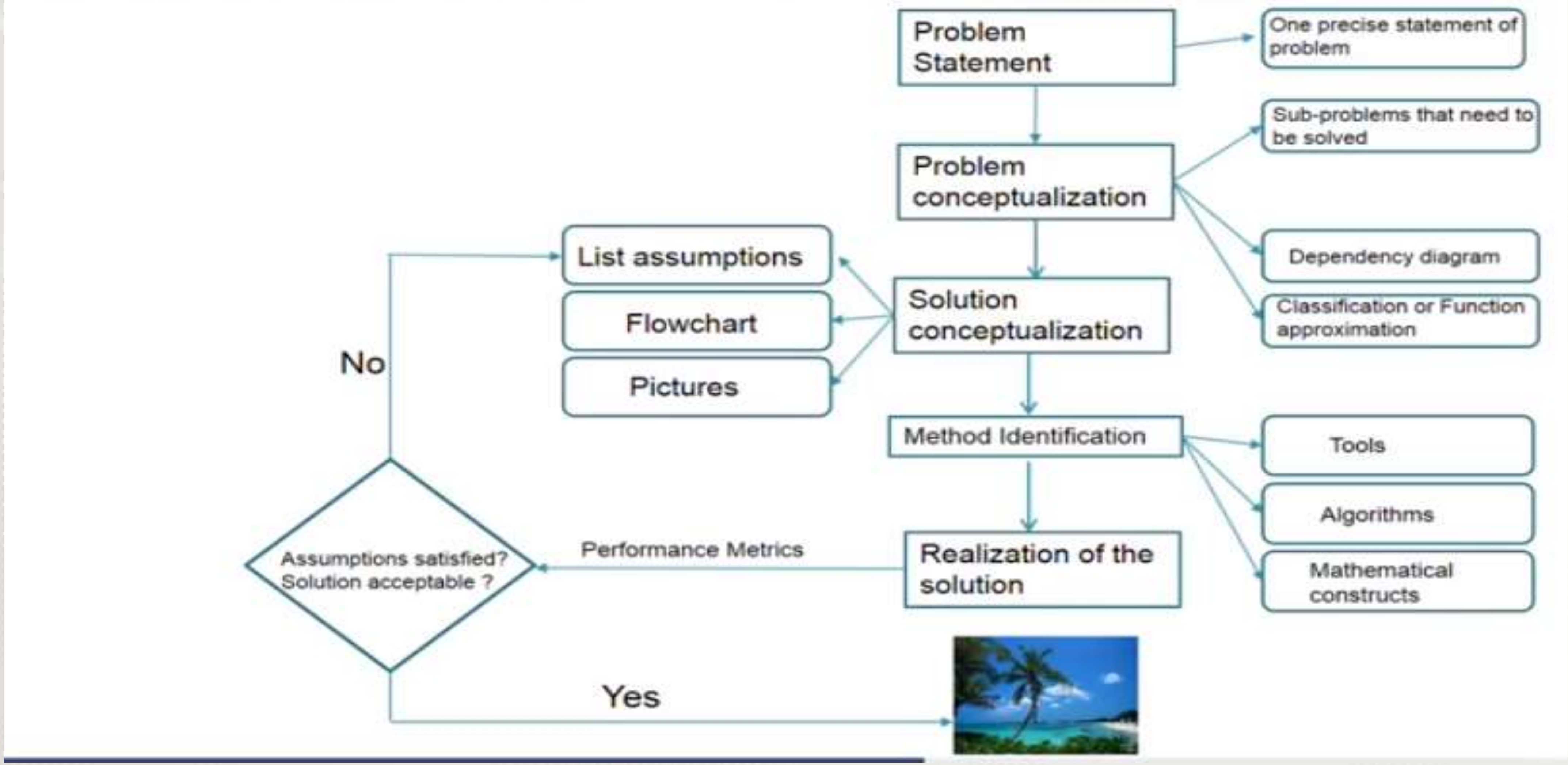
```
RangeIndex: 31978 entries, 0 to 31977
Data columns (total 13 columns):
age                 31978 non-null int64
JobType             31978 non-null object
EdType              31978 non-null object
maritalstatus       31978 non-null object
occupation          31978 non-null object
relationship        31978 non-null object
race                31978 non-null object
gender              31978 non-null object
capitalgain         31978 non-null int64
capitalloss         31978 non-null int64
hoursperweek        31978 non-null int64
nativecountry       31978 non-null object
SalStat             31978 non-null object
```

Data Analytics Frame work

Data analytics framework



Problem conceptualization

Framework

- Problem conceptualization
  - Develop an income classifier for individuals with reduced no. of variables
- Problem characterization- Classification

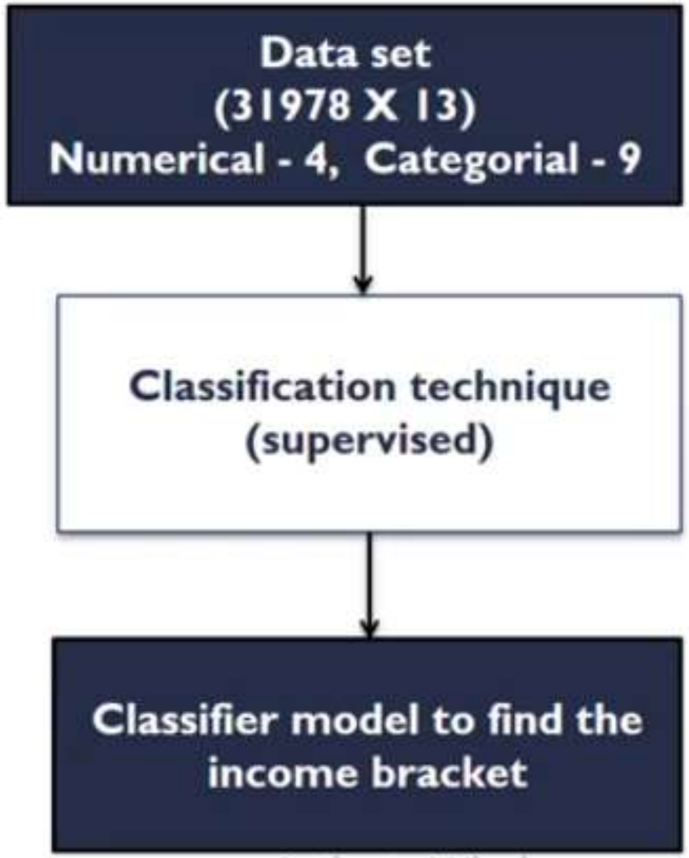
Apriori Known:

✓ Dependent variable

categorical (binary)

✓ Independent variables

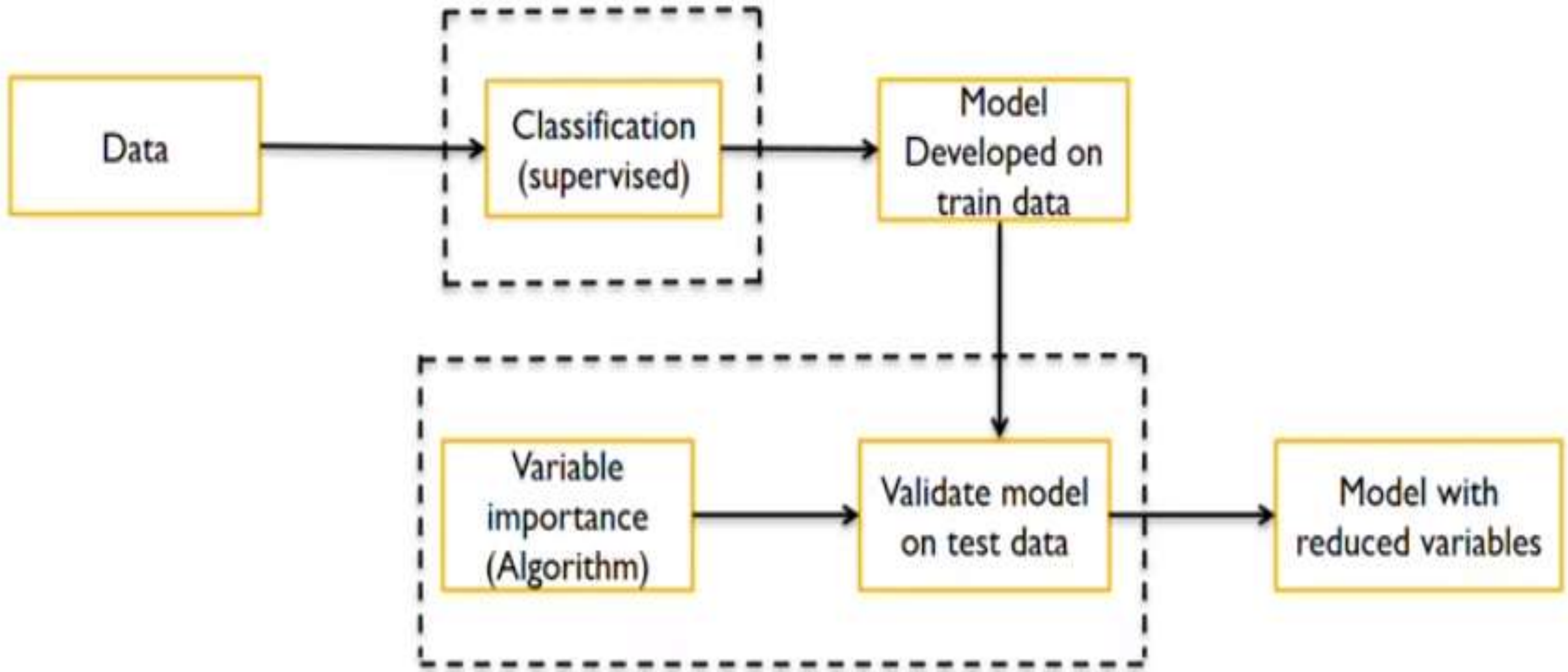
numerical + categorical



Framework

Framework

- Flow chart:



Solution conceptualization

Framework

- Solution conceptualization
  - Identify if data is clean
  - Look for missing values
  - Identify variables influencing salary status and look for possible relationships between variables
    - Correlation, chi-square test, box plots, scatter plots etc.
  - Identify if categories can be combined
  - Build a model with reduced number of variables to classify the individual's salary status to plan subsidy outlay, monitor and pr misuse

Method Identification

Framework

- Method identification
  - Logistic Regression
  - Random Forest
  - K Nearest Neighbors
- Realization of solution
  - Evaluate performance metrics
  - If assumptions are satisfied and solutions are acceptable then model is

Data Exploratory Analysis

```
"""
EDA
1.getting to know the data
2.Data Preprocessin
3.Cross tables and data visualization
"""
#1.Getting to know the data
#To check variables data type
print(df_income.info())
#To find the missing values in each feature
print(df_income.isnull().sum())
#No missing values
#Summary of numerical variables
print(df_income.describe())
#Summary of categorical variables
print(df_income.describe(include="O"))
#Frequency of each categories
print(df_income["JobType"].value_counts())
```

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Data Exploratory

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```
#importing data
df_income=pd.read_csv("income.csv")
#checking for unique classes
print(np.unique((df_income["JobType"])))
print(np.unique(df_income["occupation"]))
#checking other special characters in the dataset
data=pd.read_csv("income.csv",na_values=[" ?"])
#Check missing values in each feature
print(data.isnull().sum())
missing=data[data.isnull().any(axis=1)]
```

#To consider one missing column
print(missing)

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Data Exploratory Analysis

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```
Private             22286
Self-emp-not-inc     2499
Local-gov            2067
?                    1809
State-gov            1279
Self-emp-inc         1074
Federal-gov           943
Without-pay            14
Never-worked            7
Name: JobType, dtype: int64
```

```
Prof-specialty       4038
Craft-repair         4030
Exec-managerial      3992
Adm-clerical         3721
Sales                3584
Other-service        3212
Machine-op-inspct    1966
?                    1816
Transport-moving     1572
Handlers-cleaners    1350
Farming-fishing       989
Tech-support          912
Protective-serv       644
Priv-house-serv       143
Armed-Forces            9
```

Finding missing Values and Correlation

```
#importing data
data=pd.read_csv("income.csv",na_values=[" ?"])
"""
1.missing values in jobtype -     1809
2.missing values in occupation -  1816
3.There are 1809 rows where tow soecific columns
i.e oocupation and jobtype have missing values
4.(1816-1809)=7 => still we have occupation unfilled for these rows.
because,jobtype is "never worked"
"""
data2=data.dropna(axis=0)
#correlation between independent varaibles
corr_rel=data2.corr()
print(corr_rel)
```

Output

```
Week4')
```

	age	capitalgain	capitalloss	hoursperweek
age	1.000000	0.080154	0.060165	0.101599
capitalgain	0.080154	1.000000	-0.032229	0.080432
capitalloss	0.060165	-0.032229	1.000000	0.052417
hoursperweek	0.101599	0.080432	0.052417	1.000000

Age Vs Salary status -EDA

```
#importing data
data=pd.read_csv("income.csv",na_values=[" ?"])
data2=data.dropna(axis=0)
#cross tables and data visualization
#extract the columns
print(data2.columns)
gender_tab=pd.crosstab(index=data2["gender"],columns="counts",
                       normalize=True)
print(gender_tab)

#Relation between Gender vs salary
gender_salstat=pd.crosstab(index=data2["gender"],
                           columns=data2["SalStat"],
                           margins=True,normalize="index")
print(gender_salstat)
```

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Output

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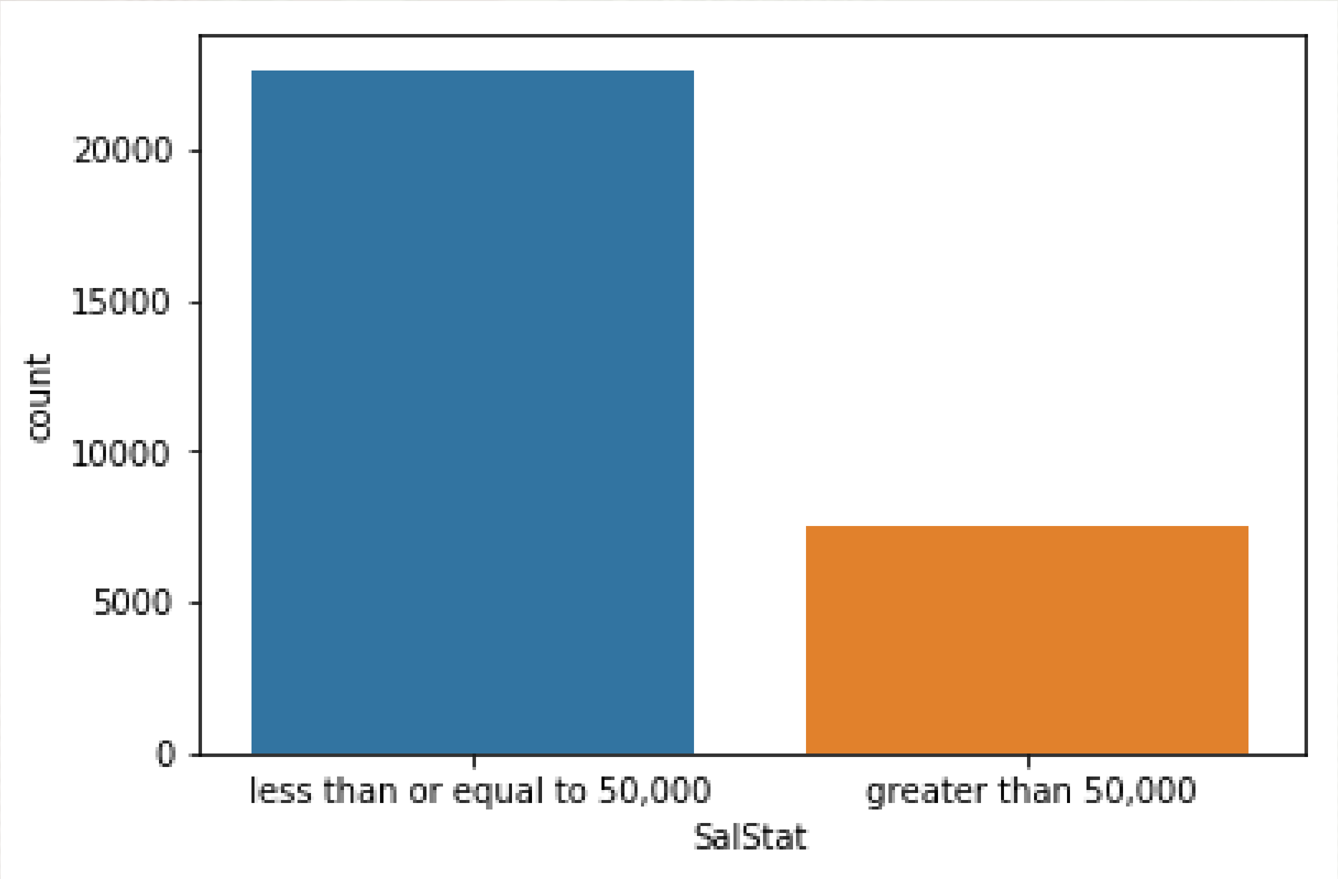
```
Index(['age', 'JobType', 'EdType', 'maritalstatus', 'occupation',
       'relationship', 'race', 'gender', 'capitalgain', 'capitalloss',
       'hoursperweek', 'nativecountry', 'SalStat'],
      dtype='object')
col_0      counts
gender
 Female  0.324315
 Male    0.675685
SalStat   greater than 50,000   less than or equal to 50,000
gender
 Female              0.113678                       0.886322
 Male                0.313837                       0.686163
All                  0.248922                       0.751078
```

Bar plot b/w Salary status


```
#importing data
data=pd.read_csv("income.csv",na_values=[" ?"])
data2=data.dropna(axis=0)
#cross tables and data visualization
#frequency distribution of salary status
SalStat=sns.countplot(data2["SalStat"])
"""
75% of people's salary status is <=50,000
25% of people's salary status is >50,000
"""
```

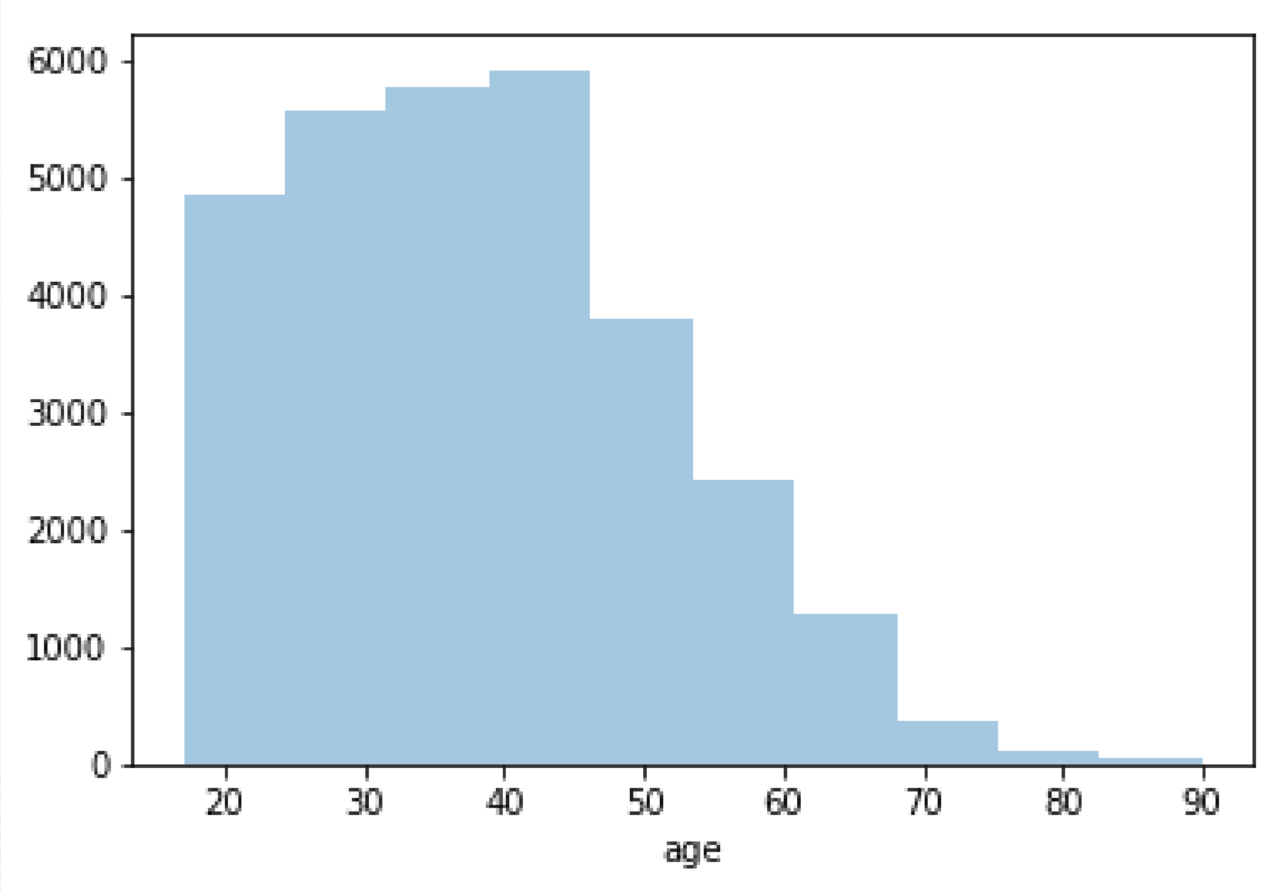
Data Exploratory



Finding Age Frequency

```
#importing data
data=pd.read_csv("income.csv",na_values=[" ?"])
data2=data.dropna(axis=0)
#histogram of Age
sns.distplot(data2["age"],bins=10,kde=False)
#people with age 20-45 age are high in frequency
```

Output

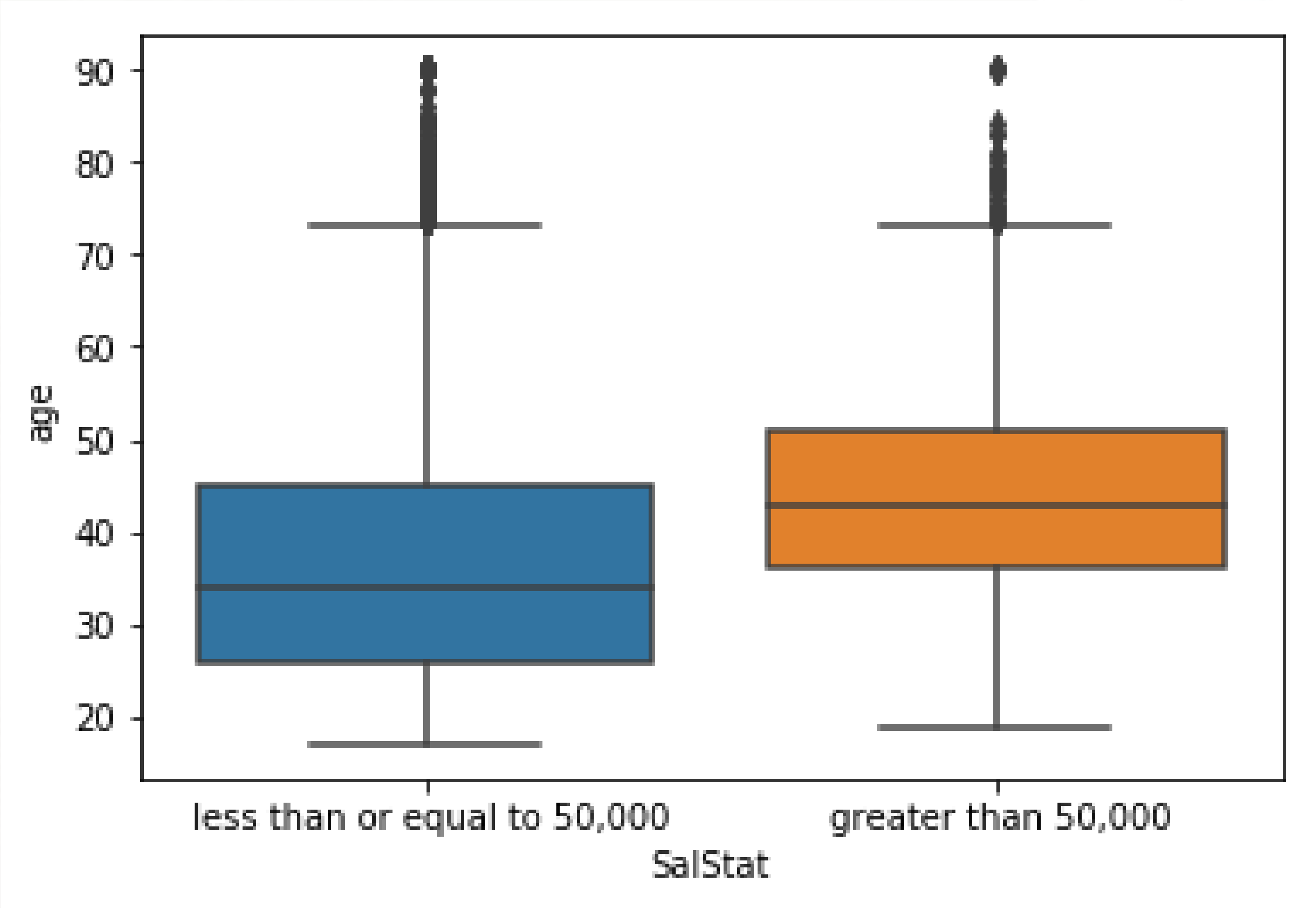


Finding the Outliers

```
#importing data
data=pd.read_csv("income.csv",na_values=[" ?"])
data2=data.dropna(axis=0)
#boxplot Age vs salary status
sns.boxplot("SalStat","age",data=data2)
"""

people with 35-50 age are more likely to earn >50000
people with 25-35 age are more likely to earn <=50000
"""
```

Output



90
80
70
60
50
40
30
20
age
less than or equal to 50,000
greater than 50,000
SalStat

Exploration of JobType vs Salary status

EDA-

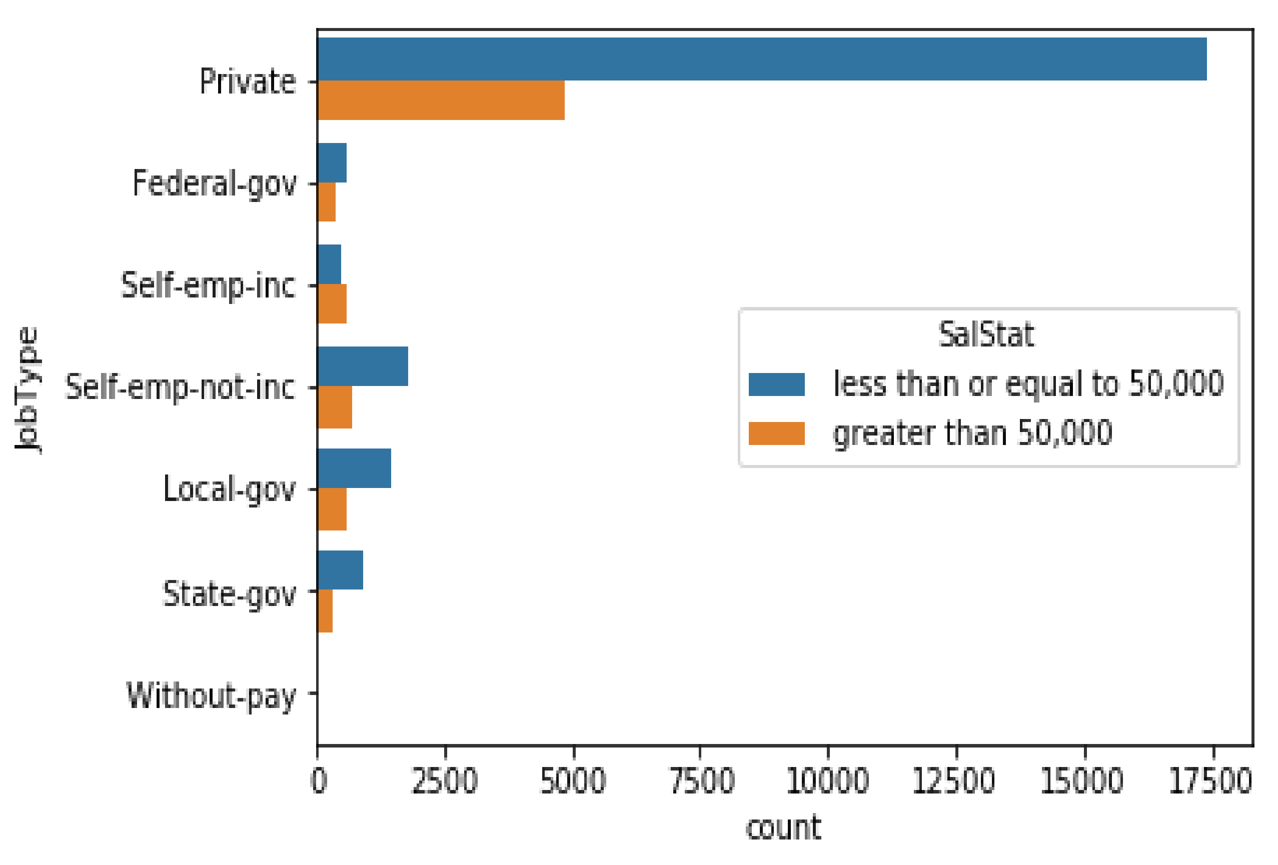
1.Jobtype VS salary status

2.create a cross table Jobtype Vs salary status

```
salStat_tab=pd.crosstab(index=data2["JobType"],
                        columns=data2["SalStat"],
                        margins=True,normalize="index")
print(salStat_tab)
#sns.countplot(y="JobType",data=data2,hue="SalStat")
"""
The above table 56% of self employed
people earn more than 50000 USD per year
"""
```

Output

SalStat	greater than 50,000	less than or equal to 50,000
JobType		
Federal-gov	0.387063	0.612937
Local-gov	0.294630	0.705370
Private	0.218792	0.781208
Self-emp-inc	0.558659	0.441341
Self-emp-not-inc	0.285714	0.714286
State-gov	0.268960	0.731040
Without-pay	0.000000	1.000000
All	0.248922	0.751078



Conclusion

You are aware of

Data Encoding

Project Life Cycle

We will proceed with

Case Study

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THANK YOU