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# Data Handling with Pandas

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# Contents

- Importing data
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# Data import from CSV files

- Need to use the function read.csv
- Need to use “/” or “\\” in the path. The windows style of path “\” doesn’t work

# Importing from CSV files

```
import pandas as pd
Sales = pd.read_csv("https://raw.githubusercontent.com/venkatareddykonasani/Datasets/master/Superstore%20Sales%20Data/Sales_by_country_v1.csv")
print(Sales)
```

# Data import from Excel files

- Need to use pandas again

# Data import from Excel files

```
wb_data = pd.read_excel("https://raw.githubusercontent.com/venkataredd
ykonasani/Datasets/master/World%20Bank%20Data/GDP.xlsx" , sheet_name="
Sheet1")
print(wb_data)
```

# Tip – You can also import zipped files

```
air_bnb_ny=pd.read_csv("https://raw.githubusercontent.com/
venkatareddykonasani/Datasets/master/AirBnB_NY/AB_NYC_2019
.zip", compression="zip")

print(air_bnb_ny.shape)
```

# Basic Commands on Datasets

- Is the data imported correctly? Are the variables imported in right format? Did we import all the rows?
- Once the dataset is inside Python, we would like to do some basic checks to get an idea on the dataset.
- Just printing the data is not a good option, always.
- Is a good practice to check the number of rows, columns, quick look at the variable structures, a summary and data snapshot

# Check list after Import

```
Sales.shape
Sales.info()
Sales.columns
Sales.head()
Sales.tail()
Sales.sample(5)
Sales.describe()
Sales["unitsSold"].describe()
Sales["salesChannel"].value_counts()
```

# Lab: Printing the data and meta info

- Import “Credit_Card_Cust_Usage/Card_Usage_v1.csv” data
- How many rows and columns are there in this dataset?
- Print only column names in the dataset
- Print first 10 observations
- Print the last 5 observations
- Take a random sample of 300 records.
- How to reproduce the same random sample again?
- Describe the field Credit_Limit – What are your findings?
- Describe the field Card_Category – What are your findings?
- Create a new dataset by taking first 30 observations from this data
- Print the resultant data
- Remove(delete) the new dataset

# Access rows

```
Sales.iloc[0:10]
Sales.iloc[[1,9,10]]
```

# Access Columns

```
column_names=['custId', 'custName', 'custCountry']
Sales[column_names]
Sales.iloc[:,0:4]
Sales.iloc[0:5:,0:4]
```

# .iloc vs .loc

```
Sales1=Sales.iloc[20:30]
```

What is the difference?

```
Sales1.iloc[0:5]
Sales1.loc[0:5]
```

# .iloc vs .loc

```
Sales1=Sales.iloc[20:30]
```

What is the difference?

```
Sales1.iloc[0:5] #index location
Sales1.loc[0:5] #index values or names
```

What is the difference?

```
Sales.loc[0:5, 0:2]
Sales.loc[0:5, column_names]
```

# Accessing Specific type of Columns only

```
Sales_numerics = Sales.select_dtypes(include=["int64","float64"])
Sales_numerics.info()

Sales_objects = Sales.select_dtypes(include=["object"])
Sales_objects.info()

Sales_non_objects = Sales.select_dtypes(exclude=["object"])
Sales_non_objects.info()
```

# Drop

```
wb_data.drop(range(0,10))
wb_data.drop(["Country_code"], axis=1)
```

# Lab: Accessing the data

- Data : "./Bank Tele Marketing/bank_market.csv“. Create separate datasets for each of the below tasks
- Select first 1000 rows only
- Select only four columns "Cust_num"  "age” "default" and  "balance"
- Select 20,000 to 40,000 observations along with four variables "Cust_num"  "job"        "marital" and   "education"
- Select 5000 to 6000 observations and drop  "poutcome“ and  "y"
- Access the last column only;(using index)
- Access all the numeric columns only

# Subset with variable filter conditions

- How to filter the data based on a variable?
- For example select all the customers with age >40 in bank market data
- Subset all the customers with age>40 and loan="no"

# Subset with variable filter conditions

```
bank_subset=bank_data[bank_data['age']>40]
bank_subset

#And condition & filters
bank_subset1=bank_data[(bank_data['age']>40) &  (bank_data['loan']=="no")]
bank_subset1

#OR condition & filters
bank_subset2=bank_data[(bank_data['age']>40) |  (bank_data['loan']=="no")]
bank_subset2
```

# Lab: Subset with variable filter conditions

- Data : "./Automobile Data Set/AutoDataset.csv"
- Create a new dataset for exclusively Toyota cars
- Create a new dataset for all cars with city.mpg greater than 30 and engine size is less than 120.
- Create a new dataset by taking only  sedan cars. Keep only four variables(Make, body style, fuel type, price) in the final dataset.
- Create a new dataset by taking Audi, BMW or Porsche company makes.

# Working with index

```
bank_data.index
bank_subset1.index
```

Reset the index, if required.

```
bank_subset1=bank_subset1.reset_index()
bank_subset1.index
```

The above code creates a new column called index, you can drop it while creating

```
bank_subset1_1=bank_subset1.reset_index(drop=True)
bank_subset1_1.index
```

# Calculated Fields

Calculate and Assign it to new variable

```
auto_data['area']=(auto_data[' length'])*(auto_data[' width'])*(auto_data
[' height'])
auto_data['area']
```

# Sorting the data

- Its ascending by default

```
Online_Retail_sort=Online_Retail.sort_values('UnitPrice')
Online_Retail_sort.head(20)
```

- Use ascending=False for descending sort

```
Online_Retail_sort=Online_Retail.sort_values('UnitPrice',ascending=False)
Online_Retail_sort.head(20)
```

- Sorting with two cols

```
Online_Retail_sort2=Online_Retail.sort_values(['Country','UnitPrice'], ascen
ding=[True, False])
Online_Retail_sort2.head(5)
```

# LAB: Sorting the data

- AutoDataset
- Sort the dataset based on price
- Sort the dataset based on price descending

# Identifying & Removing Duplicates

Datasets: Telecom Data Analysis\Bill.csv

```
#Identify duplicates records in the data
dupes=bill_data.duplicated()
dupes
sum(dupes)


#Removing Duplicates
bill_data.shape
bill_data_uniq=bill_data.drop_duplicates()
bill_data_uniq.shape
```

# Identifying & Duplicates based on Key

- What if we are not interested in overall level records
- Sometimes we may name the records as duplicates even if a key variable is repeated.
- Instead of using duplicated function on full data, we use it on one variable

```
dupe_id=bill_data["cust_id"].duplicated()
dupe_id
bill_data.shape
bill_data_cust_uniq=bill_data.drop_duplicates(['cust_id'])
bill_data_cust_uniq.shape
```

# LAB: Handling Duplicates

- DataSet: "./Telecom Data Analysis/Complaints.csv"
- Identify overall duplicates in complaints data
- Create a new dataset by removing overall duplicates in Complaints data
- Identify duplicates in complaints data based on cust_id
- Create a new dataset by removing duplicates based on cust_id in Complaints data

# Data sets merging and Joining

- Datasets: TV Commercial Slots Analysis/orders.csv & TV Commercial Slots Analysis/slots.csv

```
orders1=orders.drop_duplicates(['Unique_id'])
slots1=slots.drop_duplicates(['Unique_id'])

###Inner Join
inner_data=pd.merge(orders1, slots1, on='Unique_id', how='inner')
inner_data.shape
###Outer Join
outer_data=pd.merge(orders1, slots1, on='Unique_id', how='outer')
outer_data.shape
##Left outer Join
L_outer_data=pd.merge(orders1, slots1, on='Unique_id', how='left')
L_outer_data.shape
###Righ outer Join
R_outer_data=pd.merge(orders1, slots1, on='Unique_id', how='right')
R_outer_data.shape
```

# Data sets merging and Joining

- Datasets: TV Commercial Slots Analysis/orders.csv & TV Commercial Slots Analysis/slots.csv

```
orders1=orders.drop_duplicates(['Unique_id'])
slots1=slots.drop_duplicates(['Unique_id'])

###Inner Join
inner_data=pd.merge(orders1, slots1, on='Unique_id', how='inner')
inner_data.shape
###Outer Join
outer_data=pd.merge(orders1, slots1, on='Unique_id', how='outer')
outer_data.shape
##Left outer Join
L_outer_data=pd.merge(orders1, slots1, on='Unique_id', how='left')
L_outer_data.shape
###Righ outer Join
R_outer_data=pd.merge(orders1, slots1, on='Unique_id', how='right')
R_outer_data.shape
```

# Data sets merging and Joining

```
####Other options
left_on : a column or a list of columns
right_on : a column or a list of columns


other_data=pd.merge(orders1, slots1, left_on=['AD_ID','Product ID'],ri
ght_on=['AD_ID','Product ID'], how='outer’)

other_data.shape
```

# LAB: Data Joins

- Datasets
  - “./Telecom Data Analysis/Bill.csv”
  - “./Telecom Data Analysis/Complaints.csv”
- Import the data and remove duplicates based on cust_id
- Create a dataset for each of these requirements
  - All the customers who appear either in bill data or complaints data
  - All the customers who appear both in bill data and complaints data
  - All the customers from bill data: Customers who have bill data along with their complaints
  - All the customers from complaints data: Customers who have Complaints data along with their bill info

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# Functions on rows and columns

- Consider Credit Card usage data.
- Create a new variable credit_limit_segment by using this below condition
  - If Credit_Limit < 3000- Low
  - If Credit_Limit < 6000- medium
  - Else - high

# Using a for loop

```
cc_usage["Credit_Limit_Segment"]=0

for i in range(0, len(cc_usage)):
  if cc_usage["Credit_Limit"][i] < 3000:
    cc_usage["Credit_Limit_Segment"][i]  ="Low"
  elif cc_usage["Credit_Limit"][i] < 6000:
    cc_usage["Credit_Limit_Segment"][i]  ="Medium"
  else:
    cc_usage["Credit_Limit_Segment"][i]  ="high"
```

# tip- never use a for loop

- For loop code and iteration over each row works, but never use it.
- It is very basic and time consuming
- There are better ways
  - Vectorizing
  - apply function

# Vectorization

```
cc_usage["Credit_Limit_Segment1"]="High"
cc_usage["Credit_Limit_Segment1"][cc_usage["Credit_Limit"]< 3000]="Low"
cc_usage["Credit_Limit_Segment1"][(cc_usage["Credit_Limit"]> 3000) & (cc_usa
ge["Credit_Limit"]< 6000)]="Medium"
```

# For loop vs Vectorization

- The execution time comparison for the same operation

For loop

```
Time taken 232.56957602500916
```

Vectorization

```
Time taken 0.029158592224121094
```

# LAB: For loop vs Vectorization

- Consider Online retail sales data.
- Create a new variable unit_price_segment by using this below condition
  - If unit_price < 2- Low
  - If unit_price < 4- medium
  - Else - high
- Use vectorization- How much time does it take ?
- Use a for loop – How much time does it take?

# Apply function

- In the previous examples we worked on two different datasets, and different variables.
- In both the cases, credit limit and UnitPrice, we performed binning with different set of limits.
- Can we write a generalized binning function and then apply it on any column?

# Generalized function

```
def binning(x, limit1, limit2):
  result="High"
  if x < limit1:
    result="Low"
  if (x > limit1) & (x < limit2):
    result="Medium"
  return(result)
```

How do we apply the above function on a desired column from a dataset? – Using .apply() function

# apply() function

- `cc_usage["Credit_Limit_Segment2"]=cc_usage["Credit_Limit"].apply(lambda x:binning(x, 3000, 6000))`

- Here `lambda` is a temporary anonymous function is made in apply() itself
- `lambda` function takes each row supplies it to the binning function then returns the result of binning function

# apply() function

```
cc_usage["Credit_Limit_Segment2"]=cc_usage["Credit_Limit"]
.apply(lambda x:binning(x, 3000, 6000))

Online_Retail["UnitPrice_Segment2"]=Online_Retail["UnitPri
ce"].apply(lambda x:binning(x, 2, 4))
```

# More on .apply() function

- We need not define a function always

```
cc_usage['Customer_Age_new']=cc_usage['Customer_Age'].appl
y(lambda x: "Low" if x<50 else "high"  )
```

# .apply() on columns

- How to find the mean of each numeric column in a data frame?
- To work on each column we need to make axis=0. This sounds opposite to drop function
- axis=0 – Apply along the row index (returns for each col)
- axis=1 – Appy along the columns (returns for each row)

```
cc_usage.select_dtypes(exclude="object").apply(lambda y: round(y.mean()),
axis=0)
```

```
cc_usage.select_dtypes(exclude="object").apply(lambda y: [round(y.mean()),
 round(y.median())], axis=0)
```

# .apply() on columns

- Applying conditions on multiple columns to make a new column
- Create a new variable based on two conditions
 Total_Relationship_Count > 4 and Credit_Limit < 5000

```
def cli_flag(x):
  if x[0] > 4 and x[1]<5000:
    return(1)
  else:
    return(0)

cc_usage["Credit_Line_increase_flag"]=cc_usage[["Total_Relationship_Count","Credit_Limit"]].apply(lambda x:cli_flag(x), axis=1)
```

# LAB: .apply()

- Dataset: Bank Tele marketing data.
- Create a new column “new_bal” by taking the maximum of 0 and balance
- Count the number of missing values in each column by using apply function
- Count the number of missing values in each row by using apply function
- Create a generalized function that can apply on “job” variable
  - If the length of the string is more than 10 then “long”, else “short”.
  - Apply it on one more column

# Group-by

- Import House Sales in King County data. https://www.kaggle.com/harlfoxem/housesalesprediction
- group by “condition” of the house and find the below details
  - The number of items in each group
  - The average house price in each group

# Group-by

```
kc_house_price.groupby("condition").count()
```

This code gives us the count by each column

```
#Restrict to one column
kc_house_price.groupby("condition")["id"].count()

round(kc_house_price.groupby("condition")["price"].mean())
```

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# tip – use agg() function

```
kc_house_price.groupby("condition")["id"].count()
```

The above code works, but its better use the aggregate function. agg() function gives us many options

```
kc_house_price.groupby("condition").agg({'id':['count’]})
```

```
kc_house_price.groupby("condition").agg({'price':['mean']})
```

# One group-by but multiple aggregated values

```
kc_house_price_grp_agg=kc_house_price.groupby("condition")
.agg({'id':['count'],'price':['mean','min', 'max'] })
```

# Group-by more than one column

```
kc_house_price_grp_agg1=kc_house_price.groupby(["condition","floo
rs"]).agg({'id':['count'],'price':['mean','min', 'max'] })
```

# tip -Reset index after group by

- The group-by output gives you multi-indexed columns and rows.
- There is a tendency to use the resultant dataset directly.
- Multi-Index is confusing, better to reset the row index and rename the columns.

```
kc_house_price_grp_agg1.columns
kc_house_price_grp_agg1.index

#Updated index
kc_house_price_grp_agg1.columns=['count','avg_price','min_price',
'max_price']
kc_house_price_grp_agg1=kc_house_price_grp_agg1.reset_index()
```

# LAB: Group by and aggregate

- Dataset : Rossmann Store Sales
- https://www.kaggle.com/c/rossmann-store-sales
- Find the average sales on each day of the week.
- Find the median sales and median number of customers across all Assortment types
- For each store type and assortment calculate the
  - Avg , Min and Max sales
  - Avg , Min and Max CompetitionDistance
  - Avg , Min and Max Customers
- Reset the row-index and column names for the above result

# Cross-tabs and Pivot tables

- Dataset bank marketing data
- Calculate the response rate in each category of education

```
pd.crosstab(index=bank_data['education'], columns=bank_data['y’])
```

The above code gives the cross tab with counts. For calculation of percentage we need to use apply function on reach row.

```
pd.crosstab(index=bank_data['education'], columns=bank_data['y']).apply(lambda x: x*100/x.sum(), axis=1)
```

# Cross-tabs and Pivot tables

- Calculate the response rate in each category of job type

```
pd.crosstab(index=bank_data['job'], columns=bank_data['y']
).apply(lambda x: x*100/x.sum(), axis=1)
```

# Pivot tables

- Alternative to cross tabs. Many more parameters.
- Calculate the response rate in each category of job type

```
pd.pivot_table(data=bank_data, index='job', columns='y', v
alues='Cust_num', aggfunc='count’)
```

```
pd.pivot_table(data=bank_data, index='job', columns='y', v
alues='Cust_num', aggfunc='count').apply(lambda x: x*100/x
.sum(), axis=1)
```

# Pivot tables

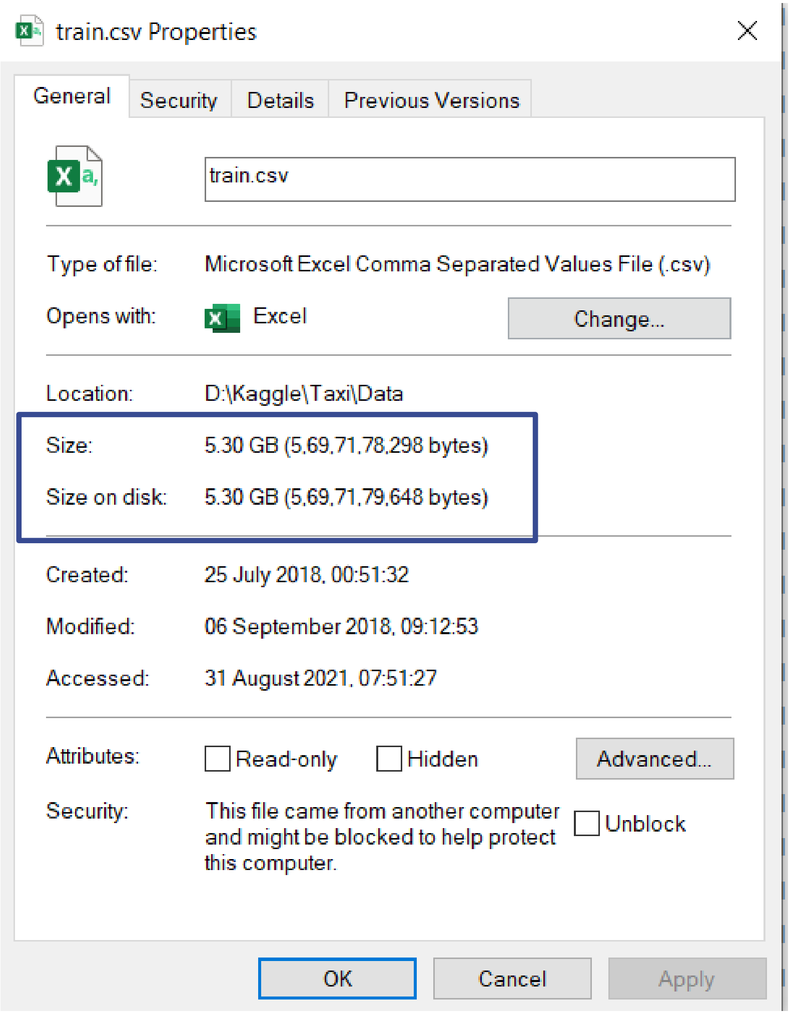
- Create a pivot table by that can calculate the average salary in responder and non-responder category inside each of the job type

```
pd.pivot_table(data=bank_data, index='job', columns='y', v
alues='balance', aggfunc='mean')
```

# LAB: Cross tabs and Pivot tables

- Dataset - rossmann_sales
  - Are they any promotions run on weekends?
  - What is the day wise average sales across all the storetypes
- Dataset - cc_usage
  - What is the attrition rate in each card category. Which category has the highest attrition rate ?
  - Compare the average transaction amount of attrition vs existing customers across each card category

# Handling Lage Datasets



# Handling Lage Dataset

- Is it possible to import this data as a pandas data frame?
- Is it possible to index and store all this data into python?
- Can you import the above dataset.
- Find out number of rows and columns
- Perform basic descriptive statistics.
- Take a random sample of 1 million records from it.

# Dask for large datasets

- Pandas data frames are very slow for large datasets(of size in GBs and TBs)
- Dask is a dedicated package  to handle large amounts of data
- Dask can store the data on RAM as well as hard-disk
- Dask can store and access the data from multiple machines in a cluster
- Dask will automatically partition and index the data while reading.

# Dask for a large dataset

- Dask doesn't really import the dataset.
- It creates the necessary partitions, pointers and indexes

```
import dask.dataframe as dd
%time taxi_fare_dd = dd.read_csv(r"D:\Kaggle\Taxi\Data\train.csv")
```

```
Wall time: 20.9 ms
```

```
taxi_fare_dd
```

**Dask DataFrame Structure:**

| | key | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count |
|---|---|---|---|---|---|---|---|---|
| **npartitions=90** | | | | | | | | |
| | object | float64 | object | float64 | float64 | float64 | float64 | int64 |
| | ... | ... | ... | ... | ... | ... | ... | ... |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| | ... | ... | ... | ... | ... | ... | ... | ... |
| | ... | ... | ... | ... | ... | ... | ... | ... |

Dask Name: read-csv, 90 tasks

# Dask for a large dataset

- When we say compute() then the parallel processing will happen to calculate the results.

```
: taxi_fare_dd.shape[0].compute()

: 55423856
```

# Check the background processing status

```
from dask.distributed import Client, progress
client = Client()
client
```

# Basic Statistics

```
taxi_fare_dd["fare_amount"].mean().compute()
```

# Sampling

```
taxi_fare_dd_sample=taxi_fare_dd.sample(frac=0.02)
```

# Converting sample into a dataframe

```
taxi_fare_dd_pd_sample=taxi_fare_dd_sample.compute()
```

```
taxi_fare_dd_pd_sample.shape
```

# Conclusion

- In this session we started with Data imploring from various sources
- We also learnt manipulating the datasets and creating new variables
- There are many more topics to discuss in data handling, these topics in the session are essential for any data scientist