

# lab02

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###

Lab Session 2

**Name: Praanesh Balakrishnan Nair**

**Roll Number: BL.EN.U4AIE23213** A1. Please refer to the “Purchase Data” worksheet of Lab Session Data.xlsx. Please load the data and segregate them into 2 matrices A & C (following the nomenclature of  $AX = C$ ). Do the following activities. - What is the dimensionality of the vector space for this data? - How many vectors exist in this vector space? - What is the rank of Matrix A? - Using Pseudo-Inverse find the cost of each product available for sale. (Suggestion: If you use Python, you can use `numpy.linalg.pinv()` function to get a pseudo-inverse.)

```
[32]: import numpy as np
import pandas as pd
import statistics
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.metrics.pairwise import cosine_similarity
file_path = r"C:\\Users\\Praanesh Nair\\Downloads\\python-learning\\Lab Session_
↪Data.xlsx"
xls = pd.ExcelFile(file_path)
```

```
[33]: try:
    df = pd.read_excel(xls, sheet_name="Purchase data")
    purchase_matrix = df.iloc[:, 1:4].values
    purchase_amounts = df.iloc[:, 4].values.reshape(-1, 1)
    dimensionality = purchase_matrix.shape[1]
    num_vectors = purchase_matrix.shape[0]
    rank_A = np.linalg.matrix_rank(purchase_matrix)
    purchase_matrix_pinv = np.linalg.pinv(purchase_matrix)
    product_costs = np.dot(purchase_matrix_pinv, purchase_amounts).flatten()
    print("A1 Results:")
    print(f"Dimensionality: {dimensionality}")
    print(f"Number of Vectors: {num_vectors}")
    print(f"Rank of A: {rank_A}")
    print(f"Product Costs: {product_costs}")
```

```

except FileNotFoundError:
    print(f"Error: File not found at {file_path}")

except ValueError: # Catches potential Excel sheet issues
    print("Error: Could not read specified sheet from Excel file.")

```

A1 Results:

Dimensionality: 3

Number of Vectors: 10

Rank of A: 3

Product Costs: [ 1. 55. 18.]

A2. Use the Pseudo-inverse to calculate the model vector X for predicting the cost of the products available with the vendor.

```
[34]: print(f"Model Vector X: {product_costs}")
```

Model Vector X: [ 1. 55. 18.]

A3. Mark all customers (in “Purchase Data” table) with payments above Rs. 200 as RICH and others as POOR. Develop a classifier model to categorize customers into RICH or POOR class based on purchase behavior.

```
[35]: df = pd.read_excel(xls, sheet_name="Purchase data")
df["Customer Class"] = np.where(df.iloc[:, 4] > 200, "RICH", "POOR")
print("A3 Result:")
print(df[["Customer Class"]])
```

A3 Result:

	Customer Class
0	RICH
1	RICH
2	RICH
3	POOR
4	RICH
5	POOR
6	RICH
7	RICH
8	POOR
9	POOR

A4. Please refer to the data present in “IRCTC Stock Price” data sheet of the above excel file. Do the following after loading the data to your programming platform. - Calculate the mean and variance of the Price data present in column D.

(Suggestion: if you use Python, you may use statistics.mean() & statistics.variance() methods).  
 - Select the price data for all Wednesdays and calculate the sample mean. Compare the mean with the population mean and note your observations.  
 - Select the price data for the month of Apr and calculate the sample mean. Compare the mean with the population mean and note your

observations. - From the Chg% (available in column I) find the probability of making a loss over the stock. (Suggestion: use lambda function to find negative values) - Calculate the probability of making a profit on Wednesday. - Calculate the conditional probability of making profit, given that today is Wednesday. - Make a scatter plot of Chg% data against the day of the week

```
[36]: df = pd.read_excel(xls, sheet_name="IRCTC Stock Price")
df["Date"] = pd.to_datetime(df["Date"])
df["Day"] = df["Date"].dt.day_name()

mean_price = statistics.mean(df["Price"])
variance_price = statistics.variance(df["Price"])
wednesday_mean = df[df["Day"] == "Wednesday"]["Price"].mean()
april_mean = df[df["Date"].dt.month == 4]["Price"].mean()
prob_loss = (df["Chg%"] < 0).mean()
prob_profit_wed = df[(df["Day"] == "Wednesday") & (df["Chg%"] > 0)]["Chg%"].
    ↪count() / df[df["Day"] == "Wednesday"]["Chg%"].count()

print("A4 Results:")
print(f"Mean Price: {mean_price}")
print(f"Variance Price: {variance_price}")
print(f"Wednesday Mean Price: {wednesday_mean}")
print(f"April Mean Price: {april_mean}")
print(f"Probability of Loss: {prob_loss}")
print(f"Probability of Profit on Wednesday: {prob_profit_wed}")

plt.figure(figsize=(10, 5))
sns.scatterplot(x=df["Day"], y=df["Chg%"])
plt.xlabel("Day of the Week") # axis labels
plt.ylabel("Change %")
plt.xticks(rotation=45)
plt.title("Change % vs. Day of the Week")
plt.tight_layout() # prevents labels from overlapping
plt.show()
```

A4 Results:

Mean Price: 1560.663453815261

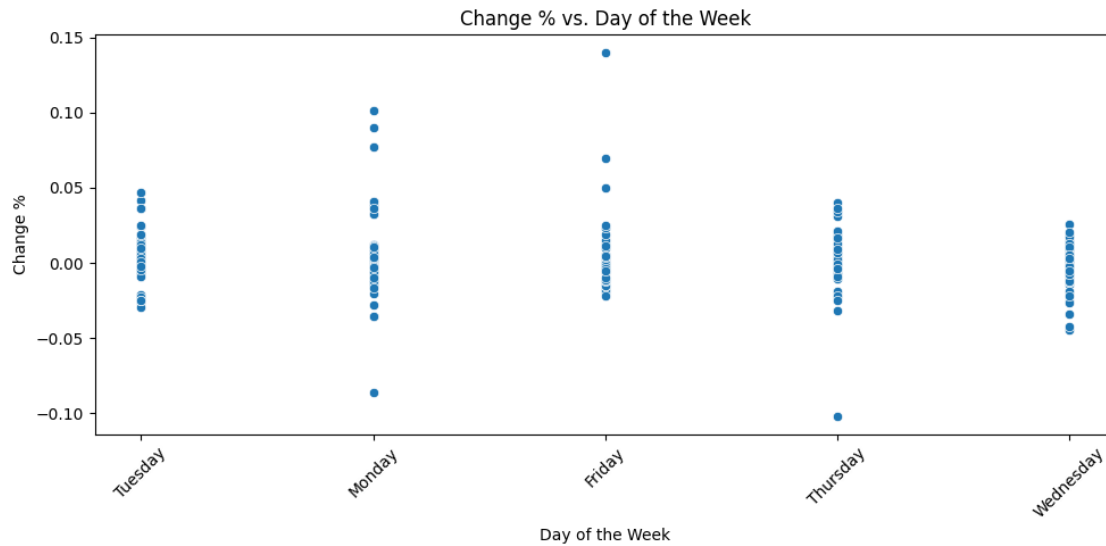
Variance Price: 58732.365352539186

Wednesday Mean Price: 1550.7060000000001

April Mean Price: 1698.9526315789474

Probability of Loss: 0.4979919678714859

Probability of Profit on Wednesday: 0.42



A5. Data Exploration: Load the data available in “thyroid0387\_UCI” worksheet. Perform the following tasks: - Study each attribute and associated values present. Identify the datatype (nominal etc.) for the attribute. - For categorical attributes, identify the encoding scheme to be employed. (Guidance: employ label encoding for ordinal variables while One-Hot encoding may be employed for nominal variables). - Study the data range for numeric variables. - Study the presence of missing values in each attribute. - Study presence of outliers in data. - For numeric variables, calculate the mean and variance (or standard deviation).

```
[37]: df = pd.read_excel(xls, sheet_name="thyroid0387_UCI")
df.replace('?', np.nan, inplace=True)
df = df.infer_objects() # Ensures proper type conversion
missing_values = df.isnull().sum()

# Converts categorical columns to string for Label Encoding
categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    df[col] = df[col].astype(str) # Converts to string
    df[col] = LabelEncoder().fit_transform(df[col])

print("A5 Results:")
print(df.describe())
print("Missing Values:\n", missing_values)
```

A5 Results:

	Record ID	age	sex	on thyroxine \
count	9.172000e+03	9172.000000	9172.000000	9172.000000
mean	8.529473e+08	73.555822	0.371348	0.135194
std	7.581969e+06	1183.976718	0.548110	0.341949
min	8.408010e+08	1.000000	0.000000	0.000000

25%	8.504090e+08	37.000000	0.000000	0.000000
50%	8.510040e+08	55.000000	0.000000	0.000000
75%	8.607110e+08	68.000000	1.000000	0.000000
max	8.701190e+08	65526.000000	2.000000	1.000000

	query on thyroxine	on antithyroid medication	sick \
count	9172.000000	9172.000000	9172.000000
mean	0.016681	0.012647	0.037505
std	0.128081	0.111752	0.190007
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	pregnant	thyroid surgery	I131 treatment	...	TT4 measured \
count	9172.000000	9172.000000	9172.000000	...	9172.000000
mean	0.011666	0.014610	0.018426	...	0.951810
std	0.107383	0.119991	0.134492	...	0.214179
min	0.000000	0.000000	0.000000	...	0.000000
25%	0.000000	0.000000	0.000000	...	1.000000
50%	0.000000	0.000000	0.000000	...	1.000000
75%	0.000000	0.000000	0.000000	...	1.000000
max	1.000000	1.000000	1.000000	...	1.000000

	TT4	T4U measured	T4U	FTI measured	FTI \
count	8730.000000	9172.000000	8363.000000	9172.000000	8370.000000
mean	108.700305	0.911797	0.976056	0.912560	113.640746
std	37.522670	0.283606	0.200360	0.282494	41.551650
min	2.000000	0.000000	0.170000	0.000000	1.400000
25%	87.000000	1.000000	0.860000	1.000000	93.000000
50%	104.000000	1.000000	0.960000	1.000000	109.000000
75%	126.000000	1.000000	1.065000	1.000000	128.000000
max	600.000000	1.000000	2.330000	1.000000	881.000000

	TBG measured	TBG	referral source	Condition
count	9172.000000	349.000000	9172.000000	9172.000000
mean	0.038051	29.870057	3.898495	22.474160
std	0.191329	21.080504	1.504564	5.942872
min	0.000000	0.100000	0.000000	0.000000
25%	0.000000	21.000000	3.000000	25.000000
50%	0.000000	26.000000	5.000000	25.000000
75%	0.000000	31.000000	5.000000	25.000000
max	1.000000	200.000000	5.000000	31.000000

[8 rows x 31 columns]

Missing Values:

Record ID 0

age	0
sex	307
on thyroxine	0
query on thyroxine	0
on antithyroid medication	0
sick	0
pregnant	0
thyroid surgery	0
I131 treatment	0
query hypothyroid	0
query hyperthyroid	0
lithium	0
goitre	0
tumor	0
hypopituitary	0
psych	0
TSH measured	0
TSH	842
T3 measured	0
T3	2604
TT4 measured	0
TT4	442
T4U measured	0
T4U	809
FTI measured	0
FTI	802
TBG measured	0
TBG	8823
referral source	0
Condition	0
dtype:	int64

```
C:\Users\Praanesh Nair\AppData\Local\Temp\ipykernel_2876\4224358239.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  df.replace('?', np.nan, inplace=True)
```

A6. Data Imputation: employ appropriate central tendencies to fill the missing values in the data variables. Employ following guidance. - Mean may be used when the attribute is numeric with no outliers - Median may be employed for attributes which are numeric and contain outliers - Mode may be employed for categorical attributes

```
[38]: df = pd.read_excel(xls, sheet_name="thyroid0387_UCI")
df.replace('?', np.nan, inplace=True)
df = df.infer_objects()
```

```

for col in df.columns:
    if df[col].dtype in ['float64', 'int64']:
        df[col] = df[col].fillna(df[col].median())
    else:
        df[col] = df[col].fillna(df[col].mode()[0])

print("A6 Results:")
print(df)

```

A6 Results:

	Record ID	age	sex	on thyroxine	query on thyroxine	\
0	840801013	29	F	f	f	
1	840801014	29	F	f	f	
2	840801042	41	F	f	f	
3	840803046	36	F	f	f	
4	840803047	32	F	f	f	
...	...	...	...	...	...	
9167	870119022	56	M	f	f	
9168	870119023	22	M	f	f	
9169	870119025	69	M	f	f	
9170	870119027	47	F	f	f	
9171	870119035	31	M	f	f	

	on antithyroid medication	sick	pregnant	thyroid surgery	I131 treatment	\
0	f	f	f	f	f	
1	f	f	f	f	f	
2	f	f	f	f	f	
3	f	f	f	f	f	
4	f	f	f	f	f	
...	...	...	...	...	...	
9167	f	f	f	f	f	
9168	f	f	f	f	f	
9169	f	f	f	f	f	
9170	f	f	f	f	f	
9171	f	f	f	f	f	

	TT4 measured	TT4	T4U measured	T4U	FTI measured	FTI	\
0	f	104.0	f	0.96	f	109.0	
1	t	128.0	f	0.96	f	109.0	
2	f	104.0	f	0.96	f	109.0	
3	f	104.0	f	0.96	f	109.0	
4	f	104.0	f	0.96	f	109.0	
...	...	...	...	...	...	...	
9167	t	64.0	t	0.83	t	77.0	
9168	t	91.0	t	0.92	t	99.0	
9169	t	113.0	t	1.27	t	89.0	
9170	t	75.0	t	0.85	t	88.0	
9171	t	66.0	t	1.02	t	65.0	

	TBG measured	TBG	referral source	Condition
0	f	26.0	other	NO CONDITION
1	f	26.0	other	NO CONDITION
2	t	11.0	other	NO CONDITION
3	t	26.0	other	NO CONDITION
4	t	36.0	other	S
...	...	...	...	...
9167	f	26.0	SVI	NO CONDITION
9168	f	26.0	SVI	NO CONDITION
9169	f	26.0	SVI	I
9170	f	26.0	other	NO CONDITION
9171	f	26.0	other	NO CONDITION

[9172 rows x 31 columns]

```
C:\Users\Praanesh Nair\AppData\Local\Temp\ipykernel_2876\2240753025.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
df.replace('?', np.nan, inplace=True)
```

A7. Data Normalization / Scaling: from the data study, identify the attributes which may need normalization. Employ appropriate normalization techniques to create normalized set of data.

```
[39]: categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns
scaler = MinMaxScaler()
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

print("A7 Results:")
print(df)
```

A7 Results:

	Record ID	age	sex	on thyroxine	query on thyroxine	\
0	0.000000e+00	0.000427	0	0	0	
1	3.410871e-08	0.000427	0	0	0	
2	9.891527e-07	0.000610	0	0	0	
3	6.934301e-05	0.000534	0	0	0	
4	6.937712e-05	0.000473	0	0	0	
...	...	...	...	...	...	
9167	9.999996e-01	0.000839	1	0	0	
9168	9.999996e-01	0.000320	1	0	0	
9169	9.999997e-01	0.001038	1	0	0	
9170	9.999997e-01	0.000702	0	0	0	



9171	1.000000e+00	0.000458	1	0	0
------	--------------	----------	---	---	---

	on antithyroid medication	sick	pregnant	thyroid surgery	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	
...	...	...	...	...	
9167	0	0	0	0	
9168	0	0	0	0	
9169	0	0	0	0	
9170	0	0	0	0	
9171	0	0	0	0	

	I131 treatment	...	TT4 measured	TT4	T4U measured	T4U	\
0	0	...	0	0.170569	0	0.365741	
1	0	...	1	0.210702	0	0.365741	
2	0	...	0	0.170569	0	0.365741	
3	0	...	0	0.170569	0	0.365741	
4	0	...	0	0.170569	0	0.365741	
...	...	...	...	...	...	...	
9167	0	...	1	0.103679	1	0.305556	
9168	0	...	1	0.148829	1	0.347222	
9169	0	...	1	0.185619	1	0.509259	
9170	0	...	1	0.122074	1	0.314815	
9171	0	...	1	0.107023	1	0.393519	

	FTI measured	FTI	TBG measured	TBG	referral source	\
0	0	0.122328	0	0.129565	5	
1	0	0.122328	0	0.129565	5	
2	0	0.122328	1	0.054527	5	
3	0	0.122328	1	0.129565	5	
4	0	0.122328	1	0.179590	5	
...	...	...	...	...	...	
9167	1	0.085948	0	0.129565	3	
9168	1	0.110960	0	0.129565	3	
9169	1	0.099591	0	0.129565	3	
9170	1	0.098454	0	0.129565	5	
9171	1	0.072306	0	0.129565	5	

Condition	
0	25
1	25
2	25
3	25
4	31
...	...

9167	25
9168	25
9169	15
9170	25
9171	25

[9172 rows x 31 columns]

A8. Similarity Measure: Take the first 2 observation vectors from the dataset. Consider only the attributes (direct or derived) with binary values for these vectors (ignore other attributes). Calculate the Jaccard Coefficient (JC) and Simple Matching Coefficient (SMC) between the document vectors. Use first vector for each document for this. Compare the values for JC and SMC and judge the appropriateness of each of them.

$$JC = \frac{f_{11}}{f_{01} + f_{10} + f_{11}}$$

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

```
[40]: vector1 = df.iloc[0, :].values
vector2 = df.iloc[1, :].values
f11 = np.sum((vector1 == 1) & (vector2 == 1))
f00 = np.sum((vector1 == 0) & (vector2 == 0))
f10 = np.sum((vector1 == 1) & (vector2 == 0))
f01 = np.sum((vector1 == 0) & (vector2 == 1))

# Check for division by zero
denominator = (f01 + f10 + f11)
JC = f11 / denominator if denominator != 0 else 0 # Handles the case where all
↪are 0
SMC = (f11 + f00) / (f00 + f01 + f10 + f11) if (f00 + f01 + f10 + f11) != 0
↪else 0

print("A8 Results:")
print(f"Jaccard Coefficient: {JC}, SMC: {SMC}")
```

A8 Results:

Jaccard Coefficient: 0.25, SMC: 0.8571428571428571

A9. Cosine Similarity Measure: Now take the complete vectors for these two observations (including all the attributes). Calculate the Cosine similarity between the documents by using the second feature vector for each document.

```
[41]: vector1 = df.iloc[0, :].values.reshape(1, -1)
vector2 = df.iloc[1, :].values.reshape(1, -1)
result = cosine_similarity(vector1, vector2)[0][0]
print("A9 Result:", result)
```

A9 Result: 0.9977009625064738

A10. Heatmap Plot: Consider the first 20 observation vectors. Calculate the JC, SMC and COS between the pairs of vectors for these 20 vectors. Employ similar strategies for coefficient calculation as in A4 & A5. Employ a heatmap plot to visualize the similarities.

```
[42]: df_subset = df.iloc[:20, :] # Uses a subset for better visualization
      similarity_matrix = np.zeros((20, 20))

      for i in range(20):
          for j in range(20):
              if i != j:
                  similarity_matrix[i, j] = np.linalg.norm(df_subset.iloc[i] -
                  ↪df_subset.iloc[j]) # Euclidean distance

      plt.figure(figsize=(10, 8))
      sns.heatmap(similarity_matrix, annot=False, cmap='coolwarm') # (annot=False)
      ↪for cleaner heatmap
      plt.title("Heatmap of Euclidean Distances (Dissimilarity)")
      plt.tight_layout()
      plt.show()
```

