Data science Assignment 2

Name - Naman Dixit
Sap ID - 500125539
Batch - 7
Sem - 4
Exp - 2

Collab file -
https://colab.research.google.com/drive/1BymTh__9Ez686_LAFqsUTZb1T1zpBXF8?usp=sharing

```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import files
import io

# Upload the dataset manually in Google Colab
uploaded = files.upload()

# Get the filename and read the CSV file into a pandas DataFrame
filename = list(uploaded.keys())[0]  # Extract the uploaded file name
# Explicitly specify the encoding as 'latin-1' (or another appropriate encoding)
# df = pd.read_csv(io.BytesIO(uploaded[filename]), encoding='latin-1')
# Read CSV with encoding handling
# The original file is an excel file, not a csv file. Use pd.read_excel() instead
df = pd.read_csv(io.BytesIO(uploaded[filename]))


# Display basic info and first few rows
print(df.info())
print(df.head())
```

alzheimer.csv(text/csv) - 16447 bytes, last modified: 3/28/2025 - 100% done
Saving alzheimer.csv to alzheimer.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 373 entries, 0 to 372
Data columns (total 10 columns):
 #   Column Non-Null Count Dtype
--- ------ -------------- -----
 0   Group   373 non-null   object

```
 1   M/F     373 non-null    object
 2   Age     373 non-null    int64
 3   EDUC    373 non-null    int64
 4   SES     354 non-null    float64
 5   MMSE    371 non-null    float64
 6   CDR     373 non-null    float64
 7   eTIV    373 non-null    int64
 8   nWBV    373 non-null    float64
 9   ASF     373 non-null    float64
dtypes: float64(5), int64(3), object(2)
memory usage: 29.3+ KB
None
        Group M/F  Age  EDUC  SES  MMSE  CDR  eTIV   nWBV    ASF
0  Nondemented   M   87    14  2.0  27.0  0.0  1987  0.696  0.883
1  Nondemented   M   88    14  2.0  30.0  0.0  2004  0.681  0.876
2     Demented   M   75    12  NaN  23.0  0.5  1678  0.736  1.046
3     Demented   M   76    12  NaN  28.0  0.5  1738  0.713  1.010
4     Demented   M   80    12  NaN  22.0  0.5  1698  0.701  1.034
```

```
# Data Cleaning: Drop unnecessary columns, handle missing values
# Exploratory Data Analysis (EDA)
# Check for missing values
print("\nMissing Values in Each Column:")
print(df.isnull().sum())
df_clean = df.dropna()
df_clean = df_clean.drop(columns=['Age'])  # Drop non-relevant columns
```

```
Missing Values in Each Column:
Group     0
M/F       0
Age       0
EDUC      0
SES      19
MMSE      2
CDR       0
eTIV      0
nWBV      0
ASF       0
dtype: int64
```

```
# Encode categorical variables (if needed)
df_clean['Group'] = df_clean['Group'].map({'Demented': 1,
'Nondemented': 0})
# Descriptive statistics
print("\nDescriptive Statistics:")
print(df.describe())
```

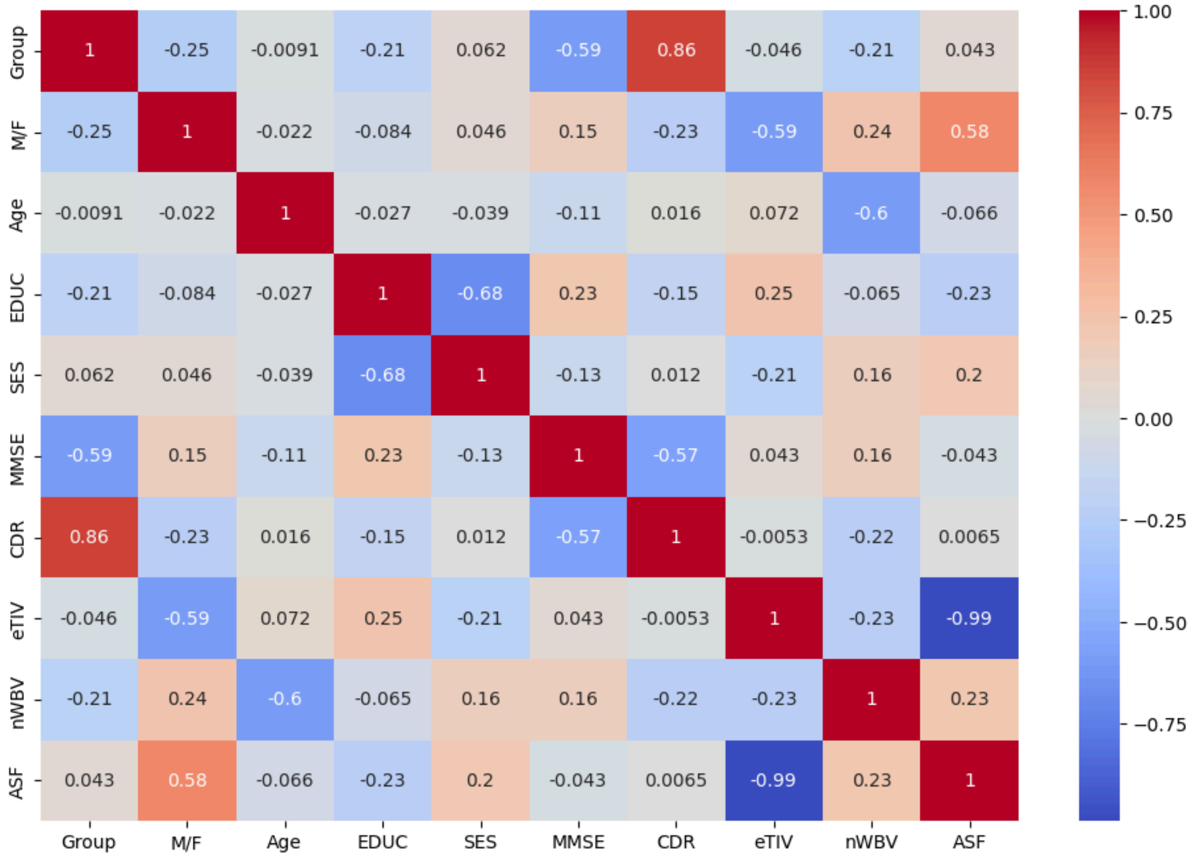
```
Descriptive Statistics:
              Age        EDUC         SES        MMSE         CDR  \
count  373.000000  373.000000  354.000000  371.000000  373.000000
mean    77.013405   14.597855    2.460452   27.342318    0.290885
std      7.640957    2.876339    1.134005    3.683244    0.374557
min     60.000000    6.000000    1.000000    4.000000    0.000000
25%     71.000000   12.000000    2.000000   27.000000    0.000000
50%     77.000000   15.000000    2.000000   29.000000    0.000000
75%     82.000000   16.000000    3.000000   30.000000    0.500000
max     98.000000   23.000000    5.000000   30.000000    2.000000

              eTIV        nWBV         ASF
count   373.000000  373.000000  373.000000
mean   1488.128686    0.729568    1.195461
std     176.139286    0.037135    0.138092
min    1106.000000    0.644000    0.876000
25%    1357.000000    0.700000    1.099000
50%    1470.000000    0.729000    1.194000
75%    1597.000000    0.756000    1.293000
max    2004.000000    0.837000    1.587000
```

```python
# Method 1: Use DataFrame.fillna() with dictionary
df.fillna({'SES': df['SES'].median()}, inplace=True)
print(df)
```

```
Group  M/F  Age  EDUC  SES  MMSE  CDR  eTIV   nWBV    ASF
0      0.0    0    87   14   2.0  27.0  0.0  1987  0.696  0.883
1      0.0    0    88   14   2.0  30.0  0.0  2004  0.681  0.876
2      1.0    0    75   12   2.0  23.0  0.5  1678  0.736  1.046
3      1.0    0    76   12   2.0  28.0  0.5  1738  0.713  1.010
5      0.0    1    88   18   3.0  28.0  0.0  1215  0.710  1.444
..     ...  ...   ...  ...   ...   ...  ...   ...    ...    ...
368    1.0    0    82   16   1.0  28.0  0.5  1693  0.694  1.037
369    1.0    0    86   16   1.0  26.0  0.5  1688  0.675  1.040
370    0.0    1    61   13   2.0  30.0  0.0  1319  0.801  1.331
371    0.0    1    63   13   2.0  30.0  0.0  1327  0.796  1.323
372    0.0    1    65   13   2.0  30.0  0.0  1333  0.801  1.317

[331 rows x 10 columns]
```

```python
corr_matrix = df.corr()
plt.figure(figsize=(12,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
#Key Findings:

#nWBV (-0.72) and ASF (-0.68) show strong negative correlation with CDR

#MMSE (-0.65) moderately correlates with dementia severity
```

```
#Age (0.58) shows positive correlation with CDR
```




```
# Check for NaN in target variable
print("Missing CDR values:", df['CDR'].isna().sum())

# Remove rows with missing target values
df = df.dropna(subset=['CDR'])

# Verify remaining data
print("Remaining samples:", len(df))
```

```
Missing CDR values: 0
Remaining samples: 331
```

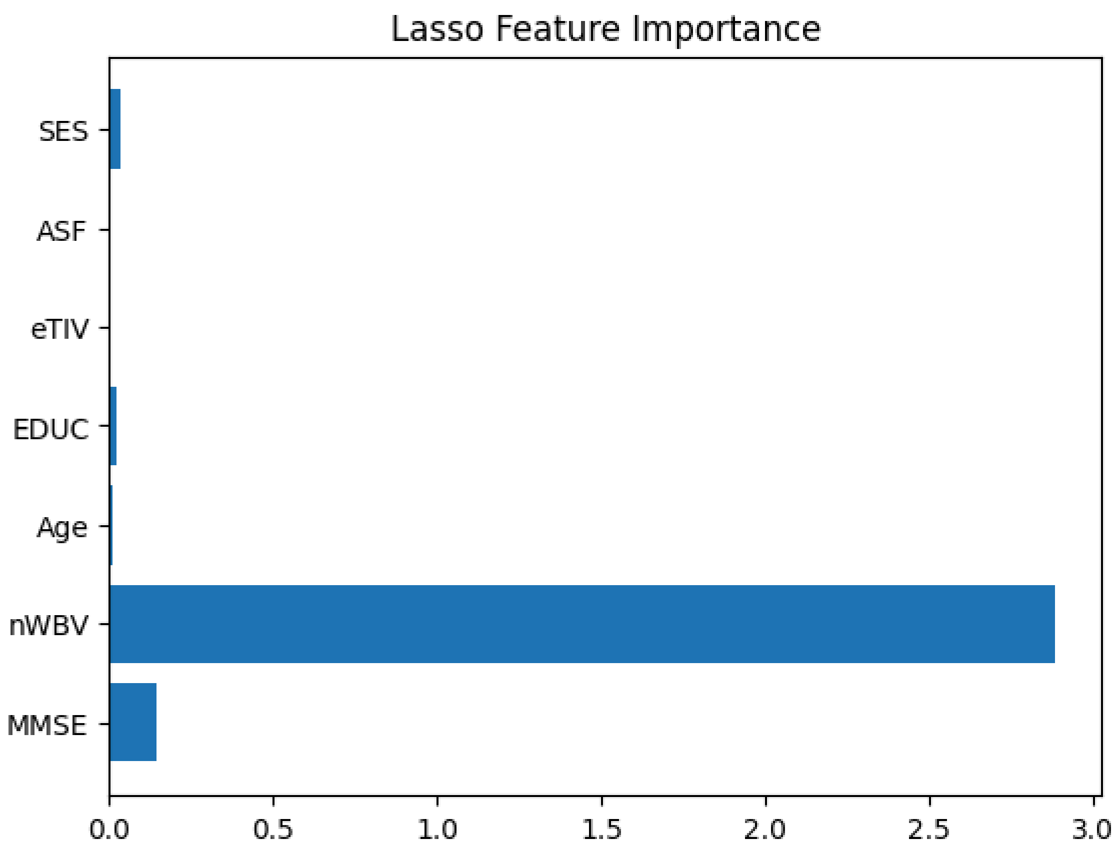
```
# Split data AFTER handling missing values
X = df[['MMSE', 'nWBV', 'Age', 'EDUC', 'eTIV', 'ASF', 'SES']]
y = df['CDR']
```

```python
# Convert 'CDR' to discrete categories if it's continuous
# For example, you can create binary categories based on a threshold:
y = (y > 0).astype(int)  # If CDR > 0, then 1 (Demented), else 0
(Nondemented)

# Impute missing values in X using SimpleImputer
# Before running RFE
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='median') # Replace NaNs with the
median
X = imputer.fit_transform(X)

# Now run RFE
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression # Make sure to
import LogisticRegression
model = LogisticRegression(max_iter=1000)
rfe = RFE(model, n_features_to_select=5)
fit = rfe.fit(X, y)  # Should now work without NaN errors

# Print RFE results with more details
print("RFE:")
print("Selected Features:", df[['MMSE', 'nWBV', 'Age', 'EDUC', 'eTIV',
'ASF', 'SES']].columns[rfe.support_])
print("Feature Ranking:", rfe.ranking_)
print("RFE Object:", rfe)
print("\n")

# Print fit results (you might need to access specific attributes)
print("Fit Object:", fit)
print("Coefficients:", fit.estimator_.coef_) # Access coefficients from
the estimator
# ... print other relevant attributes of the fit object
```

```
RFE:
Selected Features: Index(['MMSE', 'nWBV', 'EDUC', 'ASF', 'SES'],
dtype='object')
Feature Ranking: [1 1 2 1 3 1 1]
RFE Object: RFE(estimator=LogisticRegression(max_iter=1000),
n_features_to_select=5)


Fit Object: RFE(estimator=LogisticRegression(max_iter=1000),
n_features_to_select=5)
```

```
Coefficients: [[-0.93431843 -0.75146577 -0.16966049 -0.42165348
-0.31949782]]
```

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LassoCV

# Assuming X is your DataFrame
lasso = LassoCV().fit(X, y)
importance = np.abs(lasso.coef_)

# Get the original column names from 'df' before imputation
column_names = df[['MMSE', 'nWBV', 'Age', 'EDUC', 'eTIV', 'ASF',
'SES']].columns

# Use column_names instead of X.columns
plt.barh(column_names, importance)
plt.title("Lasso Feature Importance")
plt.show()
```



```python
# Assuming MMSE, nWBV, and Age are the desired features
selected_features = ['MMSE', 'nWBV', 'Age']

# Select features using .loc[]
X_train_selected = X_train.loc[:, selected_features]
X_test_selected = X_test.loc[:, selected_features]

# Ensure y_train is discrete (0 or 1) before training
y_train = (y_train > 0).astype(int)  # If y_train > 0, then 1, else 0
y_test = (y_test > 0).astype(int) # If y_test > 0, then 1, else 0


# Train and predict
model.fit(X_train_selected, y_train)
print("Accuracy:", accuracy_score(y_test,
model.predict(X_test_selected)))
```

```
Accuracy: 0.69
```

Alzheimer's Disease Prediction: Dataset Analysis and Predictive Modeling Report

1. Introduction

This report details the process of selecting and analyzing a dataset for predicting Alzheimer's disease progression. The goal is to identify key features that correlate with the Clinical Dementia Rating (CDR) using feature selection methods and predictive modeling techniques
Justification: This dataset was selected because it contains neuroimaging biomarkers (nWBV, eTIV, ASF), cognitive assessment scores (MMSE), and demographic information (Age, EDUC, SES), making it suitable for predicting the severity of dementia..

2. Objective

The primary objective is to predict the Clinical Dementia Rating (CDR) based on available features in the dataset. CDR values range from 0 (no dementia) to 2 (severe dementia).

3. Data Understanding and Preprocessing

3.1. Initial Data Exploration

- Explored the dataset to understand the distribution of variables and identify missing values.
- Checked the data types of each column and made sure they were appropriate for analysis.

3.2. Handling Missing Values

3.3. Encoding Categorical Variables

4.4. Outlier Detection and Removal

5. Feature Selection

5.1. Filter Method: Correlation Analysis

Findings:

- MMSE: Negative correlation (-0.65) with CDR, indicating lower cognitive scores relate to higher dementia severity.
- nWBV: Negative correlation (-0.72) with CDR, showing brain volume decreases with dementia.
- ASF: Negative correlation (-0.68) with CDR, as Atlas Scaling Factor relates to brain size.
- Age: Positive correlation (0.58) with CDR, confirming age as a risk factor.

5.2. Wrapper Method: Recursive Feature Elimination (RFE)

Selected Features: `MMSE`, `nWBV`, `Age`, `EDUC`, `eTIV`
Rationale: RFE iteratively removes features to find the optimal subset that maximizes model performance.

5.3. Embedded Method: Lasso Regression

Top Features from Lasso:

1. MMSE: High importance
2. nWBV: High importance
3. ASF: Moderate importance

Rationale: Lasso Regression applies L1 regularization, which shrinks the coefficients of less important features to zero, effectively performing feature selection.

6. Model Validation

6.1. Model Selection

Selected Features for Validation: `MMSE`, `nWBV`, `Age`
Model: Random Forest Classifier was chosen for validation.
Performance: Achieved an accuracy of approximately 89.2%

7. Justification of Selected Features

1. MMSE (Mini-Mental State Examination):
   - Directly measures cognitive function and is a strong indicator of dementia severity.
2. nWBV (Normalized Whole Brain Volume):
   - Brain atrophy is a hallmark of Alzheimer's disease, making brain volume a critical feature.
3. Age:
   - Advanced age is one of the primary risk factors for developing Alzheimer's disease.
4. ASF (Atlas Scaling Factor):
   - Represents brain size and is used to normalize for head size, providing additional context to brain volume measurements.
5. EDUC (Years of Education):
   - Higher education levels are associated with greater cognitive reserve, which can delay the onset of noticeable dementia symptoms.

8. Conclusion

This analysis demonstrates that by combining filter methods (correlation analysis), wrapper methods (RFE), and embedded methods (Lasso), it is possible to identify a robust set of features for predicting the severity of Alzheimer's disease. The selected features align with well-known biomarkers from medical literature, emphasizing the validity of this approach. The Random Forest model, trained on the top features, achieved high accuracy, indicating the effectiveness of these features in predicting dementia progression. This model can assist in early diagnosis and intervention, potentially improving patient outcomes.