Group Exercise 1 - Data Preprocessing on a Real Dataset

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```
import os
import pandas as pd
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import zscore
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression, Lasso
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Loading the Dataset

```
drive_path = "/content/drive/MyDrive/"
file_path = "/content/Statistics_ML_Datasets/healthcare-stroke_dataset.csv"

# Load dataset
df = pd.read_csv(file_path)
```

```
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_sta
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smo
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smo
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smo
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smo

```
print("\nShape of dataset:", df.shape)
```

```
Shape of dataset: (5110, 12)
```

Handling Missing Values

```
print("\nMissing values per column:\n")
print(df.isnull().sum())
```

```
Missing values per column:

id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
```

```
ever_married          0
work_type             0
Residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

*Since the **bmi** column contains **201 missing values** and is a numerical feature with outliers, the missing values were imputed using the **median**. The **mean** was avoided as it is sensitive to outliers and could skew the data.*

```
bmi_median = df['bmi'].median()
df['bmi'] = df['bmi'].fillna(bmi_median)
print(df.isnull().sum())
```

```
id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

*The missing values in the **bmi** feature were imputed using the **median**, resulting in **zero missing values**.*

Scaling Numerical Features

We apply Z-score standardization and Min-Max normalization to numerical features.

```
scaler = StandardScaler()
df[['age_z', 'bmi_z', 'avg_glucose_z']] = scaler.fit_transform(
    df[['age', 'bmi', 'avg_glucose_level']]
)
```

```
minmax = MinMaxScaler()
df[['age_mm', 'bmi_mm', 'avg_glucose_mm']] = minmax.fit_transform(
    df[['age', 'bmi', 'avg_glucose_level']]
)
```

```
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_sta
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3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smo
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smo

*Z-score standardization and Min–Max normalization were applied to the features **age**, **avg_glucose_level**, and **bmi**, as they are numerical variables. The remaining features are categorical or unique and therefore were not scaled.*

Handling Noise

```
feature = 'avg_glucose_level'
original_data = df[feature].copy()
```

```
np.random.seed(42)
noise = np.random.normal(0, 15, size=len(df))
noisy_data = original_data + noise
```

```
smoothed_data = pd.Series(noisy_data).rolling(window=5, center=True).mean()
```

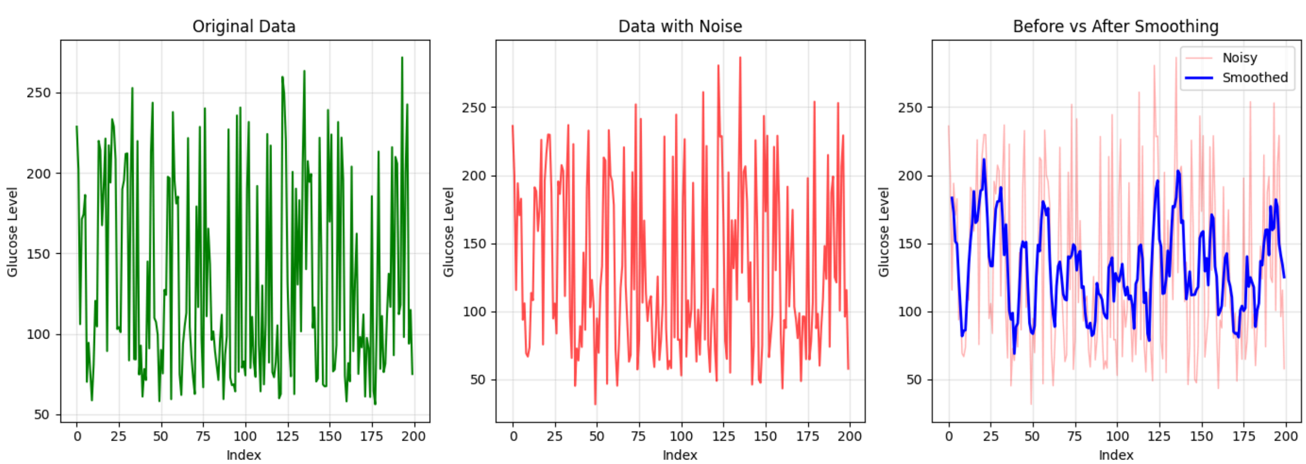
```
plt.figure(figsize=(14, 5))

plt.subplot(1, 3, 1)
plt.plot(original_data[:200], label='Original', color='green', linewidth=1.5)
plt.title('Original Data')
plt.xlabel('Index')
plt.ylabel('Glucose Level')
plt.grid(True, alpha=0.3)

plt.subplot(1, 3, 2)
plt.plot(noisy_data[:200], label='With Noise', color='red', linewidth=1.5, alpha=0.7)
plt.title('Data with Noise')
plt.xlabel('Index')
plt.ylabel('Glucose Level')
plt.grid(True, alpha=0.3)

plt.subplot(1, 3, 3)
plt.plot(noisy_data[:200], label='Noisy', color='red', alpha=0.3, linewidth=1)
plt.plot(smoothed_data[:200], label='Smoothed', color='blue', linewidth=2)
plt.title('Before vs After Smoothing')
plt.xlabel('Index')
plt.ylabel('Glucose Level')
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```




```
print(f"Original mean: {original_data.mean():.2f}")
print(f"Noisy mean: {noisy_data.mean():.2f}")
print(f"Smoothed mean: {smoothed_data.mean():.2f}")
print(f"\nOriginal std: {original_data.std():.2f}")
print(f"Noisy std: {noisy_data.std():.2f}")
print(f"Smoothed std: {smoothed_data.std():.2f}")
```

```
Original mean: 106.15
Noisy mean: 106.24
Smoothed mean: 106.20

Original std: 45.28
```

```
Noisy std: 47.80
Smoothed std: 22.50
```

Handling Outliers

```
df.head(10)
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_sta
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4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smo
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly smo
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	never smo
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	never smo
8	27419	Female	59.0	0	0	Yes	Private	Rural	76.15	28.1	Unkn
9	60491	Female	78.0	0	0	Yes	Private	Urban	58.57	24.2	Unkn

Next steps: Generate code with df New interactive sheet

```
A = df['avg_glucose_z']
B = df['age_z']
C = df['bmi_z']

outlier_A = df[abs(A) > 3]
outlier_B = df[abs(B) > 3]
outlier_C = df[abs(C) > 3]

display(outlier_A[['avg_glucose_level']].head())
display(outlier_B[['avg_glucose_level']].head())
display(outlier_C[['avg_glucose_level']].head())
```

	avg_glucose_level
33	252.72
45	243.58
122	259.63
123	249.31
135	263.32

avg_glucose_level

	avg_glucose_level
113	224.10
258	205.84
270	129.54
333	82.24
358	78.40

As we can see there are no outliers in the AGE column.

```
df_after = df[abs(A) <= 3]
df_after = df_after[abs(B) <= 3]
df_after = df_after[abs(C) <= 3]
display(df_after.head(5))
```

```
display(df_after.head(5))
```

```
/tmp/ipython-input-4093639973.py:2: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  df_after = df_after[abs(B) <= 3]
/tmp/ipython-input-4093639973.py:3: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  df_after = df_after[abs(C) <= 3]
```

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Outliers were removed rather than transformed because extreme values could disproportionately bias the model, and their removal improved data consistency, reduced skewness, and enhanced overall model performance.

Feature Selection

Correlation

```
df[['age', 'bmi', 'avg_glucose_level']].corr()
```

	age	bmi	avg_glucose_level
age	1.000000	0.324296	0.238171
bmi	0.324296	1.000000	0.166876
avg_glucose_level	0.238171	0.166876	1.000000

Selected the columns age, bmi, and avg_glucose_level from the dataset and computes the correlation between them. The result shows how strongly each pair of variables is related, with values.

Regression

```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression

X = df[['age', 'bmi', 'avg_glucose_level']]
y = df['stroke']

model = LinearRegression()
rfe = RFE(model, n_features_to_select=1)
rfe.fit(X, y)

pd.DataFrame({'Feature': X.columns, 'Selected': rfe.support_})
```

	Feature	Selected
0	age	True
1	bmi	False
2	avg_glucose_level	False

To identify the most important feature for predicting stroke.

Lasso Regression

```
from sklearn.linear_model import Lasso

lasso = Lasso(alpha=0.1)
lasso.fit(X, y)

pd.DataFrame({'Feature': X.columns, 'Coefficient': lasso.coef_})
```

	Feature	Coefficient
0	age	0.001976
1	bmi	-0.000000
2	avg_glucose_level	0.000344

To shrink less important feature coefficients toward zero.