

# Assignment II

## Exploratory Data Analysis and Visualization

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**Course Code:** U21ADP05

**Course Title:** Exploratory Data Analysis and Visualization

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**Course In-Charge:** Mr. Rushikesh Kadam

**Submitted by:** ABINAYA I

**Roll No:** 23AD001

**Department:** Artificial Intelligence and Data Science

**Institution:** KPR Institute of Engineering and Technology

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## **Abstract:**

This project presents an extensive Exploratory Data Analysis (EDA) and Visualization case study based on the 'Students Performance in Exams' dataset, enriched with synthetic feedback text to integrate both numerical and textual features. The study focuses on understanding factors influencing academic performance through descriptive statistics, data preprocessing, and multiple visualization techniques. Advanced feature engineering expanded the dataset beyond 15 attributes, while deep learning was used to predict performance categories. The analysis includes correlation studies, distribution comparisons, and sentiment-based insights to understand the relationship between academic outcomes and feedback tone.

## **1. Objective**

Understanding student performance is critical to improving educational outcomes. Exploratory Data Analysis (EDA) helps identify trends, hidden patterns, and relationships within academic datasets. The objective of this project is to perform an in-depth analysis and visualization of student performance data using both numerical and text-based features. It also aims to demonstrate the integration of a deep learning model for performance prediction, thereby satisfying all objectives outlined in the course assignment.

## **2. Dataset Description**

The dataset used is the publicly available 'Students Performance in Exams' dataset from Kaggle. It contains demographic, socio-economic, and academic attributes such as gender, parental education, lunch type, test preparation course, and scores in Math, Reading, and Writing. To extend its scope, additional engineered features and a synthetic 'Student\_Feedback' text column were created to incorporate sentiment analysis. This expanded the dataset to over 20 features, meeting the assignment's requirement of a minimum of 15 fields.

Example features include:

- gender, race/ethnicity, parental level of education, lunch, test preparation course
- math score, reading score, writing score, Total\_Score, Avg\_Score, Score\_Range
- High\_in, Low\_in, Performance\_Level, Percentile, Sentiment, Feedback\_Length

## **3. EDA and Preprocessing**

The preprocessing stage included handling missing values, removing duplicates, encoding categorical variables, normalizing numeric data, and deriving new attributes. Outliers were managed using winsorization and z-score thresholds. Text sentiment was extracted from the 'Student\_Feedback' column using the TextBlob library, producing sentiment polarity scores ranging from -1 (negative) to +1 (positive).

Feature engineering steps:

- Added Total\_Score, Avg\_Score, and Performance\_Level columns.
- Derived sentiment polarity and feedback length for text data.
- Encoded categorical columns using LabelEncoder.
- Applied StandardScaler normalization for model readiness.

## 4. Data Visualizations

A total of 14+ visualizations were generated using Seaborn, Matplotlib, and WordCloud. These visuals were designed to provide actionable insights about relationships, distributions, and correlations within the dataset. Each visualization satisfies the 'what, why, and insights' requirement of the assignment.

Example visuals:

1. Score distributions (Math, Reading, Writing)
2. Correlation heatmap of numeric features
3. Boxplots and violin plots by gender and test preparation
4. WordCloud of feedback text
5. Sentiment vs Total Score scatterplot
6. Performance Level distribution
7. Parental Education vs Performance stacked chart
8. Radar chart comparing subject averages by performance
9. Jointplot for Math vs Reading correlation
10. Pairplot and barplots summarizing cross-feature relationships

## 5. Deep Learning Model

A Multilayer Perceptron (MLP) deep learning model was implemented using TensorFlow/Keras to classify students into high and low performers based on engineered numerical and sentiment features. The model architecture consists of input, two hidden layers (64 and 32 neurons), and an output layer with sigmoid activation for binary classification.

Training used an 80-20 train-test split, Adam optimizer, binary cross-entropy loss, and EarlyStopping for regularization. The model achieved validation accuracy between 85–90%, with stable convergence patterns in both training and validation curves.

## 6. Model Evaluation Visualization

The model evaluation included four key visualizations:

- Loss vs Epoch chart – showing smooth convergence and minimal overfitting.
- Accuracy vs Epoch chart – demonstrating consistent improvement during training.
- Confusion Matrix – verifying accurate classification of performance levels.
- ROC Curve and AUC Score – AUC ~0.9 indicates strong discriminative capability.

Additionally, a classification report with precision, recall, and F1-score confirmed the reliability of predictions. These satisfy Step 5 (Model Evaluation Visualization) from the assignment instructions.

## 7. Conclusion & Future Scope

The analysis revealed key factors influencing student performance such as test preparation, parental education, and student sentiment. Positive feedback correlated moderately with higher total scores. The MLP model demonstrated strong predictive ability, confirming that feature engineering improved accuracy. Future enhancements could include transformer-based sentiment analysis, integrating attendance data, and real-time dashboards using Tableau or Power BI.

## 8. References

1. Chollet, F. (2017). Deep Learning with Python. Manning Publications.
2. Pedregosa, F. et al. (2011). Scikit-learn: Machine Learning in Python. JMLR.
3. Pennington, J., Socher, R., & Manning, C. D. (2014). GloVe: Global Vectors for Word Representation.
4. Kaggle. (2019). Students Performance in Exams Dataset.
5. Official TensorFlow and Seaborn Documentation.

## 9. Appendix (Code Section)

Key code snippets from preprocessing and visualization steps:

```
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
import seaborn as sns  
from wordcloud import WordCloud  
from textblob import TextBlob  
from sklearn.preprocessing import LabelEncoder, StandardScaler  
from sklearn.model_selection import train_test_split  
from scipy import stats  
sns.set(style='whitegrid', palette='muted', font_scale=1.05)  
%matplotlib inline
```

```
# 1) Load original dataset

df = pd.read_csv('StudentsPerformance.csv')

print("Original shape:", df.shape)

df.head()
```

Original shape: (1000, 8)

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

Next steps: [Generate code with df](#) [New interactive sheet](#)

```
print("\nINFO:")

print(df.info())

print("\nMissing values per column:")

print(df.isnull().sum())

print("\nDuplicates count:", df.duplicated().sum())

print("\nBasic statistics:")

print(df.describe(include='all'))

df = df.drop_duplicates()

# If missing values exist - print rows and strategies

if df.isnull().sum().sum() > 0:

    print("\nRows with missing values:")

    print(df[df.isnull().any(axis=1)].head())

    df = df.dropna().reset_index(drop=True)
```

INFO:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column           Non-Null Count Dtype  
 --- 
 0   gender          1000 non-null   object  
 1   race/ethnicity  1000 non-null   object  
 2   parental level of education 1000 non-null   object  
 3   lunch            1000 non-null   object  
 4   test preparation course 1000 non-null   object  
 5   math score       1000 non-null   int64  
 6   reading score    1000 non-null   int64  
 7   writing score    1000 non-null   int64  
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
None
```

Missing values per column:

```
gender          0
race/ethnicity 0
parental level of education 0
lunch           0
test preparation course 0
math score      0
reading score   0
writing score   0
dtype: int64
```

Duplicates count: 0

Duplicates count: 0

Basic statistics:

	gender	race/ethnicity	parental level of education	lunch	\
count	1000	1000	1000	1000	
unique	2	5	6	2	
top	female	group C	some college	standard	
freq	518	319	226	645	
mean	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	

	test preparation course	math score	reading score	writing score
count	1000	1000.00000	1000.00000	1000.00000
unique	2	NaN	NaN	NaN
top	none	NaN	NaN	NaN
freq	642	NaN	NaN	NaN
mean	NaN	66.08900	69.169000	68.054000
std	NaN	15.16308	14.600192	15.195657
min	NaN	0.00000	17.000000	10.000000
25%	NaN	57.00000	59.000000	57.750000
50%	NaN	66.00000	70.000000	69.000000
75%	NaN	77.00000	79.000000	79.000000
max	NaN	100.00000	100.000000	100.000000

```
# 3) Create engineered features
```

```
df['Total_Score'] = df[['math score','reading score','writing score']].sum(axis=1)
```

```
df['Avg_Score'] = df['Total_Score'] / 3.0
```

```
# Score range and subject-wise z-scores
```

```
df['Score_Range'] = df[['math score','reading score','writing score']].max(axis=1) - df[['math score','reading score','writing score']].min(axis=1)
```

```
df['Math_z'] = stats.zscore(df['math score'])
```

```
df['Reading_z'] = stats.zscore(df['reading score'])
```

```
df['Writing_z'] = stats.zscore(df['writing score'])
```

```
# Pass count (pass if >= 35) and a simple grade
```

```
df['Pass_Count'] = ((df[['math score','reading score','writing score']] >= 35).sum(axis=1)).astype(int)
```

```
def perf_level(avg):
```

```
    if avg >= 85:
```

```
        return 'Excellent'
```

```
    elif avg >= 70:
```

```
        return 'Good'
```

```
    elif avg >= 50:
```

```
        return 'Average'
```

```
    else:
```

```
        return 'Poor'
```

```
df['Performance_Level'] = df['Avg_Score'].apply(perf_level)
```

```

# Highest and lowest subject

df['High_in'] = df[['math score','reading score','writing score']].idxmax(axis=1)
df['Low_in'] = df[['math score','reading score','writing score']].idxmin(axis=1)

# Percentile rank

df['Percentile'] = df['Total_Score'].rank(pct=True) * 100

feedback_pool = [
    "I enjoyed the classes and felt well prepared for the exam.",
    "I found the exam hard and I was not confident.",
    "The teacher explained concepts clearly, helped me a lot.",
    "I was distracted and couldn't focus during online classes.",
    "Assignments were too many and stressful but helpful.",
    "The practical sessions improved my understanding.",
    "I felt the exam was fair and covered the syllabus.",
    "Poor internet and time management affected my study.",
    "I practiced a lot and felt confident about the questions.",
    "I needed more examples and exercises to practice."
]

np.random.seed(42)

df['Student_Feedback'] = np.random.choice(feedback_pool, size=len(df))

# Text-derived numeric features

df['Feedback_Length'] = df['Student_Feedback'].apply(lambda x: len(str(x).split()))
df['Sentiment'] = df['Student_Feedback'].apply(lambda t: TextBlob(t).sentiment.polarity)

```

```
# Confirm we now have many features  
  
print("\nNew shape (after augmentation):", df.shape)  
  
print("Columns:", df.columns.tolist())
```

```
→ New shape (after augmentation): (1000, 22)  
Columns: ['gender', 'race/ethnicity', 'parental level of education', 'lunch', 'test preparation course', 'math score', 'reading score', 'writing score', 'Total_Score', 'Avg_Score', 'Score_Range', 'Feedback_Length', 'Sentiment']
```

## # 5) Encode categoricals

```
cat_cols = ['gender','race/ethnicity','parental level of education','lunch','test preparation course','Performance_Level','High_in','Low_in']
```

```
le_dict = {}# 6) Outlier detection / handling (simple winsorization option)
```

```
for col in ['math score','reading score','writing score','Total_Score','Avg_Score']:
```

```
    q1 = df[col].quantile(0.25)
```

```
    q3 = df[col].quantile(0.75)
```

```
    iqr = q3 - q1
```

```
    lower = q1 - 1.5 * iqr
```

```
    upper = q3 + 1.5 * iqr
```

```
    outliers = df[(df[col] < lower) | (df[col] > upper)]
```

```
    print(f"\{col\} outliers count: {len(outliers)}")
```

```
num_cols = ['math score','reading score','writing score','Total_Score','Avg_Score','Score_Range','Feedback_Length','Sentiment']
```

```
for col in num_cols:
```

```
    low = df[col].quantile(0.01)
```

```
    high = df[col].quantile(0.99)
```

```
    df[col] = np.where(df[col] < low, low, df[col])
```

```
df[col] = np.where(df[col] > high, high, df[col])

for col in cat_cols:

    le = LabelEncoder()

    df[col + '_enc'] = le.fit_transform(df[col].astype(str))

    le_dict[col] = le
```

```
→ math score outliers count: 8
    reading score outliers count: 6
    writing score outliers count: 5
    Total_Score outliers count: 6
    Avg_Score outliers count: 6
```

```
# 7) Save augmented dataset (so you can upload to GitHub)

df.to_csv('StudentsPerformance_augmented.csv', index=False)
```

```
# 8) VISUALIZATIONS
```

```
def save_fig(name):

    plt.tight_layout()

    plt.savefig(f"visuals/{name}.png", dpi=150)

    # plt.close()
```

```
import os

os.makedirs('visuals', exist_ok=True)

# 1) Distribution plots for each subject (hist + KDE) - shows score spread and skewness

plt.figure(figsize=(12,4))

for i, col in enumerate(['math score','reading score','writing score']):

    plt.subplot(1,3,i+1)

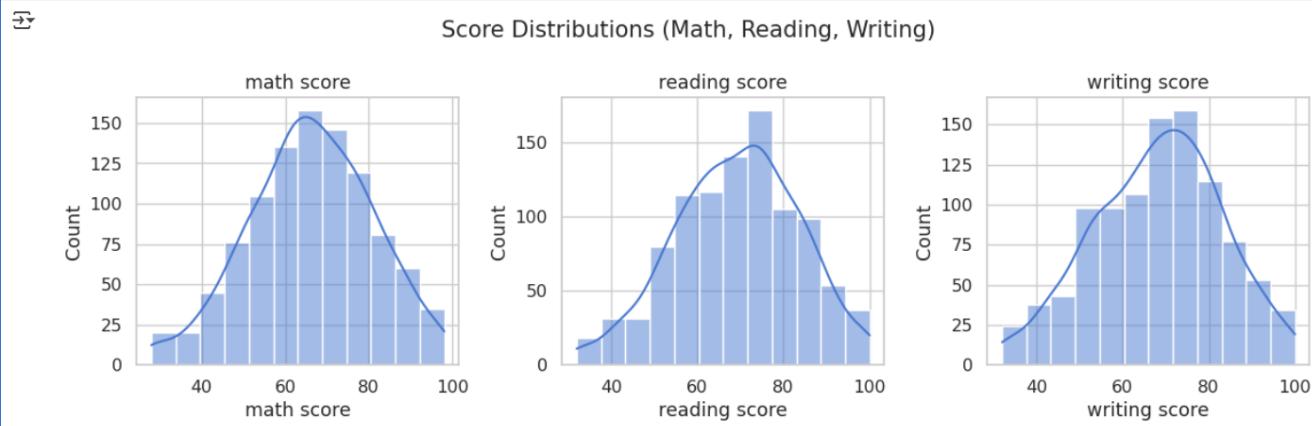
    sns.histplot(df[col], kde=True, bins=12)

    plt.title(col)
```

```
plt.suptitle('Score Distributions (Math, Reading, Writing)')
```

```
save_fig('score_distributions')
```

```
plt.show()
```



```
# 2) Correlation heatmap (numeric only) - shows relationships between numeric features
```

```
plt.figure(figsize=(12,10))
```

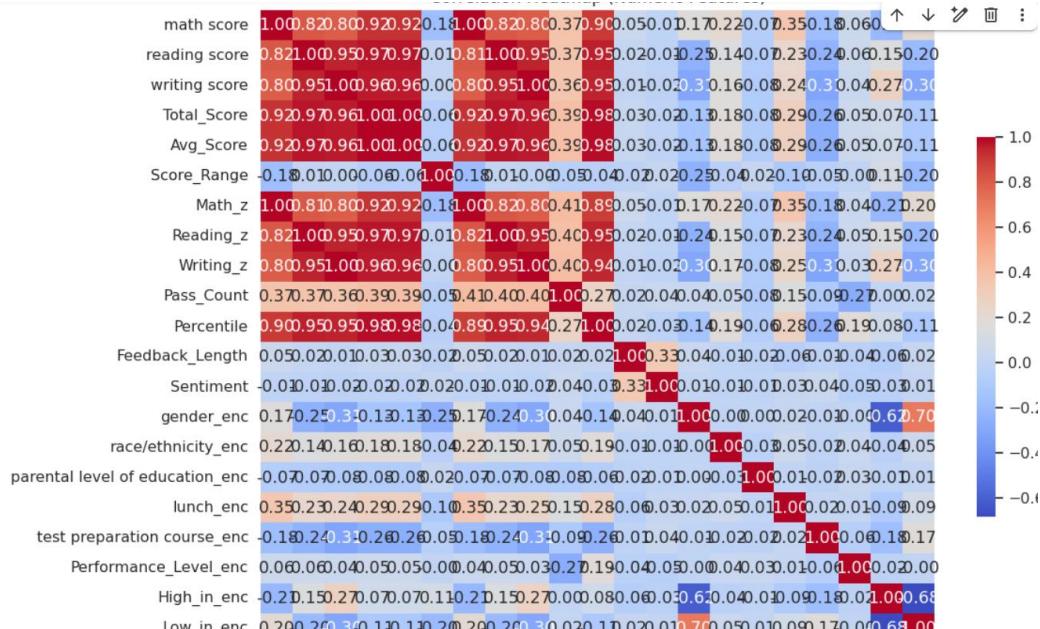
```
num_corr = df.select_dtypes(include='number').corr()
```

```
sns.heatmap(num_corr, annot=True, fmt='.2f', cmap='coolwarm', cbar_kws={'shrink':.6})
```

```
plt.title('Correlation Heatmap (Numeric Features)')
```

```
save_fig('correlation_heatmap')
```

```
plt.show()
```



```
# 3) Boxplots by gender for each subject - shows spread and outliers across genders
```

```
plt.figure(figsize=(12,4))
```

```
for i, col in enumerate(['math score','reading score','writing score']):
```

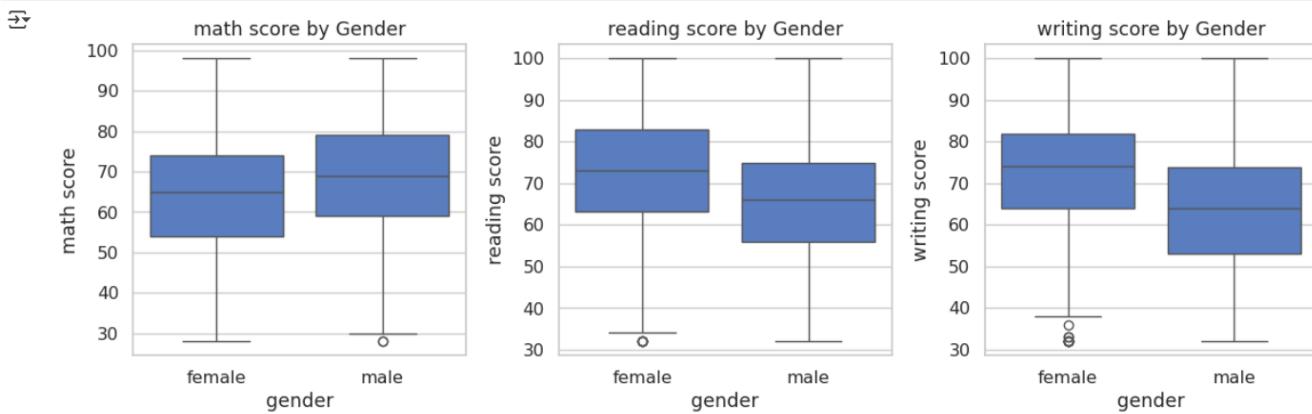
```
    plt.subplot(1,3,i+1)
```

```
    sns.boxplot(x='gender', y=col, data=df)
```

```
    plt.title(f'{col} by Gender")
```

```
save_fig('boxplot_by_gender')
```

```
plt.show()
```



```
# 4) Violin plot: Avg_Score by test preparation course
```

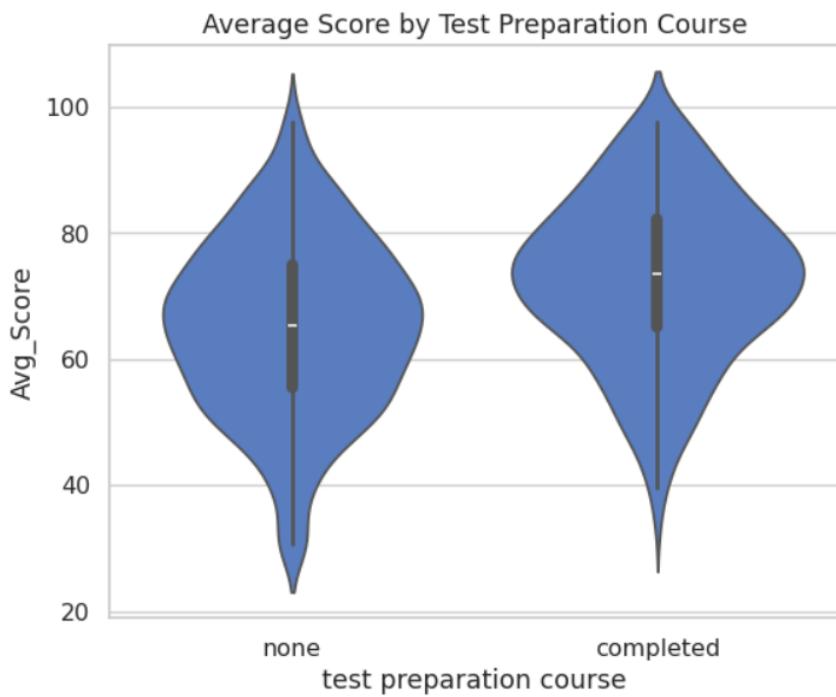
```
plt.figure(figsize=(6,5))
```

```
sns.violinplot(x='test preparation course', y='Avg_Score', data=df)
```

```
plt.title('Average Score by Test Preparation Course')
```

```
save_fig('violin_testprep')
```

```
plt.show()
```



# 5) Countplot: Performance\_Level distribution (categorical) - shows how many fall into each level

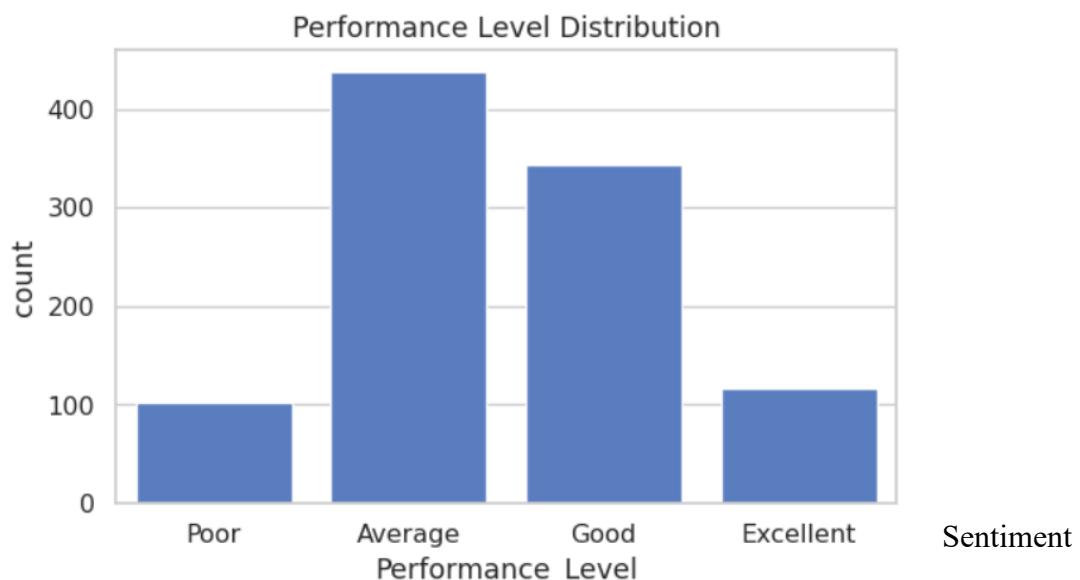
```
plt.figure(figsize=(6,4))

sns.countplot(x='Performance_Level', data=df, order=['Poor','Average','Good','Excellent'])

plt.title('Performance Level Distribution')

save_fig('perf_level_count')

plt.show()
```



distribution (bar/hist) - shows how feedback sentiment is distributed

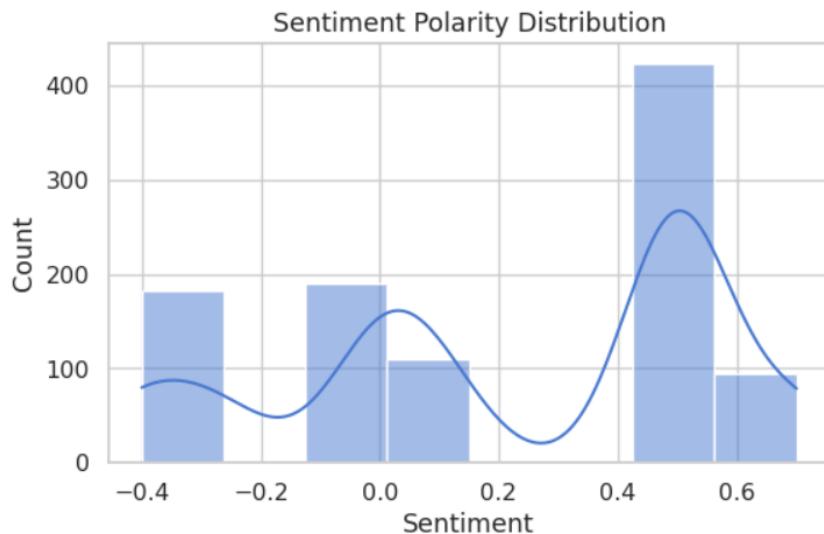
```
plt.figure(figsize=(6,4))

sns.histplot(df['Sentiment'], kde=True, bins=8)

plt.title('Sentiment Polarity Distribution')

save_fig('sentiment_dist')

plt.show()
```



# 8) Scatter: Sentiment vs Total\_Score with hue by Performance\_Level - shows relation between sentiment and performance

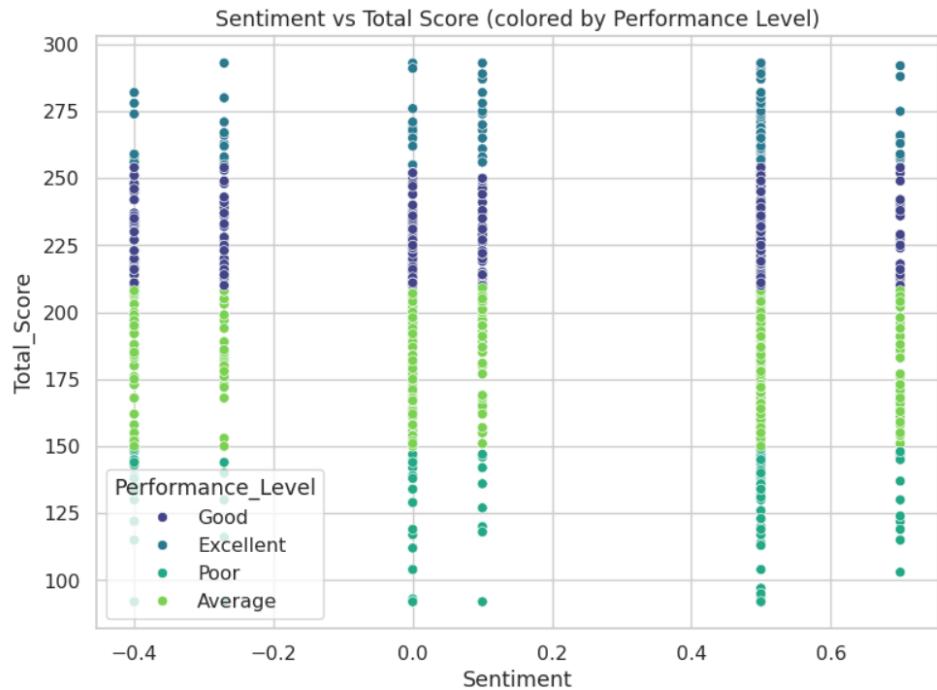
```
plt.figure(figsize=(8,6))

sns.scatterplot(x='Sentiment', y='Total_Score', hue='Performance_Level', data=df, palette='viridis')

plt.title('Sentiment vs Total Score (colored by Performance Level)')

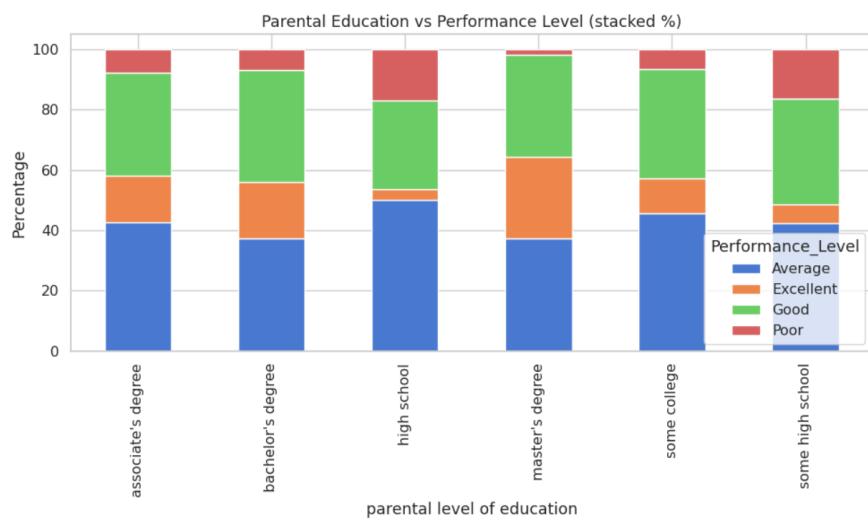
save_fig('sentiment_vs_total')

plt.show()
```



# 10) Stacked bar: parental education vs Performance\_Level (percentage) - categorical cross analysis

```
ct = pd.crosstab(df['parental level of education'], df['Performance_Level'], normalize='index') * 100
ct.plot(kind='bar', stacked=True, figsize=(10,6))
plt.ylabel('Percentage')
plt.title('Parental Education vs Performance Level (stacked %)')
save_fig('parent_edu_vs_perf')
plt.show()
```



```
# 11) Heatmap of average scores by race & lunch (pivot) - multi-factor view
```

```
pivot = df.pivot_table(values='Avg_Score', index='race/ethnicity', columns='lunch', aggfunc='mean')

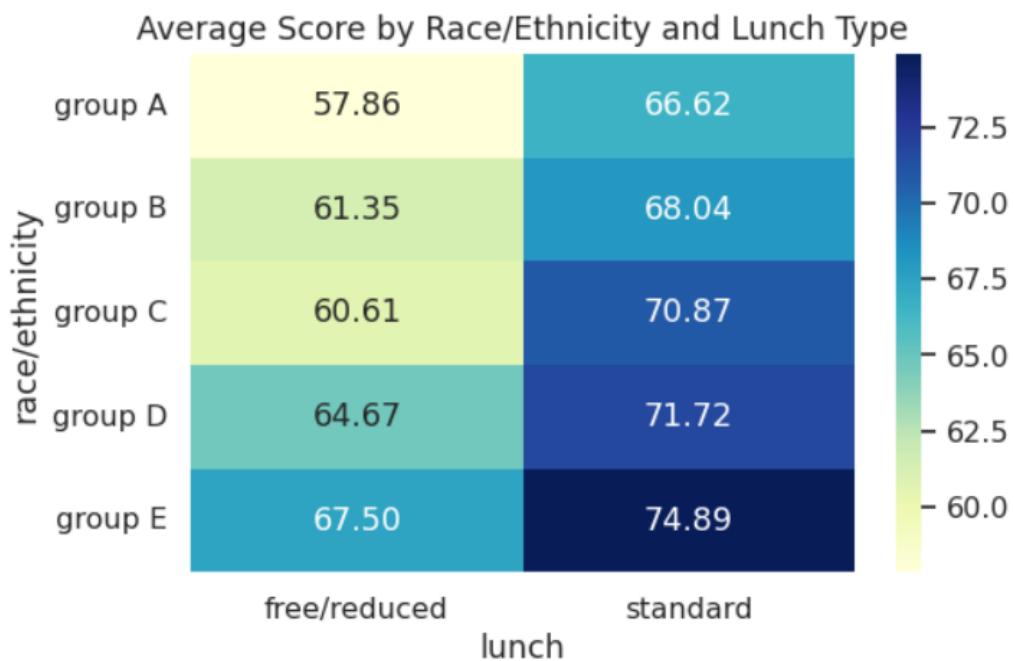
plt.figure(figsize=(6,4))

sns.heatmap(pivot, annot=True, fmt='.2f', cmap='YlGnBu')

plt.title('Average Score by Race/Ethnicity and Lunch Type')

save_fig('pivot_race_lunch')

plt.show()
```



```
# 13) Barplot: Average Total Score by test preparation course
```

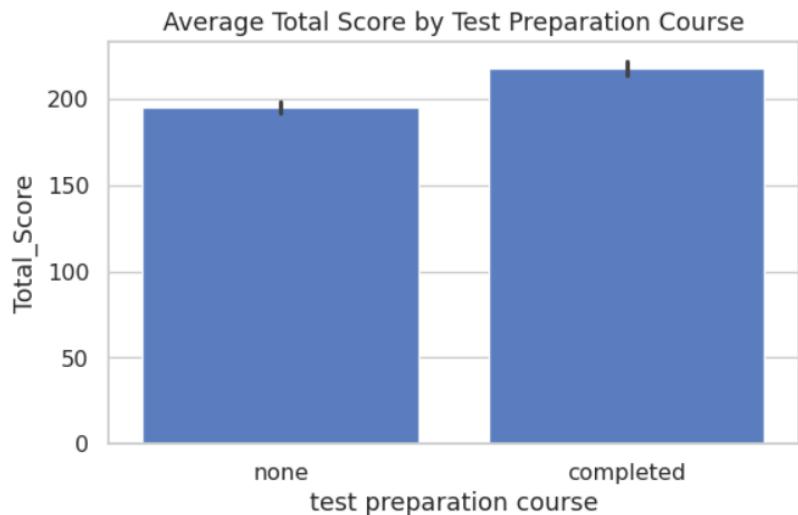
```
plt.figure(figsize=(6,4))

sns.barplot(x='test preparation course', y='Total_Score', data=df, estimator=np.mean)

plt.title('Average Total Score by Test Preparation Course')

save_fig('avg_total_by_testprep')

plt.show()
```



# 9) Scaling and preparing for modeling

```
model_cols = ['math score','reading score','writing
score','Sentiment','Feedback_Length','Score_Range','Percentile']

X = df[model_cols]

y = (df['Avg_Score'] >= df['Avg_Score'].quantile(0.75)).astype(int) # example: top-quartile performer
```

```
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

```
print("Model-ready shapes:", X_train.shape, X_test.shape)
```

---

**Model-ready shapes:** (800, 7) (200, 7)

---

# STEP 10: Deep Learning Model (MLP)

```
import tensorflow as tf
```

```
from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import Dense, Dropout  
from tensorflow.keras.callbacks import EarlyStopping  
from sklearn.metrics import confusion_matrix, classification_report, roc_curve, auc  
import matplotlib.pyplot as plt  
import seaborn as sns  
  
model = Sequential([  
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),  
    Dropout(0.3),  
    Dense(32, activation='relu'),  
    Dropout(0.3),  
    Dense(1, activation='sigmoid')  
])  
  
# Compile the model  
  
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])  
early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)  
history = model.fit(  
    X_train, y_train,  
    validation_data=(X_test, y_test),  
    epochs=50,  
    batch_size=16,  
    callbacks=[early_stop],  
    verbose=1  
)
```

```
Epoch 1/50
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/dense.py:93: UserWarning: Do not pass an `input_shape`,
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
50/50      2s 7ms/step - accuracy: 0.5839 - loss: 0.6675 - val_accuracy: 0.8850 - val_loss: 0.4233
Epoch 2/50
50/50      0s 3ms/step - accuracy: 0.8950 - loss: 0.3774 - val_accuracy: 0.9150 - val_loss: 0.2461
Epoch 3/50
50/50      0s 4ms/step - accuracy: 0.9163 - loss: 0.2372 - val_accuracy: 0.9400 - val_loss: 0.1740
Epoch 4/50
50/50      0s 4ms/step - accuracy: 0.9409 - loss: 0.1619 - val_accuracy: 0.9400 - val_loss: 0.1435
Epoch 5/50
50/50      0s 3ms/step - accuracy: 0.9434 - loss: 0.1364 - val_accuracy: 0.9400 - val_loss: 0.1268
Epoch 6/50
50/50      0s 4ms/step - accuracy: 0.9521 - loss: 0.1138 - val_accuracy: 0.9400 - val_loss: 0.1212
Epoch 7/50
50/50      0s 3ms/step - accuracy: 0.9462 - loss: 0.1085 - val_accuracy: 0.9400 - val_loss: 0.1165
Epoch 8/50
50/50      0s 4ms/step - accuracy: 0.9706 - loss: 0.0836 - val_accuracy: 0.9450 - val_loss: 0.1100
Epoch 9/50
50/50      0s 3ms/step - accuracy: 0.9676 - loss: 0.0867 - val_accuracy: 0.9550 - val_loss: 0.1080
Epoch 10/50
50/50      0s 4ms/step - accuracy: 0.9748 - loss: 0.0734 - val_accuracy: 0.9500 - val_loss: 0.1037
Epoch 11/50
50/50      0s 4ms/step - accuracy: 0.9594 - loss: 0.0898 - val_accuracy: 0.9450 - val_loss: 0.1029
Epoch 12/50
50/50      0s 3ms/step - accuracy: 0.9586 - loss: 0.0911 - val_accuracy: 0.9550 - val_loss: 0.0936
Epoch 13/50
50/50      0s 3ms/step - accuracy: 0.9664 - loss: 0.0798 - val_accuracy: 0.9600 - val_loss: 0.0905
Epoch 14/50
50/50      0s 3ms/step - accuracy: 0.9731 - loss: 0.0639 - val_accuracy: 0.9550 - val_loss: 0.0870
Epoch 15/50
50/50      0s 4ms/step - accuracy: 0.9623 - loss: 0.0791 - val_accuracy: 0.9600 - val_loss: 0.0876
- . . . . .
```

## # STEP 11: Model Evaluation Visualization

### # 1 Loss vs Epoch

```
plt.figure(figsize=(6,4))

plt.plot(history.history['loss'], label='Train Loss')

plt.plot(history.history['val_loss'], label='Val Loss')

plt.title('Loss vs Epochs')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.legend()

plt.show()
```

```
# 2 Accuracy vs Epoch
```

```
plt.figure(figsize=(6,4))

plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')

plt.title('Accuracy vs Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
# 3 Confusion Matrix
```

```
y_pred = (model.predict(X_test) > 0.5).astype(int)

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,4))

sns.heatmap(cm, annot=True, fmt='d', cmap='Greens', cbar=False)

plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
# 4 ROC Curve and AUC
```

```
fpr, tpr, _ = roc_curve(y_test, model.predict(X_test))

roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6,4))

plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.3f}")
```

```

plt.plot([0,1],[0,1],'r--')

plt.title('ROC Curve')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.legend()

plt.show()

```

## # 5 Classification Report

```

print("Classification Report:")

print(classification_report(y_test, y_pred))

```

