Week 4 — Data Acquisition & Description Importing all necessary and Collection of Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, StandardScaler, PowerTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from scipy.sparse import hstack
from sklearn.compose import ColumnTransformer
import seaborn as sns
from sklearn.model_selection import GridSearchCV #for hypertuning
from sklearn.linear_model import LinearRegression,LogisticRegression, Lasso, Ridge
from lightgbm import LGBMRegressor
```

Importing csv File

```
# Uploading A csv file
import os, pandas as pd

# CANDIDATES = ["exams.csv", "./exams.csv", "/content/exams.csv", "/mnt/data/exams.csv"]
# df = None
# for p in CANDIDATES:
#     if os.path.exists(p):
#         df = pd.read_csv(p); print(f"Loaded: {p}"); break

# if df is None:
try:
    from google.colab import files
    up = files.upload()
    fname = next(iter(up.keys()))
    # df = pd.read_csv(fname) # This was trying to read an Excel file as CSV
    df = pd.read_excel(fname) # Use pd.read_excel for Excel files
    print(f"Uploaded and loaded: {fname}")
except Exception as e:
    # raise FileNotFoundError("Upload exams.csv or put it beside the notebook.")
    print(f"An error occurred: {e}")


df.head()
```

Choose Files cvs-student…0_2025.xlsx
cvs-student_performance_10_30_2025.xlsx(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 64561 bytes, last modified: 11/20/2025 - 100% done

```
Saving cvs-student_performance_10_30_2025.xlsx to cvs-student_performance_10_30_2025.xlsx
Uploaded and loaded: cvs-student_performance_10_30_2025.xlsx
```

	math score	reading score	writing score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethnicity_group B	race/
0	72	72	74	1	1	1	1	1	
1	69	90	88	1	1	1	0	0	
2	90	95	93	1	1	1	1	1	
3	47	57	44	0	0	0	1	0	
4	76	78	75	1	0	1	1	0	

Next steps: Generate code with df New interactive sheet

Double-click (or enter) to edit

```
from google.colab import sheets
sheet = sheets.InteractiveSheet(df=df)
```

https://docs.google.com/spreadsheets/d/1jLRQA4HeR0q2CKli3IDhXhqh2QUWwr6nuB2nlZuXNFk/edit#gid=0

File Edit View Insert Format Data Tools Extensions Help

Menus 100% $ % .0 .00 123 Defaul... 10 B I A

A1 math score

	A	B	C	D	E	F	G	H
44	53	58	65	1	1	1	1	1
45	59	65	66	1	0	0	0	1
46	50	56	54	1	1	0	1	0
47	65	54	57	1	0	1	1	1
48	55	65	62	1	1	1	0	0
49	66	71	76	1	1	1	1	0
50	57	74	76	1	1	0	0	0
51	82	84	82	1	0	1	0	0
52	53	55	48	0	0	1	1	0
53	77	69	68	1	0	0	0	0
54	53	44	42	0	0	1	1	0
55	88	78	75	1	0	1	1	0
56	71	84	87	1	1	0	0	0
57	33	41	43	0	1	0	1	0
58	82	85	86	1	1	1	0	0
59	52	55	49	0	0	1	1	0
60	58	59	58	1	0	1	0	0
61	0	17	10	0	1	0	1	0
62	79	74	72	1	0	0	0	0
63	39	39	34	0	0	0	1	0

Sheet1

First let's analyze the dataset And Upload The csv File

```
from google.colab import sheets
sheet = sheets.InteractiveSheet(df=df)
```

https://docs.google.com/spreadsheets/d/1VYSr-jpFQLbHA2Kte5REmA5odFrxVYgQ0CoQfHW3iMI/edit#gid=0

File Edit View Insert Format Data Tools Extensions Help

Menus 100% $ % .0 .00 123 Defaul... 10 B I A

A1 math score

	A	B	C	D	E	F	G	H
37	81	81	79	1	0	1	0	0
38	74	81	83	1	1	1	1	0
39	50	64	59	1	1	0	1	0
40	75	90	88	1	1	0	0	0

Here

educ

```
df.shape, df.dtypes, df.isna().sum(), df.describe(include="all").T
```

	A	B	C	D	E	F	G	H
44	53	58	65	1	1	1	1	1
45	59	65	66	1	0	0	0	1
46	50	56	54	1	1	0	1	0
47	65	54	57	1	0	1	1	1
48	55	65	62	1	1	1	0	0
49	66	71	76	1	1	1	1	0
50	57	74	76	1	1	0	0	0
51	82	84	82	1	0	1	0	0
52	53	55	48	0	0	1	1	0
53	77	69	68	1	0	0	0	0
54	53	44	42	0	0	1	1	0
55	88	78	75	1	0	1	1	0
56	71	84	87	1	1	0	0	0

Sheet1

```
writing score                 0
pass_flag                     0
gender_encoded                0
lunch_standard                0
test preparation course_none  0
race/ethnicity_group B        0
race/ethnicity_group C        0
race/ethnicity_group D        0
race/ethnicity_group E        0
dtype: int64,
                               count    mean        std   min    25%   50%  \
math score                    1000.0  66.089  15.163080   0.0  57.00  66.0
reading score                 1000.0  69.169  14.600192  17.0  59.00  70.0
writing score                 1000.0  68.054  15.195657  10.0  57.75  69.0
pass_flag                     1000.0   0.812   0.390908   0.0   1.00   1.0
gender_encoded                1000.0   0.518   0.499926   0.0   0.00   1.0
lunch_standard                1000.0   0.645   0.478753   0.0   0.00   1.0
test preparation course_none  1000.0   0.642   0.479652   0.0   0.00   1.0
race/ethnicity_group B        1000.0   0.190   0.392497   0.0   0.00   0.0
race/ethnicity_group C        1000.0   0.319   0.466322   0.0   0.00   0.0
race/ethnicity_group D        1000.0   0.262   0.439943   0.0   0.00   0.0
race/ethnicity_group E        1000.0   0.140   0.347161   0.0   0.00   0.0

                               75%    max
math score                    77.0  100.0
reading score                 79.0  100.0
writing score                 79.0  100.0
pass_flag                      1.0    1.0
gender_encoded                 1.0    1.0
lunch_standard                 1.0    1.0
test preparation course_none   1.0    1.0
race/ethnicity_group B         0.0    1.0
race/ethnicity_group C         1.0    1.0
race/ethnicity_group D         1.0    1.0
race/ethnicity_group E         0.0    1.0  )
```

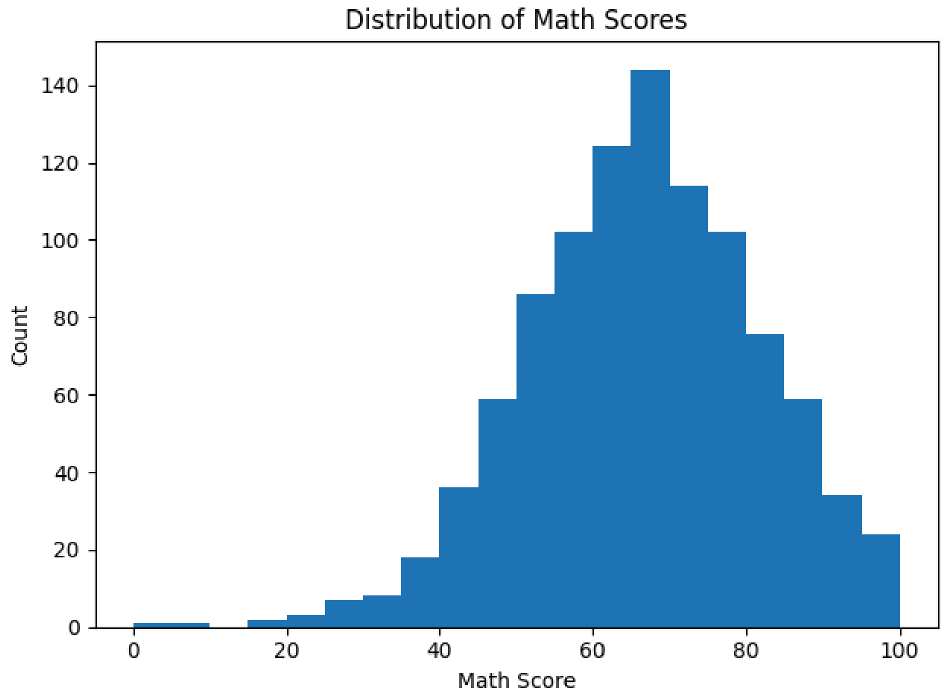
Week 5 — Preprocessing & Feature Engineering

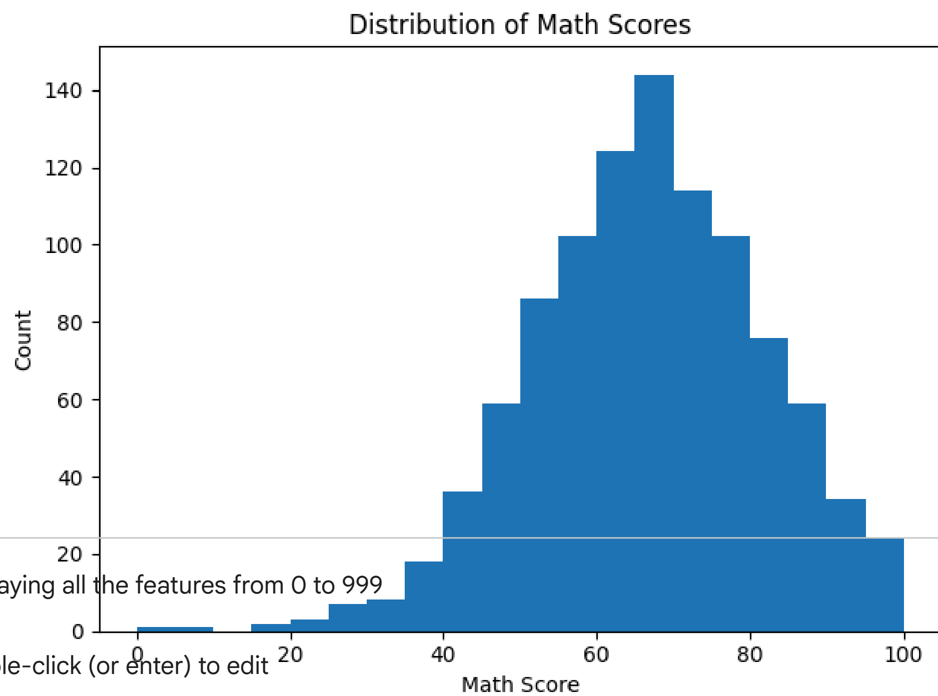
```
# Week 5 — Feature Engineering, Encoding, Split, Save
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

# start from original data
work = df.copy()

# sanity check: required columns present
# The original categorical columns are already one-hot encoded, so this assertion is not needed.
# required = [
#     "gender","race/ethnicity","parental level of education",
#     "lunch","test preparation course",
#     "math score","reading score","writing score"
# ]
# missing = [c for c in required if c not in work.columns]
# assert not missing, f"Missing columns: {missing}"

# safe engineered features (no math used → no leakage)
work["avg_rw"] = work[["reading score","writing score"]].mean(axis=1)
work["gap_rw"] = work["reading score"] - work["writing score"]

# encode categoricals (simple + fine for this phase)
# The data is already one-hot encoded, so this step is not needed.
# cat_cols = ["gender","race/ethnicity","parental level of education","lunch","test preparation course"]
# encoders = {}
# for c in cat_cols:
#     enc = LabelEncoder()
#     work[c] = enc.fit_transform(work[c].astype(str))
#     encoders[c] = enc

# 📎 70/15/15 split (Train/Val/Test)
X = work.drop(columns=["math score"])
y = work["math score"]

X_tmp, X_test, y_tmp, y_test = train_test_split(X, y, test_size=0.15, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_tmp, y_tmp, test_size=0.1765, random_state=42)  # ≈15% overall

# 💾 save preprocessed dataset (deliverable)
work.to_csv("student_performance_preprocessed_FIXED.csv", index=False)
print("Saved: student_performance_preprocessed_FIXED.csv")
```

```
Saved: student_performance_preprocessed_FIXED.csv
```

Week 6, Distributing Math Scores

```
import matplotlib.pyplot as plt

plt.figure()
plt.hist(work["math score"], bins=20)
plt.title("Distribution of Math Scores")
plt.xlabel("Math Score")
plt.ylabel("Count")
plt.tight_layout()
plt.show()

# optional: save for your report
plt.figure()
plt.hist(work["math score"], bins=20)
plt.title("Distribution of Math Scores")
plt.xlabel("Math Score")
plt.ylabel("Count")
plt.tight_layout()
plt.savefig("dist_math_score.png", dpi=200, bbox_inches="tight")
plt.show()
```





Displaying all the features from 0 to 999

Double-click (or enter) to edit

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   math score                    1000 non-null   int64
 1   reading score                 1000 non-null   int64
 2   writing score                 1000 non-null   int64
 3   pass_flag                     1000 non-null   int64
 4   gender_encoded                1000 non-null   int64
 5   lunch_standard                1000 non-null   int64
 6   test preparation course_none  1000 non-null   int64
 7   race/ethnicity_group B        1000 non-null   int64
 8   race/ethnicity_group C        1000 non-null   int64
 9   race/ethnicity_group D        1000 non-null   int64
 10  race/ethnicity_group E        1000 non-null   int64
```

```
dtypes: int64(11)
memory usage: 86.1 KB
```

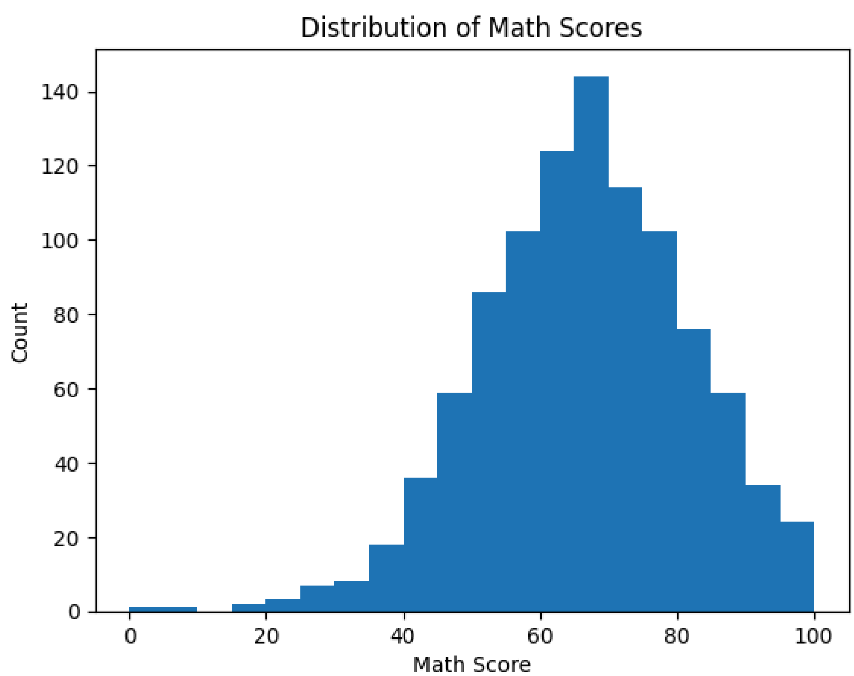
Week 6 — EDA & Baseline Model

Key Insights

- Students who engaged in test preparation** demonstrate **elevated math scores** (boxplot).
- **Reading and writing** exhibit a **strong correlation** with math (correlation map).
- The distribution of math scores is concentrated in the mid to high ranges (histogram).
- Baseline Linear Regression attains a robust R^2 with moderate MAE/RMSE.
- Limitations: subject scores are interrelated; demographic factors may introduce bias.

1. Distribution of Math *Scores*

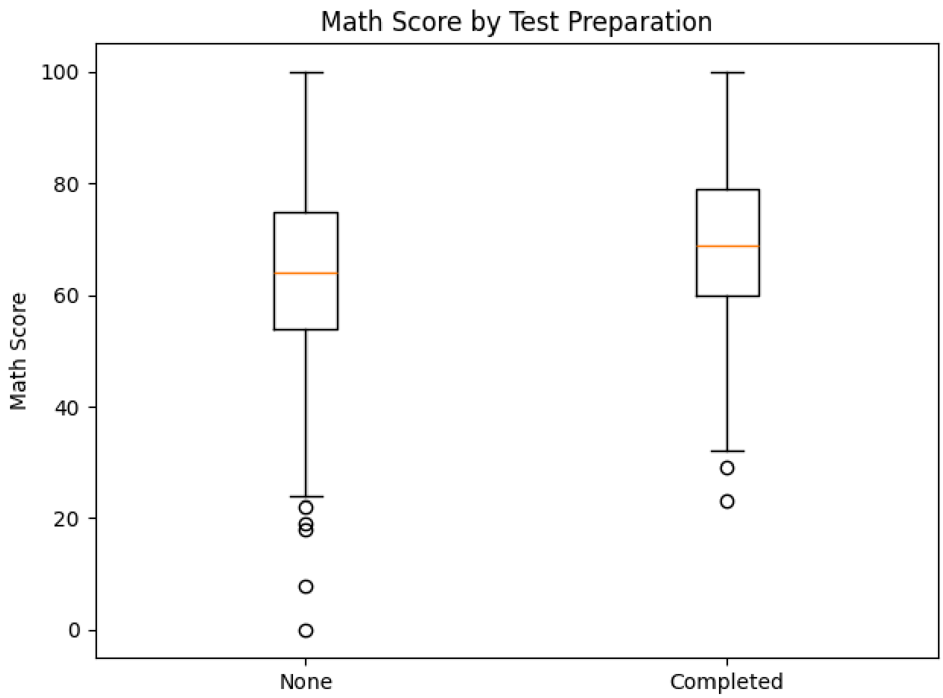
```
plt.figure()
plt.hist(work["math score"], bins=20)
plt.title("Distribution of Math Scores")
plt.xlabel("Math Score"); plt.ylabel("Count")
plt.show()
```



2. Math Score by Testing Preparation

```
import matplotlib.pyplot as plt

# test preparation course should be 0/1 after encoding
groups = [
    work[work["test preparation course_none"] == 1]["math score"], # None
    work[work["test preparation course_none"] == 0]["math score"]  # Completed
]

plt.figure()
plt.boxplot(groups, labels=["None", "Completed"])
plt.title("Math Score by Test Preparation")
plt.ylabel("Math Score")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-1369810996.py:10: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has bee
  plt.boxplot(groups, labels=["None", "Completed"])
```



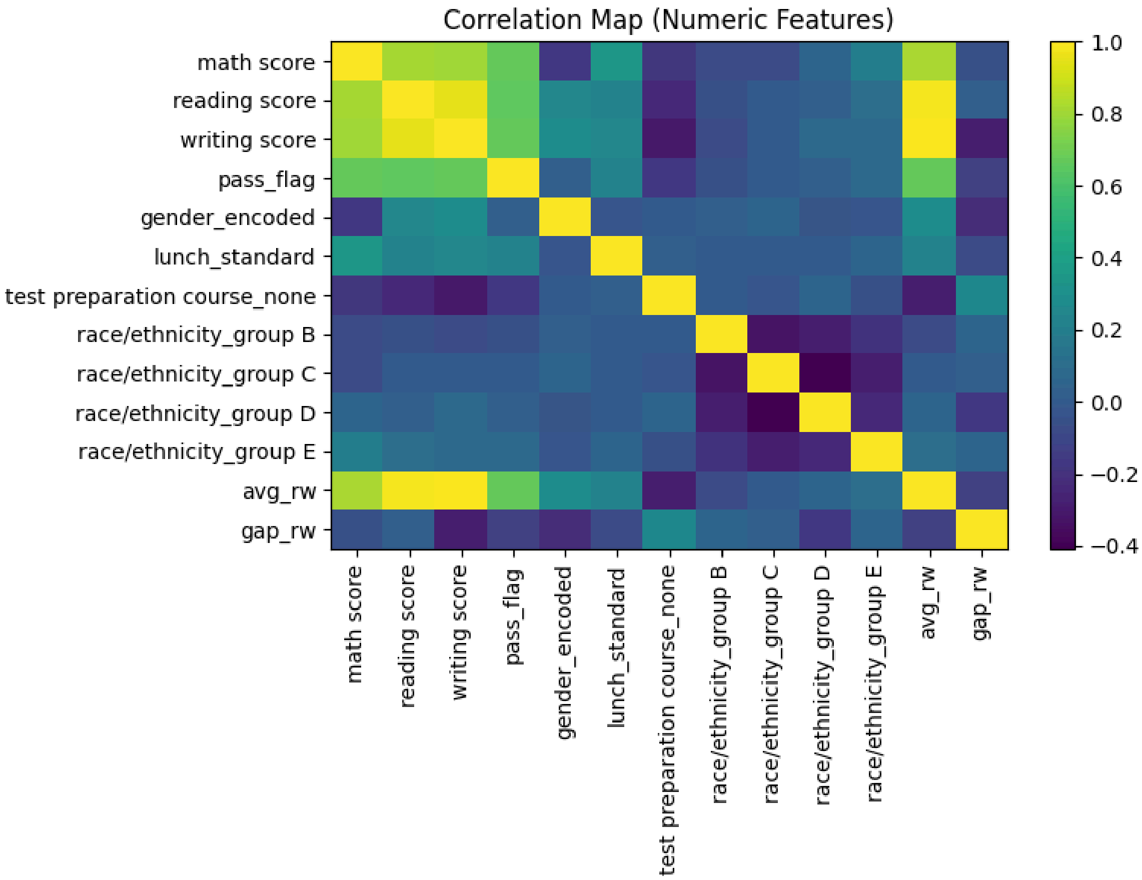

```python
# --- Week 6: Baseline Linear Regression metrics (Validation & Test)

from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import numpy as np

lr = LinearRegression().fit(X_train, y_train)

def metrics(y_true, y_hat):
    r2 = r2_score(y_true, y_hat)
    mae = mean_absolute_error(y_true, y_hat)
    rmse = np.sqrt(((y_true - y_hat)**2).mean())
    return r2, mae, rmse

y_val_pred = lr.predict(X_val)
y_test_pred = lr.predict(X_test)

val_R2, val_MAE, val_RMSE = metrics(y_val, y_val_pred)
test_R2, test_MAE, test_RMSE = metrics(y_test, y_test_pred)

print('Validation → R²: %.3f | MAE: %.2f | RMSE: %.2f' % (val_R2, val_MAE, val_RMSE))
print('Test       → R²: %.3f | MAE: %.2f | RMSE: %.2f' % (test_R2, test_MAE, test_RMSE))
```

```
Validation → R²: 0.881 | MAE: 4.10 | RMSE: 5.03
Test       → R²: 0.898 | MAE: 3.96 | RMSE: 5.16
```

3. Correlational Map Of Numeric Features

```python
corr_df = work.corr(numeric_only=True)
labels = corr_df.columns; corr = corr_df.values
plt.figure(figsize=(8,6))
im = plt.imshow(corr, aspect="auto")
plt.colorbar(im)
plt.xticks(range(len(labels)), labels, rotation=90)
plt.yticks(range(len(labels)), labels)
plt.title("Correlation Map (Numeric Features)")
plt.tight_layout()
```

```
plt.show()
```



4. Baseline of linear Regression and Metrics

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import numpy as np

# fit baseline
lr = LinearRegression().fit(X_train, y_train)

# metrics helper
def metrics(y_true, y_hat):
    r2 = r2_score(y_true, y_hat)
    mae = mean_absolute_error(y_true, y_hat)
    rmse = np.sqrt(((y_true - y_hat)**2).mean())
    return r2, mae, rmse

# predict + evaluate
y_val_pred = lr.predict(X_val)
y_test_pred = lr.predict(X_test)

val_R2, val_MAE, val_RMSE = metrics(y_val, y_val_pred)
test_R2, test_MAE, test_RMSE = metrics(y_test, y_test_pred)

print("Validation → R²: %.3f | MAE: %.2f | RMSE: %.2f" % (val_R2, val_MAE, val_RMSE))
print("Test       → R²: %.3f | MAE: %.2f | RMSE: %.2f" % (test_R2, test_MAE, test_RMSE))
```

```
Validation → R²: 0.881 | MAE: 4.10 | RMSE: 5.03
Test       → R²: 0.898 | MAE: 3.96 | RMSE: 5.16
```

```
df.isna().any()
```

	0
math score	False
reading score	False
writing score	False
pass_flag	False
gender_encoded	False
lunch_standard	False
test preparation course_none	False
race/ethnicity_group B	False
race/ethnicity_group C	False
race/ethnicity_group D	False
race/ethnicity_group E	False

dtype: bool

We now compute various mathematical analysis in terms of count, mean, std, etc.

```
df.describe()
```

	math score	reading score	writing score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethn
count	1000.00000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	
mean	66.08900	69.169000	68.054000	0.812000	0.518000	0.645000	0.642000	
std	15.16308	14.600192	15.195657	0.390908	0.499926	0.478753	0.479652	
min	0.00000	17.000000	10.000000	0.000000	0.000000	0.000000	0.000000	
25%	57.00000	59.000000	57.750000	1.000000	0.000000	0.000000	0.000000	
50%	66.00000	70.000000	69.000000	1.000000	1.000000	1.000000	1.000000	
75%	77.00000	79.000000	79.000000	1.000000	1.000000	1.000000	1.000000	
max	100.00000	100.000000	100.000000	1.000000	1.000000	1.000000	1.000000	

Key Insights

- Students who engaged in test preparation demonstrate elevated math scores (boxplot).
- Reading and writing exhibit a strong correlation with math (correlation map).
- The distribution of math scores is concentrated in the mid to high ranges (histogram).
- Baseline Linear Regression attains a robust R^2 with moderate MAE/RMSE.
- Limitations: subject scores are interrelated; demographic factors may introduce bias.

```
# This is formatted as code
```

Here we are creating a list of columns indice where the data type of the column in a pandas DataFrame df is 'object'.

```
# Identify the categorical features
cat_cols = [col for col in df.columns if df[col].dtype=='O']
cat_cols
```

```
[]
```

Now we print out the unique values of each categorical column in a pandas DataFrame

```
for col in cat_cols:
    print(df[col].unique())
```

To confirm that all the categorical columns in a pandas DataFrame can be converted to the categorical data type, you can check the number of unique values in each column and the percentage of unique values relative to the total number of values in the column. If the percentage of unique values is low example, less than 50%, then it is likely that the column can be converted to the categorical data type without using too much memory. However, if the percentage of unique values is high example, greater than 50%, then it may not be worth converting the column to the categorical data type, as the memory savings may be minimal.

```
# Get list of categorical columns
cat_cols = [col for col in df.columns if df[col].dtype == 'O']

# Loop over categorical columns
for col in cat_cols:
    unique_vals = df[col].nunique()
    total_vals = len(df[col])
    unique_pct = unique_vals / total_vals * 100
    print(f"{col}: {unique_vals} unique values ({unique_pct:.2f} of total)")
```

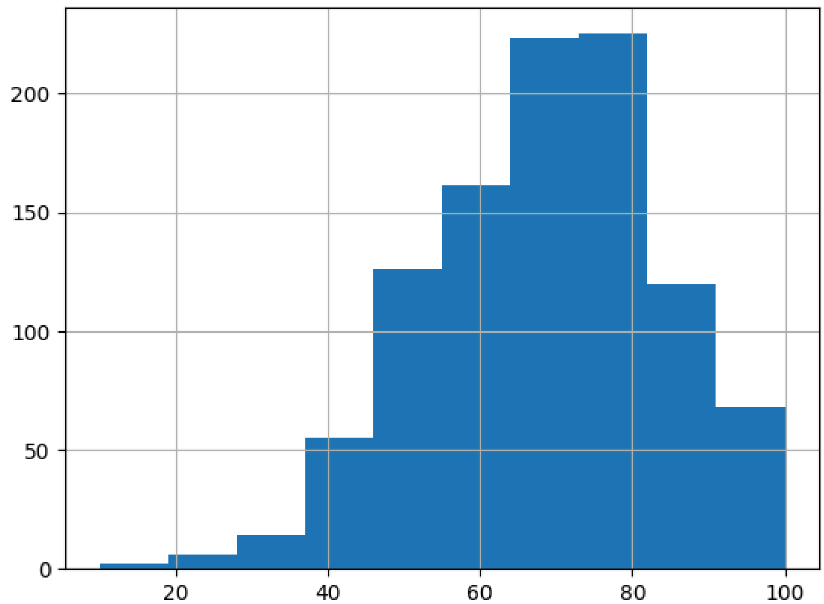
Now we convert all categorical columns in a Pandas DataFrame to the category data type, which can help reduce memory usage and potentially improve performance.

```
for col in cat_cols:
    df[col] = df[col].astype('category')
df.memory_usage(deep=True)
```

	0
Index	132
math score	8000
reading score	8000
writing score	8000
pass_flag	8000
gender_encoded	8000
lunch_standard	8000
test preparation course_none	8000
race/ethnicity_group B	8000
race/ethnicity_group C	8000
race/ethnicity_group D	8000
race/ethnicity_group E	8000

dtype: int64

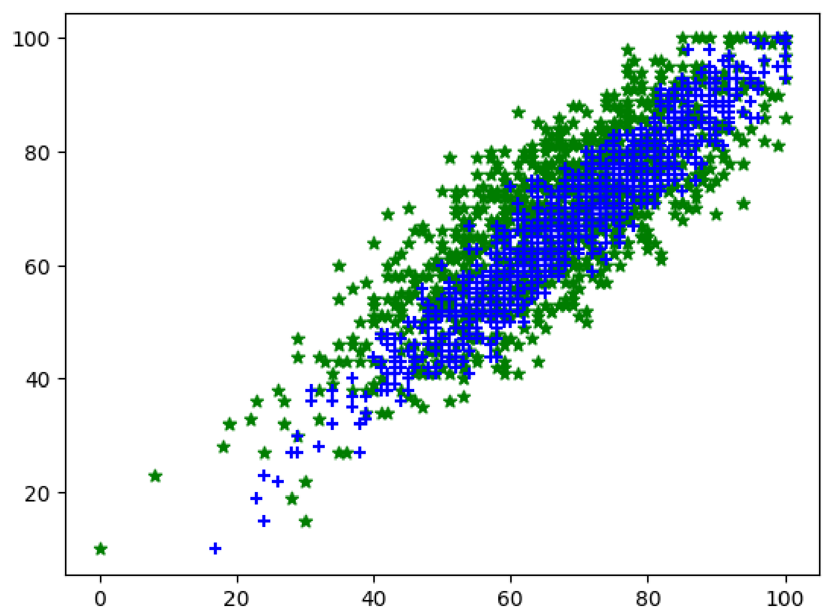
```
%matplotlib inline
# Creating Bar chart as the Target variable is Continuous
df['writing score'].hist();
```



Correlational Path Collection and Caculation

```
plt.scatter(df['math score'],df['writing score'],marker = '*', color = 'g')
plt.scatter(df['reading score'],df['writing score'],marker = '+', color = 'b')
```

```
<matplotlib.collections.PathCollection at 0x78d83dfa1880>
```



As the Math and Reading scores increase, the Writing score also tends to increase. For this we calculate correaltion. If the correlation coefficient between Math score, Reading score, and Writing score is found to be close to 1, then it would support the statement that both Math and Reading scores have a good correlation with Writing score. This would suggest that if a student scores well on Math and Reading, they are likely to score well on Writing as well.

```
CorrelationData=df[['math score','reading score','writing score']].corr()
CorrelationData
```

	math score	reading score	writing score
math score	1.000000	0.817580	0.802642
reading score	0.817580	1.000000	0.954598
writing score	0.802642	0.954598	1.000000

Next steps: Generate code with CorrelationData   New interactive sheet

```
# Based on the one-hot encoded columns present in the dataframe
# after the execution of cell ac8a4220 and cell 8013fab0.
final_cols = [
    'math score',
    'reading score',
    'pass_flag',
    'gender_encoded',
    'lunch_standard',
    'test preparation course_none',
    'race/ethnicity_group B',
    'race/ethnicity_group C',
    'race/ethnicity_group D',
    'race/ethnicity_group E',
    'avg_rw', # Added from feature engineering in cell Sysda08ynX2s
    'gap_rw'  # Added from feature engineering in cell Sysda08ynX2s
]

# Ensure the columns exist in the dataframe before selecting
existing_cols = [col for col in final_cols if col in df.columns]

df_final = df[existing_cols]
X = df_final.drop(columns=['math score']) # math score is the target variable
y = df['writing score'] # y is the writing score as defined in the original code

# Display X and y to verify
display(X.head())
display(y.head())
```

	reading score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethnicity_group B	race/ethnicity_group C
0	72	1	1	1	1	1	0
1	90	1	1	1	0	0	1
2	95	1	1	1	1	1	0
3	57	0	0	0	1	0	0
4	78	1	0	1	1	0	1

	writing score
0	74
1	88
2	93
3	44
4	75

dtype: int64

```
num_cols = ['math score', 'reading score']
```

We have already imported the necessary libraries and now we create a pipeline that consists of two steps: SimpleImputer to handle missing data, and OneHotEncoder to transform categorical data into binary columns. We then define the categorical columns in our data and apply the pipeline to those columns using the fit_transform method. Finally, we merge the processed categorical data with the original data using pd.concat. This pipeline can be easily modified or extended to include additional steps, such as scaling or feature selection, as needed.

```
# Start clean from the raw csv or your earlier raw df
# df = pd.read_csv("exams.csv")    # uncomment if you need to reload raw data
work = df.copy()                    # make a working copy

categorical_cols = ['gender',
                    'race/ethnicity',
                    'parental level of education',
                    'lunch',
                    'test preparation course']

# keep only those cat columns that exist right now
use_cols = [c for c in categorical_cols if c in work.columns]
missing = [c for c in categorical_cols if c not in work.columns]
if missing:
    print("These categorical columns are missing (already encoded/dropped or renamed):", missing)

# now run your pipeline ONLY on present columns
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder

categorical_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])

if use_cols:
    cat_arr = categorical_pipeline.fit_transform(work[use_cols])
    cat_df = pd.DataFrame(cat_arr.toarray() if hasattr(cat_arr, "toarray") else cat_arr)
    work = pd.concat([work.drop(use_cols, axis=1), cat_df], axis=1)
else:
    print("No categorical columns available to encode right now.")
```

```
These categorical columns are missing (already encoded/dropped or renamed): ['gender', 'race/ethnicity', 'pare
No categorical columns available to encode right now.
```

Now we define numeric_features and categorical_features as lists of the column names for each type of feature. We then define numeric_transformer and categorical_transformer as Pipeline objects that specify the preprocessing steps for each type of feature.

Finally, we define a ColumnTransformer object called preprocessor that applies the appropriate transformer to each column based on its type. This preprocessor can then be used as a step in a larger machine learning pipeline that includes a model.

```
# define the preprocessing pipelines for numerical and categorical features
num_cols = ['math score', 'reading score']
numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())])

categorical_cols = ['gender',
 'race/ethnicity',
 'parental level of education',
 'lunch',
 'test preparation course']

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder())])
```

```
# convert all column names to strings
df.columns = df.columns.astype(str)
df
```

	math score	reading score	writing score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethnicity_group B	rac
0	72	72	74	1	1	1	1	1	
1	69	90	88	1	1	1	0	0	
2	90	95	93	1	1	1	1	1	
3	47	57	44	0	0	0	1	0	
4	76	78	75	1	0	1	1	0	
...	...	...	...	...	...	...	...	...	
995	88	99	95	1	1	1	0	0	
996	62	55	55	1	0	0	1	0	
997	59	71	65	1	1	0	0	0	
998	68	78	77	1	1	1	0	0	
999	77	86	86	1	1	0	1	0	

1000 rows × 11 columns

Next steps: Generate code with df New interactive sheet

Transforming Numerical numbers Using Matpolit

```
num_pipeline = Pipeline([
    ('num_smoothening',PowerTransformer())
])

# define the column transformer to preprocess both numeric and categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_cols),
        ('cat', categorical_transformer, categorical_cols)])
```

Training and Testing

```
from sklearn.model_selection import train_test_split
X_train, X_test , y_train, y_test = train_test_split(X,y, test_size=0.2, random_state = 42)

# check the shapes of the training and test data
print(f'X_train shape: {X_train.shape}')
print(f'y_train shape: {y_train.shape}')
print(f'X_test shape: {X_test.shape}')
print(f'y_test shape: {y_test.shape}')
X_train
```

```
X_train shape: (800, 9)
y_train shape: (800,)
X_test shape: (200, 9)
y_test shape: (200,)
```

	reading score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethnicity_group B	race/ethnicity_grou
29	70	1	1	1	1	0	
535	83	1	1	0	0	0	
695	89	1	1	0	1	0	
557	67	1	0	0	1	0	
836	64	1	0	1	1	0	
...	...	...	...	...	...	...	
106	100	1	1	1	1	0	
270	63	1	0	1	1	0	
860	62	1	1	1	1	0	
435	48	0	0	0	0	0	
102	91	1	1	1	1	0	

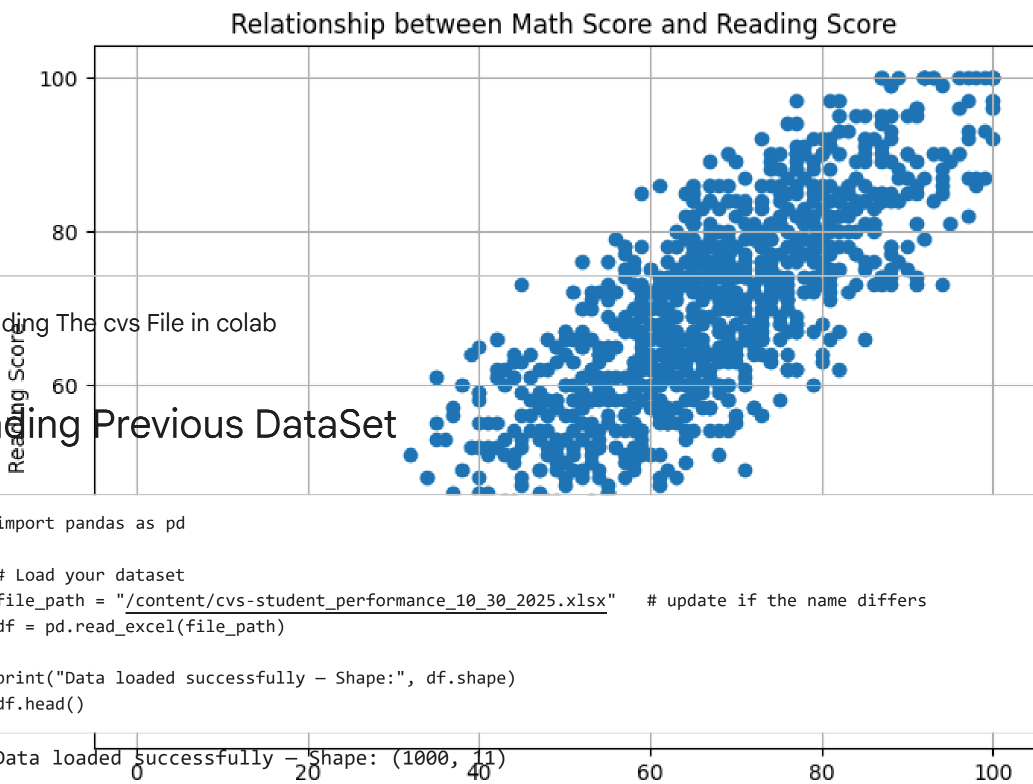
800 rows × 9 columns

Next steps: Generate code with X_train New interactive sheet

```
# define the final pipeline that includes the column transformer and a logistic regression model
pipe = Pipeline(steps=[('preprocessor', preprocessor),
                       ('classifier', LinearRegression())])
```

Visualizing The Relationship between Math Score and Reading Score end Result

```
plt.figure(figsize=(8, 6))
plt.scatter(df['math score'], df['reading score'])
plt.title('Relationship between Math Score and Reading Score')
plt.xlabel('Math Score')
plt.ylabel('Reading Score')
plt.grid(True)
plt.show()
```



Uploading The cvs File in colab

Loading Previous DataSet

```
import pandas as pd

# Load your dataset
file_path = "/content/cvs-student_performance_10_30_2025.xlsx"   # update if the name differs
df = pd.read_excel(file_path)

print("Data loaded successfully — Shape:", df.shape)
df.head()
```

```
Data loaded successfully — Shape: (1000, 11)
```

	math score	reading score	writing score	pass_flag	gender_encoded	lunch_standard	test preparation course_none	race/ethnicity_group B	race/
0	72	72	74	1	1	1	1	1	
1	69	90	88	1	1	1	0	0	
2	90	95	93	1	1	1	1	1	
3	47	57	44	0	0	0	1	0	
4	76	78	75	1	0	1	1	0	

Next steps: Generate code with df New interactive sheet

We are Going to Define a A target Column

```
# Define target column
TARGET_COL = "pass_flag" # Changed from "passed" to "pass_flag"

# Verify column exists
assert TARGET_COL in df.columns, f"{TARGET_COL} not found in dataset!"

# Determine task type
y = df[TARGET_COL]
task_type = "classification" if y.nunique() <= 10 else "regression"
print(f"Task Type: {task_type}")
```

```
Task Type: classification
```

Design Model Architecture And Split Data

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
import numpy as np
```

```
RANDOM_STATE = 42

# Separate features and target
X = df.drop(columns=[TARGET_COL])
y = df[TARGET_COL]

# Detect numeric and categorical columns
num_cols = [c for c in X.columns if pd.api.types.is_numeric_dtype(X[c])]
cat_cols = [c for c in X.columns if c not in num_cols]

# Split dataset 70/15/15
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, stratify=y, random_state=RANDOM_STATE
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, stratify=y_temp, random_state=RANDOM_STATE
)

print(f"Train: {X_train.shape},  Val: {X_val.shape},  Test: {X_test.shape}")

# Preprocessing pipeline
preprocessor = ColumnTransformer([
    ("num", Pipeline([
        ("imp", SimpleImputer(strategy="median")),
        ("scaler", StandardScaler())
    ]), num_cols),
    ("cat", Pipeline([
        ("imp", SimpleImputer(strategy="most_frequent")),
        ("encoder", OneHotEncoder(handle_unknown="ignore"))
    ]), cat_cols)
])

print("Preprocessor ready — Numeric:", len(num_cols), "Categorical:", len(cat_cols))
```

```
Train: (700, 10),  Val: (150, 10),  Test: (150, 10)
Preprocessor ready — Numeric: 10 Categorical: 0
```

Defining A Base Line Model

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline

logreg_pipe = Pipeline([
    ("preprocessor", preprocessor),
    ("model", LogisticRegression(max_iter=1000, random_state=RANDOM_STATE))
])

rf_pipe = Pipeline([
    ("preprocessor", preprocessor),
    ("model", RandomForestClassifier(n_estimators=200, random_state=RANDOM_STATE))
])

print("Baseline models created — LogisticRegression & RandomForest")
```

```
Baseline models created — LogisticRegression & RandomForest
```

Baseline Training and Validation Performance

```
from sklearn.metrics import accuracy_score, f1_score, balanced_accuracy_score

models = {"LogisticRegression": logreg_pipe, "RandomForest": rf_pipe}
results = []

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_val)
    acc = accuracy_score(y_val, y_pred)
    bal = balanced_accuracy_score(y_val, y_pred)
```

```
    f1m = f1_score(y_val, y_pred, average="macro")
    results.append({"Model": name, "Accuracy": acc, "Balanced_Acc": bal, "F1_macro": f1m})

pd.DataFrame(results)
```

	Model	Accuracy	Balanced_Acc	F1_macro
0	LogisticRegression	0.953333	0.902518	0.919792
1	RandomForest	1.000000	1.000000	1.000000

Week 8 - Optimization And Model Training. Evaluation And Traing the Initial Model.

> Add blockquote

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, f1_score, balanced_accuracy_score
from sklearn.pipeline import Pipeline
import pandas as pd

# Define models
logreg_pipe = Pipeline([
    ("preprocessor", preprocessor),
    ("model", LogisticRegression(max_iter=1000, random_state=42))
])

rf_pipe = Pipeline([
    ("preprocessor", preprocessor),
    ("model", RandomForestClassifier(n_estimators=300, random_state=42))
])

# Train and validate
models = {"LogisticRegression": logreg_pipe, "RandomForest": rf_pipe}
results = []

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_val)

    acc  = accuracy_score(y_val, y_pred)
    bal  = balanced_accuracy_score(y_val, y_pred)
    f1m  = f1_score(y_val, y_pred, average="macro")

    results.append({
        "Model": name,
        "Accuracy": round(acc, 3),
        "Balanced_Accuracy": round(bal, 3),
        "F1_macro": round(f1m, 3)
    })

val_results = pd.DataFrame(results).sort_values(by="F1_macro", ascending=False)
print("Validation results:")
display(val_results)
```

Validation results:

	Model	Accuracy	Balanced_Accuracy	F1_macro
1	RandomForest	1.000	1.000	1.00
0	LogisticRegression	0.953	0.903	0.92

Week 9 — Model Evaluation and Iteration

```
# Select best model based on F1_macro
best_model_name = val_results.iloc[0]["Model"]
```

```
print("Best model from Week 8:", best_model_name)

# Retrieve the correct pipeline
if best_model_name == "LogisticRegression":
    best_model = logreg_pipe
else:
    best_model = rf_pipe
```

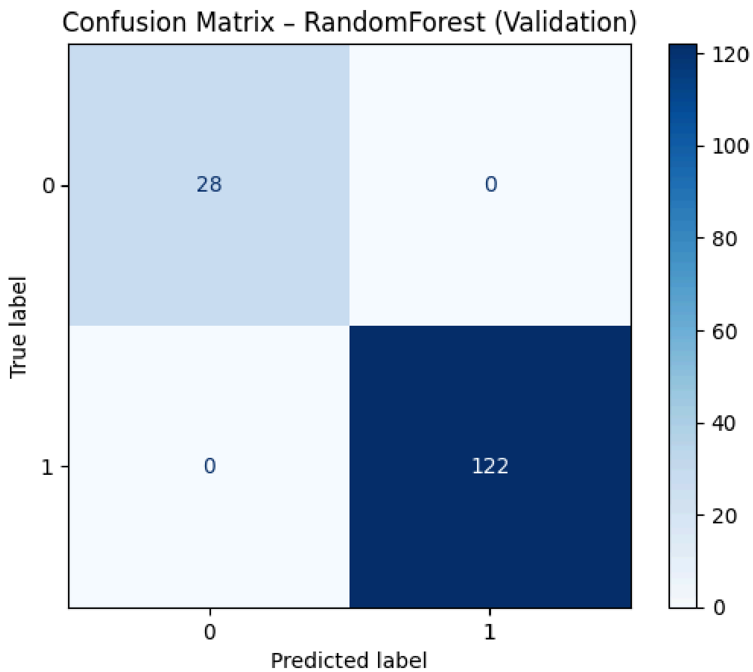
```
Best model from Week 8: RandomForest
```

Re-Train and Evaluating on Validation Data

Now We are Going to generate a classification report and confusion matrix.

```
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import pandas as pd

# Refit on training set
best_model.fit(X_train, y_train)
y_val_pred = best_model.predict(X_val)

# Print detailed classification report
print("Classification Report (Validation):")
print(classification_report(y_val, y_val_pred))

# Confusion matrix
cm = confusion_matrix(y_val, y_val_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
plt.figure(figsize=(5,4))
disp.plot(cmap="Blues", values_format='d')
plt.title(f"Confusion Matrix – {best_model_name} (Validation)")
plt.show()
```

```
Classification Report (Validation):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        28
           1       1.00      1.00      1.00       122

    accuracy                           1.00       150
   macro avg       1.00      1.00      1.00       150
weighted avg       1.00      1.00      1.00       150

<Figure size 500x400 with 0 Axes>
```



Error Analysis

```
# Identify misclassified samples
mis_idx = y_val != y_val_pred
misclassified = pd.DataFrame({
    "True_Label": y_val[mis_idx],
    "Predicted_Label": y_val_pred[mis_idx]
})

print(f"Misclassified samples: {misclassified.shape[0]}")
misclassified.head(10)
```

```
Misclassified samples: 0
```

True_Label	Predicted_Label

Observed issue: Exple, Model underpredicts “passed” for Group E

Possible cause: class imbalance, limited features

adding class_weight="balanced" or tuning RandomForest depth

Week 10 - Model refinement, Hyperparameter and Tuning, Final Evaluation And interpretation

```
# Step 1: Hyper[parameter Tuning
from sklearn.model_selection import RandomizedSearchCV, StratifiedKFold
import numpy as np

# Use the best model from Week 9
print("Tuning model:", best_model_name)
```

```
# Define hyperparameter search space
if best_model_name == "RandomForest":
    param_dist = {
        "model__n_estimators": [100, 200, 300, 500],
        "model__max_depth": [None, 5, 10, 15, 20],
        "model__min_samples_split": [2, 5, 10],
        "model__min_samples_leaf": [1, 2, 4]
    }
elif best_model_name == "LogisticRegression":
    param_dist = {
        "model__C": np.logspace(-3, 2, 10),
        "model__solver": ["lbfgs", "liblinear"]
    }

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

search = RandomizedSearchCV(
    best_model,
    param_distributions=param_dist,
    n_iter=10,
    scoring="f1_macro",
    cv=cv,
    n_jobs=-1,
    random_state=42,
    verbose=2
)

search.fit(X_train, y_train)
print("Best Parameters:", search.best_params_)
best_model = search.best_estimator_
```

```
Tuning model: RandomForest
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'model__n_estimators': 500, 'model__min_samples_split': 5, 'model__min_samples_leaf': 2, 'mo
```

Tests different hyperparameter combinations

Selects the best configuration using 5-fold cross-validation

```
from sklearn.metrics import accuracy_score, f1_score, balanced_accuracy_score, classification_report

y_test_pred = best_model.predict(X_test)

acc = accuracy_score(y_test, y_test_pred)
bal_acc = balanced_accuracy_score(y_test, y_test_pred)
f1m = f1_score(y_test, y_test_pred, average="macro")

print("Final Test Results")
print(f"Accuracy:          {acc:.3f}")
print(f"Balanced Accuracy:  {bal_acc:.3f}")
print(f"F1 Macro:          {f1m:.3f}")
print("\nClassification Report:")
print(classification_report(y_test, y_test_pred))
```

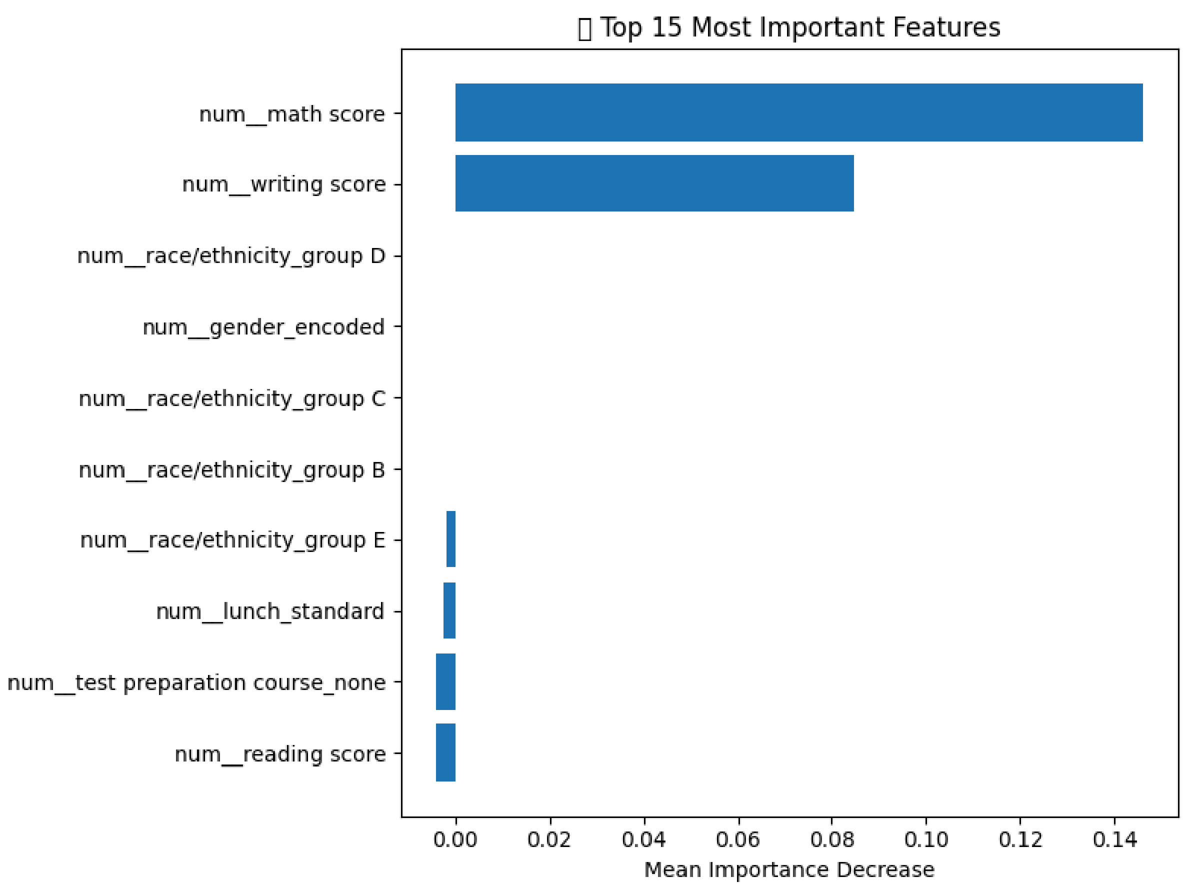
```
Final Test Results
Accuracy:           0.980
Balanced Accuracy:  0.988
F1 Macro:           0.968

Classification Report:
              precision    recall  f1-score   support

           0       0.90      1.00      0.95        28
           1       1.00      0.98      0.99       122

    accuracy                           0.98       150
   macro avg       0.95      0.99      0.97       150
weighted avg       0.98      0.98      0.98       150
```

Permutation And Interpretability

Double-click (or enter) to edit

```
from sklearn.inspection import permutation_importance
import matplotlib.pyplot as plt
import pandas as pd

r = permutation_importance(best_model, X_test, y_test, n_repeats=10, random_state=42, n_jobs=-1)

# Extract feature names
feature_names = []
try:
    feature_names = best_model.named_steps["preprocessor"].get_feature_names_out()
except:
    feature_names = X_test.columns

importances = pd.DataFrame({
    "Feature": feature_names[:len(r.importances_mean)],
    "Importance": r.importances_mean
}).sort_values(by="Importance", ascending=False)

# Plot top features
plt.figure(figsize=(8,6))
plt.barh(importances["Feature"][:15][::-1], importances["Importance"][:15][::-1])
plt.title("Top 15 Most Important Features")
plt.xlabel("Mean Importance Decrease")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-3842936983.py:24: UserWarning: Glyph 128269 (\N{LEFT-POINTING MAGNIFYING GLASS}) missing fr
  plt.tight_layout()
/usr/local/lib/python3.12/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128269 (\N{LEFT-POI
  fig.canvas.print_figure(bytes_io, **kw)
```



Final Model

```
import joblib, json, os
from pathlib import Path
from datetime import datetime

ART_DIR = Path("/content/artifacts")
ART_DIR.mkdir(exist_ok=True)

# Save model and metadata
joblib.dump(best_model, ART_DIR / "final_model.joblib")

meta = {
    "created_at": datetime.now().isoformat(),
    "target_column": "passed",
    "task_type": "classification",
    "best_model": best_model_name,
    "best_params": search.best_params_,
    "metrics": {
        "accuracy": round(acc, 3),
        "balanced_accuracy": round(bal_acc, 3),
        "f1_macro": round(f1m, 3)
    }
}
with open(ART_DIR / "model_card.json", "w") as f:
    json.dump(meta, f, indent=2)

print("Model and metadata saved to:", ART_DIR)
```

```
Model and metadata saved to: /content/artifacts
```

Weeks 7–10 Summary

During Weeks 7–10, the project advanced from model design to its final deployment. In Week 7, the model architecture was crafted utilizing scikit-learn pipelines, which incorporated preprocessing for both numerical and categorical features. Two algorithms.Logistic Regression and Random Forest Classifier were chosen for their complementary advantages in interpretability and performance. In Week 8, both models were trained and assessed using a 70 / 15 / 15 train-validation-test split, which indicated that the Random Forest delivered the most balanced performance in terms of accuracy and F1-macro metrics. Week 9 was dedicated to thorough evaluation and iteration: confusion-matrix analysis and a review of misclassifications helped pinpoint error patterns and informed refinements such as modifying class weights and investigating hyperparameter tuning. Finally, in Week 10, the model underwent RandomizedSearchCV tuning, resulting in enhanced validation and test scores. Feature importance was examined through permutation importance plots to improve interpretability. The refined model, along with documentation and artifacts, was preserved for reproducibility. Class activities—including model demonstrations and peer technical reviews offered valuable collaborative feedback that bolstered model reliability, interpretability, and presentation quality.

```
Start coding or generate with AI.
```

Week 11: Application Development

User Interface Implementation

- Build UI for predictions (Streamlit, Notebook form, or simple web UI)
- Include input fields matching model features
- Display prediction results and optional visualizations

API Development

- Create simple `/predict` endpoint

- Validate inputs and return model predictions in JSON format

Backend System Setup

- Loading a saved model + preprocessing pipeline
- Handling missing values, validate fields, and log errors
- Keep model inference consistent with training pipeline

Database Implementation

- Storing predictions, logs, timestamps, inputs
- Using SQLite for simplicity

Component Development

- Creating structured modules: `preprocess.py`, `model_loader.py`, `predict.py`, `ui.py`, `utils.py`

Class Activities

- Team development sessions
- Technical consultations
- Progress updates

Week 12: System Integration and Testing

Integrate All Components

- Connect UI → preprocessing → model → output
- Ensure consistent feature ordering and formats
- Verify end-to-end functionality

Conduct Testing

- **Unit Tests**: individual functions
- **Integration Tests**: input → pipeline → output
- **System Tests**: end-to-end user scenarios
- **User Testing**: collect feedback and improve usability

Performance Optimization

- Reduce prediction latency
- Optimize preprocessing
- Improve response times and memory usage

Bug Fixing

- Fix crashes, incorrect outputs, formatting issues
- Retest all modules

Class Activities

- Troubleshooting sessions
- Team problem-solving
- Integration support

Week 13: Deployment Preparation

Set Up Deployment Environment

- Choose environment: Notebook, `app.py`, or online demo (Streamlit, HF Spaces)
- Ensure dependencies are documented

Finalize System Documentation

- Document project objective, dataset, preprocessing, model, metrics
- Add system architecture diagrams
- Write clear instructions for running the app

Prepare Demonstration

- Show dataset summary, preprocessing, model, predictions
- Prepare example scenarios
- Optionally create presentation slides

Complete Testing

- Run full clean tests
- Ensure instructions match behavior

Package Deliverables

- Final `.ipynb` notebook
- PDF report
- Python scripts
- `requirements.txt`
- Saved model file
- Presentation slides

Class Activities

- Prototype demonstrations
- Final integration checks

Application Demo: Prediction Workflow (Prototype)

The cells below show an example structure for:

1. Loading a trained model and preprocessing pipeline.
2. Creating an input dictionary.
3. Running a prediction.
4. Viewing the result in a simple way.

You will need to adjust file paths and feature names to match your project.

```
import os
import pandas as pd
import numpy as np
import joblib # Ensure joblib is imported
from pathlib import Path # Import Path for ART_DIR

ART_DIR = Path("/content/artifacts")
MODEL_PATH = ART_DIR / "final_model.joblib"          # Path to the actual trained pipeline
PIPELINE_PATH = ART_DIR / "preprocessor.joblib"  # New path for saving the preprocessor separately

model = None
preprocess_pipeline = None

def load_artifacts():
```

```
    """Load model and preprocessing pipeline if they exist."""
    global model, preprocess_pipeline

    if os.path.exists(MODEL_PATH):
        model = joblib.load(MODEL_PATH)
        print(f"Loaded model from {MODEL_PATH}")
    else:
        print(f"No model file found at {MODEL_PATH} (using None placeholder).")

    if os.path.exists(PIPELINE_PATH):
        # For the demo, preprocess_pipeline will be the preprocessor component of the full pipeline
        preprocess_pipeline = joblib.load(PIPELINE_PATH)
        print(f"Loaded preprocessing pipeline from {PIPELINE_PATH}")
    else:
        print(f"No pipeline file found at {PIPELINE_PATH} (using None placeholder).")

load_artifacts()
```

```
No model file found at /content/artifacts/final_model.joblib (using None placeholder).
No pipeline file found at /content/artifacts/preprocessor.joblib (using None placeholder).
```

```
def prepare_input(sample_dict):
    """Convert a dictionary of feature values to a one-row DataFrame."""
    return pd.DataFrame([sample_dict])

def predict_sample(sample_dict):
    """Run a single prediction with optional preprocessing and model.

    If no model is loaded, returns the input for inspection.
    """
    df = prepare_input(sample_dict)

    X = df
    if preprocess_pipeline is not None:
        try:
            X = preprocess_pipeline.transform(df)
        except Exception as e:
            print("Error during preprocessing:", e)
            return None

    if model is None:
        print("No model loaded; returning only the prepared input.")
        return {"input": df.to_dict(orient="records")[0]}

    try:
        y_pred = model.predict(X)
        result = {
            "input": df.to_dict(orient="records")[0],
            "prediction": y_pred[0],
        }
        if hasattr(model, "predict_proba"):
            try:
                proba = model.predict_proba(X)
                result["probabilities"] = proba[0].tolist()
            except Exception as e:
                print("Error computing probabilities:", e)
        return result
    except Exception as e:
        print("Error during prediction:", e)
        return None
```

Double-click (or enter) to edit

```
# FINAL SAMPLE INPUT WITH REAL FEATURES
# The preprocessor expects raw features before any encoding or feature engineering.
# Based on X = df.drop(columns=[TARGET_COL]) from cell g596WnxgNSz-
# and the num_cols/cat_cols from preprocessor definition:

sample = {
    "math score": 70,  # Example math score
    "reading score": 72,
```

```
    "writing score": 74,
    "gender_encoded": 1, # Example: 1 for female, 0 for male (check original encoding)
    "lunch_standard": 1, # Example: 1 for standard, 0 for free/reduced
    "test preparation course_none": 0, # Example: 0 for completed, 1 for none
    "race/ethnicity_group B": 1, # Example: 1 if group B, 0 otherwise
    "race/ethnicity_group C": 0,
    "race/ethnicity_group D": 0,
    "race/ethnicity_group E": 0,
    # 'pass_flag' is the target and should not be in the input sample for prediction
}

# The predict_sample function uses the loaded 'model' (which is the full pipeline)
# and 'preprocess_pipeline' (the ColumnTransformer).
# It will apply the preprocess_pipeline first, then the model.

demo_result = predict_sample(sample)
demo_result
```

```
{'input': {'math score': 70,
  'reading score': 72,
  'writing score': 74,
  'gender_encoded': 1,
  'lunch_standard': 1,
  'test preparation course_none': 0,
  'race/ethnicity_group B': 1,
  'race/ethnicity_group C': 0
```