SMART
CONSULTANCY

MACHINE LEARNING

ASSIGNMENT 2

Team

:

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TASK 1:

Issues in Machine Learning

- Data Quality and Quantity: Poor-quality or insufficient data leads to biased, overfit, or underfit models, limiting generalization (e.g., non-diverse healthcare datasets).

- Feature Selection: Irrelevant features harm model accuracy; automated systems must refine predictive elements (e.g., color, texture in images).

- Hyperparameter Tuning: Optimizing hyperparameters is resource-intensive and complex due to computational constraints.

- Overfitting and Underfitting: Overfitting occurs when a model captures noise and inaccuracies from a large dataset, adversely affecting its performance. Conversely, underfitting arises from a model being too simple for the data, resulting in incomplete and inaccurate predictions.

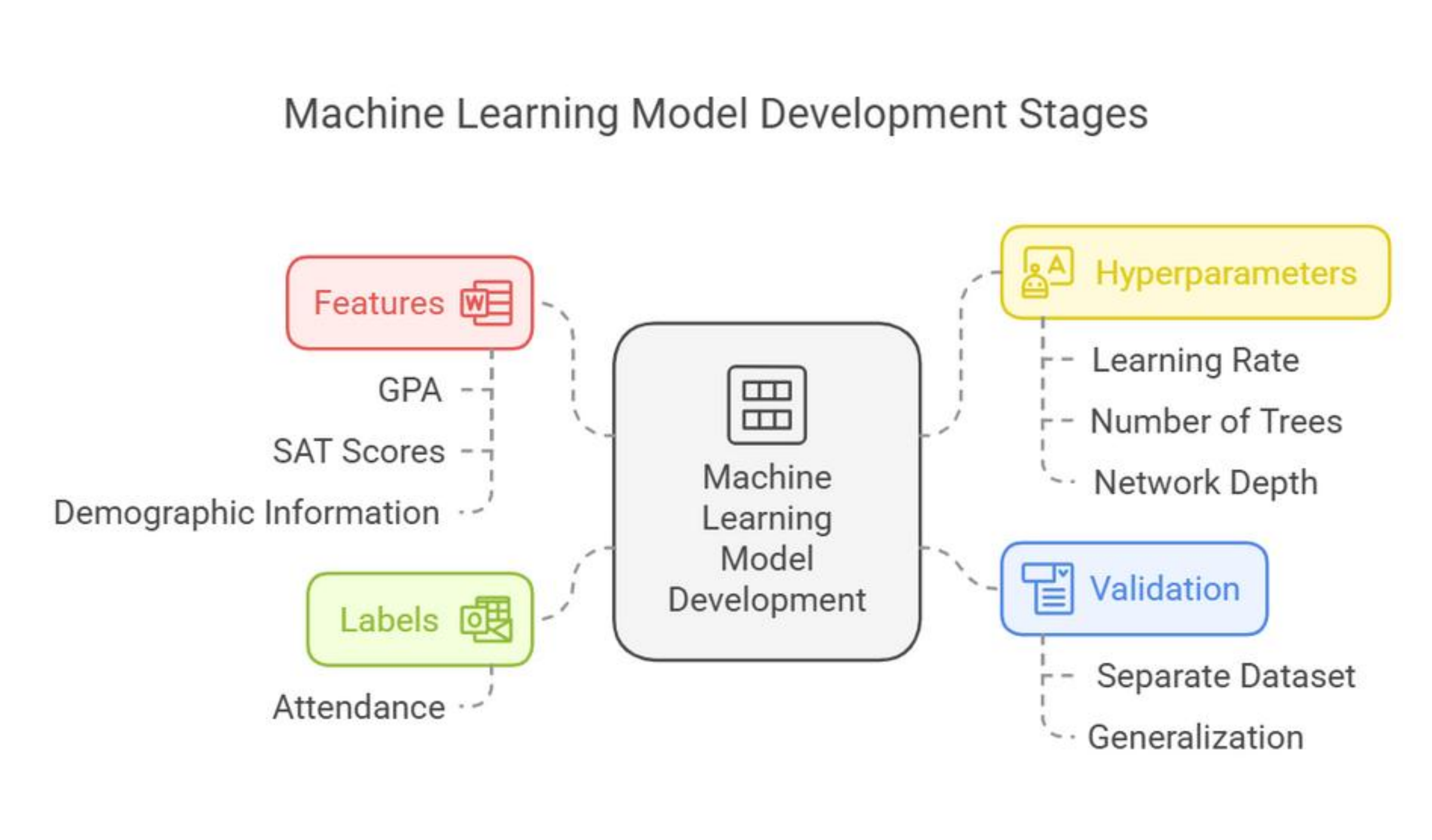
Learning Stages in ML

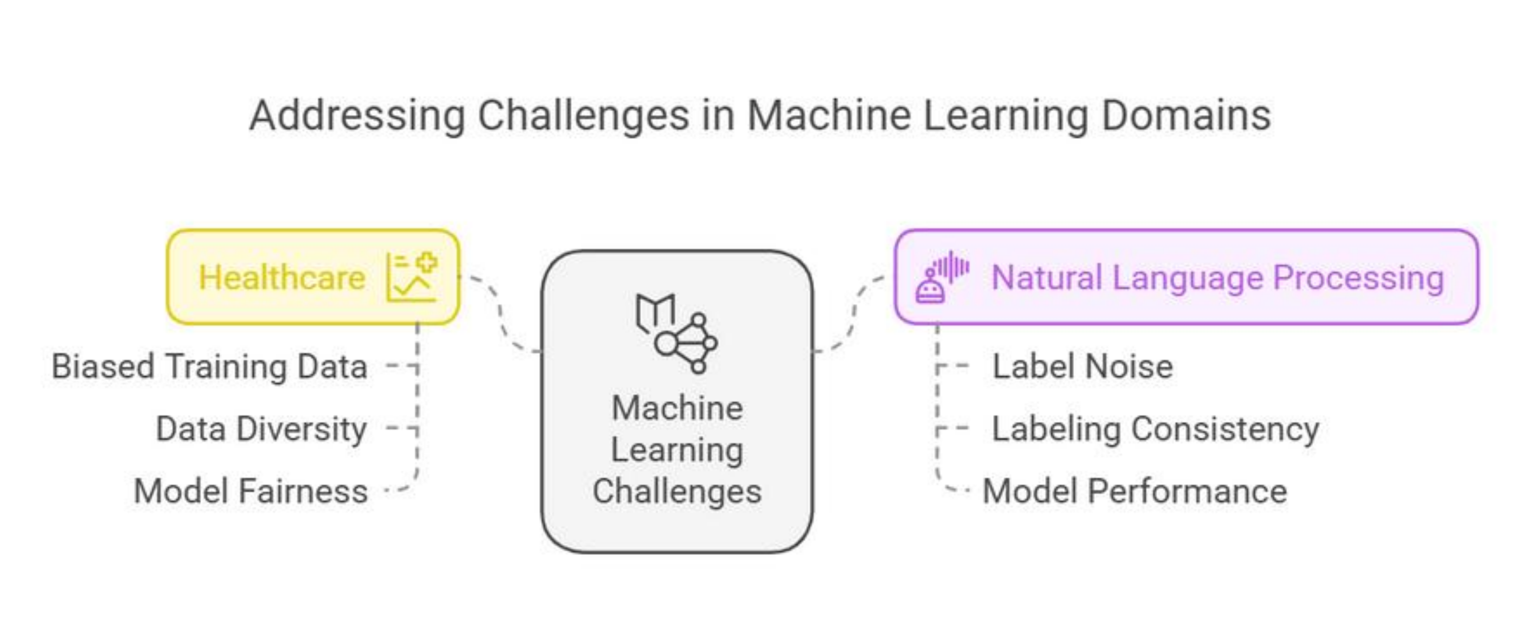
Features: Models use features as independent variables for production determination. Feature selection processes coupled with engineering techniques provide substantial benefits to model predictive abilities.

Labels :The direction my model aims to determine consists of Labels for prediction output. The model accuracy of supervised learning depends strongly on the quality of provided labels. Achieving both accurate and consistent labeling conditions fundamental for creating effective models.

Hyperparameters: Hyperparameters represent adjustable configuration settings which programmers adjust before starting the learning process. Training becomes vulnerable to their influence through controlled parameters because these settings regulate the entire training timetable.

Validation: Model performance evaluation through validation occurs by using the process to assess models against unknown data. Avoiding overfitting requires appropriate validation approaches in decision-making processes.





Real-Life Cases

Healthcare: According to Obermeyer et al. (2019) machine learning encounters significant obstacles when used in healthcare because training data proves to be biased. New methods were developed to make data more diverse while achieving fair models.

Natural Language Processing: Gururangan et al. (2018) investigated how label noise affects sentiment analysis. The study examined methods that could boost model performance through better label consistency techniques.

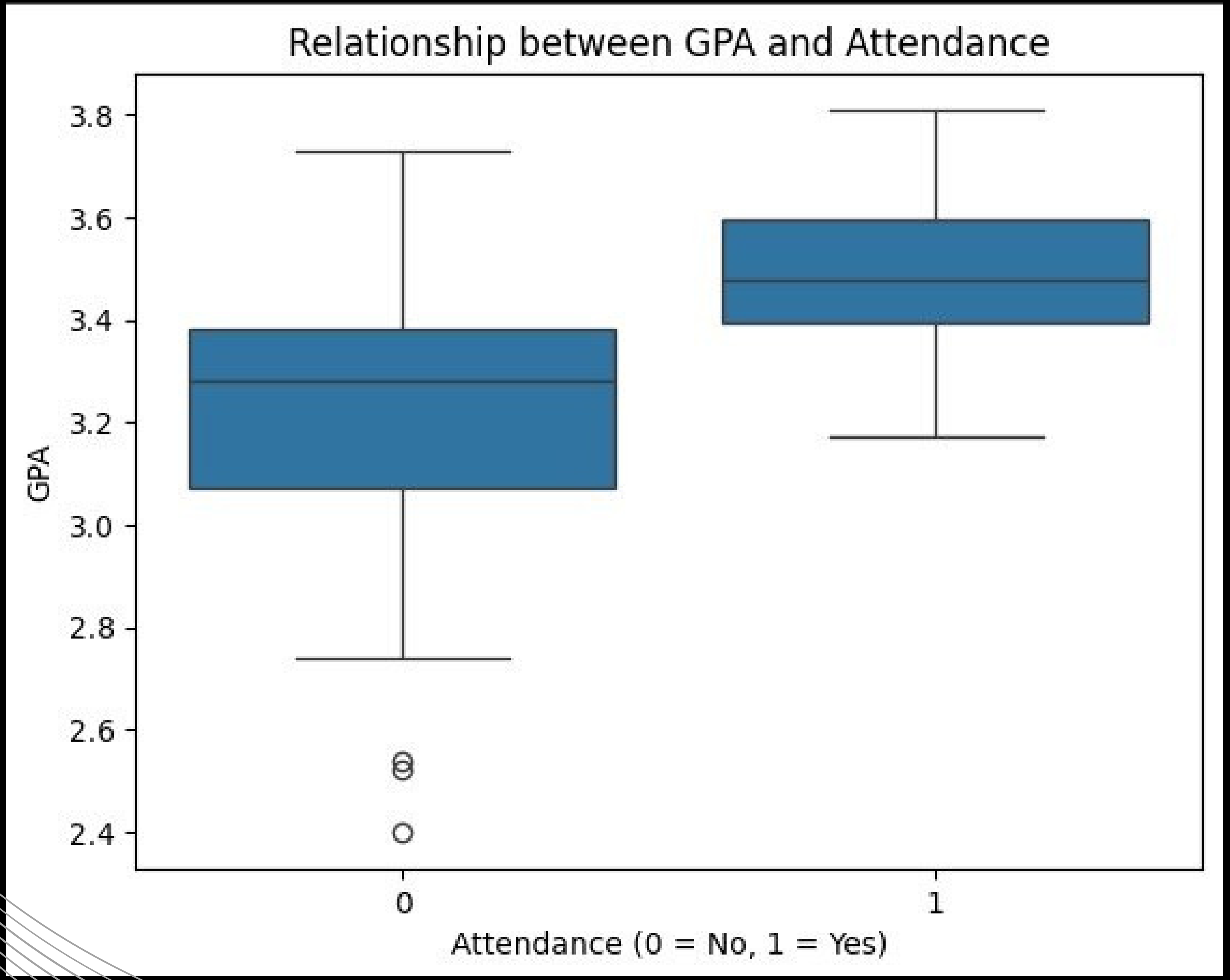
References

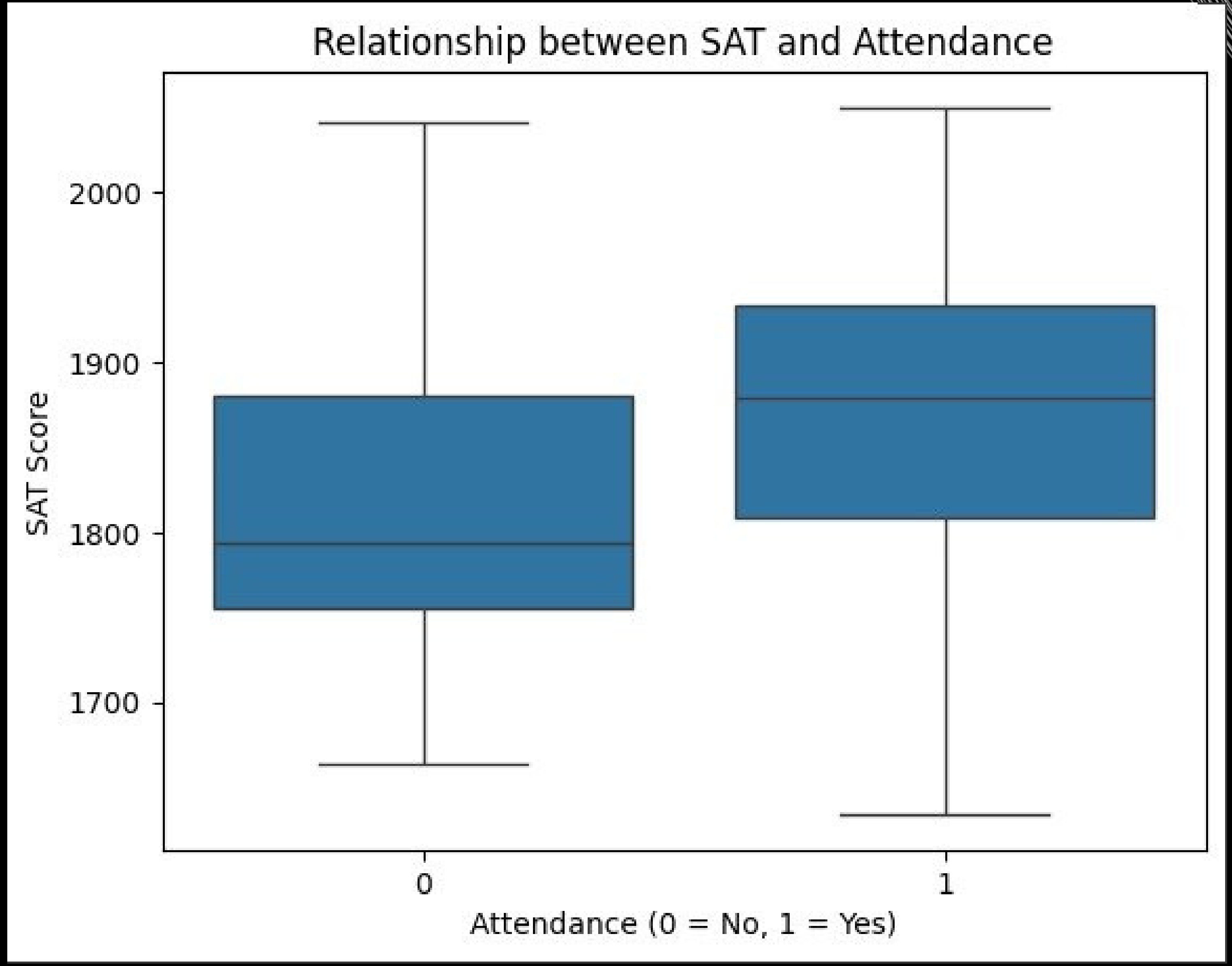
Gururangan, S., Marasović, A., Swayamdipta, S., et al. (2018). Annotation artifacts in natural language inference data. Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2018, 1-6.

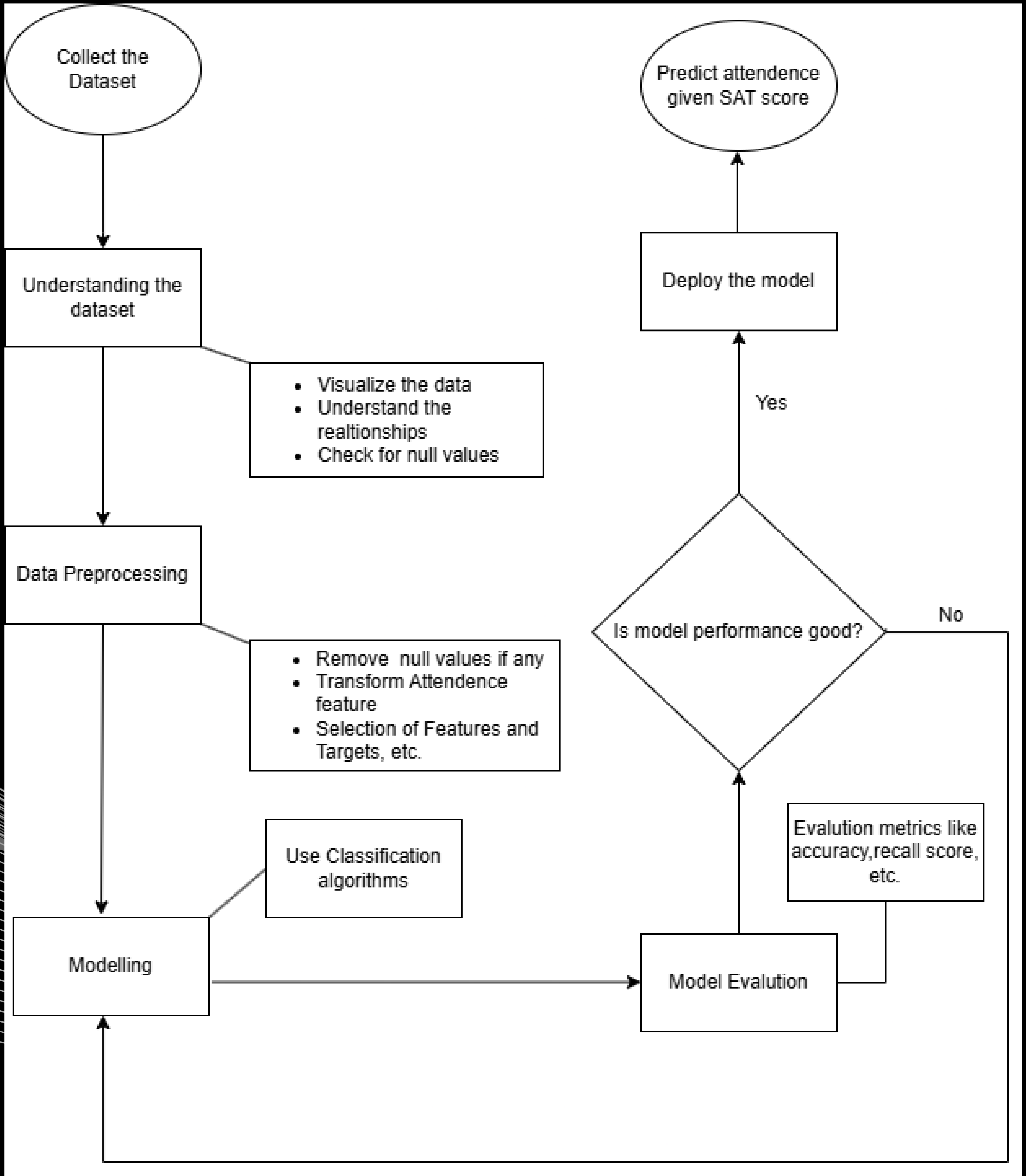
Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447-453. https://doi.org/10.1126/science.aax2342

TASK 2:

- Is there a relationship between GPA and attendance?
- What about between SAT and attendance?
- Can you predict the attendance given the SAT score?







Collect the Dataset

Understanding the dataset

- Visualize the data
- Understand the realtionships
- Check for null values

Data Preprocessing

- Remove null values if any
- Transform Attendence feature
- Selection of Features and Targets, etc.

Use Classification algorithms

Modelling

Model Evalution

Evalution metrics like accuracy,recall score, etc.

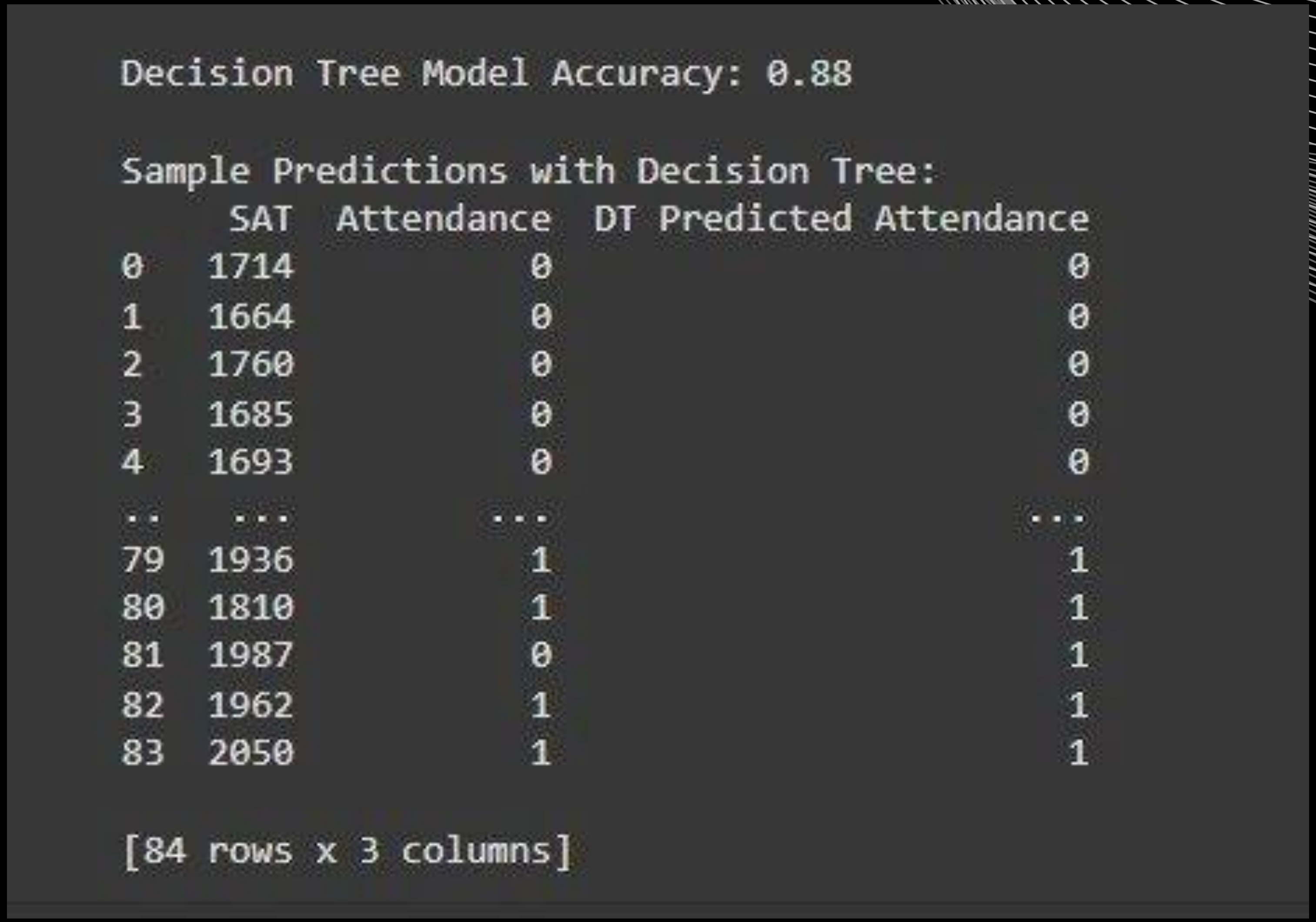
Is model performance good?

No

Yes

Deploy the model

Predict attendence given SAT score

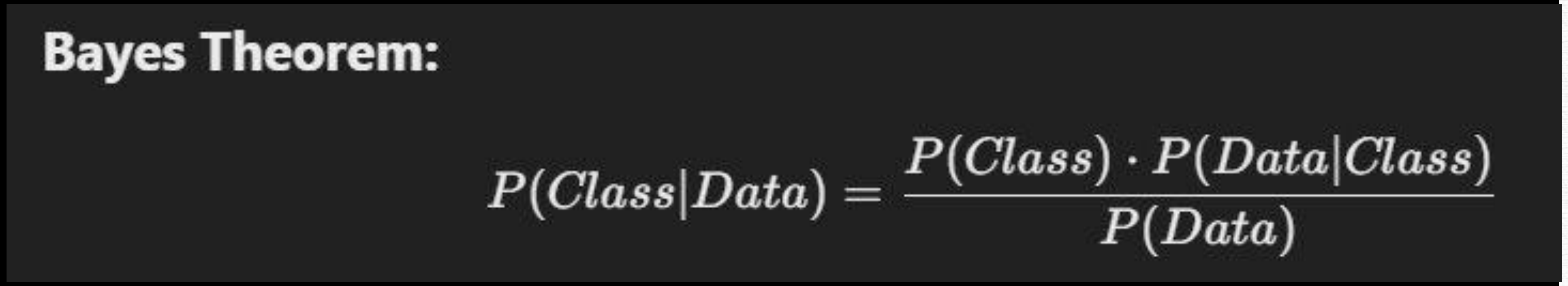


```
Decision Tree Model Accuracy: 0.88

Sample Predictions with Decision Tree:
     SAT  Attendance  DT Predicted Attendance
0   1714           0                        0
1   1664           0                        0
2   1760           0                        0
3   1685           0                        0
4   1693           0                        0
..   ...         ...                      ...
79  1936           1                        1
80  1810           1                        1
81  1987           0                        1
82  1962           1                        1
83  2050           1                        1

[84 rows x 3 columns]
```

TASK 3:

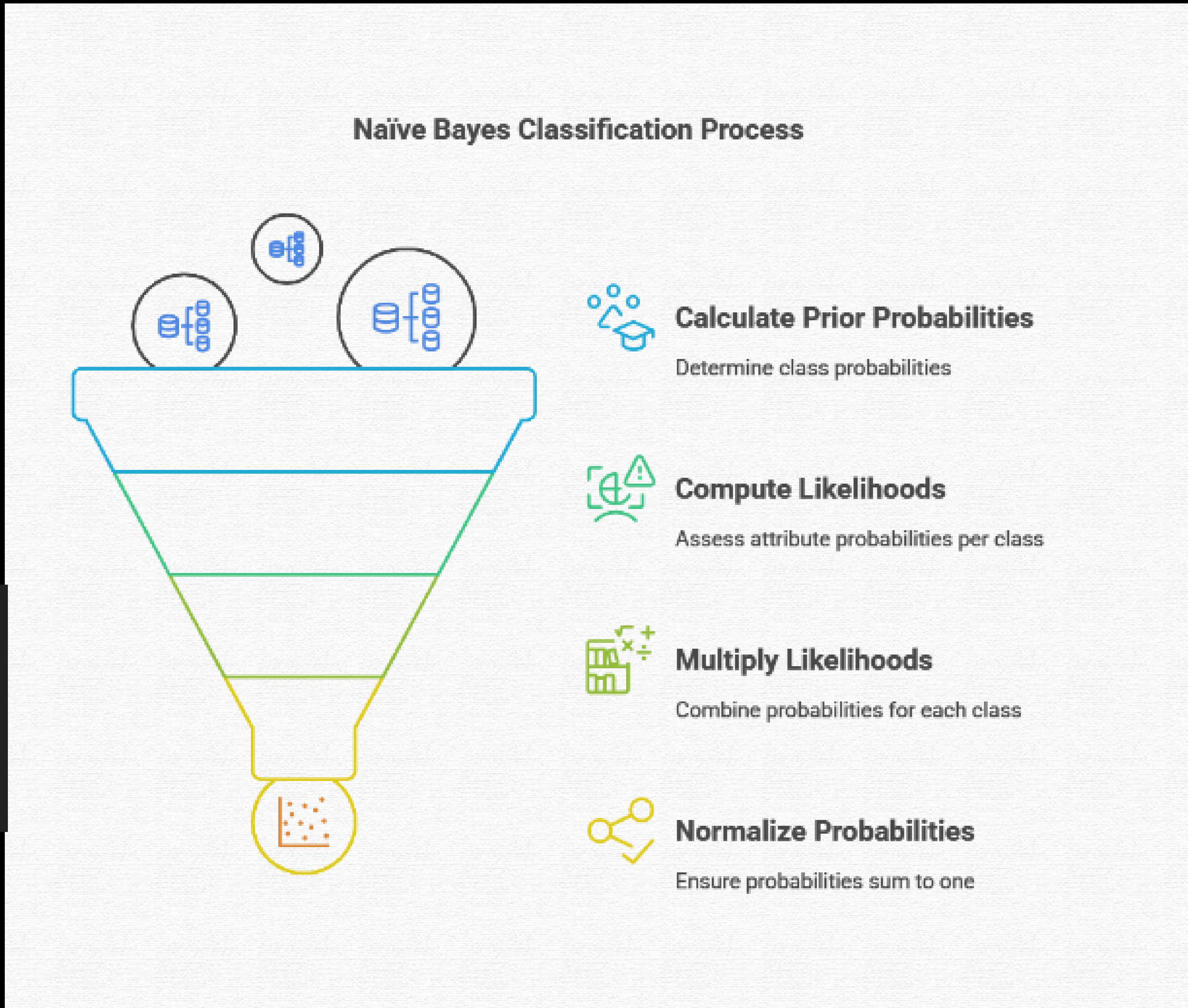
What probability should be used to make the prediction?

The probability used to make a prediction is the posterior probability for each class. The class with the highest posterior probability is chosen as the prediction. Naive Bayes uses the Bayes theorem to compute these probabilities.



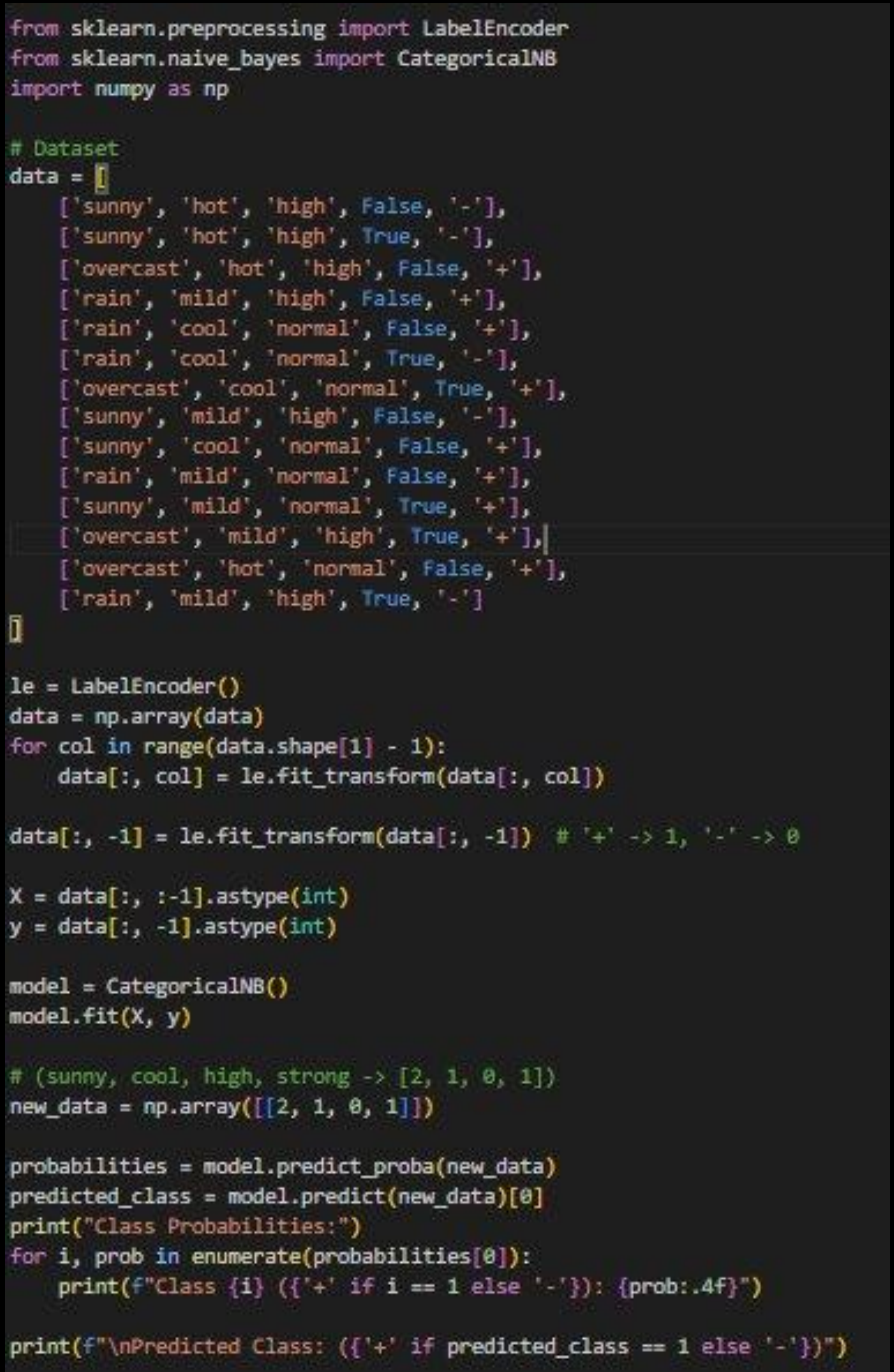
Bayes Theorem:

$$P(Class|Data) = \frac{P(Class) \cdot P(Data|Class)}{P(Data)}$$



Naïve Bayes Classification Process

Calculate Prior Probabilities
Determine class probabilities
Compute Likelihoods
Assess attribute probabilities per class
Multiply Likelihoods
Combine probabilities for each class
Normalize Probabilities
Ensure probabilities sum to one



```python
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import CategoricalNB
import numpy as np

# Dataset
data = [
    ['sunny', 'hot', 'high', False, '-'],
    ['sunny', 'hot', 'high', True, '-'],
    ['overcast', 'hot', 'high', False, '+'],
    ['rain', 'mild', 'high', False, '+'],
    ['rain', 'cool', 'normal', False, '+'],
    ['rain', 'cool', 'normal', True, '-'],
    ['overcast', 'cool', 'normal', True, '+'],
    ['sunny', 'mild', 'high', False, '-'],
    ['sunny', 'cool', 'normal', False, '+'],
    ['rain', 'mild', 'normal', False, '+'],
    ['sunny', 'mild', 'normal', True, '+'],
    ['overcast', 'mild', 'high', True, '+'],
    ['overcast', 'hot', 'normal', False, '+'],
    ['rain', 'mild', 'high', True, '-']
]

le = LabelEncoder()
data = np.array(data)
for col in range(data.shape[1] - 1):
    data[:, col] = le.fit_transform(data[:, col])

data[:, -1] = le.fit_transform(data[:, -1])  # '+' -> 1, '-' -> 0

X = data[:, :-1].astype(int)
y = data[:, -1].astype(int)

model = CategoricalNB()
model.fit(X, y)

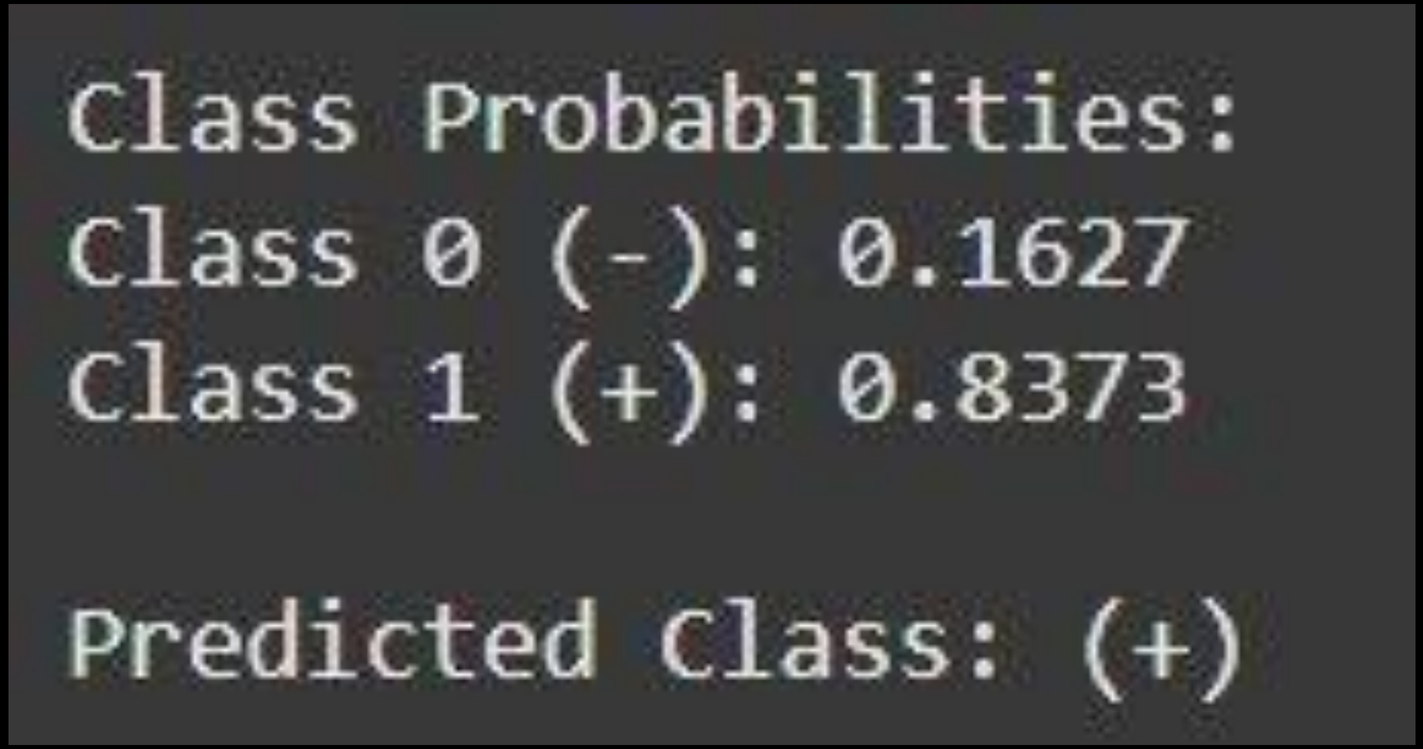
# (sunny, cool, high, strong -> [2, 1, 0, 1])
new_data = np.array([[2, 1, 0, 1]])

probabilities = model.predict_proba(new_data)
predicted_class = model.predict(new_data)[0]
print("Class Probabilities:")
for i, prob in enumerate(probabilities[0]):
    print(f"Class {i} ({'+' if i == 1 else '-'}): {prob:.4f}")

print(f"\nPredicted Class: ({'+' if predicted_class == 1 else '-'})")
```

OUTPUT

:



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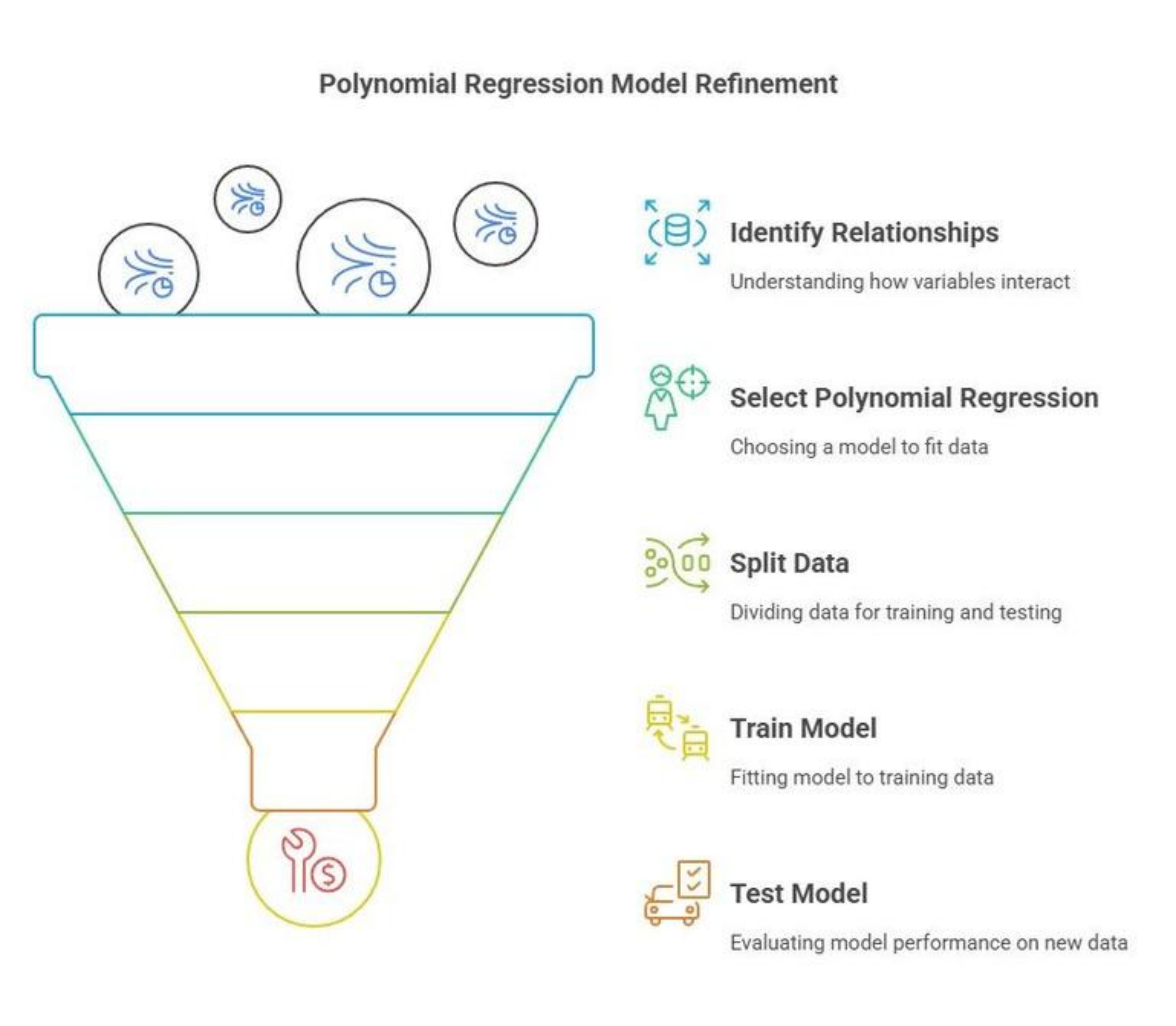
Class Probabilities:
Class 0 (-): 0.1627
Class 1 (+): 0.8373

Predicted Class: (+)
```

TASK 4:



Polynomial Regression Model Refinement

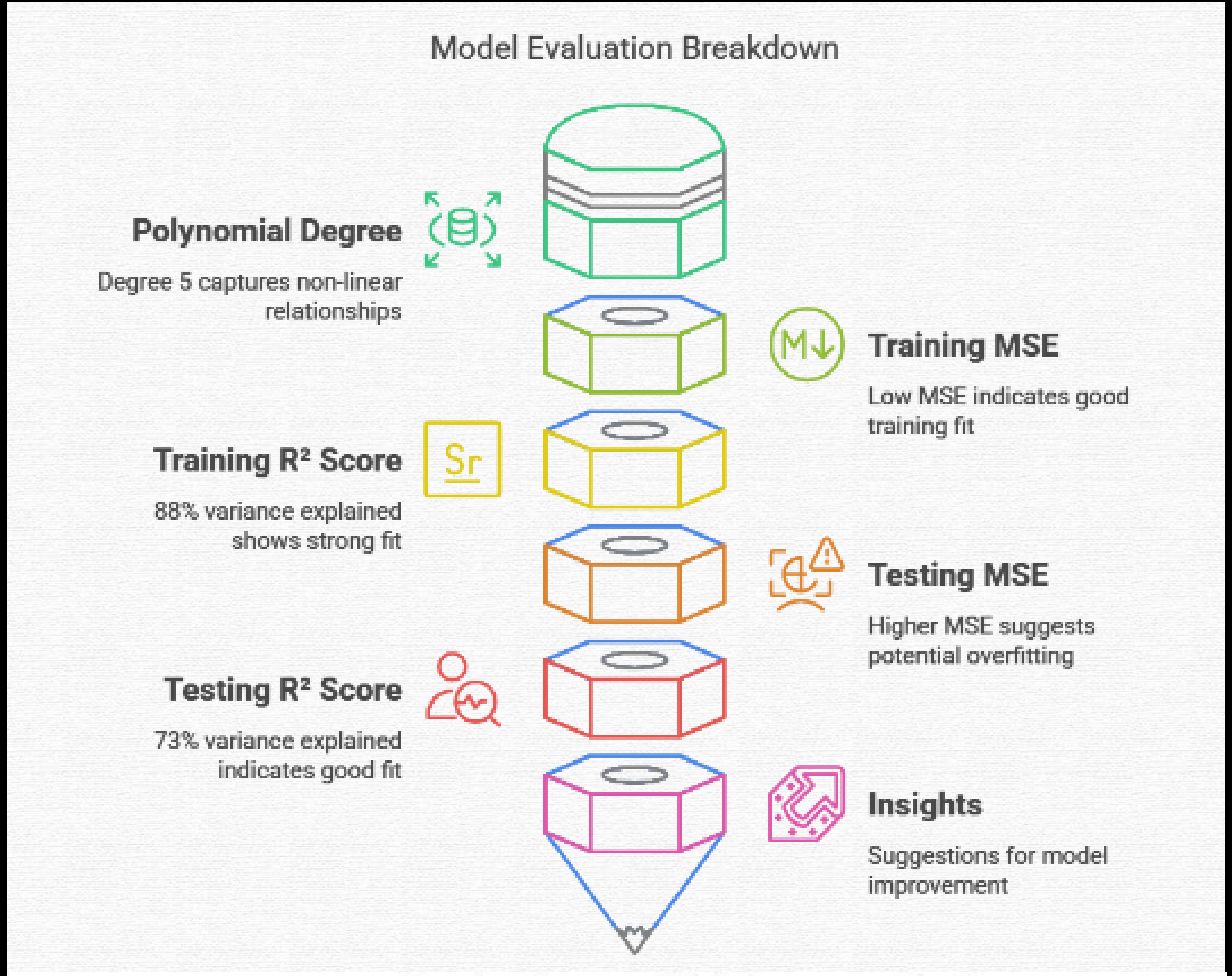
Identify Relationships
Understanding how variables interact

Select Polynomial Regression
Choosing a model to fit data

Split Data
Dividing data for training and testing

Train Model
Fitting model to training data

Test Model
Evaluating model performance on new data



Model Evaluation Breakdown

Polynomial Degree
Degree 5 captures non-linear relationships

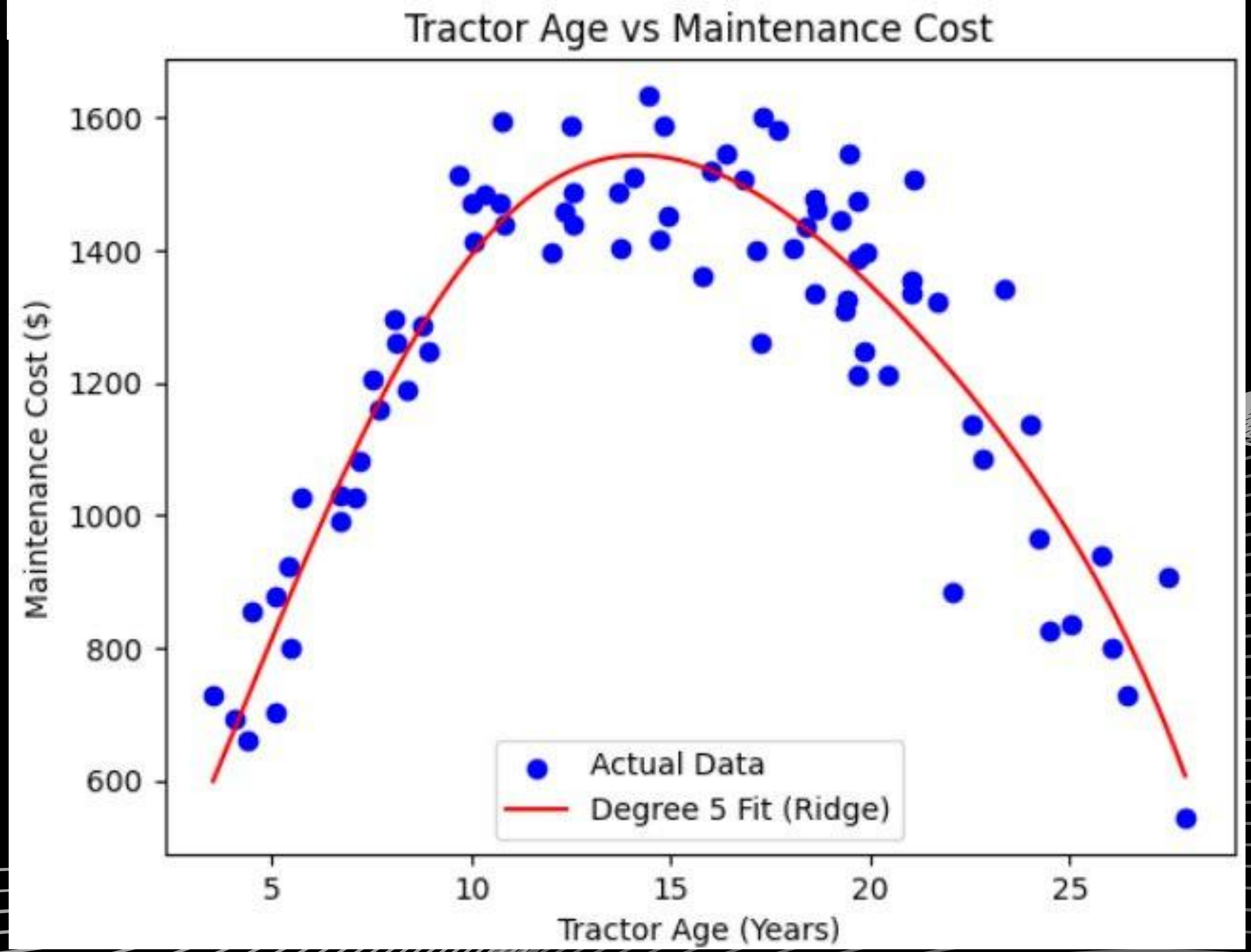
Training MSE
Low MSE indicates good training fit

Training R² Score
88% variance explained shows strong fit

Testing MSE
Higher MSE suggests potential overfitting

Testing R² Score
73% variance explained indicates good fit

Insights
Suggestions for model improvement



Tractor Age vs Maintenance Cost

Thank You