

Machine learning

Assignment-2

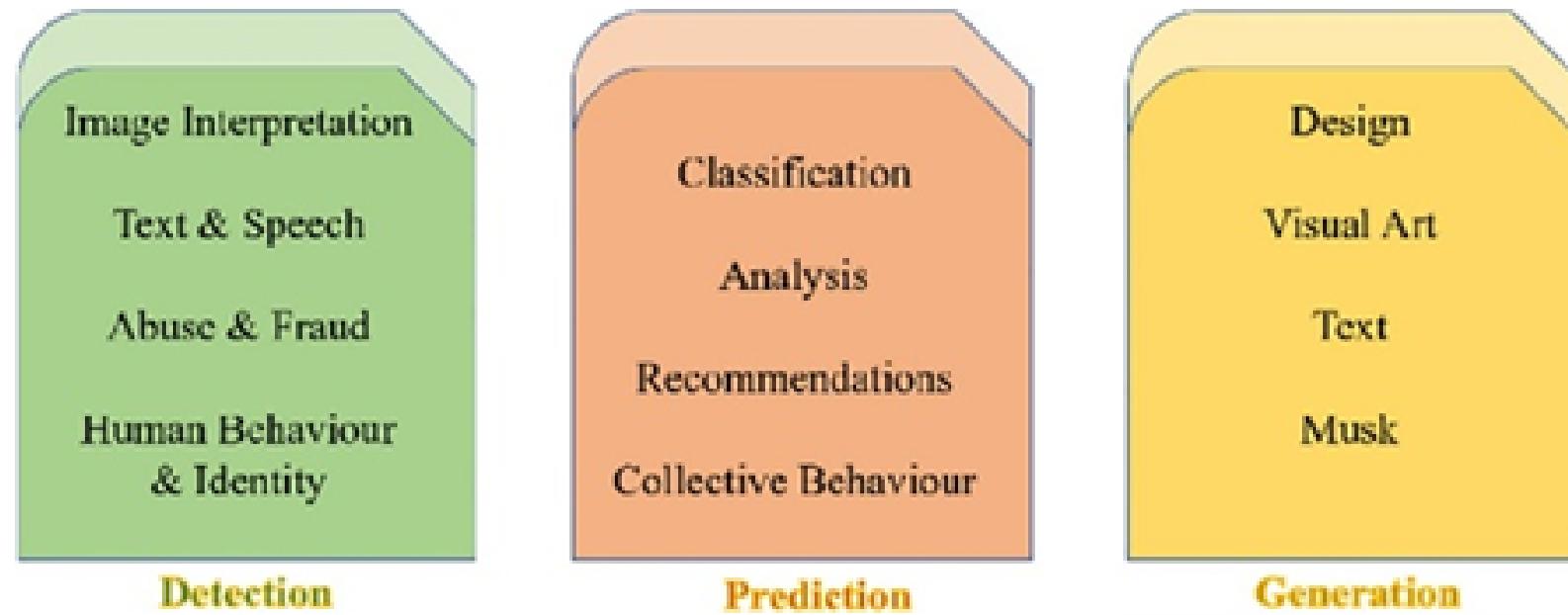
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TASK-1

Example use cases for ML

ML has a variety of applications, ranging from automation, detection and personalization to things like optimization.



Sub-fields in machine learning

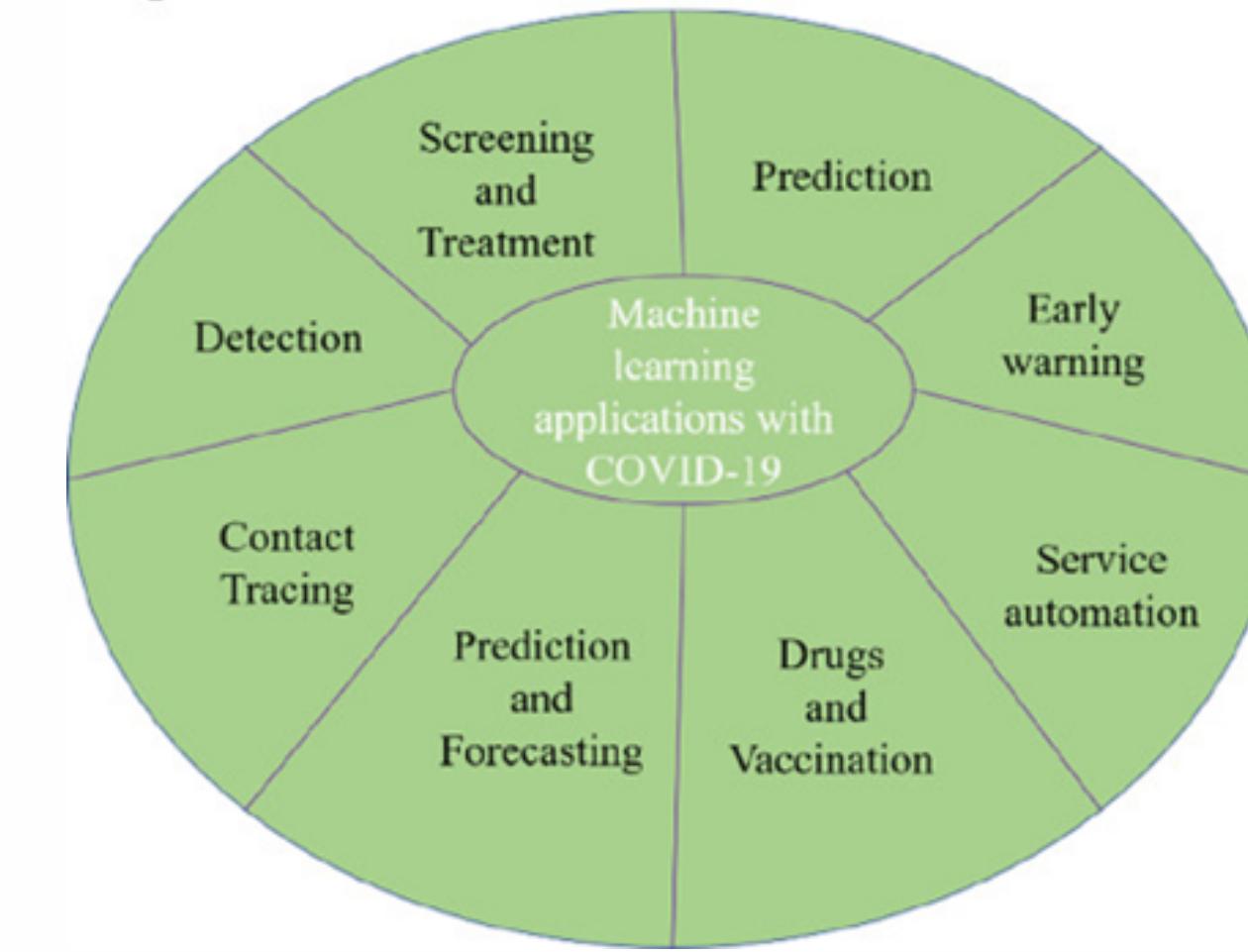


Image Source:
<https://www.sciencedirect.com/science/article/pii/S2666285X21000042#fig0003>

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TASK-1

Identifying Good Problems for ML

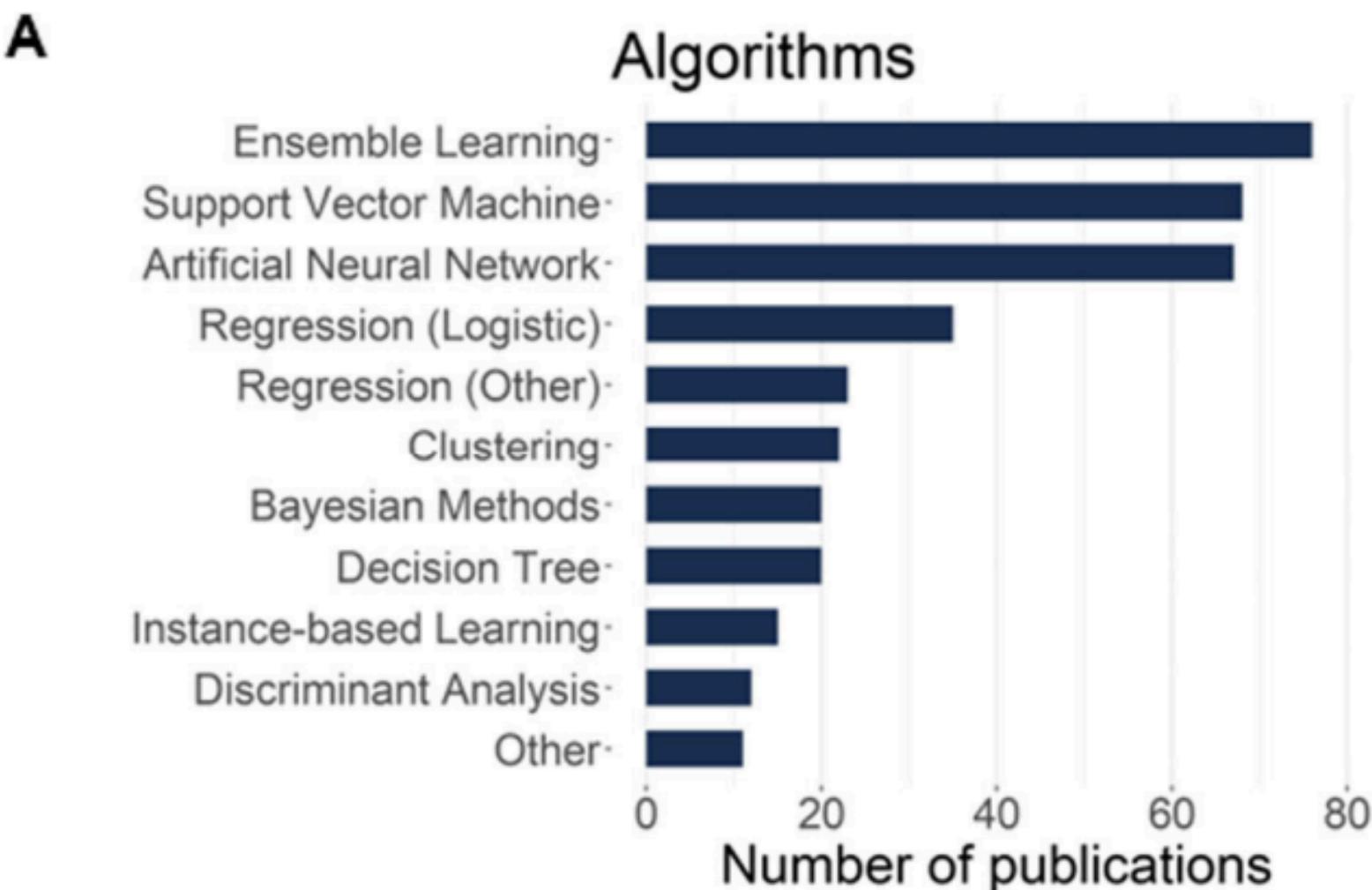
We can identify applications for Machine Learning by looking for ideal traits like:

- Large size, high quality datasets are available.
- Clear objectives exist (e.g., predicting, classifying, or clustering).
- Data patterns or correlations can be extracted from the given data.

TASK-1

Hard ML Problems

- Datasets may have less or incorrect data.
- Can degrade model performance.
- Ethical concerns such as privacy issues or bias in data.
- Ensuring models perform well on unseen, real-world data beyond training datasets.



Schaefer, J., Lehne, M., Schepers, J. et al. The use of machine learning in rare diseases: a scoping review. *Orphanet J Rare Dis* 15, 145 (2020). <https://doi.org/10.1186/s13023-020-01424-6>

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TASK-1

References

Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN COMPUT. SCI.* 2, 160 (2021).
<https://doi.org/10.1007/s42979-021-00592-x>

Khan, M. A., Bahadur, A., Khan, M. S., et al. (2021). Machine learning: Algorithms, real-world applications, and research directions. *SN Computer Science*, 2(3), 160. <https://doi.org/10.1007/s42979-021-00592-x>

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<https://doi.org/10.1186/s13023-020-01424-6>

TASK-2

Problem 3: Is there a relationship between the daily minimum and maximum temperature? Can you predict the maximum temperature given the minimum temperature?

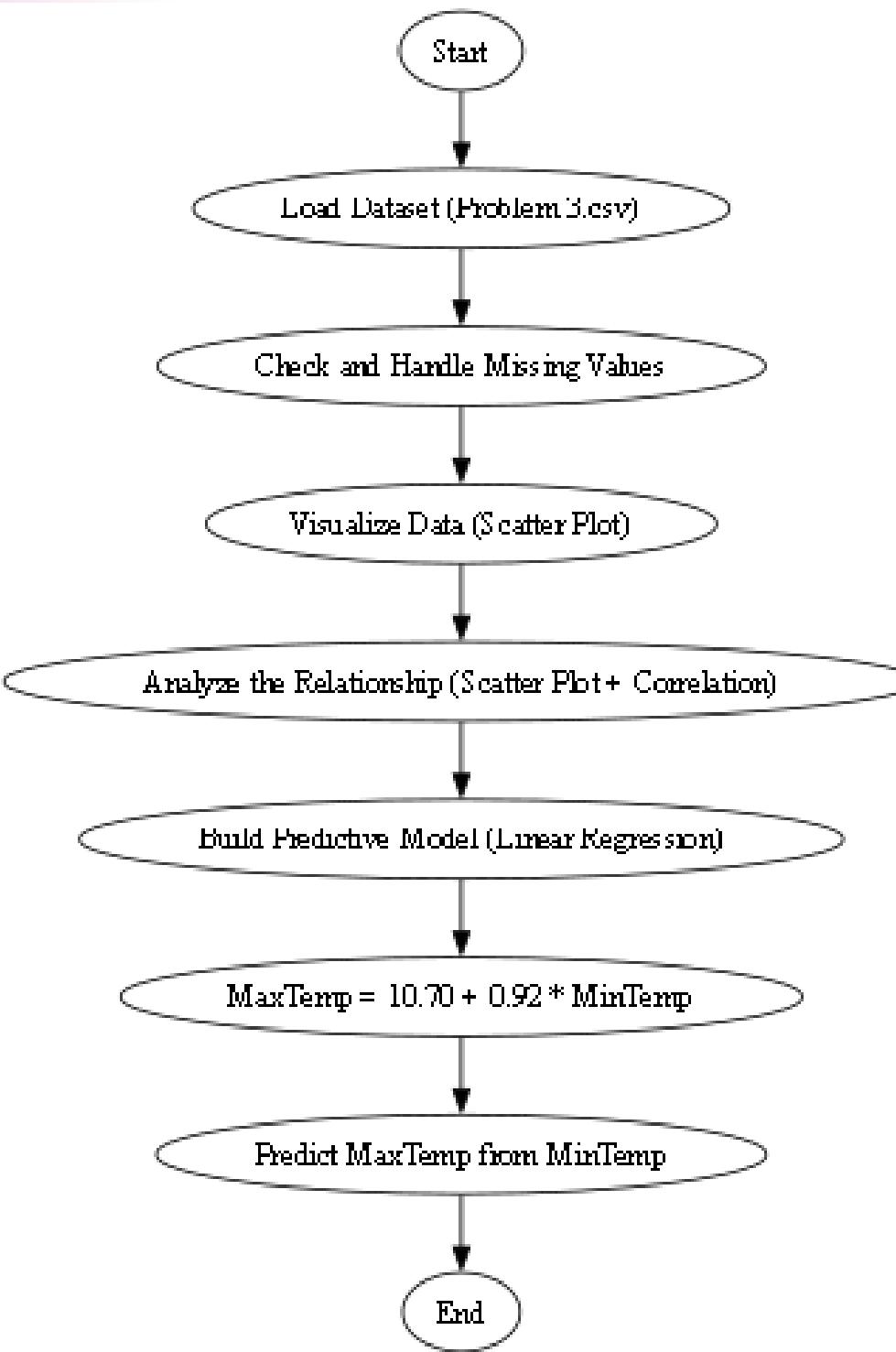
To create the flowchart, we used the Graphviz library to visualize the workflow of our temperature analysis process.

1. Nodes: Represented each key step in the process (e.g., loading data, cleaning data, visualization, regression modeling, and prediction).
2. Edges: Connected the steps in logical order to show the flow of actions.
3. Regression Equation: Included the linear equation from the model as part of the flow.
4. Output: Rendered the flowchart as a PNG image for use in the presentation.

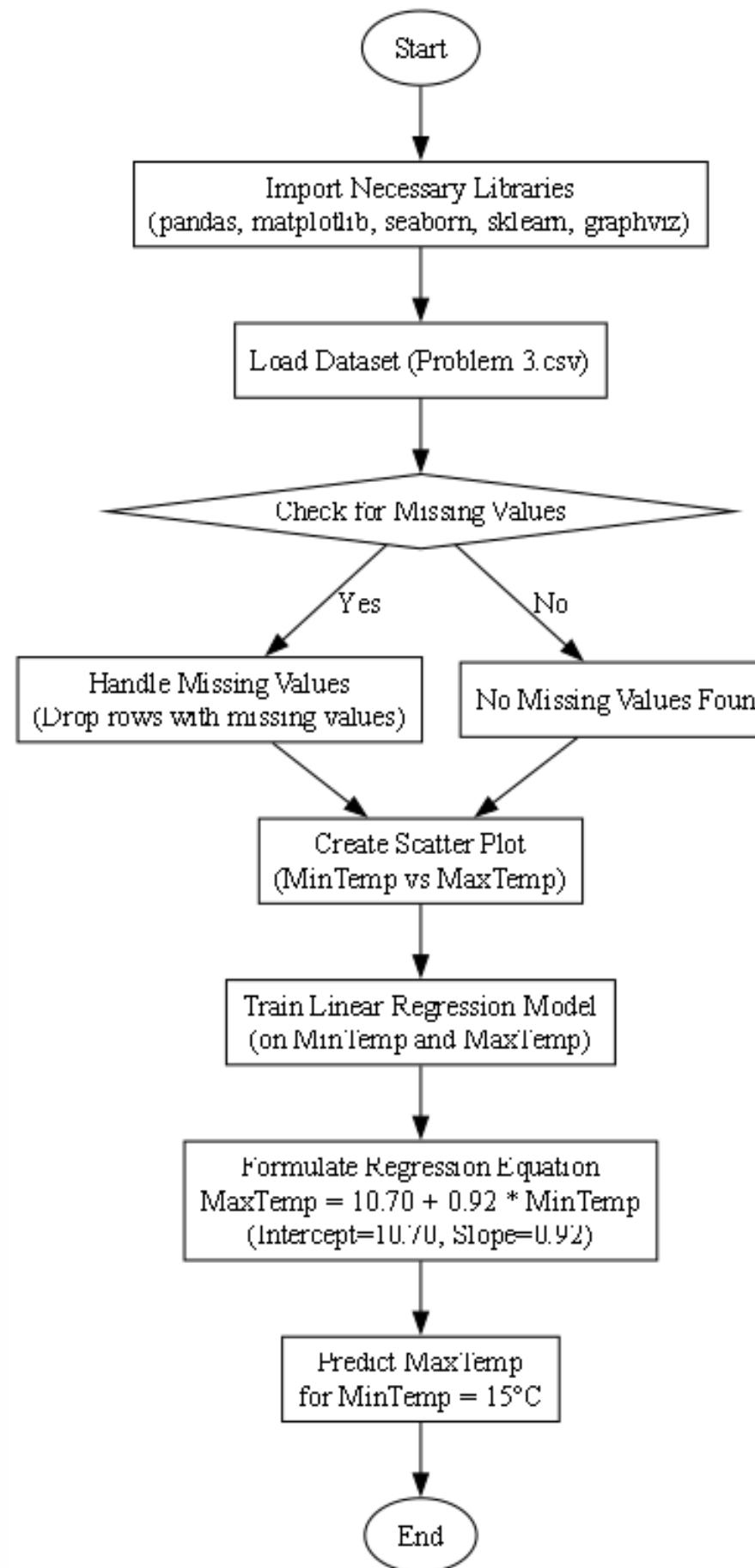
This flowchart visually summarizes the entire analytical process from data input to prediction.

TASK-2

Initial Result:



Final Result:



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TASK-3

“Predict playing tennis when <sunny, cool, high, strong> What probability should be used to make the prediction? How to compute the probability?”

Naive Bayes Classification:
 $P(\text{Play} | \text{sunny, cool, high, strong})$
This represents the likelihood of playing tennis given specific weather conditions.

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)}$$

Diagram illustrating the components of the Naive Bayes formula:

- Likelihood of the Evidence given that the Hypothesis is True (Yellow)
- Prior Probability of the Hypothesis (Red)
- Posterior Probability of the Hypothesis given that the Evidence is True (Blue)
- Prior Probability that the evidence is True (Green)

TASK-3

```
✓ 9s ⏎ import pandas as pd
from sklearn.naive_bayes import MultinomialNB
from sklearn.preprocessing import LabelEncoder

# Dataset
data = {
    "Outlook": ["sunny", "sunny", "overcast", "rain", "rain", "overcast", "sunny",
                "sunny", "rain", "sunny", "overcast", "overcast", "rain"],
    "Temperature": ["hot", "hot", "hot", "mild", "cool", "cool", "cool", "mild",
                    "mild", "mild", "hot", "mild"],
    "Humidity": ["high", "high", "high", "normal", "normal", "normal", "high",
                  "normal", "normal", "high", "normal", "high"],
    "Windy": ["false", "true", "false", "false", "true", "true", "false", "false",
              "false", "true", "true", "false", "true"],
    "Class": ["-", "-", "+", "+", "-", "+", "-", "+", "+", "+", "+", "+", "-"]
}

# Create a DataFrame
df = pd.DataFrame(data)

# Create separate LabelEncoders for each feature column
encodes = {}
for col in ["Outlook", "Temperature", "Humidity", "Windy"]:
    encodes[col] = LabelEncoder()
    df[col] = encodes[col].fit_transform(df[col])

# Encode the target variable with a separate encoder
encode_Class = LabelEncoder()
df["Class"] = encode_Class.fit_transform(df["Class"])

# Split features (X) and target (y)
X = df[["Outlook", "Temperature", "Humidity", "Windy"]]
```

```
✓ 9s ⏎ X = df[["Outlook", "Temperature", "Humidity", "Windy"]]
y = df["Class"]

# Model
model = MultinomialNB()
model.fit(X, y)

# Predict for <sunny, cool, high, strong>
# Use the correct encoders for each feature to transform the sample data
sample = pd.DataFrame({
    "Outlook": encodes["Outlook"].transform(["sunny"]),
    "Temperature": encodes["Temperature"].transform(["cool"]),
    "Humidity": encodes["Humidity"].transform(["high"]),
    "Windy": encodes["Windy"].transform(["true"])
})

# Predict and decode the result
prediction = model.predict(sample)
decoded_prediction = encode_Class.inverse_transform(prediction)

# Print Prediction
print("Prediction:", decoded_prediction[0])

# Inspect Probabilities
prob = model.predict_proba(sample)
print("Probability of +:", prob[0][1])
print("Probability of -:", prob[0][0])
```

→ Prediction: -
Probability of +: 0.6406632947915922
Probability of -: 0.35933670520840805

TASK-4

Investigate the relationship between the age of farm tractors and their maintenance costs using data collected from Putnam County, FL.

Data Points:

- Tractor Age (5,10,15,20,25)
- Maintenance Costs (600,1400,1400,1200,800)

Data Characteristics:

- Maintenance costs peak at mid-life (15 years).
- Costs reduce after the mid-life stage.

TASK-4

Model Used:

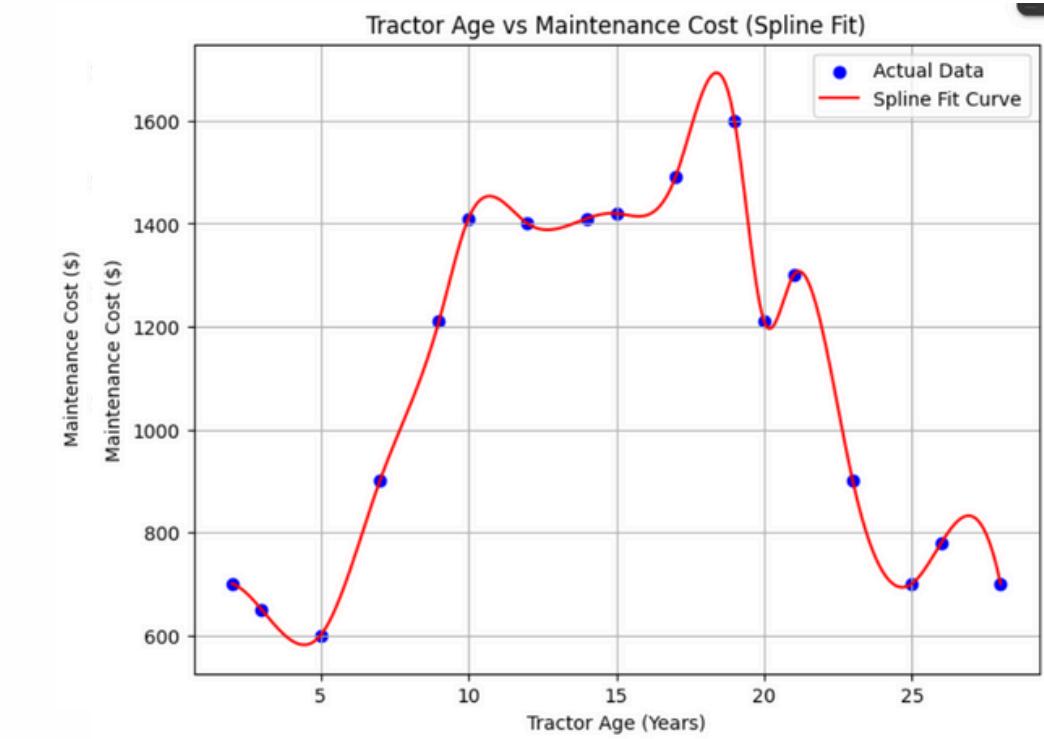
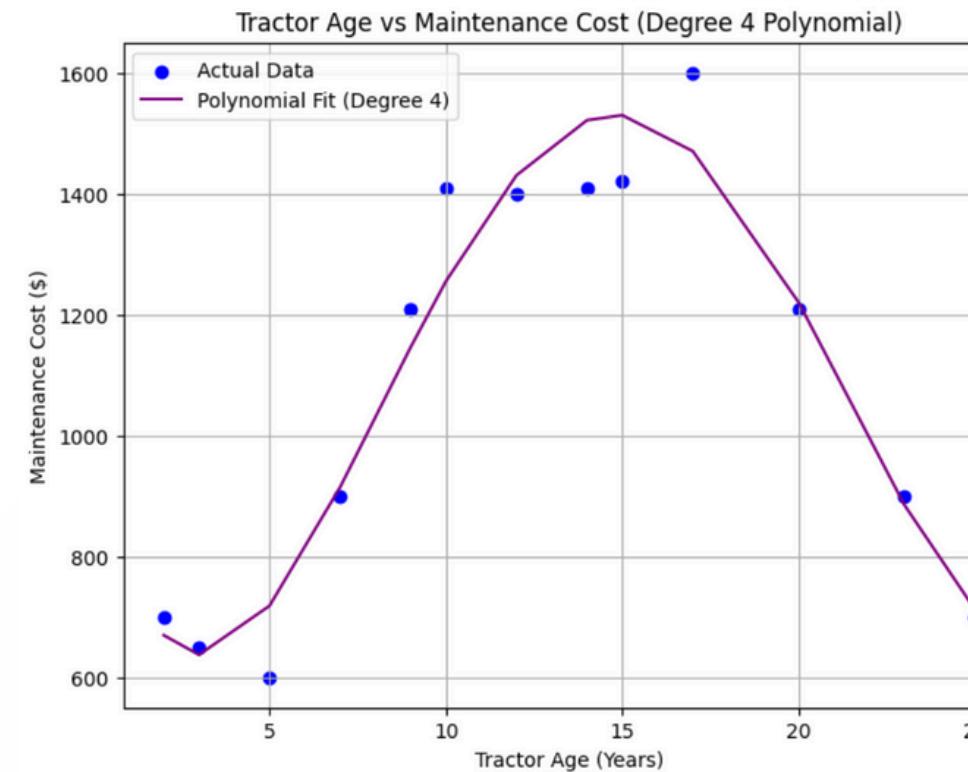
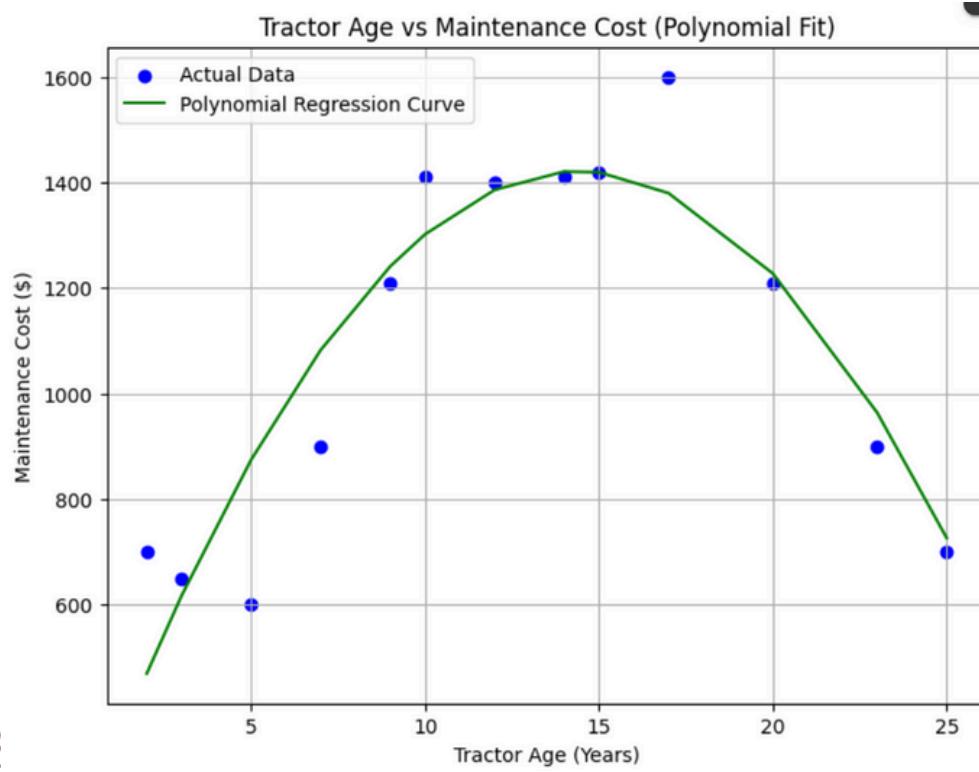
Polynomial Regression (2nd Degree), 4th degree and spline

Observation points:

1. Maintenance costs are highest at around 15 years of tractor age.
2. Younger tractors have relatively lower costs.
3. Older tractors beyond 20 years also show declining maintenance costs.

TASK-4

Practical Implications for Farmers:
Helps estimate maintenance budgets based on tractor age.
Guides decision-making for tractor replacement or servicing.



THANK YOU