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keyboard_arrow_down Aim: To Implement Inferencing with Bayesian

Network in python Naive Bayes Inference: Theory

What is Naive Bayes?

Naive Bayes is a probabilistic machine learning algorithm used for classification tasks. It's based on Bayes' Theorem with a key assumption: all features are independent of each other given the class. This "naive" independence assumption is why it's so efficient and easy to implement.

Bayes' Theorem

The foundation of Naive Bayes is Bayes' Theorem, which describes the probability of an event based on prior knowledge of conditions that might be related to the event. The formula is:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Where:

- $P(A|B)$ is the posterior probability: the probability of event A occurring given that event B has occurred.
- $P(B|A)$ is the likelihood: the probability of event B occurring given that event A has occurred.
- $P(A)$ is the prior probability: the initial probability of event A occurring.
- $P(B)$ is the marginal probability: the probability of event B occurring.

Naive Bayes for Classification

In the context of classification, we use Bayes' Theorem to find the probability of a class (C) given a set of features ($x_1, x_2, \ldots, x_n$):

$$P(C|x_1, x_2, \ldots, x_n) = \frac{P(x_1, x_2, \ldots, x_n|C) \cdot P(C)}{P(x_1, x_2, \ldots, x_n)}$$

Using the "naive" independence assumption, the likelihood term can be simplified:

$$P(x_1, x_2, \ldots, x_n|C) = P(x_1|C) \cdot P(x_2|C) \cdot \ldots \cdot P(x_n|C)$$

This simplifies the final formula for Naive Bayes to:

$$P(C|x_1, \ldots, x_n) \propto P(C) \cdot \prod_{i=1}^{n} P(x_i|C)$$

Since the denominator $P(x_1, \ldots, x_n)$ is constant for all classes, we can ignore it and focus on finding the class with the highest probability.

How Inference Works

Inference in Naive Bayes isn't just about outputting a single class label. It's about calculating the probability distribution over all possible classes for a given input. This is done by calculating the value of $P(C|x_1, \ldots, x_n)$ for each class and then normalizing them to sum to 1. This gives you the model's confidence for each possible outcome.

- Example: For a new data point, a Naive Bayes model might not just say "play tennis," but could provide the probabilities:
  - $P(\text{play tennis}|\text{weather, temp}) = 0.85$
  - $P(\text{don't play tennis}|\text{weather, temp}) = 0.15$

This probabilistic output is what makes it a powerful tool for inference, as it provides more insight than a simple classification label.

```
import numpy as np
```

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Load the data from the CSV file
df = pd.read_csv('tennis_data.csv')

# Convert categorical data to numerical data using one-hot encoding
df = pd.get_dummies(df, columns=['weather', 'temperature'], drop_first=True)
```



```
# Separate features (X) and target (y)
X = df.drop('play_tennis', axis=1)
y = df['play_tennis']

# Convert target variable to numerical
y = y.apply(lambda x: 1 if x == 'yes' else 0)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

# Initialize the Gaussian Naive Bayes classifier
model = GaussianNB()

# Train the model
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# --- Generate and display performance metrics ---
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

# Generate and print classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# --- Plot the Confusion Matrix ---
fig, ax = plt.subplots(figsize=(8, 6))
ConfusionMatrixDisplay.from_estimator(model, X_test, y_test, ax=ax)
ax.set_title("Confusion Matrix")
plt.tight_layout()
plt.savefig('confusion_matrix.png')
print("Confusion matrix saved to confusion_matrix.png")
```

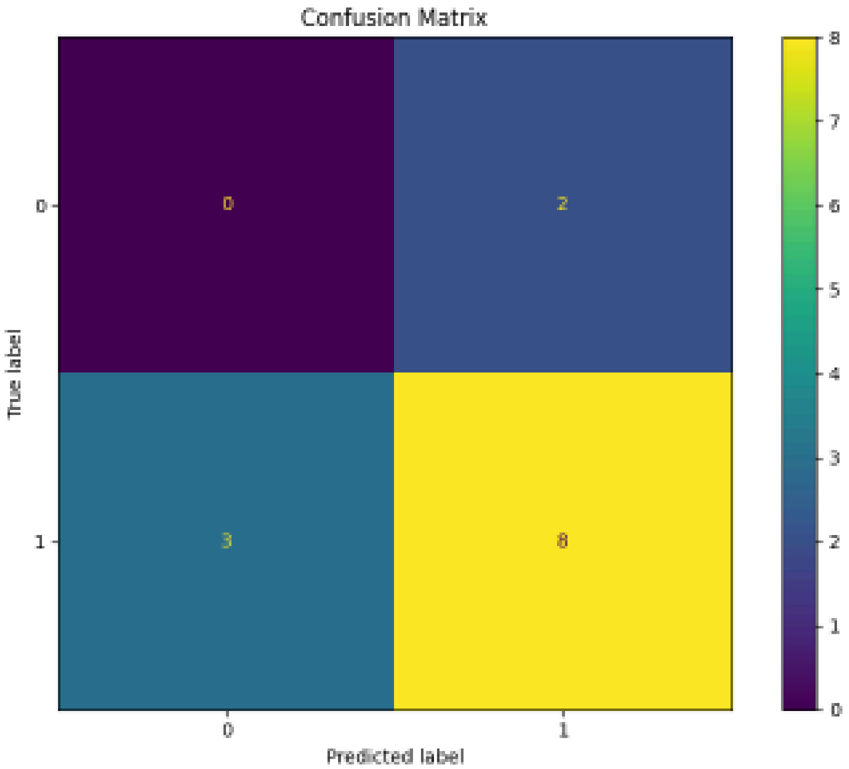
```
Accuracy: 0.62

Classification Report:
 precision recall f1-score support

 0 0.00 0.00 0.00 2
 1 0.80 0.73 0.76 11

 accuracy 0.62 13
 macro avg 0.40 0.36 0.38 13
weighted avg 0.68 0.62 0.64 13

Confusion matrix saved to confusion_matrix.png
```



keyboard_arrow_down Bayesian Networks: The Theory

A Bayesian network is a probabilistic graphical model that represents a set of variables and their conditional dependencies using a directed acyclic graph (DAG). It's a powerful tool for reasoning and inference under uncertainty.

Key Components

A Bayesian network consists of two main parts:

1. Directed Acyclic Graph (DAG): This graph represents the network's structure.
   - Nodes: Each node represents a random variable (e.g., `Burglary` , `Alarm`).
   - Edges: A directed edge from node A to node B signifies a causal or influential relationship where A is a parent of B. It means that the probability of B is conditionally dependent on the state of A. The graph must be acyclic, meaning there's no path that allows you to return to the same node.
2. Conditional Probability Distributions (CPDs): Each node has a conditional probability table (CPT) that quantifies the relationships defined by the graph.
   - For root nodes (nodes with no parents), the CPT is simply the prior probability of that variable (e.g., $P(\text{Burglary})$). For child nodes (nodes with one or more parents), the CPT specifies the conditional probability of the node's state given all possible combinations of its parents' states (e.g., $P(\text{Alarm}|\text{Burglary},\text{Earthquake})$).

The Joint Probability Distribution

The power of a Bayesian network lies in its ability to compactly represent the full joint probability distribution of all variables in the network. The joint probability of a specific state for all variables is calculated by taking the product of each node's conditional probability given its parents.

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid \text{Parents}(X_i))$$

This formula is a direct result of the conditional independence assumptions encoded in the network's structure. It allows for efficient calculation of probabilities, avoiding the need for a massive joint probability table.

Inference in Bayesian Networks

Inference is the process of calculating the posterior probability of a variable or a set of variables, given some evidence. This is the core task that Bayesian networks are designed for. You're essentially asking questions like:

- Diagnostic Inference (Reasoning from effects to causes): "What is the probability of a burglary given that the alarm is ringing?" ($P(\text{Burglary}|\text{Alarm})$

)

Predictive Inference (Reasoning from causes to effects): "What is the probability that John will call if there is a burglary?" ($P(JohnCalls|Burglary)$)

Intercausal Inference (Reasoning about competing causes): "Given that the alarm is ringing and there was no earthquake, what is the probability of a burglary?" ($P(Burglary|Alarm,\neg Earthquake)$)

Algorithms like Variable Elimination or Belief Propagation are used to perform these complex probabilistic queries by efficiently manipulating the CPTs, allowing the model to "reason" about the state of the network.

```
# Install pgmpy library
!pip install pgmpy

# Import necessary modules
from pgmpy.models import DiscreteBayesianNetwork as BayesianNetwork
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import VariableElimination


# Define the structure of the Bayesian Network
alarm_model = BayesianNetwork([('Burglary', 'Alarm'),
                               ('Earthquake', 'Alarm'),
                               ('Alarm', 'JohnCalls'),
                               ('Alarm', 'MaryCalls')])


# CPT for Burglary (B)
cpd_burglary = TabularCPD(variable='Burglary', variable_card=2,
                          values=[[0.999], [0.001]]) # P(~B)=0.999, P(B)=0.001

# CPT for Earthquake (E)
cpd_earthquake = TabularCPD(variable='Earthquake', variable_card=2,
                            values=[[0.998], [0.002]]) # P(~E)=0.998, P(E)=0.002
```



```
# CPT for Alarm (A) given Burglary and Earthquake
cpd_alarm = TabularCPD(variable='Alarm', variable_card=2,
                       values=[[0.999, 0.71, 0.06, 0.05], # P(~A|~B,~E), P(~A|B,~E), P(~A|~B,E), P(~A|B,E)
                               [0.001, 0.29, 0.94, 0.95]], # P(A|~B,~E), P(A|B,~E), P(A|~B,E), P(A|B,E)
                       evidence=['Burglary', 'Earthquake'],
                       evidence_card=[2, 2])

# CPT for JohnCalls (J) given Alarm
cpd_johncalls = TabularCPD(variable='JohnCalls', variable_card=2,
                           values=[[0.95, 0.10], # P(~J|~A), P(~J|A)
                                   [0.05, 0.90]], # P(J|~A), P(J|A)
                           evidence=['Alarm'],
                           evidence_card=[2])

# CPT for MaryCalls (M) given Alarm
cpd_marycalls = TabularCPD(variable='MaryCalls', variable_card=2,
                           values=[[0.10, 0.70], # P(~M|~A), P(~M|A)
                                   [0.90, 0.30]], # P(M|~A), P(M|A)
                           evidence=['Alarm'],
                           evidence_card=[2])

# Add the CPTs to the model
alarm_model.add_cpds(cpd_burglary, cpd_earthquake, cpd_alarm, cpd_johncalls, cpd_marycalls)

# Verify the model
print("Is the model valid? ", alarm_model.check_model())
```

```
Is the model valid? True
```

```
# Create an inference object
alarm_infer = VariableElimination(alarm_model)


# P(Burglary | JohnCalls=True, MaryCalls=True)
query1 = alarm_infer.query(variables=['Burglary'], evidence={'JohnCalls': 1, 'MaryCalls': 1})
print("Probability of a burglary if both John and Mary call:")
print(query1)
```

```
Probability of a burglary if both John and Mary call:
+-------------+-----------------+
| Burglary | phi(Burglary) |
+=============+=================+
| Burglary(0) | 0.9944 |
+-------------+-----------------+
| Burglary(1) | 0.0056 |
+-------------+-----------------+
```

```
# P(Alarm | Burglary=False, Earthquake=True)
query2 = alarm_infer.query(variables=['Alarm'], evidence={'Burglary': 0, 'Earthquake': 1})
print("\nProbability of the alarm ringing if there's an earthquake but no burglary:")
print(query2)
```

```
Probability of the alarm ringing if there's an earthquake but no burglary:
+----------+--------------+
| Alarm | phi(Alarm) |
+==========+==============+
| Alarm(0) | 0.7100 |
+----------+--------------+
| Alarm(1) | 0.2900 |
+----------+--------------+
```

```
# P(Earthquake | Alarm=True, JohnCalls=False)
query3 = alarm_infer.query(variables=['Earthquake'], evidence={'Alarm': 1, 'JohnCalls': 0})
print("\nProbability of an earthquake if the alarm is ringing and John does not call:")
print(query3)
```

```
Probability of an earthquake if the alarm is ringing and John does not call:
+---------------+-------------------+
| Earthquake | phi(Earthquake) |
+===============+===================+
| Earthquake(0) | 0.7690 |
+---------------+-------------------+
| Earthquake(1) | 0.2310 |
+---------------+-------------------+
```

keyboard_arrow_down Conclusion

This series of exercises has provided a hands-on exploration of two fundamental probabilistic models: Naive Bayes and Bayesian Networks.

Start coding or generate with AI.

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