Gaussian_Naive_Bayes

January 4, 2024

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#Gaussian Naive Bayes

Gaussian Naive Bayes modeli Naive Bayes sınıflandırmasına aittir. Bu algoritmada sürekli (continous) veri ele alınır. Her sınıfla ilişkili sürekli özellikler normal (veya Gaussian) dağılıma göre dağıtılır. Bu yöntem kullanılarak eğitim verisinden her sınıf için ortalama (mean) ve standart sapma (standard deviation) değerleri tahmin edilir. Bu sayede dağılım özetlenir.

Gaussian Naive Bayes algoritmasında her sınıfın olasılıklarına ek olarak her sınıfın ortalama ve standart sapma değerleri de saklanır. Bayes Teoermi kullanılarak çalışır:

Bayes Teoremi:

P(A|B), B olayı gerçekleştiğinde A olayının olasılığını temsil eder ve şu şekilde ifade edilir:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{1}$$

Gaussian Naive Bayes (GaussianNB) modelini oluşturan bu fonksiyonları sırayla açıklayalım:

[1]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.naive_bayes import GaussianNB  # Using sklearn's GaussianNB for␣
 ↪demonstration
```

[5]:
```python
class GaussianNB_:
    """
    Gaussian Naive Bayes classifier.
    Parameters:
    - priors (array-like, shape (n_classes,), optional): Prior probabilities of
    the classes. If specified, the priors are not adjusted based on the data.
    Default is None.
    - var_smoothing (float, optional): Portion added to the variance for
    numerical stability. Default is 1e-9.
    Attributes:
```

```
    - theta_ (array, shape (n_classes, n_features)): Mean of each feature per
    class.
    - var_ (array, shape (n_classes, n_features)): Variance of each feature per
    class.
    - class_priors_ (array, shape (n_classes,)): Prior probabilities of the
    classes.
    Methods:
    - logprior(class_ind): Compute the log prior probability of a given class.
    - loglikelihood(Xi, class_ind): Compute the log likelihood of a feature
    vector given a class.
    - posterior(Xi, class_ind): Compute the log posterior probability of a
    feature vector given a class.
    - fit(X, y): Fit the Gaussian Naive Bayes model to the training data.
    - predict(X): Predict the class labels for the input data.
    """
    def __init__(self, priors=None, var_smoothing=1e-9):
        self.priors = priors
        self.var_smoothing = var_smoothing

    def _check_input(self, X):
        """Ensure the input is a numpy array of numeric types."""
        if not isinstance(X, np.ndarray):
            try:
                X = np.array(X, dtype=np.float64)
            except ValueError:
                raise ValueError("Input data X must be a numeric array.")
        return X

    def logprior(self, class_ind):
        """Compute the log prior probability of a given class.
        Parameters:
        - class_ind (int): Index of the class.
        Returns:
        - float: Log prior probability of the specified class.
        """
        return np.log(self.class_priors_[class_ind])

    def loglikelihood(self, Xi, class_ind):
        """
        Compute the log likelihood of a feature vector given a class.
        Parameters:
        - Xi (array-like, shape (n_features,)): Input feature vector.
        - class_ind (int): Index of the class.
        Returns:
        - array: Log likelihood for each feature given the specified class.
        """
```

```
        mean = self.theta_[class_ind]
        var = self.var_[class_ind]

        # Debugging print statements
        #print("Xi type:", type(Xi), "Xi shape:", Xi.shape)
        #print("Mean type:", type(mean), "Mean shape:", mean.shape)
        #print("Var type:", type(var), "Var shape:", var.shape)

        numerator = -0.5 * np.sum(np.log(2. * np.pi * var))
        denominator = -0.5 * np.sum(((Xi - mean) ** 2) / var)
        return numerator + denominator

    def posterior(self, Xi, class_ind):
        """
        Compute the log posterior probability of a feature vector given a
        class.
        Parameters:
        - Xi (array-like, shape (n_features,)): Input feature vector.
        - class_ind (int): Index of the class.
        Returns:
        - float: Log posterior probability of the specified class for the input
        feature vector.
        """
        return self.logprior(class_ind) + self.loglikelihood(Xi, class_ind)

    def fit(self, X, y):
        """
        Fit the Gaussian Naive Bayes model to the training data.
        Parameters:
        - X (array-like, shape (n_samples, n_features)): Training data.
        - y (array-like, shape (n_samples,)): Target labels.
        """
        n_samples, n_features = X.shape
        self.classes_ = np.unique(y)
        n_classes = len(self.classes_)

        self.theta_ = np.zeros((n_classes, n_features))
        self.var_ = np.zeros((n_classes, n_features))
        self.class_priors_ = np.zeros(n_classes)

        for c_ind, c_id in enumerate(self.classes_):
            X_class = X[y == c_id]
            self.theta_[c_ind, :] = np.mean(X_class, axis=0)
            self.var_[c_ind, :] = np.var(X_class, axis=0) + self.var_smoothing
            self.class_priors_[c_ind] = np.sum(y == c_id) / n_samples

    def predict(self, X):
```

```
        """
        Predict the class labels for the input data.
        Parameters:
        - X (array-like, shape (n_samples, n_features)): Input data.
        Returns:
        - array: Predicted class labels.
        """
        X = self._check_input(X)  # Ensuring X is a NumPy array
        predictions = []
        for xi in X:
            # Debugging: Check the type of xi
            if isinstance(xi, str):
                print("Error: Non-numeric data found:", xi)
                continue

            post = [self.posterior(xi, class_ind) for class_ind in␣
 ↪range(len(self.classes_))]
            predictions.append(self.classes_[np.argmax(post)])
        return np.array(predictions)
```

#örnek kullanım

[6]:
```
X = np.array([[1.0, 2.0], [2.0, 3.0], [3.0, 4.0], [4.0, 5.0], [5.0, 6.0], [6.0,␣
 ↪7.0]])
y = np.array([0, 1, 0, 1, 0, 1])
```

[7]:
```
model = GaussianNB_()
model.fit(X, y)
```

[8]:
```
new_data = np.array([[2.5, 3.5], [4.5, 5.5]])

# Make predictions
predictions = model.predict(new_data)

print("Predictions:", predictions)
```

```
Predictions: [0 1]
```

[9]:
```
# Veri setini eğitim ve doğrulama setlerine ayırma
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Modeli eğitim setiyle eğitme
model.fit(X_train, y_train)

# Doğrulama seti üzerinde tahmin yapma
y_pred = model.predict(X_val)
```

```python
# Başarı metriklerini hesaplama
accuracy = accuracy_score(y_val, y_pred)
conf_matrix = confusion_matrix(y_val, y_pred)

print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
```

```
Accuracy: 0.5
Confusion Matrix:
 [[1 0]
 [1 0]]
```

[10]:

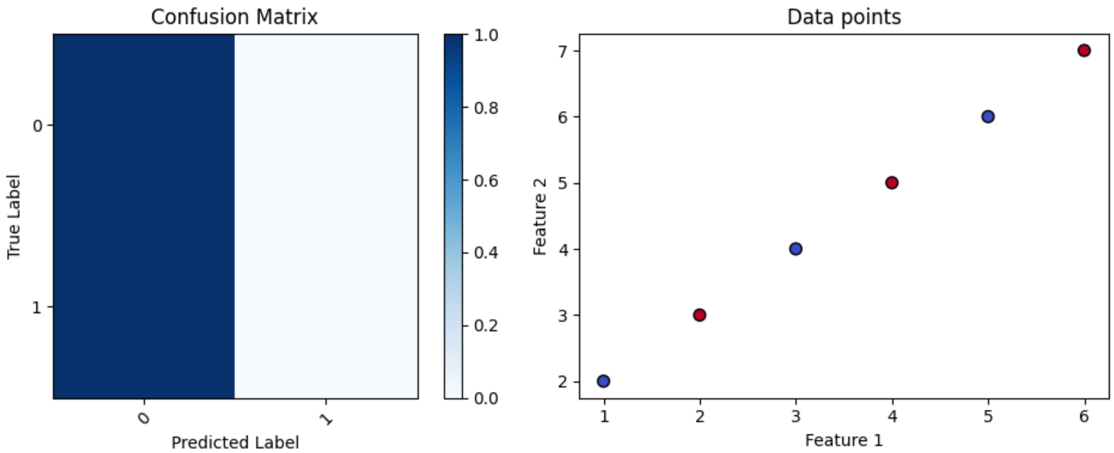
```python
# Plotting the results
plt.figure(figsize=(10, 4))

# Plotting confusion matrix
plt.subplot(1, 2, 1)
plt.imshow(conf_matrix, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(np.unique(y)))
plt.xticks(tick_marks, np.unique(y), rotation=45)
plt.yticks(tick_marks, np.unique(y))
plt.xlabel('Predicted Label')
plt.ylabel('True Label')

# Plotting samples
plt.subplot(1, 2, 2)
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.coolwarm, edgecolor='k', s=50)
plt.title('Data points')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')

plt.tight_layout()
plt.show()

# Printing accuracy
print("Accuracy:", accuracy)
```




```
Accuracy: 0.5
```

[11]:
```
model_=GaussianNB()
model_.fit(X,y)
```

[11]:
```
GaussianNB()
```

[12]:
```
new_data = np.array([[2.5, 3.5], [4.5, 5.5]])

# Make predictions
predictions = model_.predict(new_data)

print("Predictions:", predictions)
```

```
Predictions: [0 1]
```

[13]:
```
# Veri setini eğitim ve doğrulama setlerine ayırma
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Modeli eğitim setiyle eğitme
model_.fit(X_train, y_train)

# Doğrulama seti üzerinde tahmin yapma
y_pred = model_.predict(X_val)

# Başarı metriklerini hesaplama
accuracy = accuracy_score(y_val, y_pred)
conf_matrix = confusion_matrix(y_val, y_pred)

print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
```

```
Accuracy: 0.5
Confusion Matrix:
 [[1 0]
 [1 0]]
```

[14]:

```
# Plotting the results
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plt.imshow(conf_matrix, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(np.unique(y)))
plt.xticks(tick_marks, np.unique(y), rotation=45)
plt.yticks(tick_marks, np.unique(y))
plt.xlabel('Predicted Label')
plt.ylabel('True Label')

# Plotting samples
plt.subplot(1, 2, 2)
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.coolwarm, edgecolor='k', s=50)
plt.title('Data points')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')

plt.tight_layout()
plt.show()

# Printing accuracy
print("Accuracy:", accuracy)
```

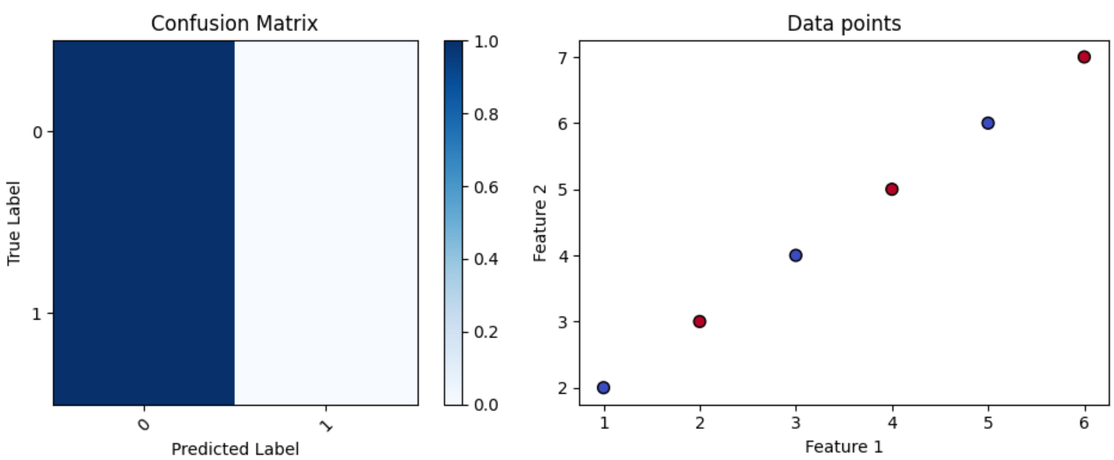

```
Accuracy: 0.5
```

hazır kütüphane ile de kontrol ettim her iki sonuçta da aynı çıkması yöntemin doğruluğunu kanıtlıyor.