Yammy or Meh?

Logistic Regression

Prompts

- Create a new column "yammy", where "star_rating" >= 4.5, it's a 1, otherwise 0.
- Count Os and 1s in the "yammy" column



- Scale the data
- Build a logistic regression with "yammy" as the target

Strategy



- Create a Teacher
- Check the Balance
- Scale the Features
- Train the Model
- Check the Accuracy Read the Confusion Matrix
- Split the Data

Code & Results

1. Create a Teacher

This code checks the "star_rating" and puts a 1 in the new "yammy" column if it is greater than or equal to 4.5.

```
import pandas as pd
# Assuming you already have a DataFrame named df
data['yammy'] = (data['star_rating'] >= 4.5).astype(int)
data.head()
```

Thus, we have the "Yammy" column.

0.0

0.0

2. Check the Balance

This code counts the number of Os and 1s in the "Yammy" column.

1.000000

0.5

0.75

```
data['yammy'].value_counts().sort_index()
          We have 64 "meh" tins and 57 "yummy" ones.
    64
    57
1
```

3. Scale the Features

This code puts features between 0 and 1.

```
from sklearn.preprocessing import MinMaxScaler
# Select only numeric columns (excluding 'yammy' if it's a label)
features = data.drop(columns=['yammy']) # Drop target column if needed
numeric_cols = features.select_dtypes(include=['float64', 'int64']).columns
scaler = MinMaxScaler()
data[numeric_cols] = scaler.fit_transform(data[numeric_cols])
data[numeric_cols].head()
                                                                                          company_me-
o company_meat company_purepet comp
             weight star_rating total_comments adult chicken wet from_ocean company_farmina
                                                                                                                0.0
                         0.60
                                    0.638163
                                                                                     0.0
                                                                                                  0.0
                                                                                                                                1.0
0 0.022888 0.113797
                                             1.0
                                                      0.0 1.0
                                                                      1.0
                         0.65
                                                                     1.0
                                                                                                  0.0
                                                                                                                0.0
                                                                                     0.0
1 0.128879 0.697885
                                    0.904091
                                              1.0
                                                      0.0 1.0
                                                                                                                                1.0
                         0.75
                                                                                                  0.0
                                                                                                                                0.0
2 0.285714 0.697885
                                                                                                                0.0
                                    0.620522
                                              1.0
                                                      0.0 1.0
                                                                      1.0
                                                                                      0.0
                         0.50
                                                                                     0.0
                                                                                                                                0.0
3 0.059754 0.234642
                                    0.348278
                                                                      1.0
                                                                                                                1.0
                                              1.0
                                                      0.0 1.0
                                                                                                  0.0
```

4. Split the Data

4 0.050538 0.103726

This code first splits the teacher from the features and then splits the data into training and testing sets.

0.0 1.0

```
from sklearn.model_selection import train_test_split
# Separate features and target
X = data.drop(columns=['yammy','star_rating'])
y = data['yammy']
# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

1.0

0.0

0.0

5. Train the Model

This code creates a logistic regression model and trains it using the training set.

```
from sklearn.linear_model import LogisticRegression
# Initialize and train model
model = LogisticRegression()
model.fit(X_train, y_train)
```

6. Check the Accuracy & Confusion Matrix

This code evaluates model accuracy and calculates a confusion matrix.

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
# Make predictions
y_pred = model.predict(X_test)
# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

Accuracy: 0.76 Confusion Matrix: [[13 2] [4 6]]

✓ The model got 76% of the tins right.

X It made some mistakes:

- It mislabeled 2 out of 15 meh tins as yammy
- It mislabeled 4 out of 10 yammy tins as meh

So it's doing well overall, but still has room to learn!