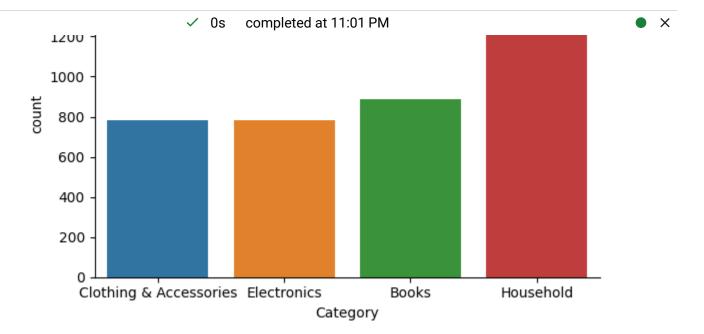
```
from google.colab import drive
drive.mount('/content/drive')
     Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
# Import E-commerce dataset from Kaggle. Add column headers to dataset.
import pandas as pd
path = '/content/drive/MyDrive/ecommerceDataset.csv'
mydata = pd.read_csv(path)
mydata.columns = ['Category', 'Product Description']
mydata = mydata[mydata['Product Description'].apply(lambda x: isinstance(x, str))] # Keep
mydata = mydata[mydata['Product Description'].map(lambda x: x.isascii())]
                                                                               # Remove rows (
mydata = mydata.sample(frac=0.10) # Shuffle rows in dataframe and keep only 10% of rows
display(mydata.head())
                                                          Product Description
                        Category
      36857 Clothing & Accessories Iana vels Men's and Women's Non-slip Stays Hol...
      33303 Clothing & Accessories
                                  IndiWeaves Girls Cottton Black Leggings Pack o...
      45829
                       Electronics
                                    Lapcare 5-in-1 Screen Cleaning Kit with Suctio...
      25170
                           Books Handbook of Chemistry About the Author An edit...
      24610
                           Books
                                    Japji Sahib Way to God in Sikhism - Book 1 (An...
# Set up feature (X) and target (Y)
X_data = mydata['Product Description']
Y_data = mydata['Category']
# Text preprocessing. Remove stop words and convert data to tf-idf representation.
import nltk
#nltk.download('stopwords')
from nltk.corpus import stopwords
from sklearn.feature extraction.text import TfidfVectorizer
stopwords = set(stopwords.words('english'))
vectorizer = TfidfVectorizer(stop words=list(stopwords))
```

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Display graphical distribution of the target classes import seaborn as sns graph = sns.catplot(x="Category", kind="count", data=mydata, height=4, aspect=1.5)



The dataset has two columns: category and product description. The product description consists of the product and description from an E-commerce website. The category consists of the 4 E-commerce categories that the product is associated with: Household, Books, Clothing and Accessories, Electronics. The trained model should be able to predict which one of the 4 categories the product belongs to based on the product and description.

log_reg = LogisticRegression(multi_class='multinomial', class_weight='balanced')

Train model using multinomial logistic regression from sklearn.linear model import LogisticRegression

log_reg.fit(X_train, y_train)

```
LogisticRegression
     LogisticRegression(class_weight='balanced', multi_class='multinomial')
# Train model using neural network
from sklearn.neural network import MLPClassifier
neural_net = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(2), random_state=1)
neural_net.fit(X_train, y_train)
                                 MLPClassifier
     MLPClassifier(hidden_layer_sizes=2, random_state=1, solver='lbfgs')
# Evaluate naive bayes trained model on the test data
from sklearn.metrics import accuracy score
nb_pred = naive_bayes.predict(X_test)
print('Accuracy Score (Naive Bayes): ', accuracy_score(y_test, nb_pred))
# Evaluate logistic regression trained model on the test data
import numpy as np
lr pred = log reg.predict(X test)
print("Accuracy Score (Logistic Regression): ", np.mean(lr_pred==y_test))
# Evaluate neural network trained model on the test data
nn pred = neural net.predict(X test)
print("Accuracy Score (Neural Network): ", np.mean(nn_pred==y_test))
    Accuracy Score (Naive Bayes): 0.8865336658354115
    Accuracy Score (Logistic Regression): 0.942643391521197
    Accuracy Score (Neural Network): 0.9102244389027432
```

I ran this code 2-3 times where each time it will spit out different accuracy scores for all 3 models since I am shuffling the rows at the beginning of this code. For my dataset, the logistic regression consistently did the best out of the 3 approaches with around 95% accuracy. The naive bayes approaches did okay with around 89% accuracy. Interestingly, with the neural network approach, the accuracy varied significantly compared to the other two approaches with accuracies of 91%, 79%, and 85%. It makes sense that the naive bayes approach did ok relatively since the dataset was not small. The neural network approach did okay as well since this approach requires a larger dataset to be more accurate and I only add one hidden layer due to the low amount of features.

