```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler
import pandas as pd
# Load the dataset
df = pd.read_csv("/content/sample_data/student-dataset.csv") # Replace with your file
print(df.head())
       school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;trave
     0 GP;"F";18;"U";"GT3";"A";4;4;"at_home";"teacher...
     1 GP;"F";17;"U";"GT3";"T";1;1;"at_home";"other";...
2 GP;"F";15;"U";"LE3";"T";1;1;"at_home";"other";...
3 GP;"F";15;"U";"GT3";"T";4;2;"health";"services...
     4 GP; "F"; 16; "U"; "GT3"; "T"; 3; 3; "other"; "other"; "h...
Start coding or generate with AI.
print(df.info())
 → <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 395 entries, 0 to 394
     Data columns (total 1 columns):
      # Column
     ---
      0 school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;tr
     dtypes: object(1)
     memory usage: 3.2+ KB
# Not applicable unless you have extra categorical columns.
# Example:
# df['source'] = LabelEncoder().fit_transform(df['source'])
Start coding or generate with AI.
# Only needed if you have additional categorical fields.
# Example:
# df = pd.get_dummies(df, columns=['category'], drop_first=True)
from sklearn.metrics import accuracy_score, classification_report
def predict fake news(text):
    vector = tfidf.transform([text]).toarray()
    scaled = scaler.transform(vector)
    pred = model.predict(scaled)[0][0]
    return "Fake News" if pred > 0.5 else "Real News"
def encode_text_input(text):
    df_input = pd.DataFrame({'text': [text]})
    tfidf_vector = tfidf.transform(df_input['text']).toarray()
    scaled_vector = scaler.transform(tfidf_vector)
    return scaled vector
def final_grade(text):
    result = predict_fake_news(text)
    return f"The article is classified as: {result}"
from sklearn.metrics import accuracy_score, classification_report
```

Explain code KeyError Explain code X •••

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Please explain this code.

Okay, let's break down this part of the code:

## Splitting Data for Training and Testing

This section of code is crucial for evaluating how well a machine learning model will perform on unseen data. It uses a function called train\_test\_split from the sklearn.model\_selection module.

from sklearn.model\_selection import train\_test\_
X\_train, X\_test, y\_train, y\_test = train\_test\_s
 X\_scaled, y, test\_size=0.2, random\_state=42
)

Use code with caution

Here's a breakdown:

- from sklearn.model\_selection import train\_test\_split: This line imports the train\_test\_split function, which is specifically designed for splitting data into training and testing sets.
- 2. X\_train, X\_test, y\_train, y\_test = train\_test\_split(...): This line is where the actual splitting happens. The function is called with some important parameters, and it returns four objects:
  - X\_train: This will contain the features (input data) used to train the machine learning model.
  - X\_test: This will hold the features that are held back and used to test the trained model's performance.
  - y\_train: This contains the corresponding target values (what you're trying to predict) for the training data.
  - y\_test: This contains the target values for the testing data, used to evaluate the model's predictions.
- 3. X\_scaled, y: These are the inputs to the
   train\_test\_split function:
  - X\_scaled: This likely represents your feature data after it has been scaled using the StandardScaler. Scaling is often important to ensure that features with different ranges don't disproportionately influence the model.
  - y: This represents your target variable—what you're trying to predict. For example, in a fake news detection system, this would be a variable indicating whether an article is real or fake.
- 4. test\_size=0.2: This parameter controls the proportion of the data that is allocated to the testing set. In this case, 20% (0.2) of the data will be used for testing, and the remaining 80% will be used for training.
- 5. random\_state=42: This ensures that the data is split in the same way every time the code is run.

This is important for reproducibility so you can compare results across different runs consistently.

In simpler terms, imagine you have a deck of cards and want to teach someone a card game. You'd first split the deck into two piles: one for practice (training) and one to see how well they learned (testing). train\_test\_split is doing something similar with your data. It's creating two sets of data to train and test the accuracy of your machine-learning model.

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Gemini can make mistakes so double-check responses and use code with caution.  $\underline{\text{Learn more}}$