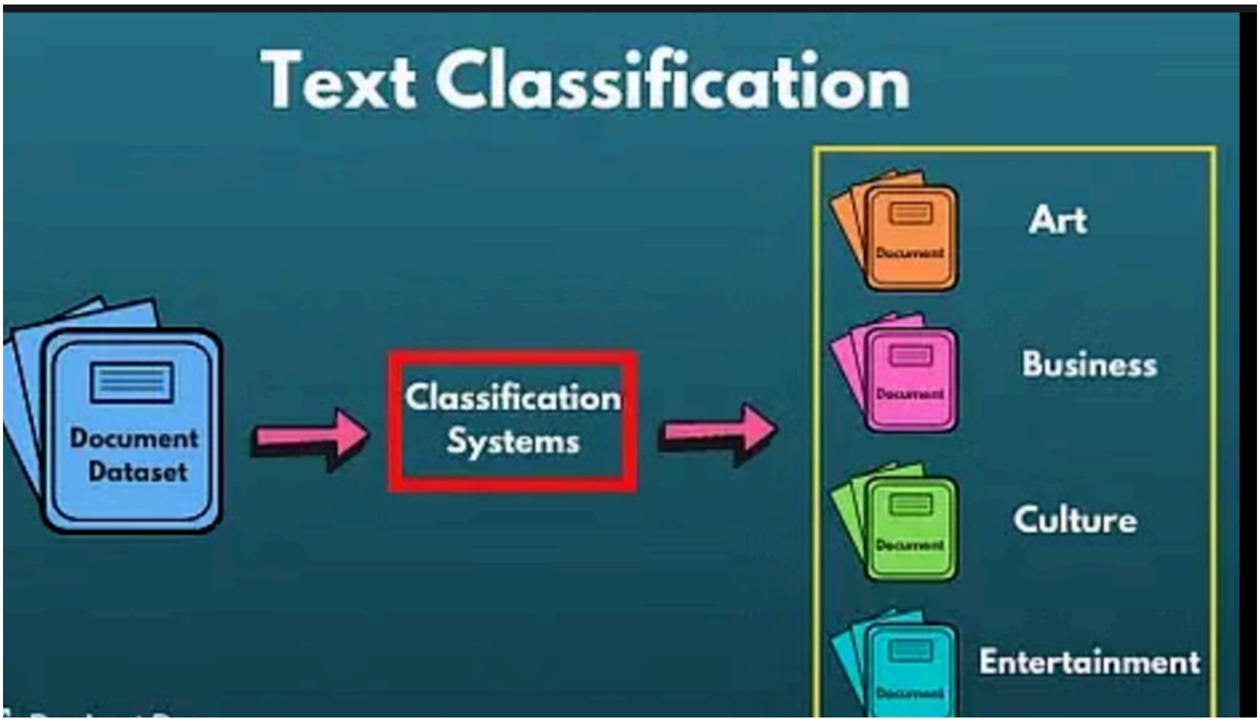
Task 2 - Text Classification using NLP



Objective of project

The main objective of this project is to build a Text classification model that can automatically predict the automatically predict the catagory of given sentence .The model should classify input text into one of the following 10 catagories such as Education,Ecommerce,Technology,Healthcare,Entertainment,Finance,News,Travel,Sports and other.

Problem Statments:

Since we are provided with unlabled dataset cointaining noisy and diverse sentences. These sentence may include emojis,URL,mixed casting,informal language or slang. My task is complely to understand a dataset and Clean the text and remove noise,Label the data into the appropriate categories using rule-based logic,Preprocess the text for modeling (e.g., vectorization),Train and evaluate a classification model,Save the model and vectorizer last but not the least to demonstrate 10 test predictions and accuracy metrics.

Tools & Libraries Used

- Pandas : for data handling
- Scikit-learn : for TF-IDF vectorization,

Step 1 : Loading the data using pandas library

```
import pandas as pd
data = pd.read_csv("/content/drive/MyDrive/dataset.csv")
data.head(5)
```

	text
0	Turn on the profile picture guard to make your...
1	▶▶▶hier klicken: http://bit.ly/freiheitsdressu...
2	Weekend deal alert! Outdo Santa, today only, w...
3	THIS TEENAGE GIRL SHARES THE BIGGEST SECRET OF...
4	Easy & convenient access to professional guida...

Next steps: View recommended plots New interactive sheet

checking missing value and droping it

```
# checking missing value
missing_values = data.isnull().sum()
missing_values
```

	0
text	9493

dtype: int64

```
# removing missing value
data = data.dropna()
data
```

	text
0	Turn on the profile picture guard to make your...
1	▶▶▶hier klicken: http://bit.ly/freiheitsdressu...
2	Weekend deal alert! Outdo Santa, today only, w...
3	THIS TEENAGE GIRL SHARES THE BIGGEST SECRET OF...
4	Easy & convenient access to professional guida...
...	...
99995	What are you doing to keep in shape this winte...
99996	Nature""s Hidden Gems: Top Natural Antibioti...
99997	After over a year of playing shows, we are ext...
99998	Tried, tested, and trusted by the world""s b...
99999	Do you love someone? TAG SOMEONE WHO WOULD RE...

90507 rows × 1 columns

Next steps: View recommended plots New interactive sheet

```
# rechecking once
missing_values = data.isnull().sum()
missing_values
```

	0
text	0

dtype: int64

step 2: cleaning the text

In this step i follow a series of step that help me to get a clean text started with creating function which will help me to clean my text handling URLs,lowercase,emojis and symbol, extra whitespace and many more.

```
def clean_text(text):
  #step1: convert to lowercase for uniformity
  text= text.lower()
  # step2: remove link pattern such as www
```

```
    if "http" in text or "www" in text or "bit.ly" in text:
      text = text.split("http")[0] # here trying to remove everything after http
    # step 3: here tring to remove emoji and symbol just trying to keep letter n num
    text = ''.join(char for char in text if char.isalnum() or char.isspace())
    # step 4: remove extra spaces
    text = ' '.join(text.split())
    return text
```

applying this custom function or helper fun to our dataset

```
# appying the clean fun to the column that we have i.e text
data['clean_text']=data['text'].astype(str).apply(clean_text)
```

```
# lets see the result after changes or fun apply
data[['text','clean_text']].head(5)
```

	text	clean_text
0	Turn on the profile picture guard to make your...	turn on the profile picture guard to make your...
1	▶▶▶hier klicken: http://bit.ly/freiheitsdressu...	hier klicken
2	Weekend deal alert! Outdo Santa, today only, w...	weekend deal alert outdo santa today only with...
3	THIS TEENAGE GIRL SHARES THE BIGGEST SECRET OF...	this teenage girl shares the biggest secret of...
4	Easy & convenient access to professional guida...	easy convenient access to professional guidanc...

Since we have sucessfully handle lowecase ,url.emojis punctuation extra white space within few text preprocesing step

```
data.shape
```

```
(90507, 2)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 90507 entries, 0 to 99999
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   text        90507 non-null  object
 1   clean_text  90507 non-null  object
dtypes: object(2)
memory usage: 2.1+ MB
```

Step 3: creating a label function/helper fun based on keywords as per question such as Ecommerce ,Eduction and many more

```
def label_category(text):
  text = text.lower()
  if any(word in text for word in['buy','deal','offer','sales']):
    return 'Ecommerce'
  elif any(word in text for word in['learn','study','Education','course','class']):
    return 'Education'
  elif any(word in text for word in['Technology','tech','ai','data','machine learning']):
    return 'Technology'
  elif any(word in text for word in['health','doctor','clinic','hospital']):
    return 'Healthcare'
  elif any(word in text for word in['movies','music','song','entertainment','tv']):
    return 'Entertainment'
  elif any(word in text for word in['finance','loan','bank','money']):
    return 'Finance'
  elif any(word in text for word in['news','breaking','headline']):
    return 'News'
  elif any(word in text for word in['travel','flight','hotels','trip']):
    return 'Travel'
  elif any(word in text for word in['match','cricket','football','sports']):
    return 'Sports'
  else:
    return 'Other'
```

Applying our custom or label fun to our clean text

```
data['category'] = data['clean_text'].apply(label_category)
```

Checking the output or changes after applying the label function

```
data[['clean_text','category']].head(10)
```

	clean_text	category
0	turn on the profile picture guard to make your...	Other
1	hier klicken	Other
2	weekend deal alert outdo santa today only with...	Ecommerce
3	this teenage girl shares the biggest secret of...	Other
4	easy convenient access to professional guidanc...	Healthcare
5	detroit wallpaper co finds design inspiration ...	Other
6	your favorite cozy fall drink meets your favor...	Other
7	on 6 7 december affiliate world is taking over...	Other
8	november 29 11 am make room in your wardrobe o...	Technology
9	no compromises no annual contracts only from a...	Ecommerce

as shown above we have create the catagory label sucessfully

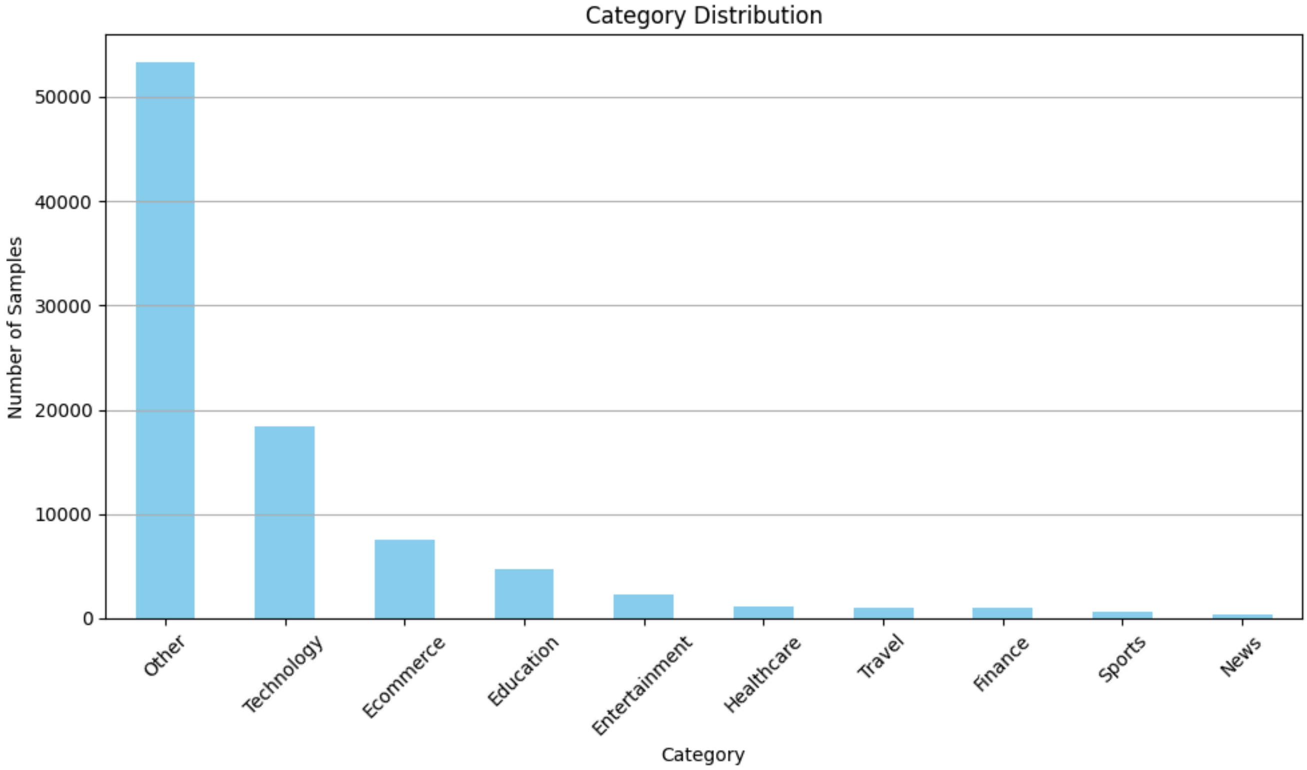
checking class weight for each catagory

```
import pandas as pd
import matplotlib.pyplot as plt

# Step 1: Check value counts for each class
category_counts = data['category'].value_counts()
print(category_counts)

# Step 2: Plot bar chart
plt.figure(figsize=(10, 6))
category_counts.plot(kind='bar', color='skyblue')
plt.title("Category Distribution")
plt.xlabel("Category")
plt.ylabel("Number of Samples")
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```

```
category
Other            53294
Technology       18368
Ecommerce         7599
Education         4742
Entertainment     2343
Healthcare        1145
Travel            1032
Finance            999
Sports             582
News               403
Name: count, dtype: int64
```



Since our class is imbalance other class i.e majority class dominates minority class such as News, sports ,finance and soon so we need to handle it

Step 4 : VECTORIZED AND TRAIN THE MODEL

In this step i am going to use vectorize such as TF-IDF vectorizer to conver text into number since model dont understand text directly.

After that will be training the classification model

At the end i will be checking my model accuracy as well

Double-click (or enter) to edit

```
# Data handling
import pandas as pd
import numpy as np
# Model selection & validation
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
# Text vectorization
from sklearn.feature_extraction.text import TfidfVectorizer
# Classifiers
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
# Evaluation metrics
from sklearn.metrics import accuracy_score, f1_score, classification_report
# Handling class imbalance
from imblearn.over_sampling import SMOTE
# Saving model and vectorizer
import joblib
```

TF-IDF Vectorization

```
vectorizer = TfidfVectorizer(max_features=3000)
X = data['clean_text']
y = data['category']
X_vec = vectorizer.fit_transform(X)
```

Importing all the required library

```
# Data handling
import pandas as pd
import numpy as np
# Model selection & validation
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
# Text vectorization
from sklearn.feature_extraction.text import TfidfVectorizer
# Classifiers
from sklearn.linear_model import LogisticRegression
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# Evaluation metrics
from sklearn.metrics import accuracy_score, f1_score, classification_report
# Handling class imbalance
from imblearn.over_sampling import SMOTE
# Saving model and vectorizer
import joblib
```

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from imblearn.over_sampling import SMOTE

# Step 1: Prepare features and labels
X = data['clean_text']
y = data['category']

# Step 2: TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=10000)
X_vec = vectorizer.fit_transform(X)

# Step 3: Stratified Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(
    X_vec, y, test_size=0.2, stratify=y, random_state=42
)

# Step 4: Apply SMOTE to training data
smote = SMOTE(random_state=42)
X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
```

trying with different model

Logistic regression

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from imblearn.over_sampling import SMOTE

# Step 1: Prepare features and labels
X = data['clean_text']
y = data['category']

# Step 2: TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=10000)
X_vec = vectorizer.fit_transform(X)

# Step 3: Stratified Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(
    X_vec, y, test_size=0.2, stratify=y, random_state=42
)
```

```
# Step 4: Apply SMOTE to training data
smote = SMOTE(random_state=42)
X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, classification_report

logreg = LogisticRegression(max_iter=1000, random_state=42)
logreg.fit(X_train_sm, y_train_sm)

y_pred_logreg = logreg.predict(X_test)

print(f"Logistic Regression Accuracy: {accuracy_score(y_test, y_pred_logreg):.4f}")
print(f"Logistic Regression F1 Score: {f1_score(y_test, y_pred_logreg, average='weighted'):.4f}")
print("Classification Report:\n", classification_report(y_test, y_pred_logreg))
```

```
Logistic Regression Accuracy: 0.8223
Logistic Regression F1 Score: 0.8309
Classification Report:
                precision    recall  f1-score   support

    Ecommerce       0.94      0.91      0.92      1520
    Education       0.93      0.90      0.92       948
Entertainment       0.35      0.79      0.49       469
      Finance       0.69      0.82      0.75       200
   Healthcare       0.55      0.82      0.66       229
         News       0.62      0.73      0.67        81
        Other       0.90      0.83      0.87     10659
       Sports       0.55      0.78      0.64       116
   Technology       0.77      0.74      0.75      3674
       Travel       0.40      0.79      0.53       206

     accuracy                           0.82     18102
    macro avg       0.67      0.81      0.72     18102
 weighted avg       0.85      0.82      0.83     18102
```

2.Training and Evaluate SVM (LinearSVC)

```
from sklearn.svm import LinearSVC

# Initialize model
svm_model = LinearSVC()

# Fit the model
svm_model.fit(X_train_sm, y_train_sm)

# Predict
y_pred_svm = svm_model.predict(X_test)

# Evaluate
print(f"SVM Accuracy: {accuracy_score(y_test, y_pred_svm):.4f}")
print(f"SVM F1 Score: {f1_score(y_test, y_pred_svm, average='weighted'):.4f}")
print("Classification Report:\n", classification_report(y_test, y_pred_svm))
```

```
SVM Accuracy: 0.8365
SVM F1 Score: 0.8457
Classification Report:
                precision    recall  f1-score   support

    Ecommerce       0.95      0.95      0.95      1520
    Education       0.93      0.92      0.93       948
Entertainment       0.35      0.76      0.48       469
      Finance       0.65      0.82      0.73       200
   Healthcare       0.53      0.83      0.65       229
         News       0.68      0.70      0.69        81
        Other       0.91      0.84      0.87     10659
       Sports       0.51      0.77      0.61       116
   Technology       0.81      0.78      0.79      3674
       Travel       0.40      0.79      0.53       206

     accuracy                           0.84     18102
    macro avg       0.67      0.82      0.72     18102
 weighted avg       0.86      0.84      0.85     18102
```

3.Training and Evaluating Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, f1_score, classification_report
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split

# Step 1: Split with stratification
X_train, X_test, y_train, y_test = train_test_split(X_vec, y, test_size=0.2, stratify=y, random_state=42)

# Step 2: Apply SMOTE to balance training set
smote = SMOTE(random_state=42)
X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)

# Step 3: Initialize optimized Random Forest
rf_model = RandomForestClassifier(
    n_estimators=50,     # reduce trees
    max_depth=20,        # control depth
    n_jobs=-1,           # use all cores
    random_state=42
)

# Step 4: Train model
rf_model.fit(X_train_sm, y_train_sm)

# Step 5: Predict and evaluate
y_pred = rf_model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred, average='weighted')

print("Random Forest Accuracy:", round(acc, 4))
print("Random Forest F1 Score:", round(f1, 4))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Random Forest Accuracy: 0.7314
Random Forest F1 Score: 0.7228
Classification Report:
               precision    recall  f1-score   support

    Ecommerce       0.77      0.88      0.82      1520
    Education       0.52      0.86      0.65       948
Entertainment       0.49      0.74      0.59       469
      Finance       0.33      0.81      0.47       200
   Healthcare       0.50      0.83      0.63       229
         News       0.30      0.75      0.43        81
        Other       0.82      0.83      0.83     10659
       Sports       0.30      0.76      0.43       116
   Technology       0.74      0.33      0.46      3674
```