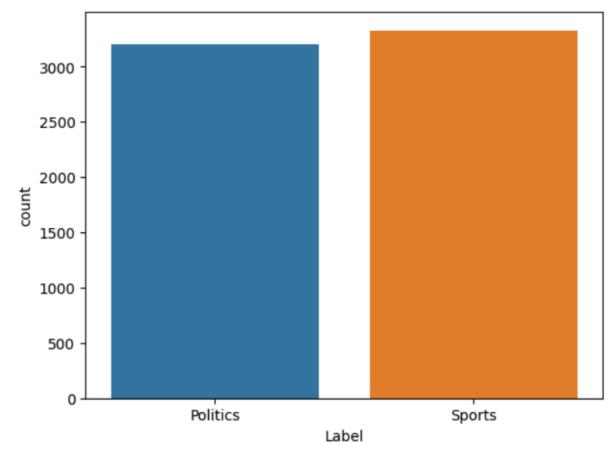
# Task Report: Twitter Text Classification

## I. Data Exploration:

- 1. Data Loading and Visualization:
  - Loaded the training and test datasets using `pd.read\_csv`:

train\_data = pd.read\_csv('/kaggle/input/deeptweets/train.csv')
test\_data = pd.read\_csv('/kaggle/input/deeptweets/test.csv')

- Utilized Seaborn to visualize the distribution of labels in the training set using `sns.countplot`:



## **II. Data Preprocessing:**

#### 1. Word Clouds Visualization:

- Created word clouds for both "Politics" and "Sports" labels to visually explore frequent terms in each category.
  - Word clouds were generated using the WordCloud library.

#### WordCloud for "Politics"



## WordCloud for "Sports"



## 2. Text Processing:

- Defined a text processing function `Text\_Processing` to clean and preprocess the tweet text.
- Converted text to lowercase, removed special characters, and URLs using regular expressions.
  - Tokenized the text using NLTK's `word\_tokenize`.
  - Applied stemming using the PorterStemmer to reduce words to their root form.
- Created a new column `ProcessedText` in the training dataset to store the preprocessed text.

```
# Initialization of the stemmer
stemmer = PorterStemmer()

def Text_Processing(text):
    text = text.lower()
    # Remove special characters and URLs
    text = re.sub(r'http\S+', '', text)
    text = re.sub(r'[^a-zA-Z\s]', '', text)
# Tokenize the text
    text = word_tokenize(text)
# Stemming words
    text = [stemmer.stem(word) for word in text]
# Join the processed words back into a sentence
    text = ' '.join(text)
    return text
```

### **III. Data Splitting:**

- Split the dataset into training and testing sets using `train\_test\_split`:

```
# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=42)
```

## IV. Model Building:

#### 1. Logistic Regression Pipeline:

- Constructed a machine learning pipeline using 'Pipeline' from scikit-learn.
- Utilized a bag-of-words representation with `CountVectorizer` (unigrams and bigrams).
- Employed a logistic regression classifier ('LogisticRegression') as the predictive model.

```
LR = Pipeline([
        ('bag_of_word' , CountVectorizer(ngram_range=(1,2))),
        ('LR' , LogisticRegression())

])
LR.fit(X_train, y_train)
y_pred = LR.predict(X_test)
print(classification_report(y_test, y_pred))
```

#### 2. Model Training and Evaluation:

- Fitted the pipeline on the training data (`X\_train`, `y\_train`).
- Made predictions on the test data and printed a classification report using `classification\_report`.
  - Displayed a confusion matrix to visualize model performance.

### V. Results and Analysis:

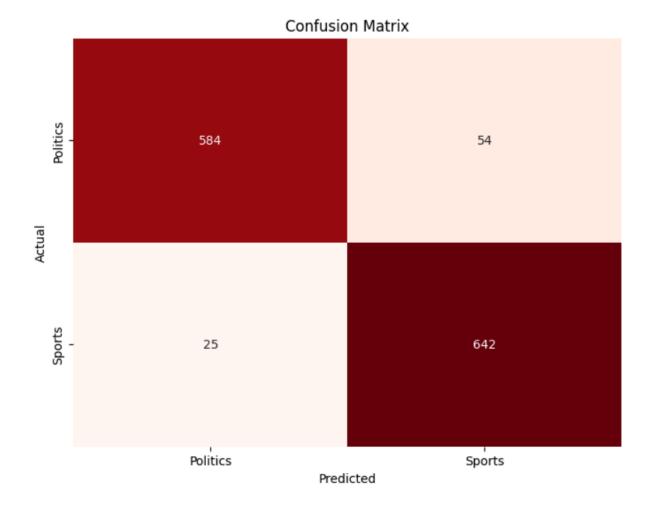
#### 1. Classification Report:

- Examined precision, recall, and F1-score for both "Politics" and "Sports" labels.
- Assessed the overall model performance on the test set.

	precision	recall	f1-score	support
Politics	0.96	0.92	0.94	638
Sports	0.92	0.96	0.94	667
accuracy			0.94	1305
macro avg	0.94	0.94	0.94	1305
weighted avg	0.94	0.94	0.94	1305

#### 2. Confusion Matrix Visualization:

- Visualized the confusion matrix using Seaborn's heatmap to understand model predictions.
  - The heatmap displays actual vs. predicted labels.



### VI. Conclusion:

- Summarized key findings, including model performance metrics.
- Provided insights into the effectiveness of the chosen model and preprocessing techniques.
- Suggested potential areas for improvement, such as experimenting with different vectorization techniques or exploring other classification algorithms.