22CB903

MINI-PROJECT 2

OBJECTIVE:

To build a text classification model that classifies text messages as either "ham" (non-spam) or "spam", using two different feature extraction methods: TF-IDF (Term Frequency-Inverse Document Frequency) and Word Embeddings (Word2Vec).

ALGORITHM:

Data Preprocessing:

1. Load the dataset containing text messages and their respective labels (ham/spam).
2. Text Cleaning:
   - Convert the text to lowercase.
   - Remove punctuation and special characters.
   - Remove digits if present.
   - Tokenize the text by splitting it into words.
3. Label Encoding: Convert the "ham" and "spam" labels into numerical values (e.g., ham → 0, spam → 1).

Feature Engineering:

1. TF-IDF Approach:
   - Use the TfidfVectorizer from scikit-learn to convert the cleaned text into numerical features. This assigns a weight to each word based on its frequency in the document and its inverse frequency in the entire dataset.
   - Transform the text data into TF-IDF features for both training and test sets.
2. Word Embeddings Approach (Word2Vec):

- Train a Word2Vec model on the tokenized text to learn 100-dimensional word embeddings.
- For each message, compute the average word vector by averaging the vectors of all the words in the message.
- Use these average vectors as features for both training and test sets.

Model Training:

1. Train a Logistic Regression model using the extracted features from both the TF-IDF and Word Embedding (Word2Vec) approaches.

Model Evaluation:

1. Predict the labels for the test set using both models (TF-IDF and Word2Vec).
2. Evaluate the performance using the following metrics:
    - Accuracy: The proportion of correctly classified messages.
    - Precision: The proportion of predicted positive cases (spam) that are truly positive.
    - Recall: The proportion of actual positive cases (spam) that were correctly identified.
    - F1-score: The harmonic mean of precision and recall.
3. Compare the performance of both models based on these metrics.

CODE:

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import classification_report

from sklearn.preprocessing import LabelEncoder

import re

import string

from gensim.models import Word2Vec

import numpy as np
```

```
# Data preprocessing function: clean and tokenize the text
def preprocess_text(text):
    text = text.lower()  # Lowercase the text
    text = re.sub(f"[{string.punctuation}]", "", text)  # Remove punctuation
    text = re.sub(r"\d+", "", text)  # Remove digits
    return text

# Load the dataset
dataset = pd.read_csv(r"C:\stuff\college stuff\study\cb903\22CB903-Machine-
Learning-MiniProjects\02-Text Classification\dataset.csv")

# Preprocess the text messages
dataset['cleaned_message'] = dataset['Message'].apply(preprocess_text)

# Encode the labels: ham -> 0, spam -> 1
label_encoder = LabelEncoder()
dataset['label'] = label_encoder.fit_transform(dataset['Category'])

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    dataset['cleaned_message'], dataset['label'], test_size=0.2,
random_state=42
)

# Step 2: TF-IDF Feature Engineering
tfidf = TfidfVectorizer(max_features=5000)
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)

# Step 3: Train a Logistic Regression model on TF-IDF features
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train_tfidf, y_train)

# Make predictions and evaluate the model
```

```
y_pred_tfidf = lr_model.predict(X_test_tfidf)

report_tfidf = classification_report(y_test, y_pred_tfidf,
target_names=['ham', 'spam'])

print("TF-IDF Model Performance:\n", report_tfidf)


# Step 4: Word Embedding (Word2Vec) Feature Engineering

# Tokenize the cleaned text for Word2Vec input

tokenized_messages = dataset['cleaned_message'].apply(lambda x: x.split())


# Train a Word2Vec model

word2vec_model = Word2Vec(sentences=tokenized_messages, vector_size=100,
window=5, min_count=1, workers=4)


# Function to get the average word vector for a sentence

def get_avg_word2vec(sentence, model, vector_size):

    words = sentence.split()

    avg_vector = np.zeros(vector_size)

    valid_words = 0

    for word in words:

        if word in model.wv:

            avg_vector += model.wv[word]

            valid_words += 1

    if valid_words > 0:

        avg_vector /= valid_words

    return avg_vector


# Transform the dataset using the average word vectors

X_train_w2v = np.array([get_avg_word2vec(sentence, word2vec_model, 100) for
sentence in X_train])

X_test_w2v = np.array([get_avg_word2vec(sentence, word2vec_model, 100) for
sentence in X_test])


# Train a Logistic Regression model on Word2Vec features

lr_w2v_model = LogisticRegression(max_iter=1000)

lr_w2v_model.fit(X_train_w2v, y_train)
```

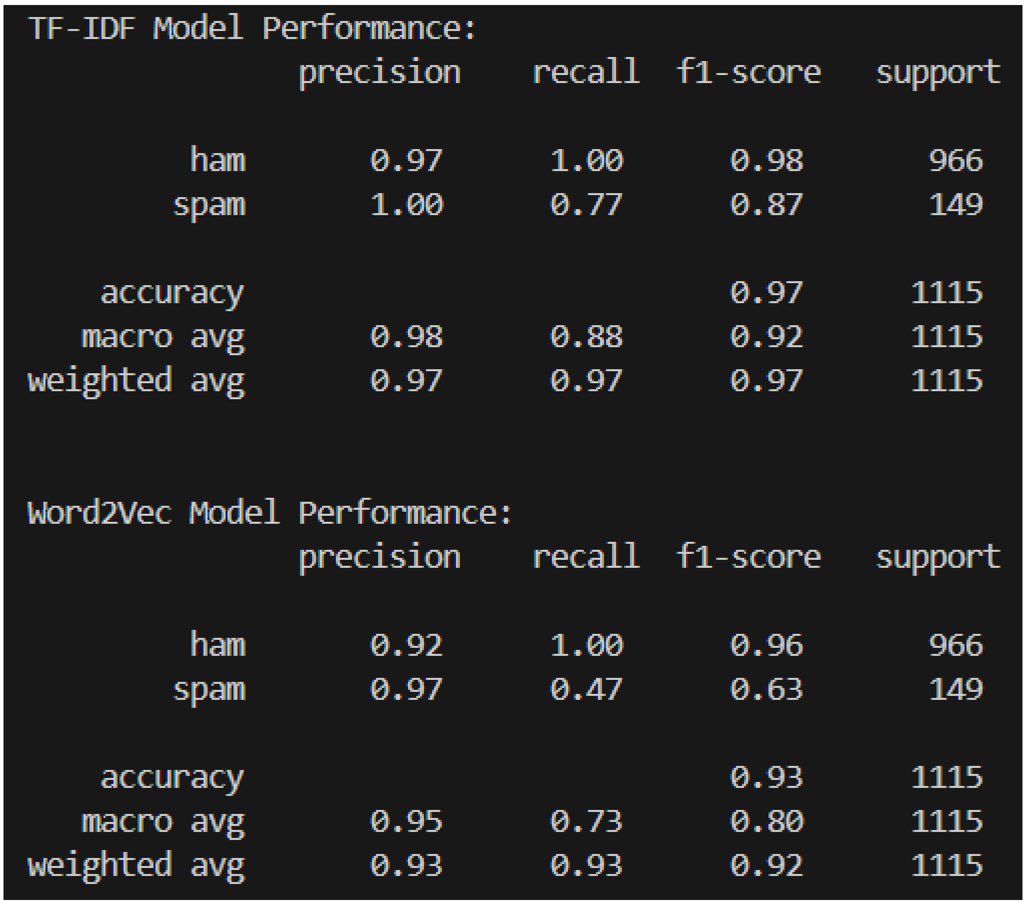
```
# Make predictions and evaluate the Word2Vec model

y_pred_w2v = lr_w2v_model.predict(X_test_w2v)

report_w2v = classification_report(y_test, y_pred_w2v, target_names=['ham',
'spam'])

print("\nWord2Vec Model Performance:\n", report_w2v)
```

OUTPUT:



```
TF-IDF Model Performance:
               precision    recall  f1-score   support

         ham       0.97      1.00      0.98       966
        spam       1.00      0.77      0.87       149

    accuracy                           0.97      1115
   macro avg       0.98      0.88      0.92      1115
weighted avg       0.97      0.97      0.97      1115


Word2Vec Model Performance:
               precision    recall  f1-score   support

         ham       0.92      1.00      0.96       966
        spam       0.97      0.47      0.63       149

    accuracy                           0.93      1115
   macro avg       0.95      0.73      0.80      1115
weighted avg       0.93      0.93      0.92      1115
```

OBSERVATIONS & COMPARISION:

Metric	TF-IDF Model (Logistic Regression)	Word2Vec Model (Logistic Regression)
Accuracy	97%	93%
Precision (Ham)	97%	92%
Precision (Spam)	100%	97%
Recall (Ham)	100%	100%
Recall (Spam)	77%	47%
F1-score (Ham)	98%	96%
F1-score (Spam)	87%	63%
Macro Avg (F1)	92%	80%
Weighted Avg (F1)	97%	92%

1. Accuracy:
    - The TF-IDF model achieved higher accuracy (97%) compared to the Word2Vec model (93%).
2. Precision:
    - Both models have excellent precision for detecting spam, but TF-IDF has a slight edge in precision for "ham" (non-spam) as well.
    - TF-IDF: 97% (ham) and 100% (spam) precision.
    - Word2Vec: 92% (ham) and 97% (spam) precision.
3. Recall:
    - TF-IDF has significantly higher recall for spam (77%) compared to Word2Vec (47%), meaning the TF-IDF model is much better at identifying spam messages.
    - Both models have perfect recall (100%) for detecting "ham" (non-spam).
4. F-1 Score:

    - The F1-score for spam detection is much higher in the TF-IDF model (87%) compared to Word2Vec (63%). This indicates that TF-IDF balances precision and recall more effectively for spam classification.
    - The F1-score for "ham" is high for both models, with TF-IDF slightly outperforming.

5. Macro and Weighted Averages:
    - The macro average (average of precision and recall for each class) for TF-IDF (92%) is higher than for Word2Vec (80%).
    - The weighted average of F1-scores also shows a clear advantage for TF-IDF, with 97% vs 92% for Word2Vec.

CONCLUSION:

- TF-IDF is the superior model in this case, especially in terms of accuracy, recall, and F1-score for spam detection. It performs better at balancing precision and recall, especially for the minority "spam" class.
- Word2Vec lags in spam detection due to lower recall, though its precision remains high.

By

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