

nlp-text-classification-siddhant

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1 Google Colab Lab Assignment -NLP

Course Name: Deep Learning

Lab Title: NLP Techniques for Text Classification

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Objective The objective of this assignment is to implement NLP preprocessing techniques and build a text classification model using machine learning techniques.

Learning Outcomes:

1. Understand and apply NLP preprocessing techniques such as tokenization, stopwords removal, stemming, and lemmatization.
2. Implement text vectorization techniques such as TF-IDF and CountVectorizer.
3. Develop a text classification model using a machine learning algorithm.
4. Evaluate the performance of the model using suitable metrics.

2 Assignment Instructions:

Part 1: NLP Preprocessing

Dataset Selection: <https://www.kaggle.com/datasets/thedevastator/uncovering-financial-insights-with-the-reuters-2>

Drive Link for Dataset: https://drive.google.com/drive/folders/1uLf9u9_M4nuFGGa-YTC6EmaXDSKfrFF4?usp=sharing

Choose any text dataset from **Best Datasets for Text** <https://en.innovatiana.com/post/best-datasets-for-text-classification> Classification, such as SMS Spam Collection, IMDb Reviews, or any other relevant dataset.

Download the dataset and upload it to Google Colab.

Load the dataset into a Pandas DataFrame and explore its structure (e.g., check missing values, data types, and label distribution).

Text Preprocessing:

Convert text to lowercase.

Perform tokenization using NLTK or spaCy.

Remove stopwords using NLTK or spaCy.

Apply stemming using PorterStemmer or SnowballStemmer.

Apply lemmatization using WordNetLemmatizer.

Vectorization Techniques:

Convert text data into numerical format using TF-IDF and CountVectorizer.

```
[ ]: import pandas as pd

# Load the dataset
train_df = pd.read_csv("/content/ModApte_train.csv")
test_df = pd.read_csv("/content/ModApte_test.csv")

# Display information
print("Train Data Info:")
print(train_df.info())

print("\nTest Data Info:")
print(test_df.info())

# Check for missing values
print("\nMissing Values in Train Set:")
print(train_df.isnull().sum())

print("\nMissing Values in Test Set:")
print(test_df.isnull().sum())

# Check label distribution
print("\nLabel Distribution in Train Set:")
print(train_df['topics'].value_counts())

print("\nLabel Distribution in Test Set:")
print(test_df['topics'].value_counts())
```

Train Data Info:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 9603 entries, 0 to 9602

Data columns (total 13 columns):

#	Column	Non-Null Count	Dtype
0	text	8816 non-null	object
1	text_type	9603 non-null	object
2	topics	9603 non-null	object
3	lewis_split	9603 non-null	object
4	cgis_split	9603 non-null	object
5	old_id	9603 non-null	object
6	new_id	9603 non-null	object

```

7   places      9603 non-null  object
8   people      9603 non-null  object
9   orgs        9603 non-null  object
10  exchanges   9603 non-null  object
11  date        9603 non-null  object
12  title       9549 non-null  object
dtypes: object(13)
memory usage: 975.4+ KB
None

```

Test Data Info:

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3299 entries, 0 to 3298
Data columns (total 13 columns):
#   Column          Non-Null Count  Dtype
---  -
0   text             3023 non-null  object
1   text_type        3299 non-null  object
2   topics           3299 non-null  object
3   lewis_split      3299 non-null  object
4   cgis_split       3299 non-null  object
5   old_id           3299 non-null  object
6   new_id           3299 non-null  object
7   places           3299 non-null  object
8   people           3299 non-null  object
9   orgs             3299 non-null  object
10  exchanges        3299 non-null  object
11  date             3299 non-null  object
12  title            3285 non-null  object
dtypes: object(13)
memory usage: 335.2+ KB
None

```

Missing Values in Train Set:

```

text      787
text_type    0
topics      0
lewis_split  0
cgis_split  0
old_id      0
new_id      0
places      0
people      0
orgs        0
exchanges   0
date        0
title      54
dtype: int64

```

Missing Values in Test Set:

text	276
text_type	0
topics	0
lewis_split	0
cgis_split	0
old_id	0
new_id	0
places	0
people	0
orgs	0
exchanges	0
date	0
title	14

dtype: int64

Label Distribution in Train Set:

topics	
['earn']	2840
[]	1828
['acq']	1596
['crude']	253
['trade']	251
...	
['grain' 'corn' 'rice' 'oilseed' 'soybean' 'orange']	1
['trade' 'bop' 'money-fx' 'dlr']	1
['gnp' 'cpi' 'money-fx']	1
['zinc' 'lead' 'copper']	1
['grain' 'corn' 'soybean' 'oilseed']	1

Name: count, Length: 473, dtype: int64

Label Distribution in Test Set:

topics	
['earn']	1083
['acq']	696
[]	280
['crude']	121
['money-fx']	87
...	
['trade' 'carcass']	1
['oilseed' 'soybean' 'veg-oil' 'trade']	1
['trade' 'livestock' 'carcass' 'sugar']	1
['money-fx' 'rand']	1
['money-fx' 'dlr' 'yen' 'dmk']	1

Name: count, Length: 258, dtype: int64

```
[ ]: import nltk
import spacy
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer

# Download required NLTK resources
nltk.download('stopwords')
nltk.download('wordnet')

# Load spaCy's English model
nlp = spacy.load("en_core_web_sm")

# Initialize tools
stop_words = set(stopwords.words("english"))
stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()

def preprocess_text(text):
    # Check if the text is a string and not NaN
    if isinstance(text, str):
        # Convert to lowercase
        text = text.lower()

        # Tokenization using spaCy
        doc = nlp(text)
        tokens = [token.text for token in doc if token.is_alpha] # Remove
        ↪ non-alphabetic tokens

        # Remove stopwords
        tokens = [word for word in tokens if word not in stop_words]

        # Stemming using PorterStemmer
        stemmed_tokens = [stemmer.stem(word) for word in tokens]

        # Lemmatization using WordNetLemmatizer
        lemmatized_tokens = [lemmatizer.lemmatize(word) for word in
        ↪ stemmed_tokens]

        # Return the processed text
        return " ".join(lemmatized_tokens)
    else:
        # If the value is not a string (e.g., NaN), return an empty string
        return ""

# Apply preprocessing to both train and test sets
train_df["cleaned_text"] = train_df["title"].apply(preprocess_text)
test_df["cleaned_text"] = test_df["title"].apply(preprocess_text)
```

```
# Check processed text
print("\nExample Processed Text (Train Set):")
print(train_df["cleaned_text"].head())
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

Example Processed Text (Train Set):

```
0          bahia cocoa review
1  nation averag price farmer own reserv
2      argentin grain oilse registr
3          usx debt dowgrad moodi
4  champion product approv stock split
Name: cleaned_text, dtype: object
```

```
[ ]: from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# CountVectorizer: Converts a collection of text documents into a matrix of
↳ token counts
count_vectorizer = CountVectorizer(max_features=100) # Limiting to 100
↳ features for demonstration
X_train_count = count_vectorizer.fit_transform(train_df["cleaned_text"])
X_test_count = count_vectorizer.transform(test_df["cleaned_text"])

# Convert to DataFrame to view top words
count_df = pd.DataFrame(X_train_count.toarray(), columns=count_vectorizer.
↳ get_feature_names_out())
print("\nTop words in CountVectorizer (Train Set):")
print(count_df.head())

# TF-IDF Vectorizer: Converts text data into numerical values based on term
↳ frequency and inverse document frequency
tfidf_vectorizer = TfidfVectorizer(max_features=100) # Limiting to 100
↳ features for demonstration
X_train_tfidf = tfidf_vectorizer.fit_transform(train_df["cleaned_text"])
X_test_tfidf = tfidf_vectorizer.transform(test_df["cleaned_text"])

# Convert to DataFrame to view top words
tfidf_df = pd.DataFrame(X_train_tfidf.toarray(), columns=tfidf_vectorizer.
↳ get_feature_names_out())
print("\nTop words in TF-IDF (Train Set):")
print(tfidf_df.head())
```

Top words in CountVectorizer (Train Set):

	acquir	acquisit	american	bank	bid	bill	billion	bond	brazil	buy	\
0	0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	

	...	tender	trade	treasuri	two	unit	usda	week	wheat	year	yen
0	...	0	0	0	0	0	0	0	0	0	0
1	...	0	0	0	0	0	0	0	0	0	0
2	...	0	0	0	0	0	0	0	0	0	0
3	...	0	0	0	0	0	0	0	0	0	0
4	...	0	0	0	0	0	0	0	0	0	0

[5 rows x 100 columns]

Top words in TF-IDF (Train Set):

	acquir	acquisit	american	bank	bid	bill	billion	bond	brazil	buy	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

	...	tender	trade	treasuri	two	unit	usda	week	wheat	year	yen
0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

[5 rows x 100 columns]

Splitting the Data:

Divide the dataset into training and testing sets (e.g., 80% training, 20% testing).

Building the Classification Model:

Train a text classification model using Logistic Regression, Naïve Bayes, or any other suitable algorithm.

Implement the model using scikit-learn.

Model Evaluation:

Evaluate the model using accuracy, precision, recall, and F1-score.

Use a confusion matrix to visualize the results.

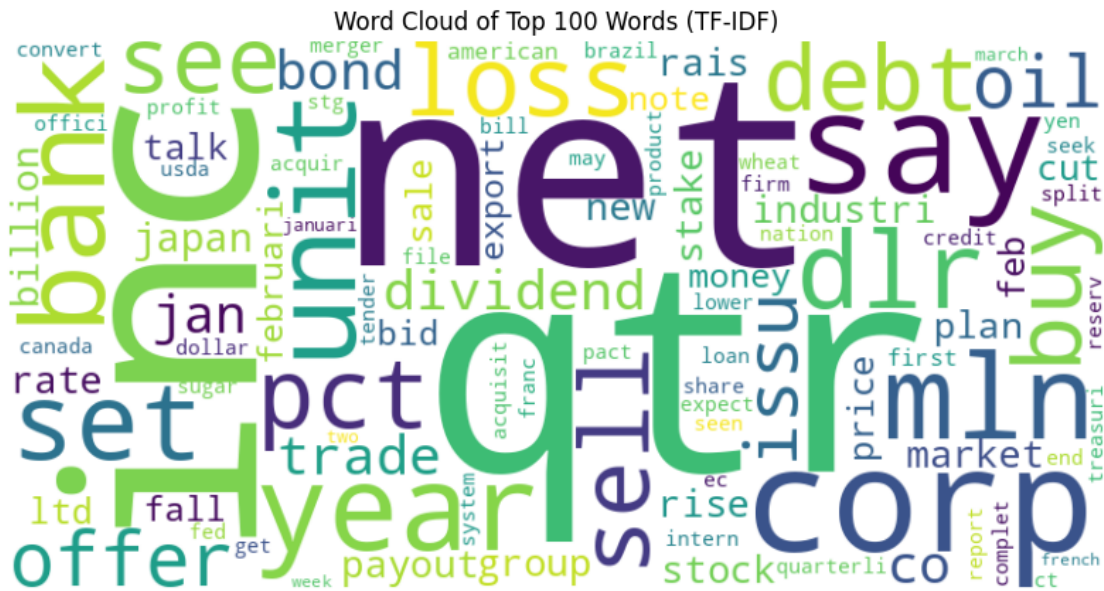
```
[ ]: import matplotlib.pyplot as plt
from wordcloud import WordCloud

# Get feature names (top 100 words from TF-IDF)
feature_names = tfidf_vectorizer.get_feature_names_out()

# Compute average TF-IDF score for each word
word_tfidf_scores = X_train_tfidf.mean(axis=0).A1 # Convert sparse matrix to array

# Create a dictionary of words and their scores
word_freq = dict(zip(feature_names, word_tfidf_scores))

# Generate word cloud
plt.figure(figsize=(10, 6))
wordcloud = WordCloud(width=800, height=400, background_color='white').
    generate_from_frequencies(word_freq)
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.title("Word Cloud of Top 100 Words (TF-IDF)")
plt.show()
```



```
[ ]: from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
import seaborn as sns
```



```

import matplotlib.pyplot as plt

# Prepare the labels
y_train = train_df['topics']
y_test = test_df['topics']

# Train a Naïve Bayes model using the CountVectorizer features (X_train_count)
nb_model = MultinomialNB()
nb_model.fit(X_train_count, y_train)

# Predict the labels for the test set
y_pred = nb_model.predict(X_test_count)

# Model Evaluation
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Visualize confusion matrix using seaborn heatmap
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=train_df['topics'].unique(), yticklabels=train_df['topics'].
            unique())
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

```

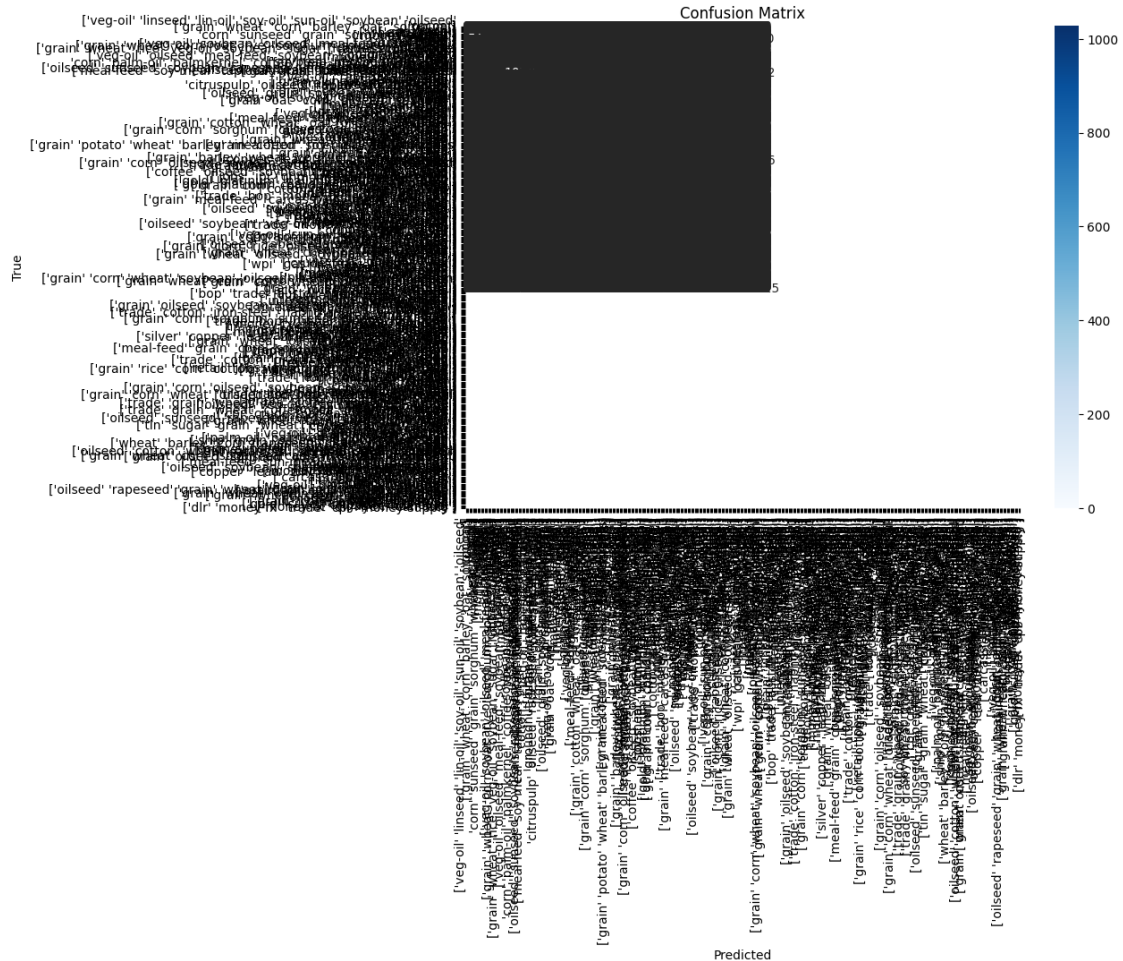
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```

Accuracy: 0.6369
Precision: 0.5276
Recall: 0.6369
F1-Score: 0.5701

```



```
[ ]: from sklearn.metrics import classification_report

# Ensure that the labels are consistent with the unique values in y_test and
# y_pred
labels = train_df['topics'].unique() # Use the unique labels from your train
# dataset

# Generate the classification report
report = classification_report(y_test, y_pred, labels=labels)
print(report)
```

```
precision    recall  f1-score   support
```

```

0.00         0.00         0.00         15                ['cocoa']
0.00         0.00         0.00         1  ['grain' 'wheat' 'corn' 'barley' 'oat' 'sorghum']
```

				['veg-oil' 'linseed' 'lin-oil' 'soy-oil']
'sun-oil' 'soybean' 'oilseed'				
'corn' 'sunseed' 'grain' 'sorghum' 'wheat']				0.00 0.00 0.00
0				
				[]
0.50	0.80	0.61	280	['earn']
0.74	0.95	0.83	1083	['acq']
0.76	0.78	0.77	696	['earn' 'acq']
0.00	0.00	0.00	0	['wheat' 'grain']
0.00	0.00	0.00	3	['copper']
0.40	0.31	0.35	13	['housing']
0.00	0.00	0.00	2	['money-supply']
0.36	0.46	0.41	28	['coffee']
0.05	0.05	0.05	22	['acq' 'ship']
0.00	0.00	0.00	0	['sugar']
0.52	0.88	0.66	25	['trade']
0.46	0.61	0.53	75	['reserves']
0.75	0.75	0.75	12	['ship']
0.00	0.00	0.00	36	['grain' 'corn']
0.19	0.21	0.20	19	['veg-oil' 'soybean' 'oilseed' 'meal-feed' 'soy-meal']
0.00	0.00	0.00	0	['grain' 'wheat' 'corn' 'oat' 'rye' 'sorghum' 'soybean' 'oilseed']
0.00	0.00	0.00	0	['cotton']
0.00	0.00	0.00	9	['grain' 'ship']
0.00	0.00	0.00	5	['carcass' 'livestock']
0.00	0.00	0.00	2	['grain']
0.67	0.20	0.31	10	['crude']
0.48	0.60	0.53	121	

				['nat-gas']
0.00	0.00	0.00	12	
				['cpi' 'gnp']
0.00	0.00	0.00	1	
				['grain' 'wheat']
0.41	0.91	0.56	32	
				['grain' 'corn' 'oat']
0.00	0.00	0.00	0	
	['veg-oil' 'oilseed' 'meal-feed' 'soybean' 'soy-oil' 'soy-meal']			
0.00	0.00	0.00	0	
				['cpi']
0.18	0.24	0.21	17	
				['money-fx' 'interest']
0.54	0.46	0.50	28	
				['interest']
0.59	0.63	0.61	81	
				['gnp' 'bop']
0.00	0.00	0.00	2	
				['grain' 'rice']
0.00	0.00	0.00	7	
				['soybean' 'red-bean' 'oilseed']
0.00	0.00	0.00	0	
	['grain' 'wheat' 'rice' 'veg-oil' 'soybean' 'sugar' 'rubber' 'copra-cake'			
	'corn' 'palm-oil' 'palmkernel' 'coffee' 'tea' 'plywood' 'soy-meal'			
	'cotton']	0.00	0.00	0.00 0
				['money-fx']
0.17	0.13	0.14	87	
				['meal-feed' 'copra-cake']
0.00	0.00	0.00	0	
				['alum']
0.00	0.00	0.00	19	
				['veg-oil' 'palm-oil']
0.00	0.00	0.00	4	
				['tea' 'cocoa' 'coffee']
0.00	0.00	0.00	0	
				['oilseed' 'soybean']
0.00	0.00	0.00	6	
				['oilseed' 'soybean' 'meal-feed' 'soy-meal']
0.00	0.00	0.00	0	
				['gold' 'platinum' 'strategic-metal']
0.00	0.00	0.00	0	
				['meal-feed' 'tapioca']
0.00	0.00	0.00	0	
				['tin']
0.00	0.00	0.00	10	
				['trade' 'bop']
0.00	0.00	0.00	5	
				['oilseed']

'sunseed'	'soybean'	'rapeseed'	'veg-oil'	'soy-oil'	'palm-oil'	
'groundnut-oil']	0.00	0.00	0.00	0		
						['gold']
0.00	0.00	0.00	20			
						['veg-oil' 'rape-oil' 'palm-oil']
0.00	0.00	0.00	0			
						['meal-feed' 'soy-meal' 'tapioca' 'grain'
'corn' 'corn' 'glutenfeed'						
'citruspulp' 'oilseed' 'rapeseed' 'rape-meal']	0.00	0.00	0.00			
0						
						['strategic-metal']
0.00	0.00	0.00	6			
						['crude' 'ship']
0.00	0.00	0.00	22			
						['grain' 'wheat' 'corn' 'barley']
0.00	0.00	0.00	0			
						['grain' 'oat']
0.00	0.00	0.00	0			
						['grain' 'wheat' 'wool' 'dlr']
0.00	0.00	0.00	0			
						['livestock' 'l-cattle']
0.00	0.00	0.00	2			
						['retail']
0.00	0.00	0.00	1			
						['gold' 'acq' 'platinum']
0.00	0.00	0.00	0			
						['ipi']
1.00	0.45	0.62	11			
						['oilseed']
0.00	0.00	0.00	0			
						['gold' 'silver']
0.00	0.00	0.00	1			
						['grain' 'corn' 'wheat' 'barley']
0.00	0.00	0.00	1			
						['iron-steel']
0.00	0.00	0.00	12			
						['rubber']
0.00	0.00	0.00	9			
						['oilseed' 'grain' 'soybean' 'wheat' 'corn']
0.00	0.00	0.00	0			
						['crude' 'nat-gas']
1.00	0.11	0.20	9			
						['livestock' 'hog']
0.00	0.00	0.00	0			
						['propane' 'heat' 'gas']
0.00	0.00	0.00	0			
						['veg-oil' 'soy-oil' 'oilseed' 'soybean']
0.00	0.00	0.00	0			

				['heat']
0.00	0.00	0.00	4	
				['gnp' 'trade']
0.00	0.00	0.00	0	
				['grain' 'oat' 'corn' 'oilseed' 'soybean']
0.00	0.00	0.00	0	
				['jobs']
0.25	0.08	0.12	12	
				['lei']
0.00	0.00	0.00	3	
				['money-fx' 'yen' 'dlr']
0.00	0.00	0.00	0	
				['bop']
0.00	0.00	0.00	9	
				['money-fx' 'saudriyal']
0.00	0.00	0.00	0	
				['earn' 'alum']
0.00	0.00	0.00	0	
				['interest' 'money-fx']
0.00	0.00	0.00	11	
				['earn' 'crude']
0.00	0.00	0.00	0	
				['coffee' 'crude']
0.00	0.00	0.00	0	
				['gnp']
0.07	0.07	0.07	15	
				['grain' 'wheat' 'barley']
0.00	0.00	0.00	0	
				['zinc']
0.00	0.00	0.00	5	
				['veg-oil' 'livestock' 'carcass']
0.00	0.00	0.00	0	
				['grain' 'corn' 'sorghum']
0.00	0.00	0.00	0	
				['oilseed' 'rapeseed']
0.00	0.00	0.00	4	
				['veg-oil']
1.00	0.27	0.43	11	
				['meal-feed' 'soy-meal' 'grain' 'corn']
0.00	0.00	0.00	1	
				['grain' 'wheat' 'ship']
0.00	0.00	0.00	1	
				['orange']
0.00	0.00	0.00	9	
				['livestock' 'carcass']
0.00	0.00	0.00	3	
				['wheat' 'corn']
0.00	0.00	0.00	0	

0.00	0.00	['grain' 'cotton' 'wheat' 'oat' 'oilseed' 'soybean']	0
		['carcass']	
0.00	0.00		5
		['pet-chem']	
0.00	0.00		6
		['dlr' 'money-fx']	
0.00	0.00		12
		['gas']	
0.00	0.00		8
		['money-fx' 'dlr']	
0.32	0.60	0.42	15
		['livestock' 'carcass' 'grain']	
0.00	0.00	0.00	0
		['grain' 'corn' 'sorghum' 'oilseed' 'sunseed' 'soybean']	
0.00	0.00	0.00	0
		['grain' 'wheat' 'cotton' 'rice']	
0.00	0.00	0.00	0
		['gold' 'copper']	
0.00	0.00	0.00	1
		['bop' 'trade' 'gnp']	
0.00	0.00	0.00	0
		['grain' 'barley' 'corn']	
0.00	0.00	0.00	0
		['gas' 'fuel']	
0.00	0.00	0.00	1
		['nat-gas' 'crude']	
0.00	0.00	0.00	2
		['livestock' 'carcass' 'trade']	
0.00	0.00	0.00	0
		['grain' 'corn' 'wheat']	
0.00	0.00	0.00	1
		['grain' 'wheat' 'oilseed' 'soybean']	
0.00	0.00	0.00	0
		['money-fx' 'trade']	
0.00	0.00	0.00	1
		['gas' 'crude']	
0.00	0.00	0.00	4
		['crude' 'gas' 'fuel']	
0.00	0.00	0.00	0
		['acq' 'earn']	
0.00	0.00	0.00	2
		['crude' 'gas']	
0.00	0.00	0.00	2
		['grain' 'cotton' 'rice' 'oilseed' 'soybean']	
0.00	0.00	0.00	0
		['bop' 'trade']	
0.00	0.00	0.00	6

[illegible]

				['trade' 'crude' 'nat-gas']
0.00	0.00	0.00	0	
				['coffee' 'oilseed' 'soybean' 'trade' 'sugar' 'cocoa']
0.00	0.00	0.00	0	
				['trade' 'grain' 'wheat']
0.00	0.00	0.00	0	
				['fishmeal' 'meal-feed']
0.00	0.00	0.00	0	
				['hog' 'livestock']
0.00	0.00	0.00	2	
				['jobs' 'ipi' 'gnp' 'income' 'trade' 'retail']
0.00	0.00	0.00	0	
				['money-supply' 'reserves']
0.00	0.00	0.00	0	
				['interest' 'gnp']
0.00	0.00	0.00	1	
				['grain' 'wheat' 'corn']
0.00	0.00	0.00	3	
				['sugar' 'corn' 'grain']
0.00	0.00	0.00	0	
				['gold' 'platinum' 'palladium' 'nickel' 'copper']
0.00	0.00	0.00	0	
				['lumber']
0.00	0.00	0.00	4	
				['ship' 'gas']
0.00	0.00	0.00	0	
				['gold' 'platinum' 'palladium' 'copper' 'nickel']
0.00	0.00	0.00	0	
				['grain' 'corn' 'corn gluten feed' 'meal-feed']
0.00	0.00	0.00	0	
				['interest' 'crude']
0.00	0.00	0.00	0	
				['crude' 'fuel' 'jet']
0.00	0.00	0.00	0	
				['tapioca' 'meal-feed']
0.00	0.00	0.00	0	
				['cotton' 'sugar' 'veg-oil' 'grain']
0.00	0.00	0.00	0	
				['instal-debt']
0.00	0.00	0.00	1	
				['trade' 'gnp' 'bop' 'dlr']
0.00	0.00	0.00	0	
				['interest' 'money-fx' 'dlr']
0.00	0.00	0.00	1	
				['gnp' 'jobs' 'cpi' 'bop' 'dfl']
0.00	0.00	0.00	0	
				['money-fx' 'gnp']
0.00	0.00	0.00	0	

				['meal-feed']
0.00	0.00	0.00	1	
				['trade' 'bop' 'money-fx' 'crude' 'gnp' 'dlr']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'dmk']
0.00	0.00	0.00	1	
				['grain' 'oilseed']
0.00	0.00	0.00	1	
				['grain' 'meal-feed' 'carcass' 'soy-meal' 'livestock']
0.00	0.00	0.00	0	
				['pet-chem' 'acq']
0.00	0.00	0.00	1	
				['meal-feed' 'fishmeal']
0.00	0.00	0.00	0	
				['acq' 'crude' 'nat-gas']
0.00	0.00	0.00	5	
				['grain' 'corn' 'sugar']
0.00	0.00	0.00	0	
				['lead']
0.00	0.00	0.00	4	
				['gnp' 'money-supply']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'trade' 'acq']
0.00	0.00	0.00	0	
				['hog' 'l-cattle' 'livestock']
0.00	0.00	0.00	0	
				['oilseed' 'soybean' 'grain' 'corn' 'wheat']
0.00	0.00	0.00	1	
				['interest' 'stg']
0.00	0.00	0.00	0	
				['grain' 'corn' 'wheat' 'oilseed']
0.00	0.00	0.00	0	
				['cocoa' 'coffee' 'sugar' 'heat']
0.00	0.00	0.00	0	
				['potato']
0.00	0.00	0.00	3	
				['carcass' 'livestock' 'hog']
0.00	0.00	0.00	0	
				['trade' 'bop' 'money-fx' 'dlr']
0.00	0.00	0.00	0	
				['grain' 'corn' 'wheat' 'rice']
0.00	0.00	0.00	0	
				['gnp' 'cpi' 'money-fx']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'rice']
0.00	0.00	0.00	1	
				['zinc' 'lead' 'copper']
0.00	0.00	0.00	0	

				['earn' 'strategic-metal']
0.00	0.00	0.00	0	
				['money-supply' 'interest']
0.00	0.00	0.00	1	
				['money-fx' 'yen' 'trade']
0.00	0.00	0.00	0	
				['money-fx' 'stg' 'can']
0.00	0.00	0.00	0	
				['oilseed' 'soybean' 'veg-oil' 'palm-oil' 'coconut-oil']
0.00	0.00	0.00	0	
				['trade' 'money-fx' 'cpi' 'reserves']
0.00	0.00	0.00	0	
				['copper' 'earn']
0.00	0.00	0.00	0	
				['money-fx' 'stg']
0.00	0.00	0.00	0	
				['trade' 'sugar']
0.00	0.00	0.00	0	
				['gas' 'grain' 'corn']
0.00	0.00	0.00	0	
				['copper' 'zinc' 'silver']
0.00	0.00	0.00	0	
				['acq' 'silver']
0.00	0.00	0.00	0	
				['acq' 'crude']
0.00	0.00	0.00	0	
				['lumber' 'plywood']
0.00	0.00	0.00	0	
				['veg-oil' 'sun-oil' 'corn-oil' 'rape-oil']
0.00	0.00	0.00	0	
				['coffee' 'ship']
0.00	0.00	0.00	0	
				['grain' 'corn' 'soybean' 'oilseed']
0.00	0.00	0.00	0	
				['grain' 'corn' 'sorghum' 'sunseed' 'oilseed']
0.00	0.00	0.00	0	
				['gas' 'fuel' 'crude']
0.00	0.00	0.00	0	
				['interest' 'retail' 'ipi']
0.00	0.00	0.00	0	
				['crude' 'nat-gas' 'iron-steel']
0.00	0.00	0.00	0	
				['ship' 'iron-steel']
0.00	0.00	0.00	0	
				['acq' 'gold']
0.00	0.00	0.00	1	
				['grain' 'wheat' 'sugar']
0.00	0.00	0.00	0	

			['oilseed' 'rapeseed' 'soybean' 'sunseed']
0.00	0.00	0.00	0
			['money-fx' 'reserves']
0.00	0.00	0.00	1
			['grain' 'corn' 'rice' 'oilseed' 'soybean' 'orange']
0.00	0.00	0.00	0
			['cocoa' 'coffee']
0.00	0.00	0.00	0
			['acq' 'trade']
0.00	0.00	0.00	1
			['earn' 'crude' 'nat-gas']
0.00	0.00	0.00	0
			['earn' 'copper']
0.00	0.00	0.00	0
			['crude' 'acq']
0.00	0.00	0.00	1
			['grain' 'wheat' 'corn' 'oilseed' 'soybean']
0.00	0.00	0.00	0
			['gnp' 'cpi' 'reserves']
0.00	0.00	0.00	0
			['grain' 'wheat' 'oilseed' 'soybean' 'cotton' 'rice']
0.00	0.00	0.00	0
			['l-cattle' 'livestock']
0.00	0.00	0.00	0
			['gnp' 'cpi']
0.00	0.00	0.00	1
			['rice' 'grain']
0.00	0.00	0.00	0
			['nickel']
0.00	0.00	0.00	1
			['ship' 'grain']
0.00	0.00	0.00	1
			['inventories']
0.00	0.00	0.00	0
			['interest' 'gnp' 'ipi' 'wpi']
0.00	0.00	0.00	0
			['crude' 'gas' 'nat-gas' 'wpi']
0.00	0.00	0.00	0
			['wpi' 'gas' 'nat-gas' 'crude' 'heat']
0.00	0.00	0.00	0
			['veg-oil' 'soy-oil']
0.00	0.00	0.00	2
			['cpi' 'gas']
0.00	0.00	0.00	0
			['pet-chem' 'crude']
0.00	0.00	0.00	0
			['iron-steel' 'zinc' 'lead']
0.00	0.00	0.00	0

				['trade' 'veg-oil']
0.00	0.00	0.00	0	
				['reserves' 'money-fx']
0.00	0.00	0.00	0	
				['ipi' 'inventories']
0.00	0.00	0.00	0	
				['money-fx' 'yen' 'gnp']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'interest']
0.00	0.00	0.00	1	
				['veg-oil' 'palm-oil' 'ship']
0.00	0.00	0.00	0	
				['money-fx' 'grain' 'corn']
0.00	0.00	0.00	0	
				['cpu']
0.00	0.00	0.00	1	
				['oilseed' 'veg-oil' 'soybean']
0.00	0.00	0.00	0	
				['money-fx' 'peseta']
0.00	0.00	0.00	0	
				['acq' 'copper']
0.00	0.00	0.00	2	
				['trade' 'gnp']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn' 'cotton' 'sorghum' 'barley' 'corn']
0.00	0.00	0.00	0	
				['grain' 'corn' 'wheat' 'oilseed' 'soybean']
0.00	0.00	0.00	3	
				['trade' 'ship' 'crude']
0.00	0.00	0.00	0	
				['trade' 'coffee']
0.00	0.00	0.00	2	
				['grain'
'corn' 'wheat' 'soybean' 'oilseed' 'barley' 'sorghum' 'cotton'				
'rice']	0.00	0.00	0.00	0
				['ship' 'crude' 'fuel']
0.00	0.00	0.00	0	
				['meal-feed' 'veg-oil']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn' 'sorghum']
0.00	0.00	0.00	0	
				['crude' 'fuel']
0.00	0.00	0.00	0	
				['acq' 'nickel' 'strategic-metal']
0.00	0.00	0.00	0	
				['soybean' 'oilseed']
0.00	0.00	0.00	0	
				['oilseed' 'veg-oil']

0.00	0.00	0.00	1	
				['bop' 'trade' 'austdlr' 'money-fx' 'interest']
0.00	0.00	0.00	0	
				['money-fx' 'austdlr']
0.00	0.00	0.00	0	
				['interest' 'money-supply']
0.00	0.00	0.00	1	
				['corn' 'grain']
0.00	0.00	0.00	1	
				['ship' 'trade' 'crude']
0.00	0.00	0.00	0	
				['livestock' 'l-cattle' 'carcass']
0.00	0.00	0.00	0	
				['veg-oil' 'soybean']
0.00	0.00	0.00	1	
				['interest' 'bop' 'money-supply']
0.00	0.00	0.00	0	
				['ipi' 'jobs']
0.00	0.00	0.00	0	
				['housing' 'interest' 'gnp']
0.00	0.00	0.00	0	
				['trade' 'grain']
0.00	0.00	0.00	1	
				['grain' 'oilseed' 'soybean']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'soybean' 'carcass' 'corn' 'cotton' 'rice']
0.00	0.00	0.00	0	
				['interest' 'trade' 'gnp' 'bop' 'cpi']
0.00	0.00	0.00	0	
				['veg-oil' 'sun-oil' 'cotton-oil']
0.00	0.00	0.00	0	
				['veg-oil' 'coconut-oil']
0.00	0.00	0.00	0	
				['zinc' 'lead']
0.00	0.00	0.00	1	
				['l-cattle']
0.00	0.00	0.00	0	
				['silver']
0.00	0.00	0.00	0	
				['trade' 'cotton' 'iron-steel' 'naphtha' 'veg-oil' 'palm-oil']
0.00	0.00	0.00	0	
				['grain' 'corn' 'veg-oil']
0.00	0.00	0.00	0	
				['grain' 'corn' 'ship']
0.00	0.00	0.00	0	
				['crude' 'nat-gas' 'earn']
0.00	0.00	0.00	0	
				['fuel']

0.00	0.00	0.00	7	
				['jet']
0.00	0.00	0.00	1	
				['grain' 'corn' 'sorghum' 'sunseed' 'oilseed' 'soybean']
0.00	0.00	0.00	0	
				['money-fx' 'nzdlr']
0.00	0.00	0.00	2	
				['trade' 'bop' 'rubber' 'veg-oil' 'palm-oil']
0.00	0.00	0.00	0	
				['trade' 'bop' 'gnp']
0.00	0.00	0.00	1	
				['income']
0.00	0.00	0.00	4	
				['money-fx' 'income' 'money-supply']
0.00	0.00	0.00	0	
				['veg-oil' 'oilseed' 'soybean']
0.00	0.00	0.00	0	
				['money-fx' 'rand']
0.00	0.00	0.00	1	
				['crude' 'earn' 'nat-gas']
0.00	0.00	0.00	0	
				['money-supply' 'money-fx' 'interest']
0.00	0.00	0.00	0	
				['heat' 'naphtha' 'jet' 'fuel']
0.00	0.00	0.00	0	
				['grain' 'rice' 'wheat' 'tea' 'sugar']
0.00	0.00	0.00	0	
				['grain' 'meal-feed']
0.00	0.00	0.00	0	
				['money-fx' 'interest' 'money-supply']
0.00	0.00	0.00	0	
				['oilseed' 'soybean' 'veg-oil']
0.00	0.00	0.00	0	
				['trade' 'iron-steel' 'cotton']
0.00	0.00	0.00	0	
				['grain' 'corn' 'oilseed' 'soybean']
0.00	0.00	0.00	3	
				['silver' 'copper' 'lead' 'zinc' 'gold' 'strategic-metal']
0.00	0.00	0.00	0	
				['lead' 'zinc']
0.00	0.00	0.00	2	
				['grain' 'rice' 'corn' 'cotton']
0.00	0.00	0.00	0	
				['livestock' 'pork-belly']
0.00	0.00	0.00	0	
				['oilseed' 'meal-feed']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'oilseed' 'soybean' 'veg-oil']

0.00	0.00	0.00	0	
				['sugar' 'grain' 'corn']
0.00	0.00	0.00	0	
				['crude' 'nat-gas' 'fuel']
0.00	0.00	0.00	0	
				['gnp' 'ringgit']
0.00	0.00	0.00	0	
				['oilseed' 'coconut']
0.00	0.00	0.00	0	
				['trade' 'oilseed' 'grain']
0.00	0.00	0.00	0	
				['interest' 'gnp' 'trade']
0.00	0.00	0.00	0	
				['meal-feed' 'grain' 'corn' 'sorghum' 'oilseed' 'soybean']
0.00	0.00	0.00	0	
				['trade' 'coffee' 'rubber' 'palm-oil']
0.00	0.00	0.00	0	
				['gnp' 'interest' 'money-fx' 'trade']
0.00	0.00	0.00	0	
				['veg-oil' 'palm-oil' 'rape-oil' 'ship']
0.00	0.00	0.00	0	
				['grain' 'corn' 'rice']
0.00	0.00	0.00	2	
				['gnp' 'cpi' 'reserves' 'grain']
0.00	0.00	0.00	0	
				['acq' 'grain' 'corn']
0.00	0.00	0.00	0	
				['gnp' 'trade' 'jobs' 'retail']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'trade']
0.00	0.00	0.00	1	
				['grain' 'barley' 'oilseed' 'rapeseed']
0.00	0.00	0.00	0	
				['grain' 'corn' 'barley']
0.00	0.00	0.00	0	
				['trade' 'cotton' 'grain' 'corn' 'wheat' 'oilseed']
0.00	0.00	0.00	0	
				['ship' 'grain' 'oilseed']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'corn']
0.00	0.00	0.00	0	
				['trade' 'veg-oil' 'coconut-oil']
0.00	0.00	0.00	0	
				['reserves' 'trade' 'money-fx']
0.00	0.00	0.00	0	
				['ipi' 'trade']
0.00	0.00	0.00	0	
				['cpi' 'wpi']

0.00	0.00	0.00	0	
				['ship' 'livestock']
0.00	0.00	0.00	0	
				['retail' 'jobs' 'gnp' 'inventories' 'trade' 'cpi']
0.00	0.00	0.00	0	
				['grain' 'rice' 'corn' 'cotton' 'wheat' 'sorghum' 'barley' 'oat']
0.00	0.00	0.00	0	
				['grain' 'sugar' 'carcass' 'livestock']
0.00	0.00	0.00	0	
				['acq' 'gold' 'silver' 'zinc' 'lead']
0.00	0.00	0.00	0	
				['acq' 'gold' 'silver' 'lead' 'zinc']
0.00	0.00	0.00	0	
				['money-fx' 'stg' 'interest']
0.00	0.00	0.00	0	
				['earn' 'ship']
0.00	0.00	0.00	0	
				['ship' 'coffee']
0.00	0.00	0.00	0	
				['earn' 'crude' 'gas']
0.00	0.00	0.00	0	
				['earn' 'crude' 'pet-chem']
0.00	0.00	0.00	0	
				['trade' 'hog' 'carcass' 'livestock']
0.00	0.00	0.00	0	
				['pet-chem' 'nat-gas']
0.00	0.00	0.00	0	
				['coffee' 'tea' 'rubber']
0.00	0.00	0.00	0	
				['veg-oil' 'sun-oil']
0.00	0.00	0.00	0	
				['silver' 'copper']
0.00	0.00	0.00	0	
				['tea' 'orange']
0.00	0.00	0.00	0	
				['rand']
0.00	0.00	0.00	0	
				['platinum']
0.00	0.00	0.00	2	
				['sugar' 'ship']
0.00	0.00	0.00	2	
				['grain' 'corn' 'oilseed' 'soybean' 'sorghum' 'sunseed']
0.00	0.00	0.00	0	
				['trade' 'iron-steel']
0.00	0.00	0.00	2	
				['money-fx' 'yen' 'interest']
0.00	0.00	0.00	0	
				['jobs' 'trade']

0.00	0.00	0.00	0	
				['saudriyal' 'money-fx']
0.00	0.00	0.00	0	
				['veg-oil' 'meal-feed' 'oilseed']
0.00	0.00	0.00	0	
				['trade' 'bop' 'interest' 'money-fx']
0.00	0.00	0.00	0	
				['trade' 'bop' 'interest' 'stg' 'money-fx']
0.00	0.00	0.00	0	
				['trade' 'crude']
0.00	0.00	0.00	0	
				['trade' 'jobs']
0.00	0.00	0.00	1	
				['trade' 'acq']
0.00	0.00	0.00	0	
				['coffee' 'cocoa' 'sugar']
0.00	0.00	0.00	0	
				['iron-steel' 'ship']
0.00	0.00	0.00	0	
				['grain' 'sugar' 'livestock' 'carcass']
0.00	0.00	0.00	0	
				['grain' 'corn' 'wheat']
'oilseed' 'soybean' 'meal-feed' 'veg-oil'				
'soy-oil' 'sorghum' 'barley']	0.00	0.00	0.00	0
['trade' 'grain' 'wheat' 'tea' 'coffee' 'iron-steel' 'crude']				
0.00	0.00	0.00	0	
				['iron-steel' 'trade']
0.00	0.00	0.00	0	
				['oilseed' 'veg-oil' 'castorseed' 'castor-oil']
0.00	0.00	0.00	0	
				['veg-oil' 'rape-oil']
0.00	0.00	0.00	0	
				['gnp' 'money-fx']
0.00	0.00	0.00	0	
				['money-fx' 'dfl']
0.00	0.00	0.00	0	
				['carcass' 'sugar']
0.00	0.00	0.00	0	
				['trade' 'grain' 'wheat' 'coffee' 'tea' 'iron-steel' 'crude']
0.00	0.00	0.00	0	
				['gold' 'silver' 'zinc' 'lead']
0.00	0.00	0.00	0	
				['gnp' 'reserves']
0.00	0.00	0.00	0	
				['gold' 'money-fx']
0.00	0.00	0.00	0	
				['cpi' 'crude' 'nat-gas' 'heat' 'propane']
0.00	0.00	0.00	0	

				['ship' 'acq']
0.00	0.00	0.00	0	
				['money-fx' 'lit']
0.00	0.00	0.00	0	
				['money-fx' 'rupiah' 'dmk' 'yen']
0.00	0.00	0.00	0	
	['oilseed' 'sunseed' 'rapeseed' 'veg-oil' 'sun-oil' 'rape-oil']			
0.00	0.00	0.00	0	
				['rubber' 'pet-chem']
0.00	0.00	0.00	0	
				['nzdrlr' 'austdlr']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn' 'sorghum' 'cotton']
0.00	0.00	0.00	0	
				['iron-steel' 'alum' 'earn']
0.00	0.00	0.00	0	
				['dlr']
0.00	0.00	0.00	3	
				['acq' 'sugar' 'crude']
0.00	0.00	0.00	0	
	['tin' 'sugar' 'grain' 'wheat' 'cocoa' 'coffee' 'rubber']			
0.00	0.00	0.00	0	
				['crude' 'nat-gas' 'sugar']
0.00	0.00	0.00	0	
				['trade' 'yen' 'dlr']
0.00	0.00	0.00	0	
				['coffee' 'sugar' 'cocoa']
0.00	0.00	0.00	0	
				['gnp' 'lei']
0.00	0.00	0.00	0	
				['crude' 'gas' 'heat']
0.00	0.00	0.00	0	
				['cotton' 'sorghum']
0.00	0.00	0.00	0	
				['grain' 'rice' 'cotton']
0.00	0.00	0.00	1	
				['veg-oil' 'grain' 'wheat' 'cotton']
0.00	0.00	0.00	0	
				['ship' 'grain' 'wheat']
0.00	0.00	0.00	0	
				['grain' 'corn' 'cotton']
0.00	0.00	0.00	0	
				['interest' 'gnp' 'money-fx']
0.00	0.00	0.00	0	
				['palm-oil' 'palmkernel' 'oilseed' 'veg-oil']
0.00	0.00	0.00	0	
				['coffee' 'acq']
0.00	0.00	0.00	0	

				['coconut' 'oilseed']
0.00	0.00	0.00	0	
				['ship' 'grain' 'oilseed' 'veg-oil' 'meal-feed']
0.00	0.00	0.00	0	
				['heat' 'gas']
0.00	0.00	0.00	0	
				['gnp' 'coffee' 'bop']
0.00	0.00	0.00	0	
				['wheat' 'barley' 'corn' 'rapeseed' 'grain' 'oilseed' 'ship']
0.00	0.00	0.00	0	
				['wheat' 'grain' 'veg-oil']
0.00	0.00	0.00	0	
				['earn' 'iron-steel']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'corn' 'soybean']
0.00	0.00	0.00	0	
				['gnp' 'coffee']
0.00	0.00	0.00	0	
				['corn' 'sunseed' 'soybean' 'grain' 'oilseed']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'stg' 'skr' 'nkr' 'dkr' 'dmk']
0.00	0.00	0.00	0	
				['acq' 'strategic-metal']
0.00	0.00	0.00	0	
				['wheat' 'corn' 'soybean' 'grain' 'oilseed']
0.00	0.00	0.00	0	
				['corn' 'sorghum' 'grain']
0.00	0.00	0.00	0	
				['rapeseed' 'oilseed']
0.00	0.00	0.00	0	
				['stg']
0.00	0.00	0.00	0	
				['stg' 'money-fx']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'sunseed' 'corn' 'soybean' 'sorghum']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'soybean' 'oilseed']
0.00	0.00	0.00	0	
				['oilseed']
				'cotton' 'wheat' 'grain' 'sunseed' 'linseed' 'rapeseed'
				'soybean' 'groundnut'] 0.00 0.00 0.00 0
				['groundnut' 'oilseed']
0.00	0.00	0.00	0	
				['interest' 'dlr']
0.00	0.00	0.00	0	
				['meal-feed' 'sun-meal' 'lin-meal' 'soy-meal']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn']

'sugar'	'carcass'	'livestock'	'groundnut'				
'oilseed'	'cotton'	'veg-oil']	0.00	0.00	0.00	0	
				['money-fx'	'interest'	'dlr']	
0.00	0.00	0.00	1				
					['trade'	'cocoa']	
0.00	0.00	0.00	0				
				['money-fx'	'interest'	'stg']	
0.00	0.00	0.00	0				
				['oilseed'	'soybean'	'soy-meal'	'veg-oil'
0.00	0.00	0.00	0				
					['money-supply'	'wpi']	
0.00	0.00	0.00	0				
					['pet-chem'	'oilseed']	
0.00	0.00	0.00	0				
				['interest'	'money-fx'	'stg']	
0.00	0.00	0.00	0				
				['money-fx'	'dlr'	'yen'	'interest']
0.00	0.00	0.00	0				
				['copper'	'lead'	'zinc'	'silver'
0.00	0.00	0.00	0				
							['nickel'
							'alum']
0.00	0.00	0.00	0				
							['wool']
0.00	0.00	0.00	0				
					['austdlr'	'dmk']	
0.00	0.00	0.00	0				
					['iron-steel'	'crude']	
0.00	0.00	0.00	0				
					['money-supply'	'gnp']	
0.00	0.00	0.00	0				
				['carcass'	'livestock'	'orange']	
0.00	0.00	0.00	0				
					['palm-oil'	'veg-oil']	
0.00	0.00	0.00	0				
					['meal-feed'	'soy-meal']	
0.00	0.00	0.00	2				
							['tea']
0.00	0.00	0.00	3				
					['pet-chem'	'ship']	
0.00	0.00	0.00	0				
					['cpi'	'gnp'	'ipi']
0.00	0.00	0.00	0				
					['soy-meal'	'meal-feed']	
0.00	0.00	0.00	0				
					['plywood'	'lumber']	
0.00	0.00	0.00	0				
				['veg-oil'	'palm-oil'	'coconut-oil']	
0.00	0.00	0.00	0				
					['barley'	'grain']	
0.00	0.00	0.00	0				

				['nat-gas' 'propane']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'soy-oil' 'corn']
0.00	0.00	0.00	0	
				['oilseed' 'rapeseed' 'grain' 'wheat' 'corn' 'palm-oil' 'soy-oil' 'ship']
0.00	0.00	0.00	0	
				['grain' 'oilseed' 'wheat' 'rapeseed']
0.00	0.00	0.00	0	
				['gold' 'reserves']
0.00	0.00	0.00	0	
				['wheat' 'barley']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn' 'sorghum' 'barley' 'oat']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'corn' 'sorghum' 'barley']
0.00	0.00	0.00	0	
				['copper' 'zinc']
0.00	0.00	0.00	0	
				['oilseed' 'soybean' 'soy-oil']
0.00	0.00	0.00	0	
				['dlr' 'dmk' 'money-fx']
0.00	0.00	0.00	0	
				['money-supply' 'money-fx']
0.00	0.00	0.00	0	
				['copper' 'nickel']
0.00	0.00	0.00	0	
				['sugar' 'livestock']
0.00	0.00	0.00	0	
				['grain' 'corn' 'oilseed' 'livestock']
0.00	0.00	0.00	0	
				['grain' 'wheat' 'veg-oil']
0.00	0.00	0.00	0	
				['gold' 'silver' 'copper' 'zinc' 'lead']
0.00	0.00	0.00	0	
				['cruzado' 'money-fx']
0.00	0.00	0.00	0	
				['gas' 'crude' 'fuel']
0.00	0.00	0.00	0	
				['money-fx' 'dlr' 'yen' 'can' 'stg']
0.00	0.00	0.00	0	
				['dlr' 'money-fx' 'trade' 'cpi' 'money-supply']
0.00	0.00	0.00	0	
				micro avg
0.64	0.67	0.65	3156	
				macro avg
0.02	0.02	0.02	3156	
				weighted avg

0.55 0.67 0.60 3156

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels
with no true samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in labels
with no true nor predicted samples. Use `zero_division` parameter to control
this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
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```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels
with no true samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in labels
with no true nor predicted samples. Use `zero_division` parameter to control
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```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
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```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
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with no true samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in labels
with no true nor predicted samples. Use `zero_division` parameter to control
this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
[ ]: from sklearn.preprocessing import LabelBinarizer
      from sklearn.metrics import precision_recall_curve, classification_report
```

```

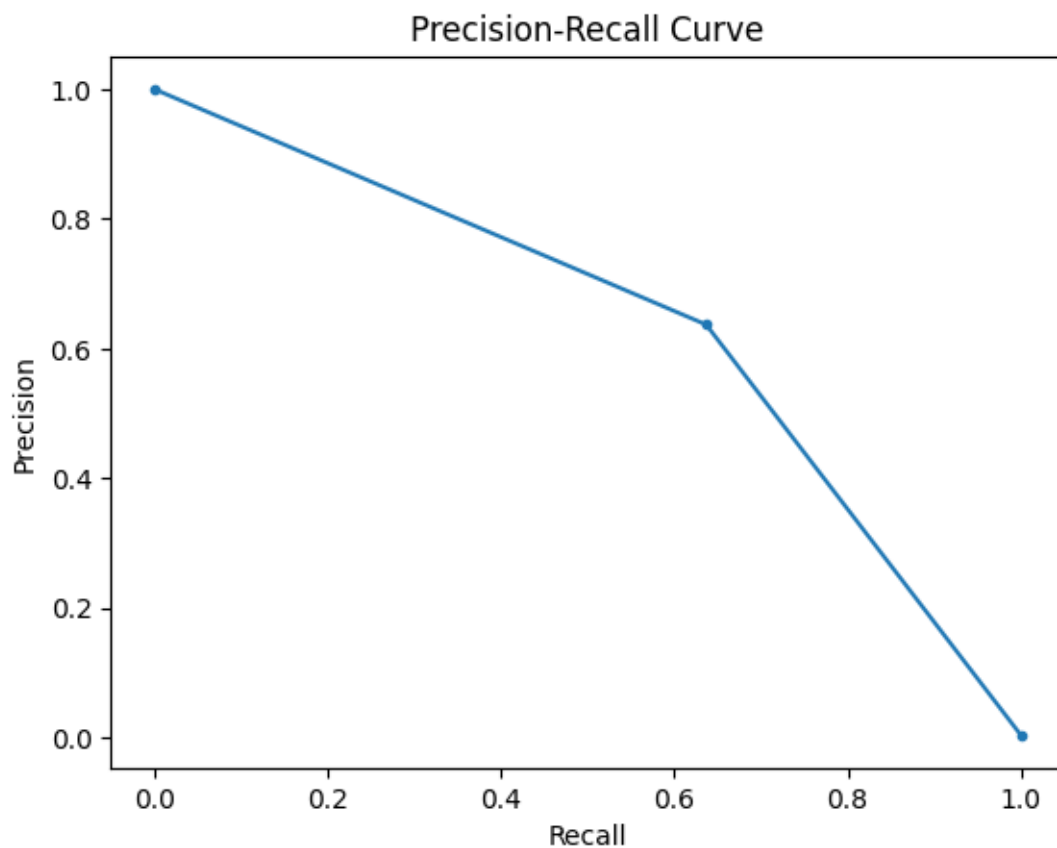
import matplotlib.pyplot as plt

# Binarize the labels
lb = LabelBinarizer()
y_test_bin = lb.fit_transform(y_test)
y_pred_bin = lb.transform(y_pred)

# Compute precision-recall curve for each class
precision, recall, _ = precision_recall_curve(y_test_bin.ravel(), y_pred_bin.
↪ravel())

# Plot Precision-Recall curve
plt.plot(recall, precision, marker='.')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.show()

```



Discussion

The dataset consists of titles of news articles. The dataset was already split into train and test. The objective of this Classification was to classify finance news.

We have used NLTK for stopwords, spaCy for tokenization, PorterStemmer for stemming and WordNetTokenizer for tokenization.

We have used Naive Bayes to train the model. Since there were around 750 unique words, the confusion matrix was unpleasant. Therefore we have used simple classification report and Precision VS Recall curve.

The metrics are as follows:

Accuracy: 0.6369

Precision: 0.5276

Recall: 0.6369

F1-Score: 0.5701

The Precision VS Recall curve shows that the model is neither very good (as it is not extending to the right), nor very poor (as it is not a straight diagonal), therefore the area under the curve is neither too poor nor too good.

Performance is affected because we have used the top 100 most appeared words only instead of all the words appearing in the dataset as you can see in the word cloud.

Submission Guidelines:

Google Colab Notebook Submission:

Save your notebook as NLP_Text_Classification_YourName.ipynb.

Ensure all code cells are executed, and the output is visible.

Include proper documentation and comments explaining each step.

Report Submission (Optional):

Prepare a short report (2-3 pages) summarizing your approach, findings, and model performance.

Upload the report along with the Colab Notebook.

Grading Criteria:

Correct implementation of NLP preprocessing (30%)

Effective use of vectorization techniques (20%)

Model accuracy and performance evaluation (30%)

Code clarity, documentation, and presentation (20%)

[]:

Declaration

I, Siddhant Mishra, confirm that the work submitted in this assignment is my own and has been completed following academic integrity guidelines. The code is uploaded on my GitHub repository account, and the repository link is provided below:

Signature: Siddhant Mishra

Submission Checklist

Ultralytics Platform Documentations Like hel file for Given Task

Code file (Python Notebook or Script)

Dataset or link to the dataset

Visualizations (if applicable)

Screenshots of model performance metrics

Readme File

Evaluation Metrics Details and discussion