# TEXT CLASSIFICATION MODEL

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#### **APPROACH**

- The dataset had two columns containing Text and Target. The text was related to the target classes like blockchain, bigdata etc.
- From this unstructured text data we needed to derive some meaningful information that must be related to the given target classes.
- For this purpose I followed Natural Language Processing technique using language Python. The following steps were taken to sove the problem:
  - Loading the dataset: using python libraries and dataset location
  - Text preprocessing: to eliminate the non or less meaningful text
  - Conversion of text into numbers: making the data understandable for computer.
  - Splitting: to split the data into training and test datasets.
  - Training the classification model
  - Evaluation of the model: this step followed by running the test dataset onto the classification model.

### Model interpretation

Importing the data

- I used Regex Expressions from Python re library to perform text preprocessing tasks for removing all non-word characters such as special characters, numbers, etc. and then spaces, single characters etc.
- Finally lemmatization and stemming was performed to reduce the word into dictionary root form.

```
In [13]: #data preprocessing
         from nltk.stem import WordNetLemmatizer
         stemmer = WordNetLemmatizer()
         for sen in range(0, len(X)):
            # Remove all the special characters
            document = re.sub(r'\W', ' ', str(X[sen]))
            # remove all single characters
            document = re.sub(r'\s+[a-zA-Z]\s+', ' ', document)
             # Remove single characters from the start
             document = re.sub(r'\^[a-zA-Z]\s+', ' ', document)
             # Substituting multiple spaces with single space
             document = re.sub(r'\s+', ' ', document, flags=re.I)
             # Removing prefixed 'b'
             document = re.sub(r'^b\s+', '', document)
             # Converting to Lowercase
             document = document.lower()
             # Lemmatization
             document = document.split()
             document = [stemmer.lemmatize(word) for word in document]
             document = ' '.join(document)
             documents.append(document)
```

In order to make the computer understand this raw text it should be converted into corresponding numerical form. In this classification
model I have used Bag Of Words +TFIDF model. In the max\_features parameter was set to 1500 so that we have 1500 most occurring
words as features for training our classifier.

```
In [18]: #converting text into numbers
    from sklearn.feature_extraction.text import CountVectorizer
    vectorizer = CountVectorizer(max_features=1500, min_df=5, max_df=0.7, stop_words=stopwords.words('english'))
    X = vectorizer.fit_transform(documents).toarray()

from sklearn.feature_extraction.text import TfidfTransformer
    tfidfconverter = TfidfTransformer()
    X = tfidfconverter.fit_transform(X).toarray()
```

- In order to train this dataset I have used RandomForestClassifier imported from(Scikit-Learn) sklearn ensemble.
- Random forest algorithm creates decision trees on data samples and then gets prediction from each of them and finally selects the solution by means of voting. It also reduces the over-fitting by averaging the result.
  - Random forest algorithm uses two key concepts:
    - Random sampling of training data points when building trees.
    - Random subsets of features considered when splitting nodes.

```
In [21]: #Training Text Classification Model and Predicting Sentiment
    from sklearn.ensemble import RandomForestClassifier
    classifier = RandomForestClassifier(n_estimators=1000, random_state=0)
    classifier.fit(X_train, y_train)

Out[21]: RandomForestClassifier(n_estimators=1000, random_state=0)

In [22]: y_pred = classifier.predict(X_test)
```

P.S.: I particularly used this model as it works well with the large datasets more efficiently.

To evaluate the trained model I have used confusion matrix and F1 measure.

```
In [23]: #evaluating the model
    from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
    print(confusion_matrix(y_test,y_pred))
    print(classification_report(y_test,y_pred))
    print(accuracy_score(y_test, y_pred))
```

## Accuracy Score

]]	332	3	8	1	74	4	1	10	4	2	12]	
]	12	81	15	1	154	6	0	5	1	3	8]	
]	33	10	223	4	234	6	4	12	1	4	10]	
]	10	0	16	5	21	0	1	3	0	0	2]	
]	81	15	39	2	1456	12	17	20	13	18	38]	
]	18	6	6	0	93	71	0	0	1	0	1]	
[	8	1	7	0	123	4	57	4	0	1	6]	
[	63	2	13	0	71	2	0	286	2	1	2]	
]	5	0	1	0	82	1	2	0	45	0	2]	
]	7	1	3	0	84	2	0	0	0	77	1]	
]	21	2	6	2	105	1	1	3	1	2	188]]	
				pre	cision	re	ecall	f1-	score	su	pport	
	Bigdata				0.56		0.74		0.64		451	
	Blockchain				0.67		0.28		0.40		286	
	Cyber Security				0.66		0.41		0.51		541	
	Data Security				0.33		0.09		0.14		58	
	FinTech				0.58		0.85		0.69		1711	
	Microservices				0.65		0.36		0.47		196	
	Neobanks				0.69		0.27		0.39		211	
	Reg Tech				0.83		0.65		0.73		442	
	Robo Advising				0.66		0.33		0.44		138	
	Stock Trading				0.71		0.44		0.54		175	
cre	credit reporting				0.70		0.57		0.62		332	
	accuracy								0.62		4541	
	macro avg				0.64		0.45		0.51		4541	
	weig	ghted	avg		0.64		0.62		0.60		4541	
0.6	21228	38042	28143	5								

From the output it can be clearly seen that the Accuracy score is 62.12%. I randomally chose all the parameters for countvectorizer and RandomForest.

#### Limitations

- The main limitation of this model is that it took a long time to train might be due to big dataset.
- Moreover, random forest algorithm takes a large number of trees that can make
  the algorithm too slow and ineffective for real-time predictions. In general, these
  algorithms are fast to train, but quite slow to create predictions once they are
  trained. A more accurate prediction requires more trees, which results in a slower
  model.
- It is a predictive modelling tool and cannot provide the relationships in our data.

# THANS