Natural Language Processing

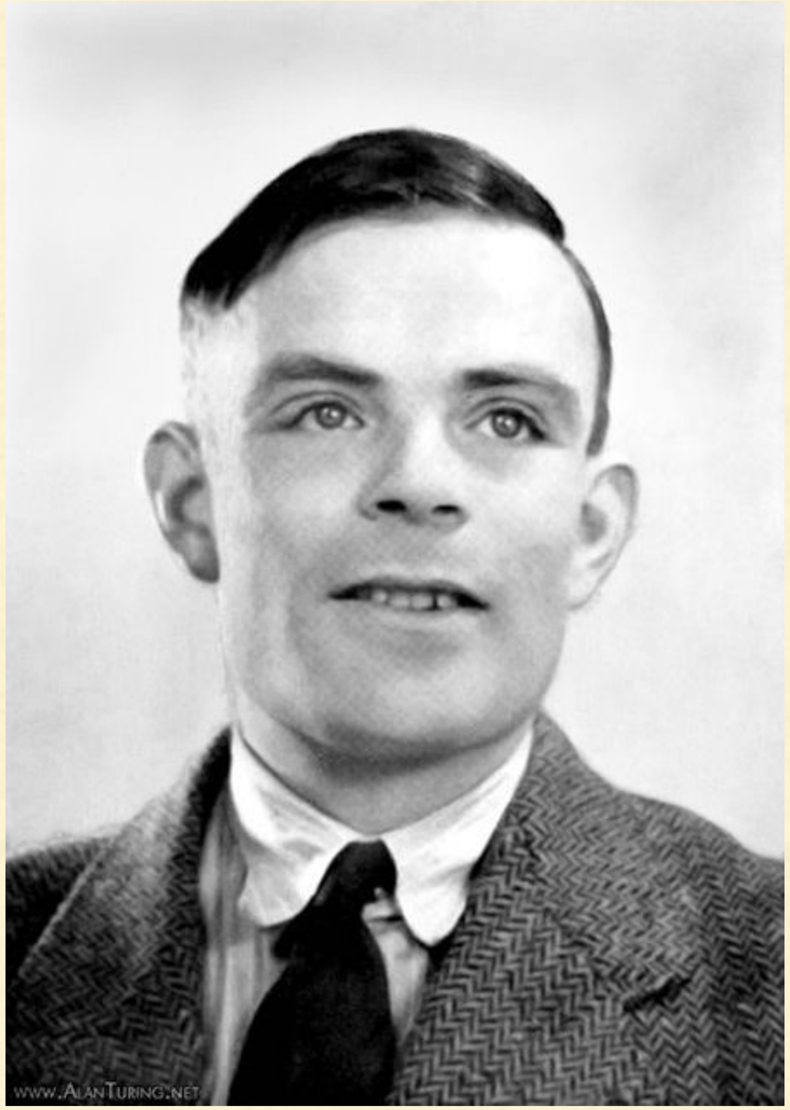
Natural Language Processing

- Natural-language processing (NLP) is an area of computer science and artificial intelligence concerned with the interactions between **computers** and **human languages**

- In particular how to program computers to fruitfully process large amounts of natural language data

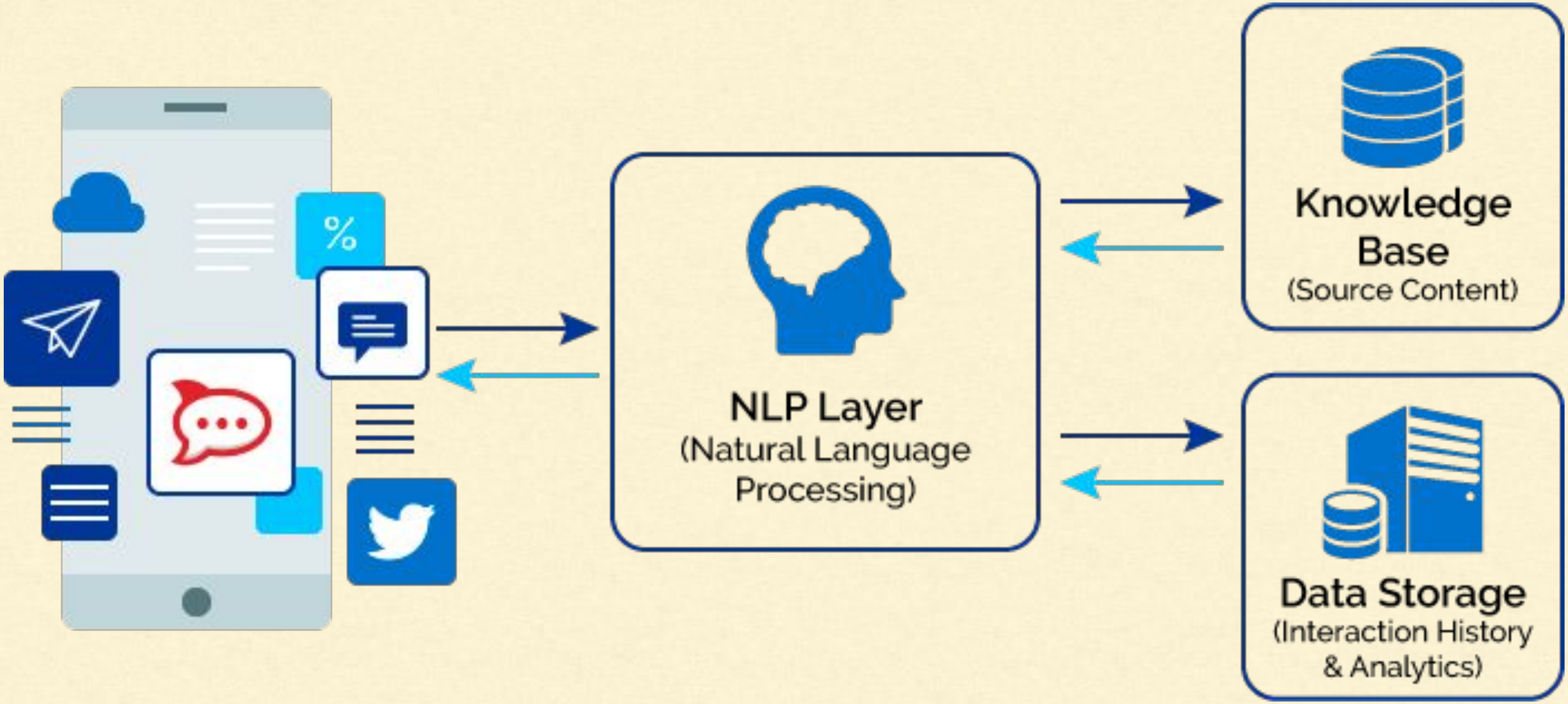
Natural Language Processing

In 1950, Alan Turing published an article titled "Computing Machinery and Intelligence" which proposed what is now called the Turing test as a criterion of intelligence.



Natural Language Processing

Basic Structure of a NLP application(chatbot considered below)

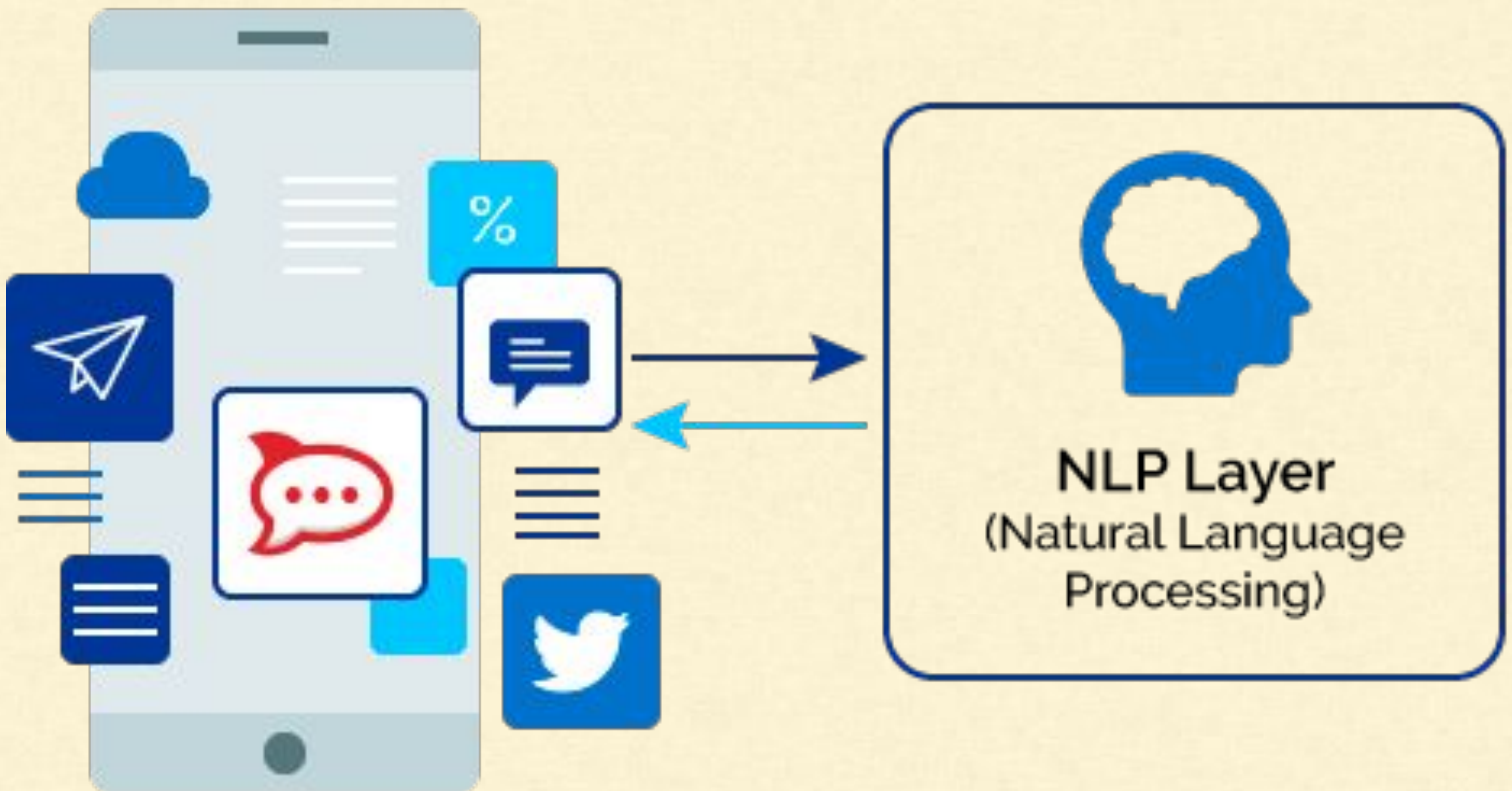


Natural Language Processing

Knowledge Base – It contains the database of information that is used to equip chatbots with the information needed to respond to queries of customers request.

Data Store – It contains interaction history of chatbot with users.

Natural Language Processing



NLP Layer – It translates users queries (free form) into information that can be used for appropriate responses.

Application Layer – It is the application interface that is used to interact with the user

Natural Language Processing - Applications

- **Speech Recognition -** The task of speech recognition is to map an acoustic signal containing a spoken natural language utterance into the corresponding sequence of words intended by the speaker.

Natural Language Processing - Applications

- **Text Classification -** Given an example of text, predict a predefined class label

Natural Language Processing - Applications

- **Caption Generation** - It is the problem of describing the contents of an image.

↑ a living room with a couch and a television

↑ a man riding a bike on a beach

Natural Language Processing - Applications

- **Machine Translation -** Machine translation is the problem of converting a source text in one language to another language.

Natural Language Processing - Applications

- **Question Answering -** It is the problem where given a subject, such as a document of text, answer a specific question about the subject.

Natural Language Processing - Tools

The most popular Natural Language Processing Tools are:

- Stanford's Core NLP Suite
- Natural Language Toolkit
- Apache Lucene and Solr
- Apache OpenNLP
- Text Blob which is a wrapper over the NLTK library

Natural Language Processing - Tools

Let us use the TextBlob library of Python to Build a program that makes a quiz out of a provided text.

It is basically a usage of NER - Named-entity recognition

TextBlob

Natural Language Processing - TextBlob

Let us begin by importing TextBlob and then selecting a text.

```
>>> from textblob import TextBlob
```

Now you can either load a text from a file as

```
>>> f = open('filename.txt')
>>> text = f.read()
```

Or assign the text to a variable as

```
>>> text = "World War II (often abbreviated to
WWII or WW2), also known as the Second World War,
was a ..... "
```

Natural Language Processing - TextBlob

Next we'll convert our text to a TextBlob object.

```
>>> text = TextBlob(text)
```

Now we are ready to apply different methods on our text.

Natural Language Processing - TextBlob

Let us understand a few things about the TextBlob api -

text.sentences - gives the sentences in a text

sentences.tags - gives the tags for each of the word in sentence. It returns a list of tuples with the word being the first element of the tuple and the tag being the second.

Natural Language Processing - TextBlob

Now to generate our quiz

- We will extract each sentence
- We will replace all the nouns and proper nouns with a blank from each sentences.
- To make it easy we will remove only after the fourth word in the sentence.

Natural Language Processing - TextBlob

```
>>> ww2b = TextBlob(ww2)
>>> for sentence in ww2b.sentences:
        new_sentence = sentence
        for index, tag in enumerate(sentence.tags):
            if tag[1] in ('NN', 'NNP') and index > 3:
                new_sentence = 
new_sentence.replace(tag[0], "____")
    print(new_sentence)
    print("\n===================\n")
```

Run it on Notebook

Natural Language Processing - Tools

Let's write a program to find Related Posts using Python's Scikit Learn

Natural Language Processing - Tools

We are given the task of finding the most related posts from a bunch of posts.

The tricky thing that we have to tackle first is how to turn text into something on which we can calculate similarity ??

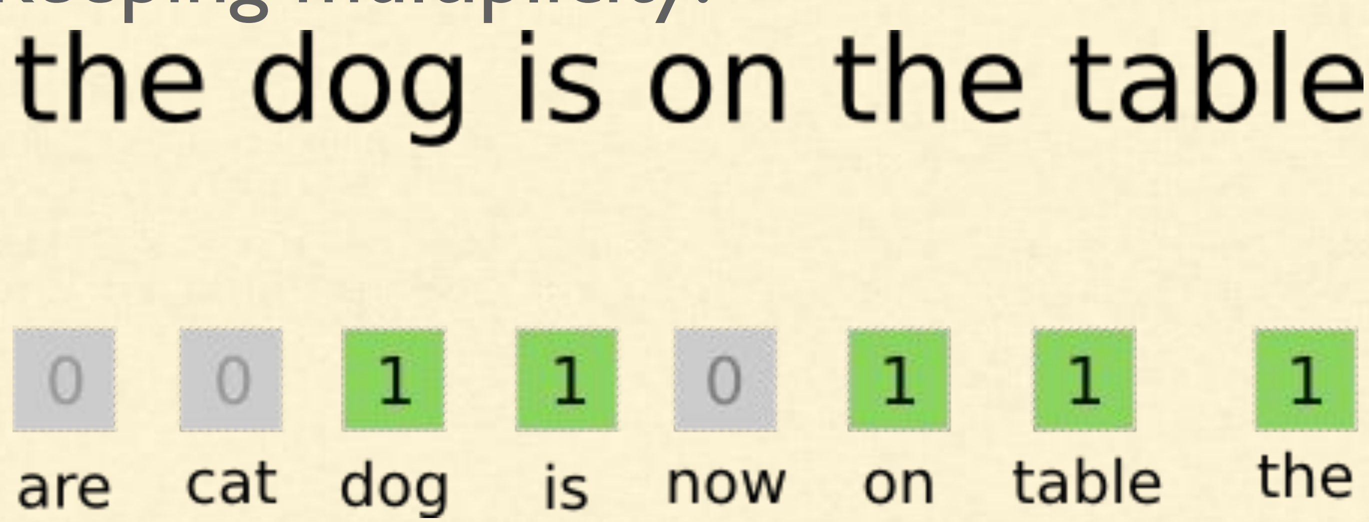
Natural Language Processing - Tools

How to do it ??

Bag of Words Approach -

It totally ignores the order of words and simply uses word counts as their basis.

In this model, a text, such as a sentence or a document is represented as the bag (multiset) of its words, disregarding grammar and even word order but keeping multiplicity.



Natural Language Processing - Tools

Vectorization

- For each word in the post, its occurrence is counted and noted in a vector.
- This step is also called **vectorization**.
- The vector is typically huge as it contains as many elements as words occur in the whole dataset.

Natural Language Processing - Tools

Vectorization - Example

For the two statements - "How to format my hard disk" and " Hard disk format problems " the vectors are shown below

Word	Occurence in post 1	Occurence in post 2
disk	1	1
format	1	1
how	1	0
hard	1	1
my	1	0
problems	0	1
to	1	0

aka Term Document Matrix

Natural Language Processing - Tools

Vectorization - Using Scikit learn

```
>>> from sklearn.feature_extraction.text import
CountVectorizer

>>> vectorizer = CountVectorizer(min_df=1)
```

The min_df parameter determines how CountVectorizer treats seldom words

- If it is set to an integer, all words occurring less than that value will be dropped
- If it is a fraction, all words that occur in less than that fraction of the overall dataset will be dropped.

Natural Language Processing - Tools

Vectorization - Using Scikit learn

```
>>> content = ["How to format my hard disk", " Hard disk format problems "]

>>> X = vectorizer.fit_transform(content)

>>> vectorizer.get_feature_names()

['disk', 'format', 'hard', 'how', 'my', 'problems', 'to']
```

Run it on Notebook

Natural Language Processing - Tools

Vectorization - Using Scikit learn

```
>>> print(X.toarray().transpose())
```

```
[[1 1]
 [1 1]
 [1 1]
 [1 0]
 [1 0]
 [0 1]
 [1 0]]
```

This means that the first sentence contains all the words except "problems",
while the second contains all but "how", "my", and "to".

Natural Language Processing - Tools

Finding Distance

We can measure distance between two vectors using the Euclidean Distance.

But first we will normalize each vectors.

The scipy.linalg module provides a function called norm.
The **norm()** function calculates the Euclidean norm (shortest distance)

Natural Language Processing - Tools

Finding Distance

```
>>> def dist_norm(v1, v2):
        v1_normalized = v1/sp.linalg.norm(v1.toarray())
        v2_normalized = v2/sp.linalg.norm(v2.toarray())
        delta = v1_normalized - v2_normalized
        return sp.linalg.norm(delta.toarray())
```

Natural Language Processing - Tools

Applying Everything we learnt on a toy dataset

Now we will consider 5 toy posts and find the similarity with a given post.

```
>>> post1 = "This is a toy post about machine learning.
Actually, it contains not much interesting stuff."
>>> post2 = "Imaging databases can get huge."
>>> post3 = "Most imaging databases save images
permanently."
>>> post4 = "Imaging databases store images."
>>>post5 = "Imaging databases store images. Imaging
databases store images. Imaging databases store images."
```

Natural Language Processing - Tools

Applying Everything we learnt on a toy dataset

Now we will build our vectorizer

```
>>> posts = [post1, post2, post3, post4, post5]
>>> X_train = vectorizer.fit_transform(posts)
>>> num_samples, num_features = X_train.shape
>>> print("#samples: %d, #features: %d" %
(num_samples, num_features))

#samples: 5, #features: 24
```

As we provided 5 different posts and there are 24 different words in them.

Natural Language Processing - Tools

Applying Everything we learnt on a toy dataset

`Finally we will iterate through all the vectors of the posts and find their distance with the new post.`

`Perform on Notebook`

Natural Language Processing

Now let us analyse a collection of text documents using Scikit Learn

Natural Language Processing

In this section we will see how to:

- Load the file contents and the categories
- Extract feature vectors suitable for machine learning
- Train a linear model to perform categorization
- Use a grid search strategy to find a good configuration of both the feature extraction components and the classifier

Natural Language Processing

Loading the 20 newsgroups dataset

To load the dataset use the code-

```
>>> categories = ['alt.atheism',
'soc.religion.christian', 'comp.graphics', 'sci.med']
>>> from sklearn.datasets import fetch_20newsgroups
>>> twenty_train = fetch_20newsgroups(subset='train',
categories=categories, shuffle=True, random_state=42)
```

Natural Language Processing

Loading the 20 newsgroups dataset

To load the dataset use the code-

```
>>> categories = ['alt.atheism',
'soc.religion.christian', 'comp.graphics', 'sci.med']
>>> from sklearn.datasets import fetch_20newsgroups
>>> twenty_train = fetch_20newsgroups(subset='train',
categories=categories, shuffle=True, random_state=42)
```

Analysing our dataset

The **target_names** holds the list of the requested category names:

```
>>> twenty_train.target_names
['alt.atheism', 'comp.graphics', 'sci.med',
'soc.religion.christian']
```

The files themselves are loaded in memory in the data attribute

```
>>> len(twenty_train.data)
2257
>>> len(twenty_train.filenames)
2257
```

Natural Language Processing

Analysing our dataset

Content of the first lines of the first loaded file

```
>>> print("\n".join(twenty_train.data[0].split("\n")[:3]))
From: sd345@city.ac.uk (Michael Collier)
Subject: Converting images to HP LaserJet III?
Nntp-Posting-Host: hampton
```

The category integer id of each sample is stored in the target attribute

```
>>> twenty_train.target[:10]
array([1, 1, 3, 3, 3, 3, 3, 2, 2, 2])
```

Natural Language Processing

Now we will apply the bag of word approach

Tokenizing text with scikit-learn

```
>>> from sklearn.feature_extraction.text import
CountVectorizer
>>> count_vect = CountVectorizer()
>>> X_train_counts =
count_vect.fit_transform(twenty_train.data)
>>> X_train_counts.shape
(2257, 35788)
```

Natural Language Processing

Occurrence count is a good start but there is an issue -

- longer documents will have higher average count values than shorter documents

To avoid these potential discrepancies we

- Divide the number of occurrences of each word in a document by the total number of words in the document: these new features are called **tf for Term Frequencies**.

How can we improve tf ?

Downscale weights for words that occur in many documents in the corpus and are therefore less informative than those that occur only in a smaller portion of the corpus.

This downscaling is called **tf–idf for "Term Frequency times Inverse Document Frequency"**.

Natural Language Processing - Tf-idf

- Tf-idf stands for **term frequency-inverse document frequency**
- Tf-idf weight is often used in
    - Information retrieval and
    - Text mining
- This weight is a used to evaluate
    - How important a word is to a
    - Document in a collection or corpus

Natural Language Processing - Tf

Term Frequency

- Measures how frequently a term occurs in a document
- It is possible that a term would appear
  - Much more times in long documents than shorter ones
  - This is why we normalize TF

TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document)

Natural Language Processing - IDF

Inverse Document Frequency

- Measures how important a term is
- In TF, all terms are considered equally important
- How ever some words and stop words appears lot of time
  - But have least importance
- In IDF we weight down frequent terms
  - And scale up rare terms

IDF(t) = log_e(Total number of documents / Number of documents with term t in it)

Natural Language Processing - Tf-idf

Example

- Consider a document containing 100 words and the word cat appears 3 times
- The term frequency(tf) for cat is
    - `(3 / 100) = 0.03`

Natural Language Processing - Tf-idf

Example

- Now, assume we have 10 million documents and
    - The word cat appears in 1,000 of these
- The inverse document frequency(idf) is
    - `log(10,000,000 / 1,000) = 4`
- Tf-idf weight is the product of tf and idf
    - `0.03 * 4 = 0.12`

Now let us apply tf-idf to our example

```
tfidf_transformer = TfidfTransformer()
>>> X_train_tfidf =
tfidf_transformer.fit_transform(X_train_counts)
>>> X_train_tfidf.shape
(2257, 35788)
```

Natural Language Processing

Training a classifier

We'll start with a **naïve Bayes classifier**, which provides a nice baseline for this task.

```
>>> from sklearn.naive_bayes import MultinomialNB
>>> clf = MultinomialNB().fit(X_train_tfidf,
twenty_train.target)
```

The multinomial variant of Naive Bayes is one the most suitable for word counts tasks.

Now let us make a prediction on a new document

To try to predict the outcome on a new document we need to extract the features using almost the same feature extracting chain as before

- We will first transform the new document to count vectors
- Then we'll transform it with the tfidf_transformer.
- Finally we'll call the predict method of the classifier

Natural Language Processing

```
>>> docs_new = ['God is love', 'OpenGL on the GPU is fast']
>>> X_new_counts = count_vect.transform(docs_new)
>>> X_new_tfidf = tfidf_transformer.transform(X_new_counts)

>>> predicted = clf.predict(X_new_tfidf)

>>> for doc, category in zip(docs_new, predicted):
...     print('%r => %s' % (doc, twenty_train.target_names[category]))
...
'God is love' => soc.religion.christian
'OpenGL on the GPU is fast' => comp.graphics
```

Run it on Notebook

Natural Language Processing

Now let us combine all the steps in the form of a pipeline

```
>>> from sklearn.pipeline import Pipeline
>>> text_clf = Pipeline([('vect', CountVectorizer()),
                      ('tfidf', TfidfTransformer()),
                      ('clf', MultinomialNB()),])
```

We can now train the model with a single command

```
>>> text_clf.fit(twenty_train.data, twenty_train.target)
Pipeline(...)
```

Natural Language Processing

Now let us perform performance evaluation on the test set

```
>>> import numpy as np
>>> twenty_test = fetch_20newsgroups(subset='test',
...     categories=categories, shuffle=True,
random_state=42)
>>> docs_test = twenty_test.data
>>> predicted = text_clf.predict(docs_test)
>>> np.mean(predicted == twenty_test.target)
0.834…
```

I.e., we achieved 83.4% accuracy

Now we'll use a different classifier and compute the performance metrics

```
>>> from sklearn.linear_model import SGDClassifier
>>> text_clf = Pipeline([('vect', CountVectorizer()),
...                      ('tfidf', TfidfTransformer()),
...                      ('clf', SGDClassifier(loss='hinge', penalty='l2',
...                                            alpha=1e-3, random_state=42,
...                                            max_iter=5, tol=None)),
... ])
```

Natural Language Processing

Now we'll use a different classifier and compute the performance metrics

```
>>> text_clf.fit(twenty_train.data, twenty_train.target)
Pipeline(...)
>>> predicted = text_clf.predict(docs_test)
>>> np.mean(predicted == twenty_test.target)
0.912...
```

Natural Language Processing

Parameter tuning using grid search

Since there are different parameters which we can choose, we'll apply grid search to find the best parameters

```
>>> parameters = {'vect__ngram_range': [(1, 1), (1, 2)],
...               'tfidf__use_idf': (True, False),
...               'clf__alpha': (1e-2, 1e-3),
... }
```

Here we'll be applying grid search for the parameters - `ngram_range`, `use_idf` and `alpha`.

Natural Language Processing

Parameter tuning using grid search

If we have multiple CPU cores at our disposal, we can tell the grid searcher to try these eight parameter combinations in parallel with the n_jobs parameter.

```
>>> gs_clf = GridSearchCV(text_clf, parameters,
n_jobs=-1)
>>> gs_clf = gs_clf.fit(twenty_train.data[:400],
twenty_train.target[:400])
```

Natural Language Processing

Predicting and finding best score

```
>>> twenty_train.target_names[gs_clf.predict(['God is
love'])[0]]
'soc.religion.christian'
>>> gs_clf.best_score_
0.900...
```

Predicting and finding best score

```
>>> for param_name in sorted(parameters.keys()):
...     print("%s: %r" % (param_name,
gs_clf.best_params_[param_name]))
...
clf__alpha: 0.001
tfidf__use_idf: True
vect__ngram_range: (1, 1)
```

Natural Language Processing - Tools

Overview of Stanford Core NLP

Natural Language Processing - Stanford NLP

- Stanford CoreNLP provides a set of human language technology tools.

- It can give
  - The base forms of words,
  - Their parts of speech,
  - Whether they are names of companies, people, etc.,
  - Mark up the structure of sentences in terms of phrases and syntactic dependencies,
  - Indicate which noun phrases refer to the same entities, indicate sentiment

Natural Language Processing - Stanford NLP

Choose Stanford CoreNLP if you need:

- An integrated NLP toolkit with a broad range of grammatical analysis tools
- A fast, robust annotator for arbitrary texts, widely used in production
- A modern, regularly updated package, with the overall highest quality text analytics

Natural Language Processing - Stanford NLP

Choose Stanford CoreNLP if you need:

- Support for a number of major (human) languages
- Available APIs for most major modern programming languages
- Ability to run as a simple web service

Programming languages and operating systems

Stanford CoreNLP is written in **Java**; recent releases require Java 1.8+.

You can interact with **CoreNLP via the command-line** or its **web service** using languages like Javascript, Python etc.

Natural Language Processing - Stanford NLP

Programming languages and operating systems

You can use **Stanford CoreNLP** from

- The command-line, via its original Java programmatic API,
- Via the object-oriented simple API,
- Via third party APIs for most major modern programming languages,

Or via a web service.

It works on **Linux**, **macOS**, and **Windows**

Natural Language Processing

More coming up on CloudxLab

- Word2vec - Vector Representations of Words
- Deep Learning - LSTM - Long Short-Term Memory
- GloVe - Global Vectors for Word Representation
- spaCY - Industrial-Strength Natural Language Processing in Python
- Hands-on using Stanford CoreNLP
- List of APIs available for chatbots etc

Thank You

https://discuss.cloudxlab.com

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