GALLOGLY COLLEGE OF ENGINEERING
SCHOOL OF COMPUTER SCIENCE
The UNIVERSITY *of* OKLAHOMA

Text Analysis

Text classification

DATA BITE
A bit on Big Data

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DATA BITE
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Would you like to be involved in research at the University of Oklahoma?

The purpose of this survey is to understand attendees' knowledge of Python and intended outcomes from attending these sessions. We are trying to gauge the demand of skills, resources, and knowledge of Python programming and associated techniques. This will, in turn, help us understand the success of the workshop and room for improvement.

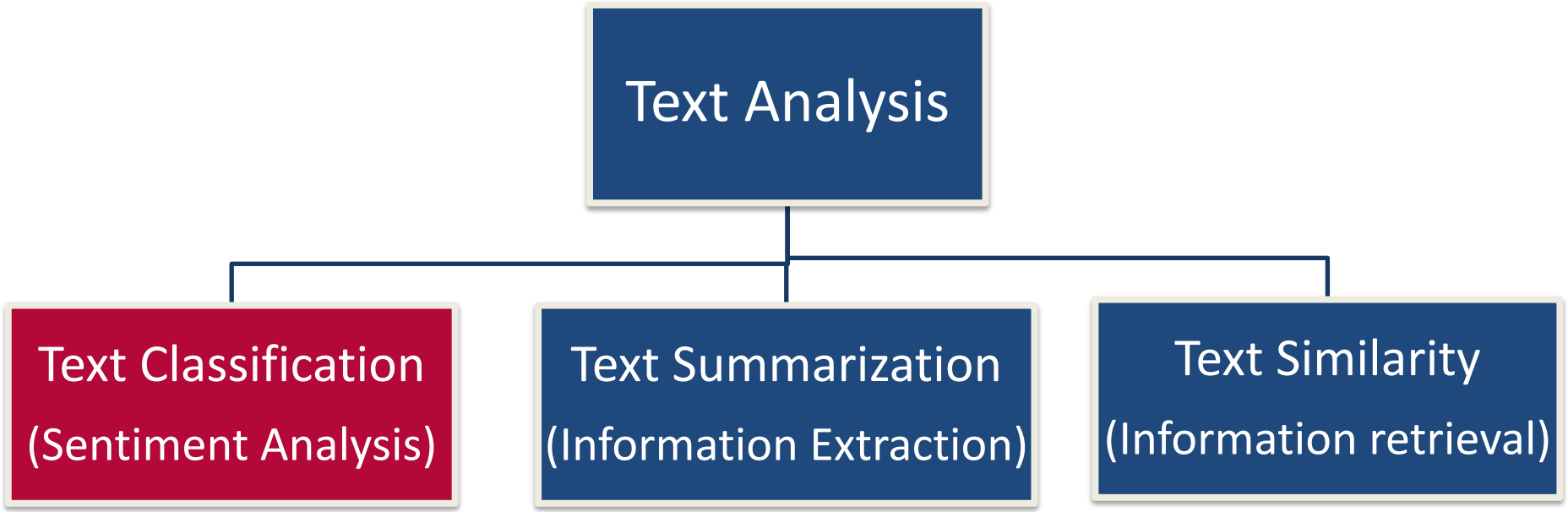
SCAN ME

Overview

- Text Analysis
- What is Text Classification?
- Machine learning approach
- Types of Text Classification
- Workflow
- Demo

Text Analysis

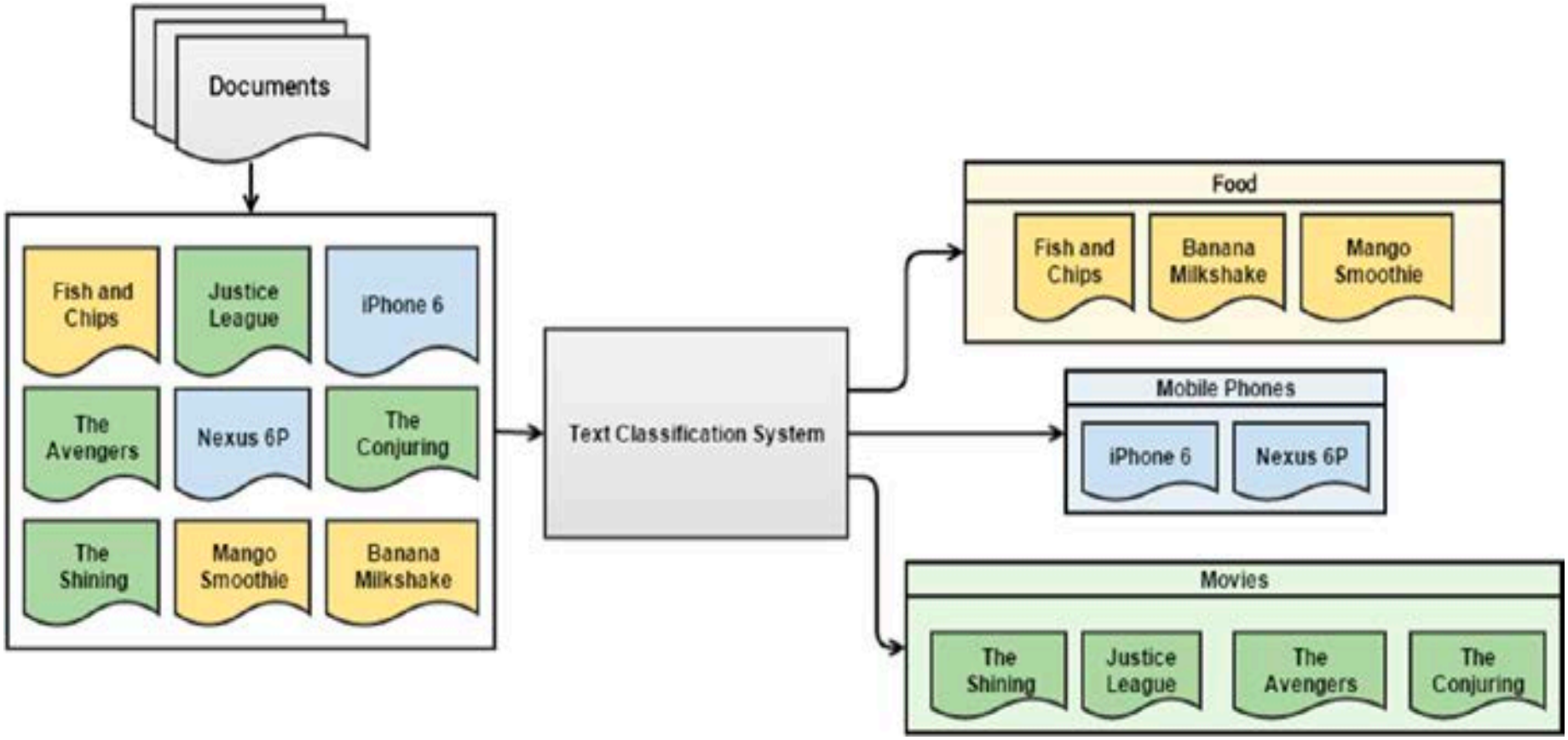
Analyze complex textual data and extract meaningful patterns and insights from it.



Sentiment Analysis

- “The movie was really amazing” -> 🙂
- “It was a really boring movie” -> 😠
- “I like the movie popcorn” -> 😕

What is Text Classification?



Source: *Text Analytics With Python : A Practical Real-World Approach To Gaining Actionable Insights From Your Data,* **Second Edition**, Dipanjan Sarkar, 2019, Apress L. P. (ISBN 978-1-4842-4353-4) (eBook ISBN 978-1-4842-4354-1) Publisher Website

Machine Learning Approaches

Supervised Learning

- Requires labeled training data
- Each data point corresponds to a class or label
- Learns meaningful patterns for each type of class
  - Sentiment analysis
  - Spam filtering
  - Topic labeling

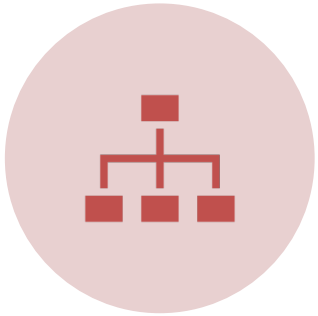
Unsupervised Learning

- Do not require any labeled training data
- Extract meaningful patterns from the data
  - Document Summarization
  - Similarity Analysis
  - Clustering (Useful in Text document categorization)

Types of Classification

BINARY CLASSIFICATION

MULTI-CLASS CLASSIFICATION

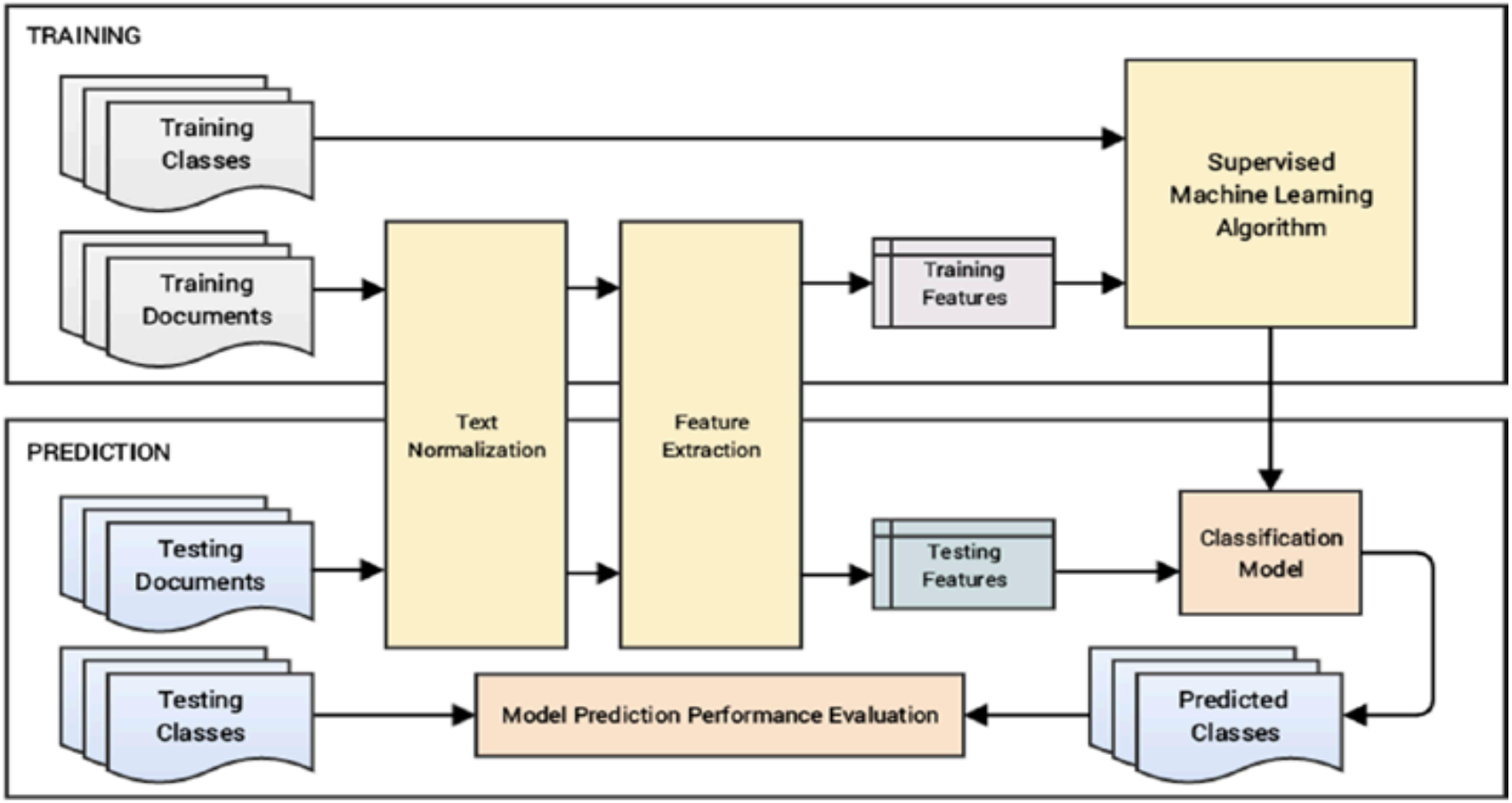


MULTI-LABEL CLASSIFICATION

Text Classification Workflow

- A typical workflow for a text classification system is as follows:
  - Train and test datasets
  - Text Normalization (‘2morrow’ -> tomorrow or removing stop words ‘the’, ‘is’, etc.)
  - Feature Extraction (convert raw text into matrix of features)
  - Model Training (Naïve bayes algorithm or Support vector machine)
  - Model Prediction

Architecture



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Text Normalization

Tokenization – Segmenting a sentence into words

Text standardization

Removing special characters and symbols

Removing stop words

Bag of Words, TF-IDF, and Advanced word vectorization models

FEATURE EXTRACTION

Bag of Words model

- Convert text document into vectors
- Vector represents the frequency of all the distinct words for specific document
- The frequency of occurrence is the weight of each word

Useful link:

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

Example

```
##Corpus is a collection of text:
corpus = ['the sky is so beautiful’,
          'sky is blue and sky is beautiful’,
          'the sky is perfectly blue’,
          'i love cream cheese’
          ]

from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(min_df=1, ngram_range=(1,1))
features = vectorizer.fit_transform(corpus)
vectorizer.get_feature_names() ##print the features name
```

```
print('The feature names: ')
print(vectorizer.get_feature_names())
print('Number of features: ', len(vectorizer.get_feature_names()))
print('The vectorized text (Encoded): ')
print(features.toarray())
```

```
The feature names:
['and', 'beautiful', 'blue', 'cheese', 'cream', 'is', 'love', 'perfectly', 'sky', 'so', 'the']
Number of features:  11
The vectorized text (Encoded):
[[0 1 0 0 0 1 0 0 1 1 1]
 [1 1 1 0 0 2 0 0 2 0 0]
 [0 0 1 0 0 1 0 1 1 0 1]
 [0 0 0 1 1 0 1 0 0 0 0]]
```

TF-IDF Model

- TF-IDF reflects the importance of a word to document in a collection
- TF – term frequency
- IDF – inverse of document frequency for each term
- TF-IDF is a combination of the above two metrics and represents a weighting of a word

Mathematically, TF-IDF is the product of two metrics and can be represented as:

$$tfidf = tf * idf$$

Useful link:
https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

Example

```
from sklearn.feature_extraction.text import TfidfVectorizer
tale_of_cities = ['it was the best of times',
                  'it was the worst of times',
                  'it was the age of wisdom',
                  'it was the age of foolishness',
                  'it was the epoch of belief'
                  ]
tfidf_vectorizer = TfidfVectorizer()
tfidf_features = tfidf_vectorizer.fit_transform(tale_of_cities)
print(tfidf_vectorizer.get_feature_names())
print(tfidf_features.shape)
```

Feature names:

['age', 'belief', 'best', 'epoch', 'foolishness', 'it', 'of', 'the', 'times', 'was', 'wisdom', 'worst']

Number of features:

(5, 12)

```
print('The feature names: ', tfidf_vectorizer.get_feature_names())
print('Number of features: ', len(tfidf_vectorizer.get_feature_names()))
print('The vectorized text (Encoded): ')
print(tfidf_features.toarray())
```

```
Number of features:  12
The vectorized text (Encoded):
[[0.         0.         0.62510433 0.         0.         0.29786556
  0.29786556 0.29786556 0.50433024 0.29786556 0.         0.        ]
 [0.         0.         0.         0.         0.         0.29786556
  0.29786556 0.29786556 0.50433024 0.29786556 0.         0.62510433]
 [0.50433024 0.         0.         0.         0.         0.29786556
  0.29786556 0.29786556 0.         0.29786556 0.62510433 0.        ]
 [0.50433024 0.         0.         0.         0.62510433 0.29786556
  0.29786556 0.29786556 0.         0.29786556 0.         0.        ]
 [0.         0.5863888  0.         0.5863888  0.         0.27941741
  0.27941741 0.27941741 0.         0.27941741 0.         0.        ]]
```

Advanced word vectorization models

- Word embeddings allows us to capture the context and semantics of word
- Useful in detecting similar meaning words
- Word2Vec – learn word embeddings
- It is a neural network-based implementation that learns distributed vector representations of words
- Gensim is a python library used for document feature extraction
- For more details on genism:

https://radimrehurek.com/gensim/index.html

Source: Rong, X. (2014). word2vec parameter learning explained. *arXiv preprint arXiv:1411.2738*.

Why we need word embeddings?

- *"Have an amazing day"*
- *"Have a great day"*
- *"Have a good day"*

- Words like "amazing", "great", and "good" have similar context
- Vector should be able to present the similarity between the words

Example

```
from gensim.test.utils import common_texts, get_tmpfile
from gensim.models import Word2Vec

# common texts data from gensim library.
common_texts
```

```
[['human', 'interface', 'computer'],
 ['survey', 'user', 'computer', 'system', 'response', 'time'],
 ['eps', 'user', 'interface', 'system'],
 ['system', 'human', 'system', 'eps'],
 ['user', 'response', 'time'],
 ['trees'],
 ['graph', 'trees'],
 ['graph', 'minors', 'trees'],
 ['graph', 'minors', 'survey']]
```

```python
# Word2Vec model
model = Word2Vec(common_texts, size=100, window=5, min_count=1)

# Vector for a specific word, for ex: human
model.wv["human"]

# Calculate the most similar words to human
model.wv.most_similar("human")
```

```
[('response', 0.08395902812480927),
 ('graph', 0.07479733973741531),
 ('time', 0.06893133372068405),
 ('survey', 0.04686649888753891),
 ('system', 0.03181909057843685 15),
 ('computer', 0.02085606381297 1115),
 ('minors', -0.02121073007583618),
 ('eps', -0.06385811418294907),
 ('user', -0.07140786200761795),
 ('interface', -0.07448561489582062)]
```

Implement Feature Extraction using Bag-of-Words, TF-IDF, word2Vec models *(FeatureExtraction.ipynb)*

DEMO

Multinomial Naïve Bayes and Support Vector Machines

(Supervised machine learning algorithm to classify data)

CLASSIFICATION ALGORITHMS

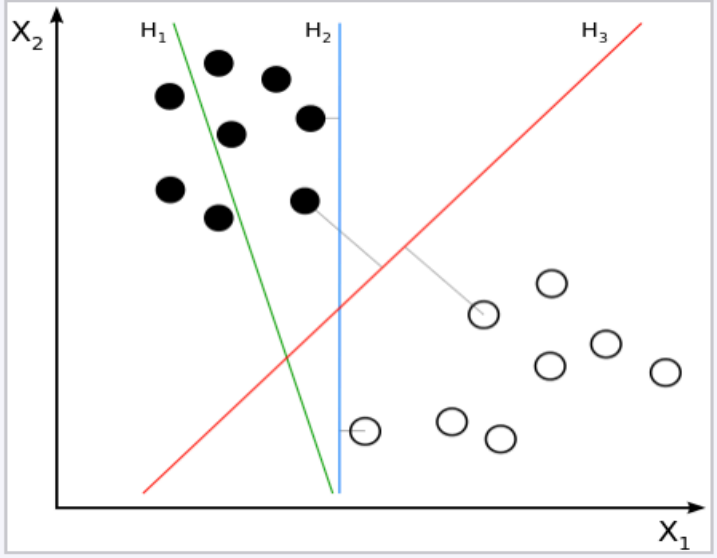
Multinomial Naïve Bayes

- This algorithm is quite effective in classifying text data.
- Special case of naïve Bayes algorithm and allows classification for problems with more than two classes

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)}$$

- Assumes each feature is independent of each other
- The feature vectors are from Bag of Words model or TF-IDF
- Scikit-learn library provides an implementation of Mutinomial naïve bayes (MultinomialNB)

Support Vector Machines



H_1 does not separate the classes.
H_2 does, but only with a small margin.
H_3 separates them with the maximal margin.

Supervised learning algorithm

SVM constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers detection

Source: https://en.wikipedia.org/wiki/Support_vector_machine

Text classification using existing packages in Scikit learn (*TextClassification_workflow.ipynb*)

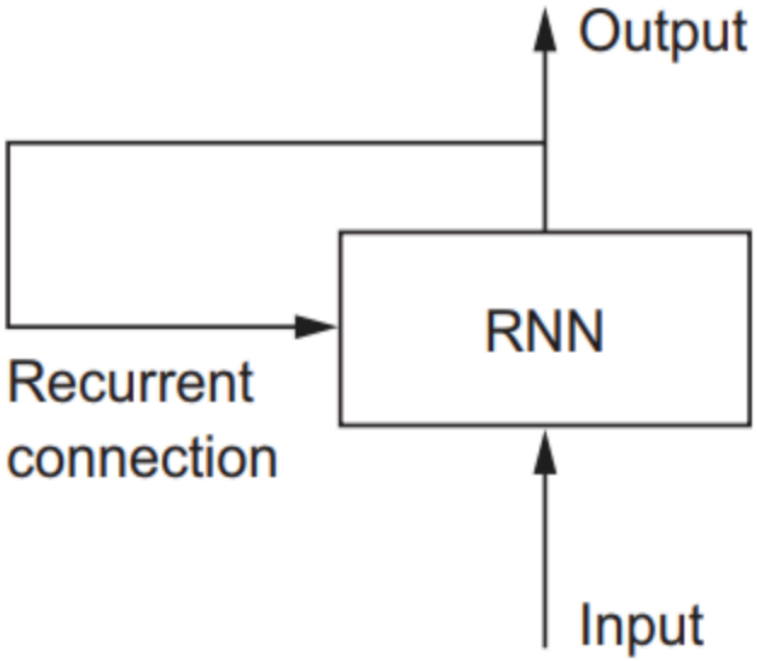
DEMO

Allows access to previous information to be used at later time during the training

Long Short-term Memory (LSTM)

Recurrent Neural Networks (RNN)

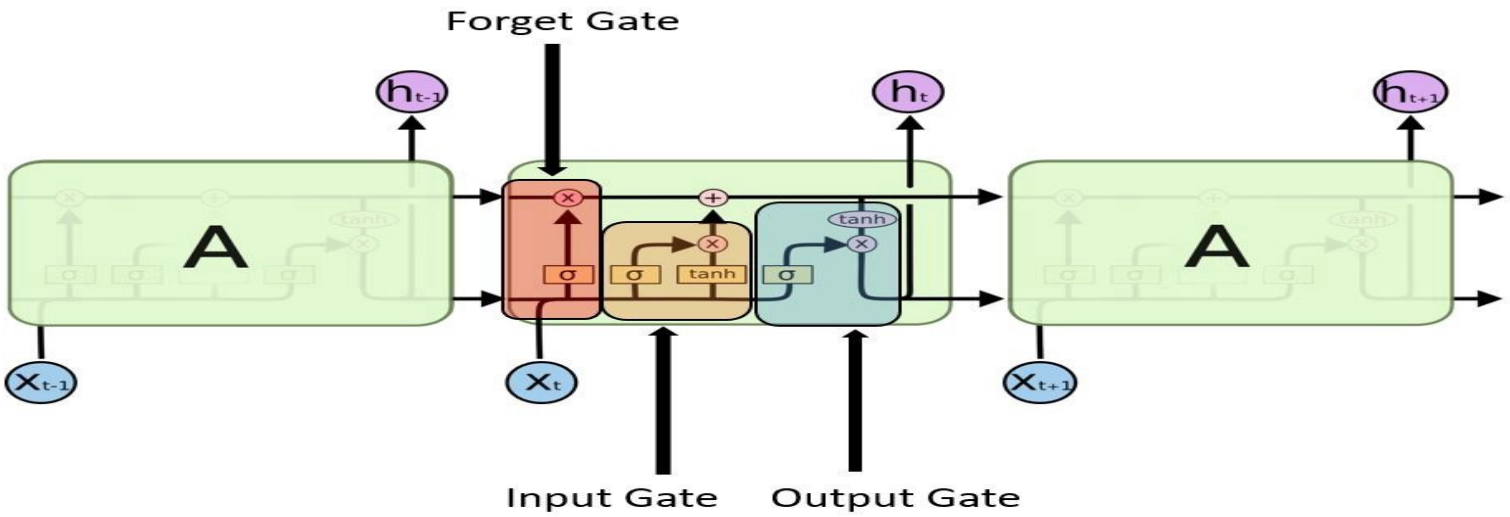
- Is a generalization of feedforward neural network that has an internal memory
- RNNs can use their internal state (memory) to process sequences of inputs.



Source: https://www.manning.com/books/deep-learning-with-python

LSTMs

- It remembers the previous data



Source: https://towardsdatascience.com/understanding-rnn-and-lstm-f7cdf6dfc14e

Sentiment analysis of IMDB dataset using Tensorflow
(IMDB_SentimentAnalysis_LSTMs.ipynb)

DEMO

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Questions?

Thank you!

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Continuous Bag-of-Words (CBOW) model