Text Classification Algorithms: A Survey

Subjects: Computer Science, Information Systems | Others

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In recent years, there has been an exponential growth in the number of complex documents and texts that require a deeper understanding of machine learning methods to be able to accurately classify texts in many applications. Many machine learning approaches have achieved surpassing results in natural language processing. The success of these learning algorithms relies on their capacity to understand complex models and non-linear relationships within data. However, finding suitable structures, architectures, and techniques for text classification is a challenge for researchers. In this paper, a brief overview of text classification algorithms is discussed. This overview covers different text feature extractions, dimensionality reduction methods, existing algorithms and techniques, and evaluation methods. Finally, the limitations of each technique and its application in real-world problems are discussed.

Keywords: text classification ; text mining ; text representation ; text categorization ; text analysis ; document classification

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Medium Text Classification

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Mendeley Add to Library

-

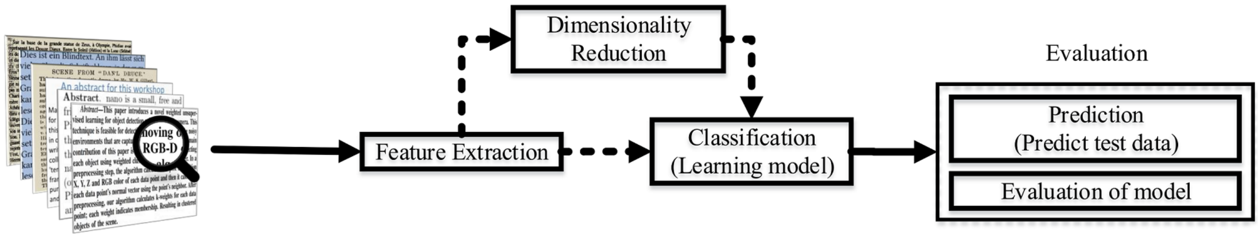
contributions welcome

arXiv 1904.08067

-

contributors 7

Introduction



Text and Document Feature Extraction

Text feature extraction and pre-processing for classification algorithms are very significant. In this section, we start to talk about text cleaning since most of the documents contain a lot of noise. In this part, we discuss two primary methods of text feature extractions- word embedding and weighted word.

Text Cleaning and Pre-processing

In Natural Language Processing (NLP), most of the text and documents contain many words that are redundant for text classification, such as stopwords, miss-spellings, slangs, and etc. In this section, we briefly explain some techniques and methods for text cleaning and pre-processing text documents. In many algorithms like statistical and probabilistic learning methods, noise and unnecessary features can negatively affect the overall performance. So, elimination of these features is extremely important.

Tokenization

Tokenization is the process of breaking down a stream of text into words, phrases, symbols, or any other meaningful elements called tokens. The main goal of this step is to extract individual words in a sentence. Along with text classification, in text mining, it is necessary to incorporate a parser in the pipeline which performs the tokenization of the documents; for example:

sentence:

```
After sleeping for four hours, he decided to sleep for another four
```

In this case, the tokens are as follows:

```
{'After', 'sleeping', 'for', 'four', 'hours', 'he', 'decided', 'to', 'sleep', 'for',
'another', 'four'}
```

Here is python code for Tokenization:

```
from nltk.tokenize import word_tokenize
text = "After sleeping for four hours, he decided to sleep for another four"
tokens = word_tokenize(text)
print(tokens)
```

Stop words

Text and document classification over social media, such as Twitter, Facebook, and so on is usually affected by the noisy nature (abbreviations, irregular forms) of the text corpora.

Here is an example from geeksforgeeks

```
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

example_sent = "This is a sample sentence, showing off the stop words filtration."

stop_words = set(stopwords.words('english'))

word_tokens = word_tokenize(example_sent)

filtered_sentence = [w for w in word_tokens if not w in stop_words]

filtered_sentence = []

for w in word_tokens:
    if w not in stop_words:
        filtered_sentence.append(w)

print(word_tokens)
print(filtered_sentence)
```

Output:

```
['This', 'is', 'a', 'sample', 'sentence', ',', 'showing',
'off', 'the', 'stop', 'words', 'filtration', '.']
['This', 'sample', 'sentence', ',', 'showing', 'stop',
'words', 'filtration', '.']
```

Capitalization

Sentences can contain a mixture of uppercase and lower case letters. Multiple sentences make up a text document. To reduce the problem space, the most common approach is to reduce everything to lower case. This brings all words in a document in the same space, but it often changes the meaning of some words, such as "US" to "us" where the first one represents the United States of America and the second one is a pronoun. To solve this, slang and abbreviation converters can be applied.

```
text = "The United States of America (USA) or America, is a federal republic composed
of 50 states"
print(text)
print(text.lower())
```

Output:

```
"The United States of America (USA) or America, is a federal republic composed of 50
states"
"the united states of america (usa) or america, is a federal republic composed of 50
states"
```

Slangs and Abbreviations

Slangs and abbreviations can cause problems while executing pre-processing steps. An abbreviation is a shortened form of a word, such as SVM stand for Support Vector Machine. Slang is a version of the language that depicts informal conversation or text that has a different meaning, such as "lost the plot", it essentially means that 'they've gone mad'. The common method to deal with these words is converting them to formal language.

Noise Removal

Another issue of text cleaning as a pre-processing step is noise removal. Text documents generally contain characters like punctuations or special characters and they are not necessary for text mining or classification purposes. Although punctuation is critical to understand the meaning of the sentence, it can affect the classification algorithms negatively.

Here is simple code to remove standard noise from the text:

```
def text_cleaner(text):
    rules = [
        {r'>\s+': u'>'},  # remove spaces after a tag opens or closes
        {r'\s+': u' '},  # replace consecutive spaces
        {r'\s*<br\s*/?>\s*': u'\n'},  # newline after a <br>
        {r'</(div)\s*>\s*': u'\n'},  # newline after </p> and </div> and <h1/>.
        {r'</(p|h\d)\s*>\s*': u'\n\n'},  # newline after </p> and </div> and <h1/>.
        {r'<head>.*<\s*(/head|body)[^>]*>': u''},  # remove <head> to </head>
        {r'<a\s+href="([^"]+)"[^>]*>.*</a>': r'\1'},  # show links instead of texts
        {r'[ \t]*<[^<]*?/?>': u''},  # remove remaining tags
        {r'^\s+': u''}  # remove spaces at the beginning
    ]
    for rule in rules:
    for (k, v) in rule.items():
        regex = re.compile(k)
        text = regex.sub(v, text)
    text = text.rstrip()
    return text.lower()
```

Spelling Correction

An optional part of the pre-processing step is correcting the misspelled words. Different techniques, such as hashing-based and context-sensitive spelling correction techniques, or spelling correction using trie and damerau-levenshtein distance bigram have been introduced to tackle this issue.

```
from autocorrect import spell

print spell('caaaar')
print spell(u'mussage')
print spell(u'survice')
print spell(u'hte')
```

Result:

```
caesar
message
service
the
```

Stemming

Text Stemming is modifying a word to obtain its variants using different linguistic processes like affixation (addition of affixes). For example, the stem of the word "studying" is "study", to which -ing.

Here is an example of Stemming from NLTK

```
from nltk.stem import PorterStemmer
from nltk.tokenize import sent_tokenize, word_tokenize

ps = PorterStemmer()

example_words = ["python","pythoner","pythoning","pythoned","pythonly"]

for w in example_words:
print(ps.stem(w))
```

Result:

```
python
python
python
python
pythonli
```

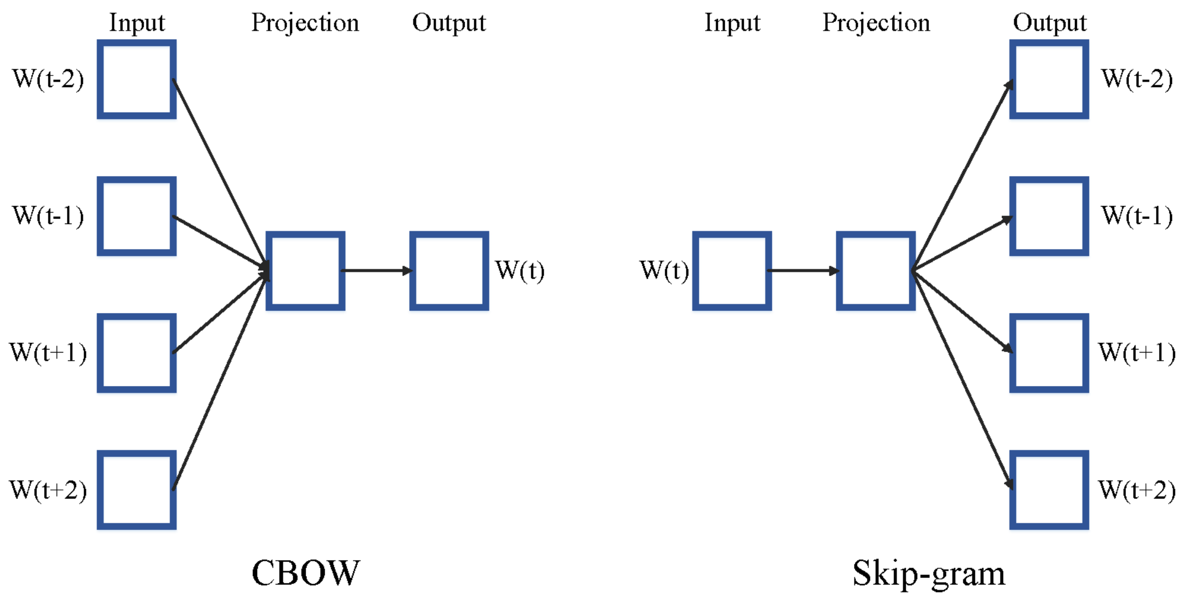
Lemmatization

Text lemmatization is the process of eliminating redundant prefix or suffix of a word and extract the base word (lemma).

```
from nltk.stem import WordNetLemmatizer

lemmatizer = WordNetLemmatizer()

print(lemmatizer.lemmatize("cats"))
```

Word Embedding

Different word embedding procedures have been proposed to translate these unigrams into consumable input for machine learning algorithms. A very simple way to perform such embedding is term-frequency (TF) where each word will be mapped to a number corresponding to the number of occurrence of that word in the whole corpora. The other term frequency functions have been also used that represent word-frequency as a Boolean or logarithmically scaled number. Here, each document will be converted to a vector of the same length containing the frequency of the words in that document. Although such an approach may seem very intuitive. It suffers from the fact that particular words that are used very commonly in language literature might dominate this sort of word representations.



Word2Vec

Original from https://code.google.com/p/word2vec/

I've copied it to a github project so that I can apply and track community patches (starting with capability for Mac OS X compilation).

- **makefile and some source has been modified for Mac OS X compilation** See https://code.google.com/p/word2vec/issues/detail?id=1#c5
- **memory patch for word2vec has been applied** See https://code.google.com/p/word2vec/issues/detail?id=2
- Project file layout altered

There seems to be a segfault in the compute-accuracy utility.

To get started:

```
cd scripts && ./demo-word.sh
```

Original README text follows:

This tool provides an efficient implementation of the continuous bag-of-words and skip-gram architectures for computing vector representations of words. These representations can be subsequently used in many natural language processing applications and for further research purposes.

this code provides an implementation of the Continuous Bag-of-Words (CBOW) and the Skip-gram model (SG), as well as several demo scripts.

Given a text corpus, the word2vec tool learns a vector for every word in the vocabulary using the Continuous Bag-of-Words or the Skip-Gram neural network architectures. The user should specify the following: - desired vector dimensionality (size of the context window for either the Skip-Gram or the Continuous Bag-of-Words model), training algorithm (hierarchical softmax and/or negative sampling), the threshold for downsampling the frequent words, number of threads to use, the format of the output word vector file (text or binary).

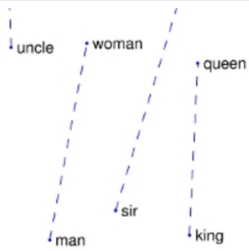
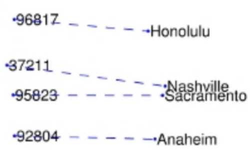
Usually, other hyper-parameters, such as the learning rate do not need to be tuned for different training sets.

The script demo-word.sh downloads a small (100MB) text corpus from the web and trains a small word vector model. After the training is finished, users can interactively explore the similarity of the words.

More information about the scripts is provided at https://code.google.com/p/word2vec/

Global Vectors for Word Representation (GloVe)

nearest neighbors of *frog*	Litoria	Leptodactylidae	Rana	Eleutherodactylus
Pictures				

<table>
<tr><th>Comparisons</th><th>man -> woman</th><th>city -> zip</th><th>comparative -> superlative</th></tr>
<tr><td>GloVe Geometry</td><td></td><td></td><td></td></tr>
</table>

An implementation of the GloVe model for learning word representations is provided, and describe how to download web-dataset vectors or train your own. See the project page or the paper for more information on glove vectors.

Contextualized Word Representations

ELMo is a deep contextualized word representation that models both (1) complex characteristics of word use (e.g., syntax and semantics), and (2) how these uses vary across linguistic contexts (i.e., to model polysemy). These word vectors are learned functions of the internal states of a deep bidirectional language model (biLM), which is pre-trained on a large text corpus. They can be easily added to existing models and significantly improve the state of the art across a broad range of challenging NLP problems, including question answering, textual entailment, and sentiment analysis.

ELMo representations are:

- **Contextual:** The representation for each word depends on the entire context in which it is used.
- **Deep:** The word representations combine all layers of a deep pre-trained neural network.
- **Character based:** ELMo representations are purely character based, allowing the network to use morphological clues to form robust representations for out-of-vocabulary tokens unseen in training.

Tensorflow implementation

Tensorflow implementation of the pre-trained biLM used to compute ELMo representations from "Deep contextualized word representations".

This repository supports both training biLMs and using pre-trained models for prediction.

We also have a pytorch implementation available in AllenNLP.

You may also find it easier to use the version provided in Tensorflow Hub if you just like to make predictions.

pre-trained models:

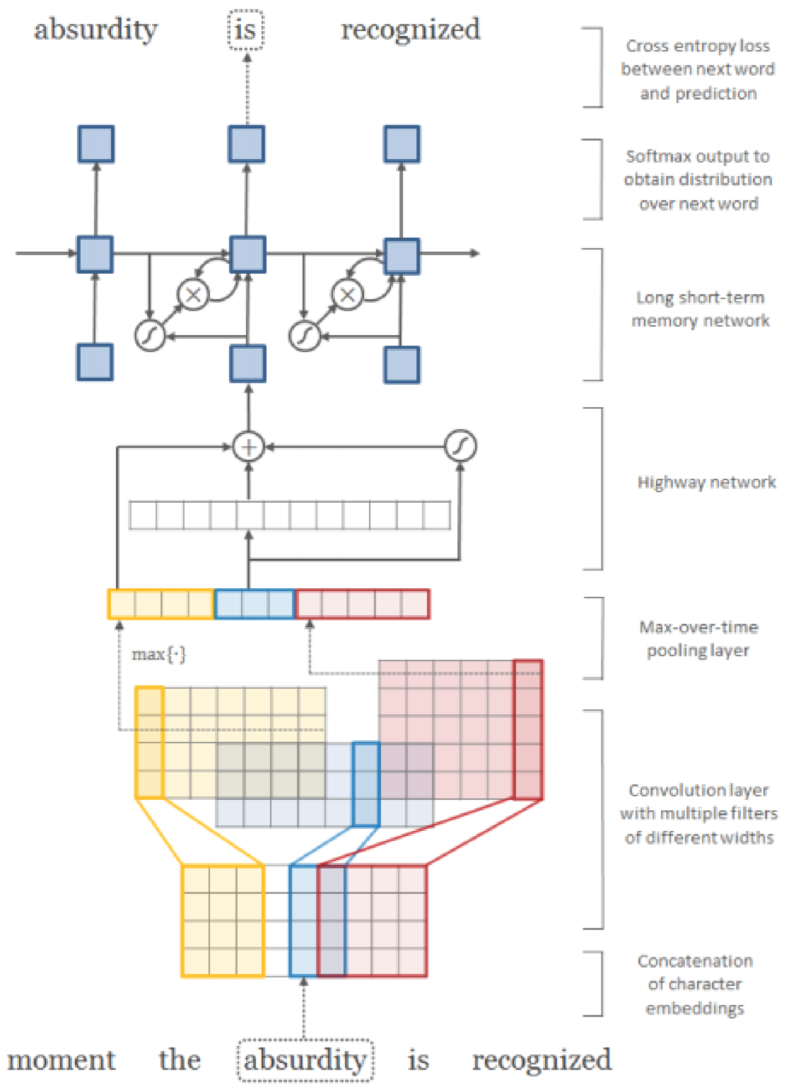
We have got several pre-trained English language biLMs available for use. Each model is specified with two separate files, a JSON formatted "options" file with hyperparameters and a hdf5 formatted file with the model weights. Links to the pre-trained models are available here.

There are three ways to integrate ELMo representations into a downstream task, depending on your use case.

1. Compute representations on the fly from raw text using character input. This is the most general method and will handle any input text. It is also the most computationally expensive.
2. Precompute and cache the context-independent token representations, then compute context dependent representations using the biLSTMs for input data. This method is less computationally expensive then #1, but is only applicable with a fixed, prescribed vocabulary.
3. Precompute the representations for your entire dataset and save to a file.

We have used all of these methods in the past for various use cases. #1 is necessary for evaluating at test time on unseen data (e.g. public SQuAD leaderboard). #2 is a good compromise for large datasets where the size of the file in is unfeasible (SNLI, SQuAD). #3 is a good choice for smaller datasets or in cases where you'd like to use ELMo in other frameworks.

In all cases, the process roughly follows the same steps. First, create a `Batcher` (or `TokenBatcher` for #2) to translate tokenized strings to NumPy arrays of character (or token) ids. Then, load the pre-trained ELMo model (class `BidirectionalLanguageModel`). Finally, for steps #1 and #2 use `weight_layers` to compute the final ELMo representations. For #3, use `BidirectionalLanguageModel` to write all the intermediate layers to a file.



Architecture of the language model applied to an example sentence [Reference: arXiv paper].

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

Nearest neighbors to "play" using GloVe and the context embeddings from a biLM.

FastText

fastText is a library for efficient learning of word representations and sentence classification.

Github: facebookresearch/fastText

Models

- Recent state-of-the-art English word vectors.
- Word vectors for 157 languages trained on Wikipedia and Crawl.
- Models for language identification and various supervised tasks.

Supplementary data :

- The preprocessed YFCC100M data .

FAQ

You can find answers to frequently asked questions on Their project website.

Cheatsheet

Also a cheatsheet is provided full of useful one-liners.

Weighted Words

Term frequency

Term frequency is Bag of words that is one of the simplest techniques of text feature extraction. This method is based on counting the number of the words in each document and assigns it to feature space.

Term Frequency-Inverse Document Frequency

The mathematical representation of the weight of a term in a document by Tf-idf is given:

$$W(d,t) = TF(d,t) * log(\frac{N}{df(t)})$$

Where N is number of documents and df(t) is the number of documents containing the term t in the corpus. The first part would improve recall and the later would improve the precision of the word embedding. Although tf-idf tries to overcome the problem of common terms in document, it still suffers from some other descriptive limitations. Namely, tf-idf cannot account for the similarity between words in the document since each word is presented as an index. In the recent years, with development of more complex models, such as neural nets, new methods has been presented that can incorporate concepts, such as similarity of words and part of speech tagging. This work uses, word2vec and Glove, two of the most common methods that have been successfully used for deep learning techniques.

```
from sklearn.feature_extraction.text import TfidfVectorizer
def loadData(X_train, X_test,MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with",str(np.array(X_train).shape[1]),"features")
    return (X_train,X_test)
```

Comparison of Feature Extraction Techniques

Model	Advantages	Limitation
Weighted Words	• **Easy to compute** • **Easy to compute the similarity between 2 documents using it** • **Basic metric to extract the most descriptive terms in a document** • **Works with an unknown word (e.g., New words in languages)**	• **It does not capture the position in the text (syntactic)** • **It does not capture meaning in the text (semantics)** • **Common words effect on the results (e.g., “am”, “is”, etc.)**

TF-IDF	• **Easy to compute** • **Easy to compute the similarity between 2 documents using it** • **Basic metric to extract the most descriptive terms in a document** • **Common words do not affect the results due to IDF (e.g., “am”, “is”, etc.)**	• **It does not capture the position in the text (syntactic)** • **It does not capture meaning in the text (semantics)**
Word2Vec	• **It captures the position of the words in the text (syntactic)** • **It captures meaning in the words (semantics)**	• **It cannot capture the meaning of the word from the text (fails to capture polysemy)** • **It cannot capture out-of-vocabulary words from corpus**
GloVe (Pre-Trained)	• **It captures the position of the words in the text (syntactic)** • **It captures meaning in the words (semantics)** • **Trained on huge corpus**	• **It cannot capture the meaning of the word from the text (fails to capture polysemy)** • **Memory consumption for storage** • **It cannot capture out-of-vocabulary words from corpus**
GloVe (Trained)	• **It is very straightforward, e.g., to enforce the word vectors to capture sub-linear relationships in the vector space (performs better than Word2vec)** • **Lower weight for highly frequent word pairs, such as stop words like “am”, “is”, etc. Will not dominate training progress**	• **Memory consumption for storage** • **Needs huge corpus to learn** • **It cannot capture out-of-vocabulary words from the corpus** • **It cannot capture the meaning of the word from the text (fails to capture polysemy)**
FastText	• **Works for rare words (rare in their character n-grams which are still shared with other words** • **Solves out of vocabulary words with n-gram in character level**	• **It cannot capture the meaning of the word from the text (fails to capture polysemy)** • **Memory consumption for storage** • **Computationally is more expensive in comparing with GloVe and Word2Vec**
Contextualized Word Representations	• **It captures the meaning of the word from the text (incorporates context, handling polysemy)**	• **Memory consumption for storage** • **Improves performance notably on downstream tasks. Computationally is more expensive in comparison to others** • **Needs another word embedding for all LSTM and feedforward layers** • **It cannot capture out-of-vocabulary words from a corpus** • **Works only sentence and document level (it cannot work for individual word level)**

Dimensionality Reduction

Principal Component Analysis (PCA)

Principle component analysis~(PCA) is the most popular technique in multivariate analysis and dimensionality reduction. PCA is a method to identify a subspace in which the data approximately lies. This means finding new variables that are uncorrelated and maximizing the variance to preserve as much variability as possible.

Example of PCA on text dataset (20newsgroups) from tf-idf with 75000 features to 2000 components:

```
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np

def TFIDF(X_train, X_test, MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with", str(np.array(X_train).shape[1]), "features")
    return (X_train, X_test)


from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train,X_test = TFIDF(X_train,X_test)

from sklearn.decomposition import PCA
pca = PCA(n_components=2000)
X_train_new = pca.fit_transform(X_train)
X_test_new = pca.transform(X_test)

print("train with old features: ",np.array(X_train).shape)
print("train with new features:" ,np.array(X_train_new).shape)

print("test with old features: ",np.array(X_test).shape)
print("test with new features:" ,np.array(X_test_new).shape)
```

output:

```
tf-idf with 75000 features
train with old features:  (11314, 75000)
train with new features: (11314, 2000)
test with old features:  (7532, 75000)
test with new features: (7532, 2000)
```

Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is another commonly used technique for data classification and dimensionality reduction. LDA is particularly helpful where the within-class frequencies are unequal and their performances have been evaluated on randomly generated test data. Class-dependent and class-independent transformation are two approaches in LDA where the ratio of between-class-variance to within-class-variance and the ratio of the overall-variance to within-class-variance are used respectively.

```
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis


def TFIDF(X_train, X_test, MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with", str(np.array(X_train).shape[1]), "features")
    return (X_train, X_test)


from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train,X_test = TFIDF(X_train,X_test)



LDA = LinearDiscriminantAnalysis(n_components=15)
X_train_new = LDA.fit(X_train,y_train)
X_train_new =  LDA.transform(X_train)
X_test_new = LDA.transform(X_test)

print("train with old features: ",np.array(X_train).shape)
print("train with new features:" ,np.array(X_train_new).shape)

print("test with old features: ",np.array(X_test).shape)
print("test with new features:" ,np.array(X_test_new).shape)
```

output:

```
tf-idf with 75000 features
train with old features:  (11314, 75000)
train with new features: (11314, 15)
test with old features:  (7532, 75000)
test with new features: (7532, 15)
```

Non-negative Matrix Factorization (NMF)

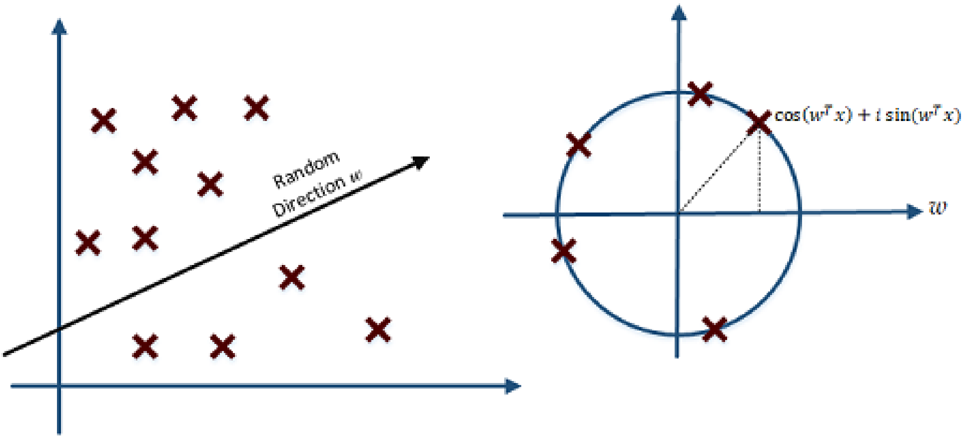
```
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn.decomposition import NMF


def TFIDF(X_train, X_test, MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with", str(np.array(X_train).shape[1]), "features")
    return (X_train, X_test)


from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train,X_test = TFIDF(X_train,X_test)



NMF_ = NMF(n_components=2000)
X_train_new = NMF_.fit(X_train)
X_train_new =  NMF_.transform(X_train)
X_test_new = NMF_.transform(X_test)

print("train with old features: ",np.array(X_train).shape)
print("train with new features:" ,np.array(X_train_new).shape)

print("test with old features: ",np.array(X_test).shape)
print("test with new features:" ,np.array(X_test_new))
```

output:

```
tf-idf with 75000 features
train with old features:  (11314, 75000)
train with new features: (11314, 2000)
test with old features:  (7532, 75000)
test with new features: (7532, 2000)
```

Random Projection

Random projection or random feature is a dimensionality reduction technique mostly used for very large volume dataset or very high dimensional feature space. Text and document, especially with weighted feature extraction, can contain a huge number of underlying features. Many researchers addressed Random Projection for text data for text mining, text classification and/or dimensionality reduction. We start to review some random projection techniques.



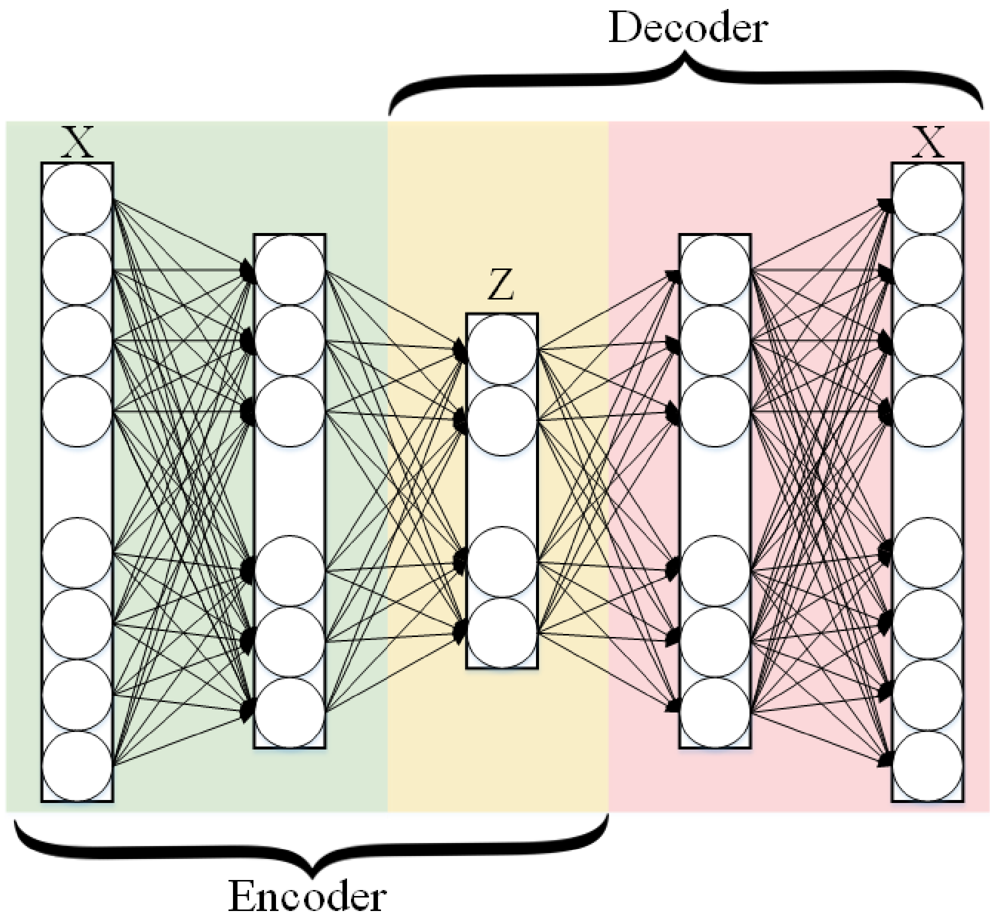

```
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np

def TFIDF(X_train, X_test, MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with", str(np.array(X_train).shape[1]), "features")
    return (X_train, X_test)


from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train,X_test = TFIDF(X_train,X_test)

from sklearn import random_projection

RandomProjection = random_projection.GaussianRandomProjection(n_components=2000)
X_train_new = RandomProjection.fit_transform(X_train)
X_test_new = RandomProjection.transform(X_test)

print("train with old features: ",np.array(X_train).shape)
print("train with new features:" ,np.array(X_train_new).shape)

print("test with old features: ",np.array(X_test).shape)
print("test with new features:" ,np.array(X_test_new).shape)
```

output:

```
tf-idf with 75000 features
train with old features:  (11314, 75000)
train with new features: (11314, 2000)
test with old features:  (7532, 75000)
test with new features: (7532, 2000)
```

Autoencoder

Autoencoder is a neural network technique that is trained to attempt to map its input to its output. The autoencoder as dimensional reduction methods have achieved great success via the powerful reprehensibility of neural networks. The main idea is, one hidden layer between the input and output layers with fewer neurons can be used to reduce the dimension of feature space. Specially for texts, documents, and sequences that contains many features, autoencoder could help to process data faster and more efficiently.



```
from keras.layers import Input, Dense
from keras.models import Model

# this is the size of our encoded representations
encoding_dim = 1500

# this is our input placeholder
input = Input(shape=(n,))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input)
# "decoded" is the lossy reconstruction of the input
decoded = Dense(n, activation='sigmoid')(encoded)

# this model maps an input to its reconstruction
autoencoder = Model(input, decoded)

# this model maps an input to its encoded representation
encoder = Model(input, encoded)



encoded_input = Input(shape=(encoding_dim,))
# retrieve the last layer of the autoencoder model
decoder_layer = autoencoder.layers[-1]
# create the decoder model
decoder = Model(encoded_input, decoder_layer(encoded_input))

autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
```

Load data:

```
autoencoder.fit(x_train, x_train,
                epochs=50,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))
```

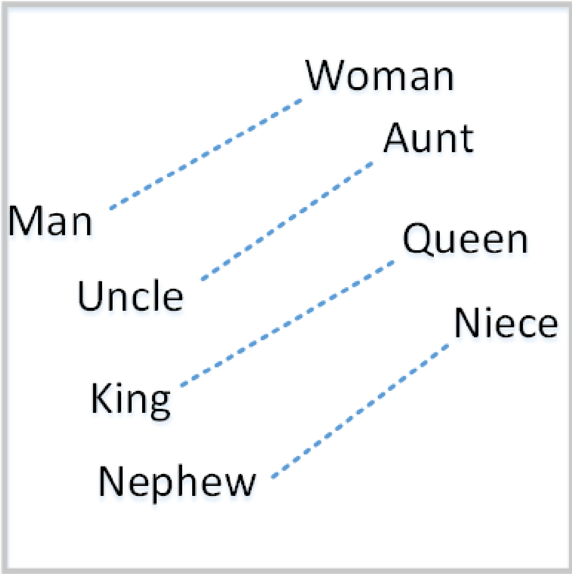
T-distributed Stochastic Neighbor Embedding (T-SNE)

T-distributed Stochastic Neighbor Embedding (T-SNE) is a nonlinear dimensionality reduction technique for embedding high-dimensional data which is mostly used for visualization in a low-dimensional space. This approach is based on G. Hinton and ST. Roweis . SNE works by converting the high dimensional Euclidean distances into conditional probabilities which represent similarities.

Example:

```
import numpy as np
from sklearn.manifold import TSNE
X = np.array([[0, 0, 0], [0, 1, 1], [1, 0, 1], [1, 1, 1]])
X_embedded = TSNE(n_components=2).fit_transform(X)
X_embedded.shape
```

Example of Glove and T-SNE for text:



Text Classification Techniques

Rocchio classification

The first version of Rocchio algorithm is introduced by rocchio in 1971 to use relevance feedback in querying full-text databases. Since then many researchers have addressed and developed this technique for text and document classification. This method uses TF-IDF weights for each informative word instead of a set of Boolean features. Using a training set of documents, Rocchio's algorithm builds a prototype vector for each class which is an average vector over all training document vectors that belongs to a certain class. Then, it will assign each test document to a class with maximum similarity that between test document and each of the prototype vectors.

When in nearest centroid classifier, we used for text as input data for classification with tf-idf vectors, this classifier is known as the Rocchio classifier.

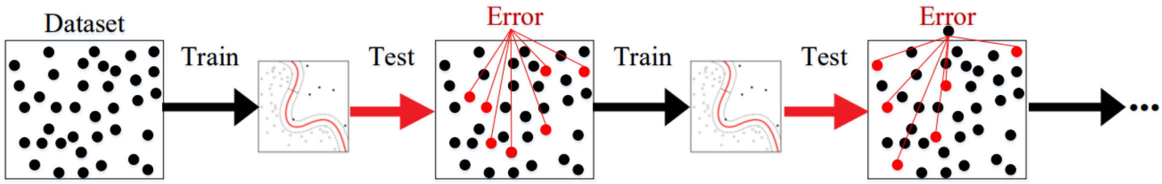
```
from sklearn.neighbors.nearest_centroid import NearestCentroid
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', NearestCentroid()),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

Output:

	precision	recall	f1-score	support
0	0.75	0.49	0.60	319
1	0.44	0.76	0.56	389
2	0.75	0.68	0.71	394
3	0.71	0.59	0.65	392
4	0.81	0.71	0.76	385
5	0.83	0.66	0.74	395
6	0.49	0.88	0.63	390
7	0.86	0.76	0.80	396
8	0.91	0.86	0.89	398
9	0.85	0.79	0.82	397
10	0.95	0.80	0.87	399
11	0.94	0.66	0.78	396
12	0.40	0.70	0.51	393
13	0.84	0.49	0.62	396
14	0.89	0.72	0.80	394
15	0.55	0.73	0.63	398
16	0.68	0.76	0.71	364
17	0.97	0.70	0.81	376
18	0.54	0.53	0.53	310
19	0.58	0.39	0.47	251
avg / total	0.74	0.69	0.70	7532

Boosting and Bagging

Boosting



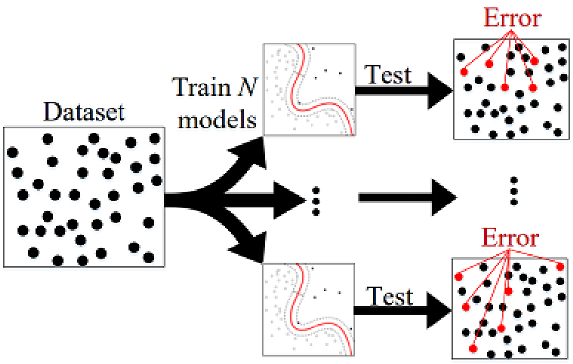
Boosting is a Ensemble learning meta-algorithm for primarily reducing variance in supervised learning. It is basically a family of machine learning algorithms that convert weak learners to strong ones. Boosting is based on the question posed by Michael Kearns and Leslie Valiant (1988, 1989) Can a set of weak learners create a single strong learner? A weak learner is defined to be a Classification that is only slightly correlated with the true classification (it can label examples better than random guessing). In contrast, a strong learner is a classifier that is arbitrarily well-correlated with the true classification.

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', GradientBoostingClassifier(n_estimators=100)),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

Output:

```
             precision    recall  f1-score   support
          0       0.81      0.66      0.73       319
          1       0.69      0.70      0.69       389
          2       0.70      0.68      0.69       394
          3       0.64      0.72      0.68       392
          4       0.79      0.79      0.79       385
          5       0.83      0.64      0.72       395
          6       0.81      0.84      0.82       390
          7       0.84      0.75      0.79       396
          8       0.90      0.86      0.88       398
          9       0.90      0.85      0.88       397
         10       0.93      0.86      0.90       399
         11       0.90      0.81      0.85       396
         12       0.33      0.69      0.45       393
         13       0.87      0.72      0.79       396
         14       0.87      0.84      0.85       394
         15       0.85      0.87      0.86       398
         16       0.65      0.78      0.71       364
         17       0.96      0.74      0.84       376
         18       0.70      0.55      0.62       310
         19       0.62      0.56      0.59       251

avg / total       0.78      0.75      0.76      7532
```

Bagging




```
from sklearn.ensemble import BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', BaggingClassifier(KNeighborsClassifier())),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

Output:

	precision	recall	f1-score	support
0	0.57	0.74	0.65	319
1	0.60	0.56	0.58	389
2	0.62	0.54	0.58	394
3	0.54	0.57	0.55	392
4	0.63	0.54	0.58	385
5	0.68	0.62	0.65	395
6	0.55	0.46	0.50	390
7	0.77	0.67	0.72	396
8	0.79	0.82	0.80	398
9	0.74	0.77	0.76	397
10	0.81	0.86	0.83	399
11	0.74	0.85	0.79	396
12	0.67	0.49	0.57	393
13	0.78	0.51	0.62	396
14	0.76	0.78	0.77	394
15	0.71	0.81	0.76	398
16	0.73	0.73	0.73	364
17	0.64	0.79	0.71	376
18	0.45	0.69	0.54	310
19	0.61	0.54	0.57	251
avg / total	0.67	0.67	0.67	7532

Naive Bayes Classifier

Naïve Bayes text classification has been used in industry and academia for a long time (introduced by Thomas Bayes between 1701-1761). However, this technique is being studied since the 1950s for text and document categorization. Naive Bayes Classifier (NBC) is generative model which is widely used in Information Retrieval. Many researchers addressed and developed this technique for their applications. We start with the most basic version of NBC which developed by using term-frequency (Bag of Word) fetaure extraction technique by counting number of words in documents

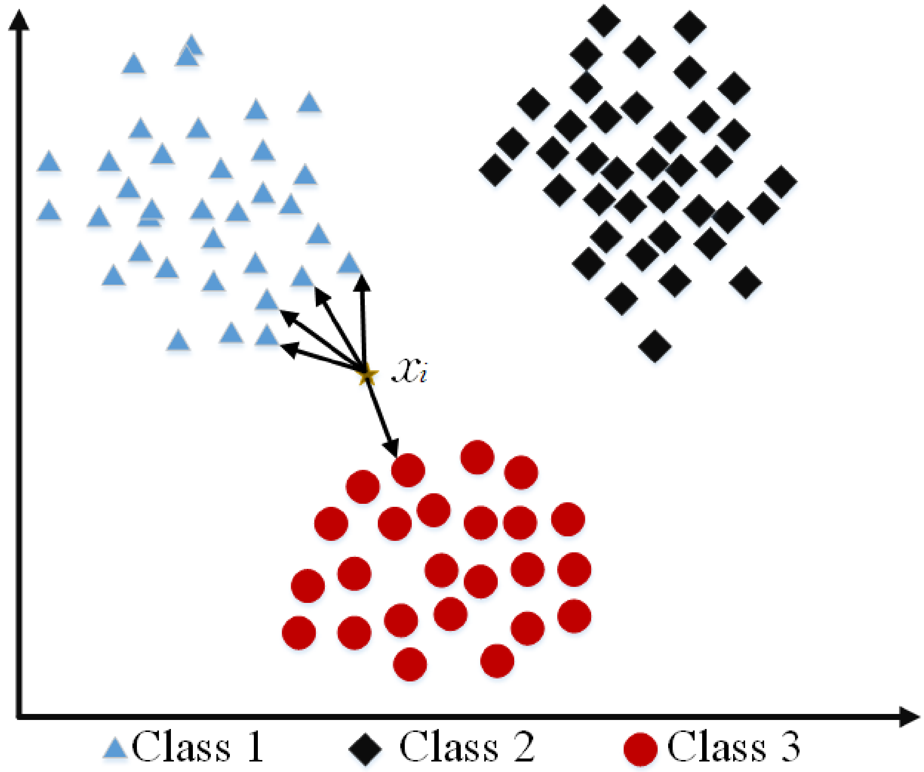
```
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', MultinomialNB()),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

Output:

```
               precision    recall  f1-score   support

          0       0.80      0.52      0.63       319
          1       0.81      0.65      0.72       389
          2       0.82      0.65      0.73       394
          3       0.67      0.78      0.72       392
          4       0.86      0.77      0.81       385
          5       0.89      0.75      0.82       395
          6       0.93      0.69      0.80       390
          7       0.85      0.92      0.88       396
          8       0.94      0.93      0.93       398
          9       0.92      0.90      0.91       397
         10       0.89      0.97      0.93       399
         11       0.59      0.97      0.74       396
         12       0.84      0.60      0.70       393
         13       0.92      0.74      0.82       396
         14       0.84      0.89      0.87       394
         15       0.44      0.98      0.61       398
         16       0.64      0.94      0.76       364
         17       0.93      0.91      0.92       376
         18       0.96      0.42      0.58       310
         19       0.97      0.14      0.24       251

avg / total       0.82      0.77      0.77      7532
```

K-nearest Neighbor

R In machine learning, the k-nearest neighbors algorithm (kNN) is a non-parametric technique used for classification. This method is used in Natural-language processing (NLP) as a text classification technique in many researches in the past decades.




```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', KNeighborsClassifier()),
                     ])

text_clf.fit(X_train, y_train)

predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

Output:

	precision	recall	f1-score	support
0	0.43	0.76	0.55	319
1	0.50	0.61	0.55	389
2	0.56	0.57	0.57	394
3	0.53	0.58	0.56	392
4	0.59	0.56	0.57	385
5	0.69	0.60	0.64	395
6	0.58	0.45	0.51	390
7	0.75	0.69	0.72	396
8	0.84	0.81	0.82	398
9	0.77	0.72	0.74	397
10	0.85	0.84	0.84	399
11	0.76	0.84	0.80	396
12	0.70	0.50	0.58	393
13	0.82	0.49	0.62	396
14	0.79	0.76	0.78	394
15	0.75	0.76	0.76	398
16	0.70	0.73	0.72	364
17	0.62	0.76	0.69	376
18	0.55	0.61	0.58	310
19	0.56	0.49	0.52	251
avg / total	0.67	0.66	0.66	7532

Support Vector Machine (SVM)

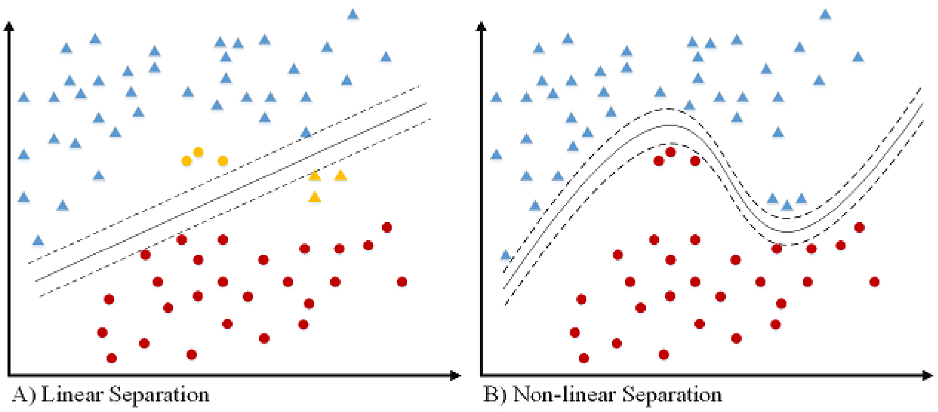
The original version of SVM was introduced by Vapnik and Chervonenkis in 1963. The early 1990s, nonlinear version was addressed by BE. Boser et al. Original version of SVM was designed for binary classification problem, but Many researchers have worked on multi-class problem using this authoritative technique.

The advantages of support vector machines are based on scikit-learn page:

- Effective in high dimensional spaces.
- Still effective in cases where number of dimensions is greater than the number of samples.
- Uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.
- Versatile: different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

The disadvantages of support vector machines include:

- If the number of features is much greater than the number of samples, avoiding over-fitting via choosing kernel functions and regularization term is crucial.
- SVMs do not directly provide probability estimates, these are calculated using an expensive five-fold cross-validation (see Scores and probabilities, below).



```
from sklearn.svm import LinearSVC
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', LinearSVC()),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

output:

```
               precision    recall  f1-score   support

          0       0.82      0.80      0.81       319
          1       0.76      0.80      0.78       389
          2       0.77      0.73      0.75       394
          3       0.71      0.76      0.74       392
          4       0.84      0.86      0.85       385
          5       0.87      0.76      0.81       395
          6       0.83      0.91      0.87       390
          7       0.92      0.91      0.91       396
          8       0.95      0.95      0.95       398
          9       0.92      0.95      0.93       397
         10       0.96      0.98      0.97       399
         11       0.93      0.94      0.93       396
         12       0.81      0.79      0.80       393
         13       0.90      0.87      0.88       396
         14       0.90      0.93      0.92       394
         15       0.84      0.93      0.88       398
         16       0.75      0.92      0.82       364
         17       0.97      0.89      0.93       376
         18       0.82      0.62      0.71       310
         19       0.75      0.61      0.68       251

avg / total       0.85      0.85      0.85      7532
```

Decision Tree

One of earlier classification algorithm for text and data mining is decision tree. Decision tree classifiers (DTC's) are used successfully in many diverse areas of classification. The structure of this technique includes a hierarchical decomposition of the data space (only train dataset). Decision tree as classification task was introduced by D. Morgan and developed by JR. Quinlan. The main idea is creating trees based on the attributes of the data points, but the challenge is determining which attribute should be in parent level and which one should be in child level. To solve this problem, De Mantaras introduced statistical modeling for feature selection in tree.

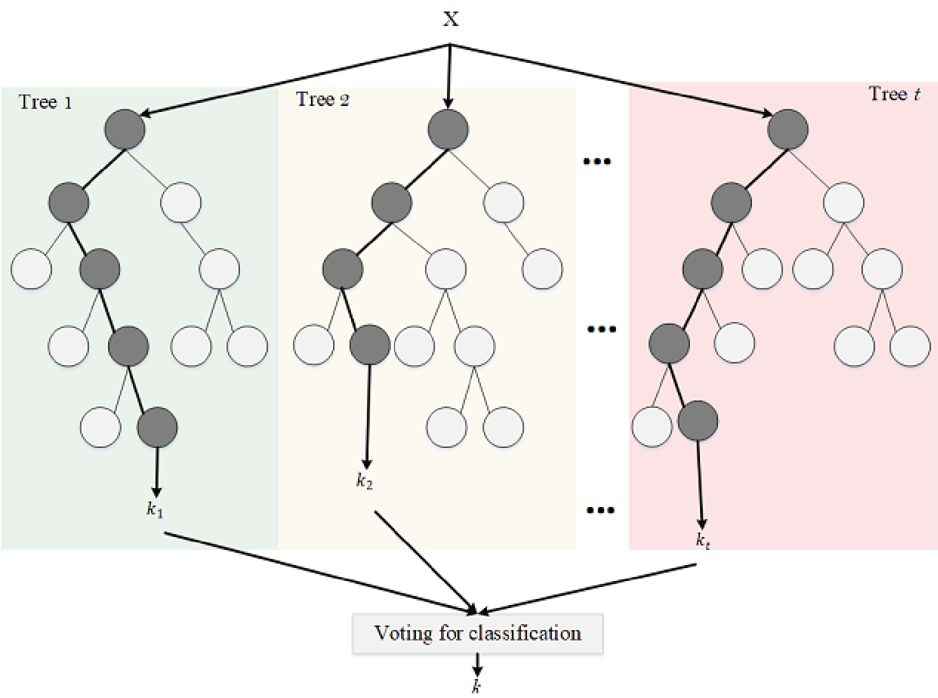
```
from sklearn import tree
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', tree.DecisionTreeClassifier()),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

output:

```
             precision    recall  f1-score   support

          0       0.51      0.48      0.49       319
          1       0.42      0.42      0.42       389
          2       0.51      0.56      0.53       394
          3       0.46      0.42      0.44       392
          4       0.50      0.56      0.53       385
          5       0.50      0.47      0.48       395
          6       0.66      0.73      0.69       390
          7       0.60      0.59      0.59       396
          8       0.66      0.72      0.69       398
          9       0.53      0.55      0.54       397
         10       0.68      0.66      0.67       399
         11       0.73      0.69      0.71       396
         12       0.34      0.33      0.33       393
         13       0.52      0.42      0.46       396
         14       0.65      0.62      0.63       394
         15       0.68      0.72      0.70       398
         16       0.49      0.62      0.55       364
         17       0.78      0.60      0.68       376
         18       0.38      0.38      0.38       310
         19       0.32      0.32      0.32       251

avg / total       0.55      0.55      0.55      7532
```

Random Forest

Random forests or random decision forests technique is an ensemble learning method for text classification. This method was introduced by T. Kam Ho in 1995 for first time which used t trees in parallel. This technique was later developed by L. Breiman in 1999 that they found converged for RF as a margin measure.



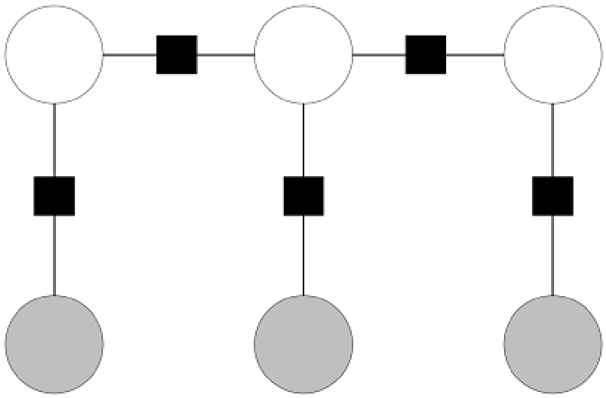
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.datasets import fetch_20newsgroups

newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

text_clf = Pipeline([('vect', CountVectorizer()),
                     ('tfidf', TfidfTransformer()),
                     ('clf', RandomForestClassifier(n_estimators=100)),
                     ])

text_clf.fit(X_train, y_train)


predicted = text_clf.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

output:

```
                precision    recall  f1-score   support

          0       0.69      0.63      0.66       319
          1       0.56      0.69      0.62       389
          2       0.67      0.78      0.72       394
          3       0.67      0.67      0.67       392
          4       0.71      0.78      0.74       385
          5       0.78      0.68      0.73       395
          6       0.74      0.92      0.82       390
          7       0.81      0.79      0.80       396
          8       0.90      0.89      0.90       398
          9       0.80      0.89      0.84       397
         10       0.90      0.93      0.91       399
         11       0.89      0.91      0.90       396
         12       0.68      0.49      0.57       393
         13       0.83      0.65      0.73       396
         14       0.81      0.88      0.84       394
         15       0.68      0.91      0.78       398
         16       0.67      0.86      0.75       364
         17       0.93      0.78      0.85       376
         18       0.86      0.48      0.61       310
         19       0.79      0.31      0.45       251

avg / total       0.77      0.76      0.75      7532
```

Conditional Random Field (CRF)

Conditional Random Field (CRF) is an undirected graphical model as shown in figure. CRFs state the conditional probability of a label sequence *Y* give a sequence of observation *X i.e.* P(Y|X). CRFs can incorporate complex features of observation sequence without violating the independence assumption by modeling the conditional probability of the label sequences rather than the joint probability P(X,Y). The concept of clique which is a fully connected subgraph and clique potential are used for computing P(X|Y). Considering one potential function for each clique of the graph, the probability of a variable configuration corresponds to the product of a series of non-negative potential function. The value computed by each potential function is equivalent to the probability of the variables in its corresponding clique taken on a particular configuration.



Example from Here Let's use CoNLL 2002 data to build a NER system CoNLL2002 corpus is available in NLTK. We use Spanish data.

```
import nltk
import sklearn_crfsuite
from sklearn_crfsuite import metrics
nltk.corpus.conll2002.fileids()
train_sents = list(nltk.corpus.conll2002.iob_sents('esp.train'))
test_sents = list(nltk.corpus.conll2002.iob_sents('esp.testb'))
```

sklearn-crfsuite (and python-crfsuite) supports several feature formats; here we use feature dicts.

```python
def word2features(sent, i):
    word = sent[i][0]
    postag = sent[i][1]

    features = {
        'bias': 1.0,
        'word.lower()': word.lower(),
        'word[-3:]': word[-3:],
        'word[-2:]': word[-2:],
        'word.isupper()': word.isupper(),
        'word.istitle()': word.istitle(),
        'word.isdigit()': word.isdigit(),
        'postag': postag,
        'postag[:2]': postag[:2],
    }
    if i > 0:
        word1 = sent[i-1][0]
        postag1 = sent[i-1][1]
        features.update({
            '-1:word.lower()': word1.lower(),
            '-1:word.istitle()': word1.istitle(),
            '-1:word.isupper()': word1.isupper(),
            '-1:postag': postag1,
            '-1:postag[:2]': postag1[:2],
        })
    else:
        features['BOS'] = True

    if i < len(sent)-1:
        word1 = sent[i+1][0]
        postag1 = sent[i+1][1]
        features.update({
            '+1:word.lower()': word1.lower(),
            '+1:word.istitle()': word1.istitle(),
            '+1:word.isupper()': word1.isupper(),
            '+1:postag': postag1,
            '+1:postag[:2]': postag1[:2],
        })
    else:
        features['EOS'] = True

    return features


def sent2features(sent):
    return [word2features(sent, i) for i in range(len(sent))]

def sent2labels(sent):
    return [label for token, postag, label in sent]

def sent2tokens(sent):
    return [token for token, postag, label in sent]

X_train = [sent2features(s) for s in train_sents]
y_train = [sent2labels(s) for s in train_sents]
```

```
X_test = [sent2features(s) for s in test_sents]
y_test = [sent2labels(s) for s in test_sents]
```

To see all possible CRF parameters check its docstring. Here we are useing L-BFGS training algorithm (it is default) with Elastic Net (L1 + L2) regularization.

```
crf = sklearn_crfsuite.CRF(
    algorithm='lbfgs',
    c1=0.1,
    c2=0.1,
    max_iterations=100,
    all_possible_transitions=True
)
crf.fit(X_train, y_train)
```

Evaluation

```
y_pred = crf.predict(X_test)
print(metrics.flat_classification_report(
    y_test, y_pred,  digits=3
))
```

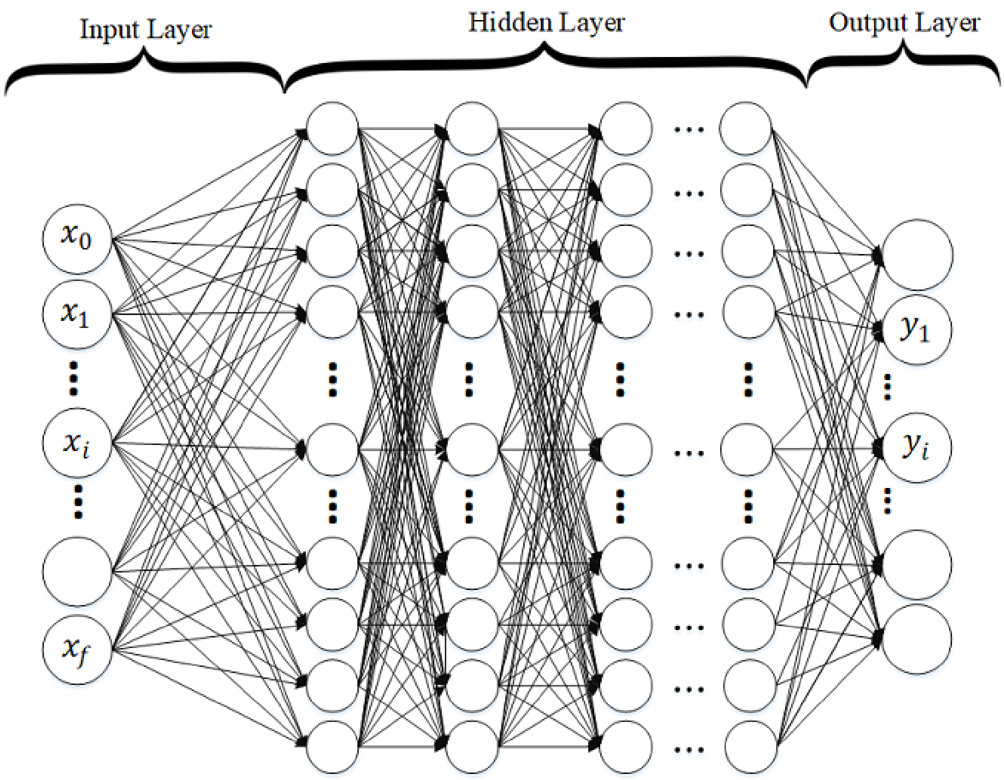
Output:

```
               precision    recall  f1-score   support

      B-LOC      0.810     0.784     0.797      1084
     B-MISC      0.731     0.569     0.640       339
      B-ORG      0.807     0.832     0.820      1400
      B-PER      0.850     0.884     0.867       735
      I-LOC      0.690     0.637     0.662       325
     I-MISC      0.699     0.589     0.639       557
      I-ORG      0.852     0.786     0.818      1104
      I-PER      0.893     0.943     0.917       634
          O      0.992     0.997     0.994     45355

avg / total      0.970     0.971     0.971     51533
```

Deep Learning

Deep Neural Networks

Deep Neural Networks architectures are designed to learn through multiple connection of layers where each single layer only receives connection from previous and provides connections only to the next layer in hidden part. The input is a connection of feature space (As discussed in Section Feature_extraction with first hidden layer. For Deep Neural Networks (DNN), input layer could be tf-ifd, word embedding, or etc. as shown in standard DNN in Figure. The output layer houses neurons equal to the number of classes for multi-class classification and only one neuron for binary classification. But our main contribution in this paper is that we have many trained DNNs to serve different purposes. Here, we have multi-class DNNs where each learning model is generated randomly (number of nodes in each layer as well as the number of layers are randomly assigned). Our implementation of Deep Neural Network (DNN) is basically a discriminatively trained model that uses standard back-propagation algorithm and sigmoid or ReLU as activation functions. The output layer for multi-class classification should use Softmax.



import packages:

```
from sklearn.datasets import fetch_20newsgroups
from keras.layers import  Dropout, Dense
from keras.models import Sequential
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn import metrics
```

convert text to TF-IDF:

```
def TFIDF(X_train, X_test,MAX_NB_WORDS=75000):
    vectorizer_x = TfidfVectorizer(max_features=MAX_NB_WORDS)
    X_train = vectorizer_x.fit_transform(X_train).toarray()
    X_test = vectorizer_x.transform(X_test).toarray()
    print("tf-idf with",str(np.array(X_train).shape[1]),"features")
    return (X_train,X_test)
```

Build a DNN Model for Text:

```
def Build_Model_DNN_Text(shape, nClasses, dropout=0.5):
    """
    buildModel_DNN_Tex(shape, nClasses,dropout)
    Build Deep neural networks Model for text classification
    Shape is input feature space
    nClasses is number of classes
    """
    model = Sequential()
    node = 512 # number of nodes
    nLayers = 4 # number of  hidden layer

    model.add(Dense(node,input_dim=shape,activation='relu'))
    model.add(Dropout(dropout))
    for i in range(0,nLayers):
        model.add(Dense(node,input_dim=node,activation='relu'))
        model.add(Dropout(dropout))
    model.add(Dense(nClasses, activation='softmax'))

    model.compile(loss='sparse_categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])

    return model
```

Load text dataset (20newsgroups):

```
newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target
```

run DNN and see our result:

```
X_train_tfidf,X_test_tfidf = TFIDF(X_train,X_test)
model_DNN = Build_Model_DNN_Text(X_train_tfidf.shape[1], 20)
model_DNN.fit(X_train_tfidf, y_train,
                              validation_data=(X_test_tfidf, y_test),
                              epochs=10,
                              batch_size=128,
                              verbose=2)

predicted = model_DNN.predict(X_test_tfidf)

print(metrics.classification_report(y_test, predicted))
```

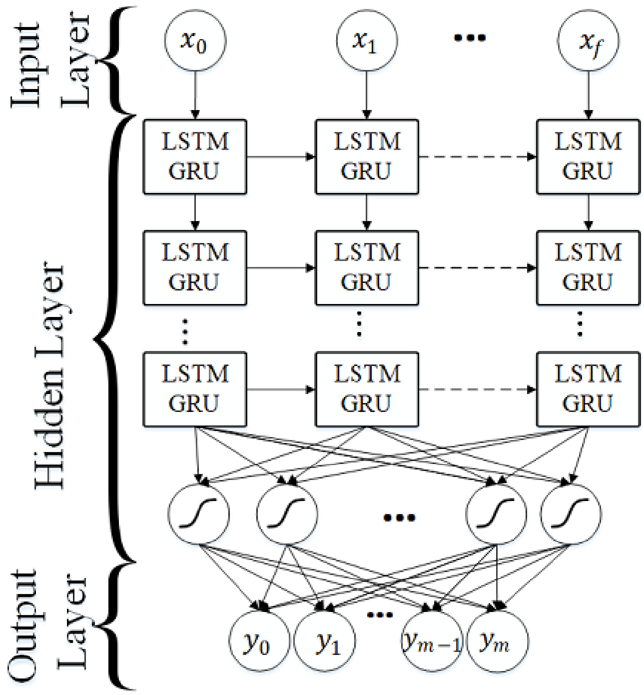
Model summary:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 512)               38400512
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 512)               262656
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_3 (Dense)              (None, 512)               262656
_________________________________________________________________
dropout_3 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_4 (Dense)              (None, 512)               262656
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_5 (Dense)              (None, 512)               262656
_________________________________________________________________
dropout_5 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 20)                10260
=================================================================
Total params: 39,461,396
Trainable params: 39,461,396
Non-trainable params: 0
_________________________________________________________________
```

Output:

```
Train on 11314 samples, validate on 7532 samples
Epoch 1/10
 - 16s - loss: 2.7553 - acc: 0.1090 - val_loss: 1.9330 - val_acc: 0.3184
Epoch 2/10
 - 15s - loss: 1.5330 - acc: 0.4222 - val_loss: 1.1546 - val_acc: 0.6204
Epoch 3/10
 - 15s - loss: 0.7438 - acc: 0.7257 - val_loss: 0.8405 - val_acc: 0.7499
Epoch 4/10
 - 15s - loss: 0.2967 - acc: 0.9020 - val_loss: 0.9214 - val_acc: 0.7767
Epoch 5/10
 - 15s - loss: 0.1557 - acc: 0.9543 - val_loss: 0.8965 - val_acc: 0.7917
Epoch 6/10
 - 15s - loss: 0.1015 - acc: 0.9705 - val_loss: 0.9427 - val_acc: 0.7949
Epoch 7/10
 - 15s - loss: 0.0595 - acc: 0.9835 - val_loss: 0.9893 - val_acc: 0.7995
Epoch 8/10
 - 15s - loss: 0.0495 - acc: 0.9866 - val_loss: 0.9512 - val_acc: 0.8079
Epoch 9/10
 - 15s - loss: 0.0437 - acc: 0.9867 - val_loss: 0.9690 - val_acc: 0.8117
Epoch 10/10
 - 15s - loss: 0.0443 - acc: 0.9880 - val_loss: 1.0004 - val_acc: 0.8070


               precision    recall  f1-score   support

          0       0.76      0.78      0.77       319
          1       0.67      0.80      0.73       389
          2       0.82      0.63      0.71       394
          3       0.76      0.69      0.72       392
          4       0.65      0.86      0.74       385
          5       0.84      0.75      0.79       395
          6       0.82      0.87      0.84       390
          7       0.86      0.90      0.88       396
          8       0.95      0.91      0.93       398
          9       0.91      0.92      0.92       397
         10       0.98      0.92      0.95       399
         11       0.96      0.85      0.90       396
         12       0.71      0.69      0.70       393
         13       0.95      0.70      0.81       396
         14       0.86      0.91      0.88       394
         15       0.85      0.90      0.87       398
         16       0.79      0.84      0.81       364
         17       0.99      0.77      0.87       376
         18       0.58      0.75      0.65       310
         19       0.52      0.60      0.55       251

avg / total       0.82      0.81      0.81      7532
```

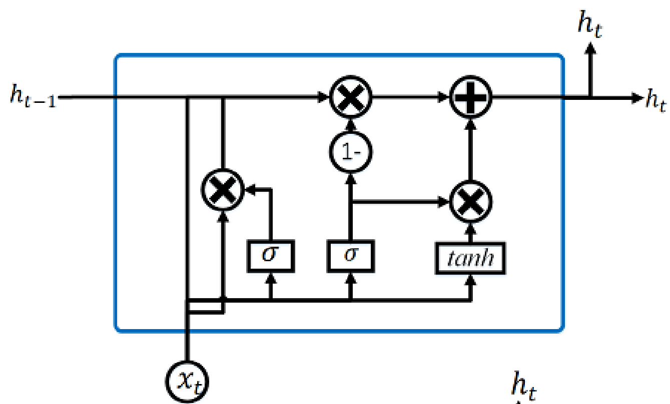
Recurrent Neural Networks (RNN)

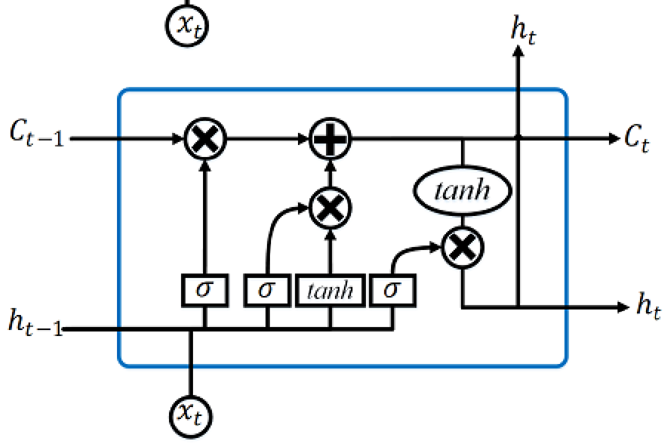


Another neural network architecture that is addressed by the researchers for text miming and classification is Recurrent Neural Networks (RNN). RNN assigns more weights to the previous data points of sequence. Therefore, this technique is a powerful method for text, string and sequential data classification. Moreover, this technique could be used for image classification as we did in this work. In RNN, the neural net considers the information of previous nodes in a very sophisticated method which allows for better semantic analysis of the structures in the dataset.

Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a gating mechanism for RNN which was introduced by J. Chung et al. and K.Cho et al.. GRU is a simplified variant of the LSTM architecture, but there are differences as follows: GRU contains two gates and does not possess any internal memory (as shown in Figure; and finally, a second non-linearity is not applied (tanh in Figure).





Long Short-Term Memory (LSTM)

Long Short-Term Memory~(LSTM) was introduced by S. Hochreiter and J. Schmidhuber and developed by many research scientists.

To deal with these problems Long Short-Term Memory (LSTM) is a special type of RNN that preserves long term dependency in a more effective way compared to the basic RNNs. This is particularly useful to overcome vanishing gradient problem. Although LSTM has a chain-like structure similar to RNN, LSTM uses multiple gates to carefully regulate the amount of information that will be allowed into each node state. Figure shows the basic cell of a LSTM model.

import packages:

```
from keras.layers import Dropout, Dense, GRU, Embedding
from keras.models import Sequential
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn import metrics
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from sklearn.datasets import fetch_20newsgroups
```

convert text to word embedding (Using GloVe):

```
def loadData_Tokenizer(X_train, X_test,MAX_NB_WORDS=75000,MAX_SEQUENCE_LENGTH=500):
    np.random.seed(7)
    text = np.concatenate((X_train, X_test), axis=0)
    text = np.array(text)
    tokenizer = Tokenizer(num_words=MAX_NB_WORDS)
    tokenizer.fit_on_texts(text)
    sequences = tokenizer.texts_to_sequences(text)
    word_index = tokenizer.word_index
    text = pad_sequences(sequences, maxlen=MAX_SEQUENCE_LENGTH)
    print('Found %s unique tokens.' % len(word_index))
    indices = np.arange(text.shape[0])
    # np.random.shuffle(indices)
    text = text[indices]
    print(text.shape)
    X_train = text[0:len(X_train), ]
    X_test = text[len(X_train):, ]
    embeddings_index = {}
                                                                     f                  =
open("C:\\Users\\kamran\\Documents\\GitHub\\RMDL\\Examples\\Glove\\glove.6B.50d.txt",
encoding="utf8")
    for line in f:

        values = line.split()
        word = values[0]
        try:
            coefs = np.asarray(values[1:], dtype='float32')
        except:
            pass
        embeddings_index[word] = coefs
    f.close()
    print('Total %s word vectors.' % len(embeddings_index))
    return (X_train, X_test, word_index,embeddings_index)
```

Build a RNN Model for Text:

```
def         Build_Model_RNN_Text(word_index,         embeddings_index,         nclasses,
MAX_SEQUENCE_LENGTH=500, EMBEDDING_DIM=50, dropout=0.5):
    """
                def    buildModel_RNN(word_index,    embeddings_index,    nclasses,
MAX_SEQUENCE_LENGTH=500, EMBEDDING_DIM=50, dropout=0.5):
    word_index in word index ,
    embeddings_index is embeddings index, look at data_helper.py
    nClasses is number of classes,
    MAX_SEQUENCE_LENGTH is maximum lenght of text sequences
    """

    model = Sequential()
    hidden_layer = 3
    gru_node = 32

    embedding_matrix = np.random.random((len(word_index) + 1, EMBEDDING_DIM))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            # words not found in embedding index will be all-zeros.
            if len(embedding_matrix[i]) != len(embedding_vector):
                                print("could  not  broadcast  input  array  from  shape",
str(len(embedding_matrix[i])),
                          "into shape", str(len(embedding_vector)), " Please make sure
your"
                                                                                  " EMBEDDING_DIM is
equal to embedding_vector file ,GloVe,")
                exit(1)
            embedding_matrix[i] = embedding_vector
    model.add(Embedding(len(word_index) + 1,
                                EMBEDDING_DIM,
                                weights=[embedding_matrix],
                                input_length=MAX_SEQUENCE_LENGTH,
                                trainable=True))



    print(gru_node)
    for i in range(0,hidden_layer):
        model.add(GRU(gru_node,return_sequences=True, recurrent_dropout=0.2))
        model.add(Dropout(dropout))
    model.add(GRU(gru_node, recurrent_dropout=0.2))
    model.add(Dropout(dropout))
    model.add(Dense(256, activation='relu'))
    model.add(Dense(nclasses, activation='softmax'))



    model.compile(loss='sparse_categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])
    return model
```

run RNN and see our result:

```
newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train_Glove,X_test_Glove,                word_index,embeddings_index          =
loadData_Tokenizer(X_train,X_test)


model_RNN = Build_Model_RNN_Text(word_index,embeddings_index, 20)

model_RNN.fit(X_train_Glove, y_train,
                              validation_data=(X_test_Glove, y_test),
                              epochs=10,
                              batch_size=128,
                              verbose=2)

predicted = model_RNN.predict_classes(X_test_Glove)

print(metrics.classification_report(y_test, predicted))
```

Model summary:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 500, 50)           8960500
_________________________________________________________________
gru_1 (GRU)                  (None, 500, 256)          235776
_________________________________________________________________
dropout_1 (Dropout)          (None, 500, 256)          0
_________________________________________________________________
gru_2 (GRU)                  (None, 500, 256)          393984
_________________________________________________________________
dropout_2 (Dropout)          (None, 500, 256)          0
_________________________________________________________________
gru_3 (GRU)                  (None, 500, 256)          393984
_________________________________________________________________
dropout_3 (Dropout)          (None, 500, 256)          0
_________________________________________________________________
gru_4 (GRU)                  (None, 256)               393984
_________________________________________________________________
dense_1 (Dense)              (None, 20)                5140
=================================================================
Total params: 10,383,368
Trainable params: 10,383,368
Non-trainable params: 0
_________________________________________________________________
```

Output:

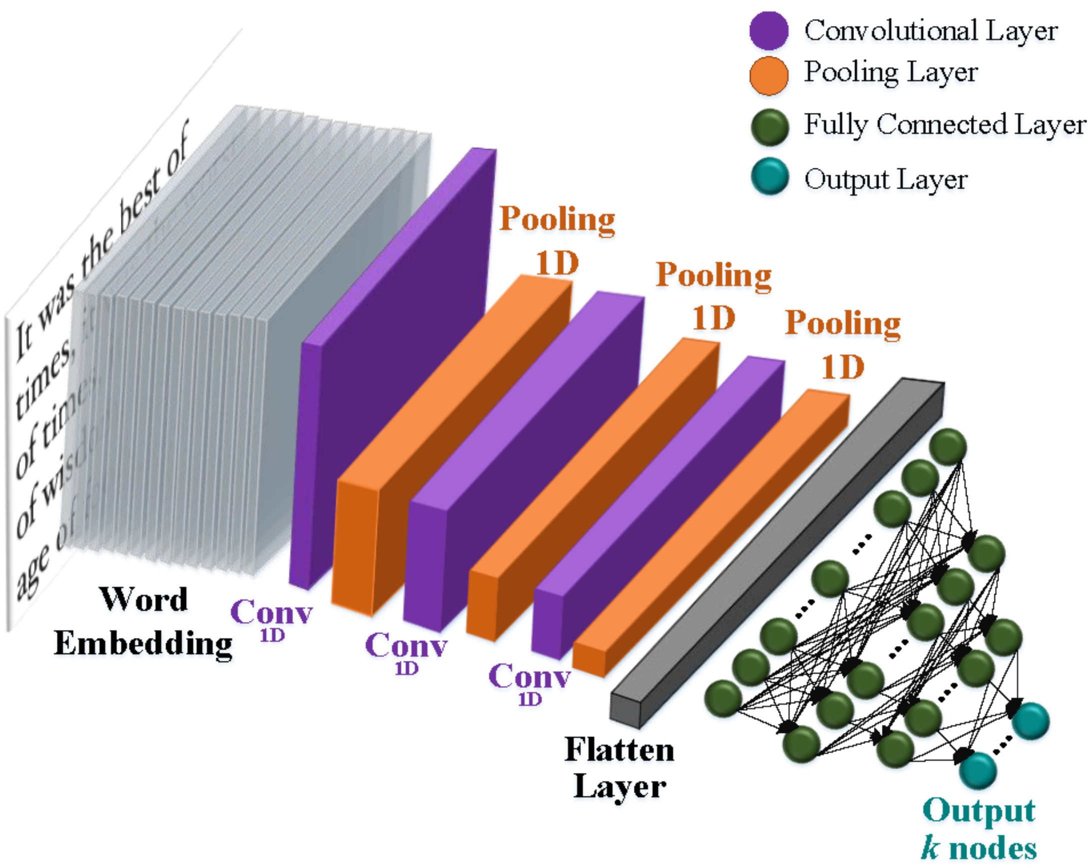
```
Train on 11314 samples, validate on 7532 samples
Epoch 1/20
 - 268s - loss: 2.5347 - acc: 0.1792 - val_loss: 2.2857 - val_acc: 0.2460
Epoch 2/20
 - 271s - loss: 1.6751 - acc: 0.3999 - val_loss: 1.4972 - val_acc: 0.4660
Epoch 3/20
 - 270s - loss: 1.0945 - acc: 0.6072 - val_loss: 1.3232 - val_acc: 0.5483
Epoch 4/20
 - 269s - loss: 0.7761 - acc: 0.7312 - val_loss: 1.1009 - val_acc: 0.6452
Epoch 5/20
 - 269s - loss: 0.5513 - acc: 0.8112 - val_loss: 1.0395 - val_acc: 0.6832
Epoch 6/20
 - 269s - loss: 0.3765 - acc: 0.8754 - val_loss: 0.9977 - val_acc: 0.7086
Epoch 7/20
 - 270s - loss: 0.2481 - acc: 0.9202 - val_loss: 1.0485 - val_acc: 0.7270
Epoch 8/20
 - 269s - loss: 0.1717 - acc: 0.9463 - val_loss: 1.0269 - val_acc: 0.7394
Epoch 9/20
 - 269s - loss: 0.1130 - acc: 0.9644 - val_loss: 1.1498 - val_acc: 0.7369
Epoch 10/20
 - 269s - loss: 0.0640 - acc: 0.9808 - val_loss: 1.1442 - val_acc: 0.7508
Epoch 11/20
 - 269s - loss: 0.0567 - acc: 0.9828 - val_loss: 1.2318 - val_acc: 0.7414
Epoch 12/20
 - 268s - loss: 0.0472 - acc: 0.9858 - val_loss: 1.2204 - val_acc: 0.7496
Epoch 13/20
 - 269s - loss: 0.0319 - acc: 0.9910 - val_loss: 1.1895 - val_acc: 0.7657
Epoch 14/20
 - 268s - loss: 0.0466 - acc: 0.9853 - val_loss: 1.2821 - val_acc: 0.7517
Epoch 15/20
 - 271s - loss: 0.0269 - acc: 0.9917 - val_loss: 1.2869 - val_acc: 0.7557
Epoch 16/20
 - 271s - loss: 0.0187 - acc: 0.9950 - val_loss: 1.3037 - val_acc: 0.7598
Epoch 17/20
 - 268s - loss: 0.0157 - acc: 0.9959 - val_loss: 1.2974 - val_acc: 0.7638
Epoch 18/20
 - 270s - loss: 0.0121 - acc: 0.9966 - val_loss: 1.3526 - val_acc: 0.7602
Epoch 19/20
 - 269s - loss: 0.0262 - acc: 0.9926 - val_loss: 1.4182 - val_acc: 0.7517
Epoch 20/20
 - 269s - loss: 0.0249 - acc: 0.9918 - val_loss: 1.3453 - val_acc: 0.7638


               precision    recall  f1-score   support

           0       0.71      0.71      0.71       319
           1       0.72      0.68      0.70       389
           2       0.76      0.62      0.69       394
           3       0.67      0.58      0.62       392
           4       0.68      0.67      0.68       385
           5       0.75      0.73      0.74       395
           6       0.82      0.74      0.78       390
           7       0.83      0.83      0.83       396
           8       0.81      0.90      0.86       398
           9       0.92      0.90      0.91       397
          10       0.91      0.94      0.93       399
```

```
          11       0.87      0.76      0.81       396
          12       0.57      0.70      0.63       393
          13       0.81      0.85      0.83       396
          14       0.74      0.93      0.82       394
          15       0.82      0.83      0.83       398
          16       0.74      0.78      0.76       364
          17       0.96      0.83      0.89       376
          18       0.64      0.60      0.62       310
          19       0.48      0.56      0.52       251

avg / total        0.77      0.76      0.76      7532
```

Convolutional Neural Networks (CNN)

Another deep learning architecture that is employed for hierarchical document classification is Convolutional Neural Networks (CNN) . Although originally built for image processing with architecture similar to the visual cortex, CNNs have also been effectively used for text classification. In a basic CNN for image processing, an image tensor is convolved with a set of kernels of size *d by d*. These convolution layers are called feature maps and can be stacked to provide multiple filters on the input. To reduce the computational complexity, CNNs use pooling which reduces the size of the output from one layer to the next in the network. Different pooling techniques are used to reduce outputs while preserving important features.

The most common pooling method is max pooling where the maximum element is selected from the pooling window. In order to feed the pooled output from stacked featured maps to the next layer, the maps are flattened into one column. The final layers in a CNN are typically fully connected dense layers. In general, during the back-propagation step of a convolutional neural network not only the weights are adjusted but also the feature detector filters. A potential problem of CNN used for text is the number of 'channels', *Sigma* (size of the feature space). This might be very large (e.g. 50K), for text but for images this is less of a problem (e.g. only 3 channels of RGB). This means the dimensionality of the CNN for text is very high.



import packages:

```
from keras.layers import Dropout, Dense,Input,Embedding,Flatten, MaxPooling1D, Conv1D
from keras.models import Sequential,Model
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn import metrics
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from sklearn.datasets import fetch_20newsgroups
from keras.layers.merge import Concatenate
```

convert text to word embedding (Using GloVe):

```
def loadData_Tokenizer(X_train, X_test,MAX_NB_WORDS=75000,MAX_SEQUENCE_LENGTH=500):
    np.random.seed(7)
    text = np.concatenate((X_train, X_test), axis=0)
    text = np.array(text)
    tokenizer = Tokenizer(num_words=MAX_NB_WORDS)
    tokenizer.fit_on_texts(text)
    sequences = tokenizer.texts_to_sequences(text)
    word_index = tokenizer.word_index
    text = pad_sequences(sequences, maxlen=MAX_SEQUENCE_LENGTH)
    print('Found %s unique tokens.' % len(word_index))
    indices = np.arange(text.shape[0])
    # np.random.shuffle(indices)
    text = text[indices]
    print(text.shape)
    X_train = text[0:len(X_train), ]
    X_test = text[len(X_train):, ]
    embeddings_index = {}
                                                                     f                  =
open("C:\\Users\\kamran\\Documents\\GitHub\\RMDL\\Examples\\Glove\\glove.6B.50d.txt",
encoding="utf8")
    for line in f:
        values = line.split()
        word = values[0]
        try:
            coefs = np.asarray(values[1:], dtype='float32')
        except:
            pass
        embeddings_index[word] = coefs
    f.close()
    print('Total %s word vectors.' % len(embeddings_index))
    return (X_train, X_test, word_index,embeddings_index)
```

Build a CNN Model for Text:

```
def         Build_Model_CNN_Text(word_index,         embeddings_index,         nclasses,
MAX_SEQUENCE_LENGTH=500, EMBEDDING_DIM=50, dropout=0.5):

    """
                       def   buildModel_CNN(word_index,   embeddings_index,   nclasses,
MAX_SEQUENCE_LENGTH=500, EMBEDDING_DIM=50, dropout=0.5):
        word_index in word index ,
        embeddings_index is embeddings index, look at data_helper.py
        nClasses is number of classes,
        MAX_SEQUENCE_LENGTH is maximum lenght of text sequences,
            EMBEDDING_DIM  is  an  int  value  for  dimention  of  word  embedding  look  at
data_helper.py
    """

    model = Sequential()
    embedding_matrix = np.random.random((len(word_index) + 1, EMBEDDING_DIM))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            # words not found in embedding index will be all-zeros.
            if len(embedding_matrix[i]) !=len(embedding_vector):
                                    print("could   not   broadcast   input   array   from
shape",str(len(embedding_matrix[i])),
                                "into shape",str(len(embedding_vector)),"  Please make
sure your"
                                   " EMBEDDING_DIM is equal to embedding_vector file
,GloVe,")
                exit(1)

            embedding_matrix[i] = embedding_vector

    embedding_layer = Embedding(len(word_index) + 1,
                                EMBEDDING_DIM,
                                weights=[embedding_matrix],
                                input_length=MAX_SEQUENCE_LENGTH,
                                trainable=True)

    # applying a more complex convolutional approach
    convs = []
    filter_sizes = []
    layer = 5
    print("Filter  ",layer)
    for fl in range(0,layer):
        filter_sizes.append((fl+2))

    node = 128
    sequence_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')
    embedded_sequences = embedding_layer(sequence_input)

    for fsz in filter_sizes:
        l_conv = Conv1D(node, kernel_size=fsz, activation='relu')(embedded_sequences)
        l_pool = MaxPooling1D(5)(l_conv)
        #l_pool = Dropout(0.25)(l_pool)
        convs.append(l_pool)

    l_merge = Concatenate(axis=1)(convs)
```

```
    l_cov1 = Conv1D(node, 5, activation='relu')(l_merge)
    l_cov1 = Dropout(dropout)(l_cov1)
    l_pool1 = MaxPooling1D(5)(l_cov1)
    l_cov2 = Conv1D(node, 5, activation='relu')(l_pool1)
    l_cov2 = Dropout(dropout)(l_cov2)
    l_pool2 = MaxPooling1D(30)(l_cov2)
    l_flat = Flatten()(l_pool2)
    l_dense = Dense(1024, activation='relu')(l_flat)
    l_dense = Dropout(dropout)(l_dense)
    l_dense = Dense(512, activation='relu')(l_dense)
    l_dense = Dropout(dropout)(l_dense)
    preds = Dense(nclasses, activation='softmax')(l_dense)
    model = Model(sequence_input, preds)

    model.compile(loss='sparse_categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])



    return model
```

run CNN and see our result:

```
newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train_Glove,X_test_Glove,                word_index,embeddings_index                =
loadData_Tokenizer(X_train,X_test)


model_CNN = Build_Model_CNN_Text(word_index,embeddings_index, 20)


model_CNN.summary()

model_CNN.fit(X_train_Glove, y_train,
                              validation_data=(X_test_Glove, y_test),
                              epochs=15,
                              batch_size=128,
                              verbose=2)

predicted = model_CNN.predict(X_test_Glove)

predicted = np.argmax(predicted, axis=1)


print(metrics.classification_report(y_test, predicted))
```

Model:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 500)	0	
embedding_1 (Embedding)	(None, 500, 50)	8960500	input_1[0][0]
conv1d_1 (Conv1D)	(None, 499, 128)	12928	embedding_1[0][0]
conv1d_2 (Conv1D)	(None, 498, 128)	19328	embedding_1[0][0]
conv1d_3 (Conv1D)	(None, 497, 128)	25728	embedding_1[0][0]
conv1d_4 (Conv1D)	(None, 496, 128)	32128	embedding_1[0][0]
conv1d_5 (Conv1D)	(None, 495, 128)	38528	embedding_1[0][0]
max_pooling1d_1 (MaxPooling1D)	(None, 99, 128)	0	conv1d_1[0][0]
max_pooling1d_2 (MaxPooling1D)	(None, 99, 128)	0	conv1d_2[0][0]
max_pooling1d_3 (MaxPooling1D)	(None, 99, 128)	0	conv1d_3[0][0]
max_pooling1d_4 (MaxPooling1D)	(None, 99, 128)	0	conv1d_4[0][0]
max_pooling1d_5 (MaxPooling1D)	(None, 99, 128)	0	conv1d_5[0][0]
concatenate_1 (Concatenate)	(None, 495, 128)	0	max_pooling1d_1[0][0] max_pooling1d_2[0][0] max_pooling1d_3[0][0] max_pooling1d_4[0][0] max_pooling1d_5[0][0]
conv1d_6 (Conv1D)	(None, 491, 128)	82048	concatenate_1[0][0]
dropout_1 (Dropout)	(None, 491, 128)	0	conv1d_6[0][0]
max_pooling1d_6 (MaxPooling1D)	(None, 98, 128)	0	dropout_1[0][0]
conv1d_7 (Conv1D)	(None, 94, 128)	82048	max_pooling1d_6[0][0]
dropout_2 (Dropout)	(None, 94, 128)	0	conv1d_7[0][0]
max_pooling1d_7 (MaxPooling1D)	(None, 3, 128)	0	dropout_2[0][0]
flatten_1 (Flatten)	(None, 384)	0	max_pooling1d_7[0][0]
dense_1 (Dense)	(None, 1024)	394240	flatten_1[0][0]
dropout_3 (Dropout)	(None, 1024)	0	dense_1[0][0]
dense_2 (Dense)	(None, 512)	524800	dropout_3[0][0]
dropout_4 (Dropout)	(None, 512)	0	dense_2[0][0]
dense_3 (Dense)	(None, 20)	10260	dropout_4[0][0]

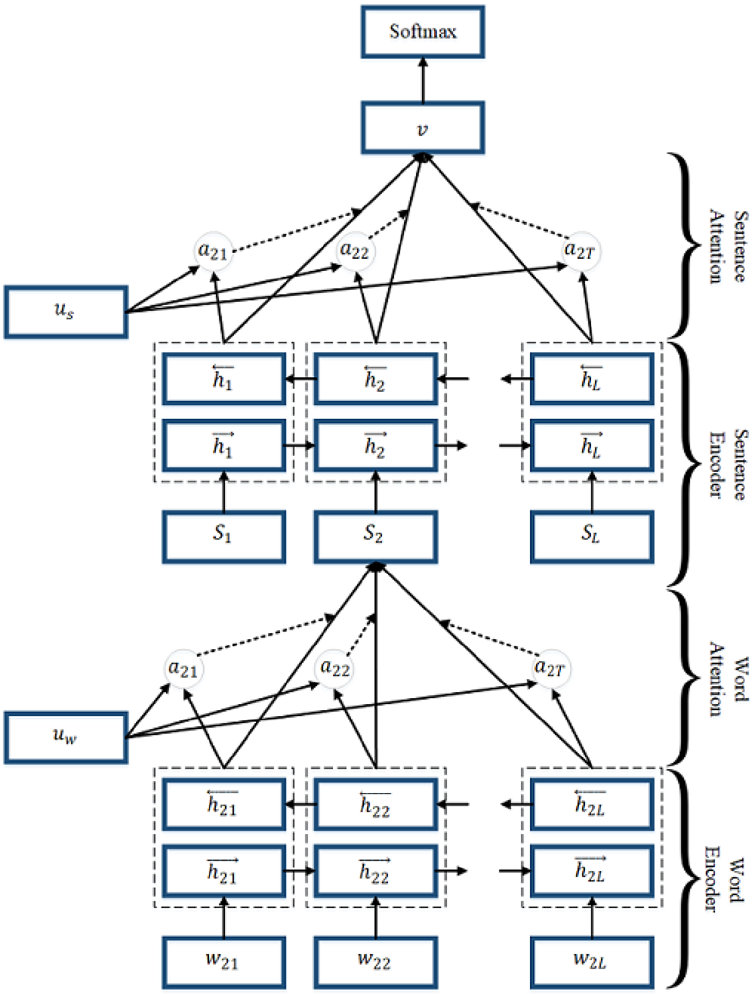
```
=================================================================================
Total params: 10,182,536
Trainable params: 10,182,536
Non-trainable params: 0
_________________________________________________________________________________
```

Output:

```
Train on 11314 samples, validate on 7532 samples
Epoch 1/15
 - 6s - loss: 2.9329 - acc: 0.0783 - val_loss: 2.7628 - val_acc: 0.1403
Epoch 2/15
 - 4s - loss: 2.2534 - acc: 0.2249 - val_loss: 2.1715 - val_acc: 0.4007
Epoch 3/15
 - 4s - loss: 1.5643 - acc: 0.4326 - val_loss: 1.7846 - val_acc: 0.5052
Epoch 4/15
 - 4s - loss: 1.1771 - acc: 0.5662 - val_loss: 1.4949 - val_acc: 0.6131
Epoch 5/15
 - 4s - loss: 0.8880 - acc: 0.6797 - val_loss: 1.3629 - val_acc: 0.6256
Epoch 6/15
 - 4s - loss: 0.6990 - acc: 0.7569 - val_loss: 1.2013 - val_acc: 0.6624
Epoch 7/15
 - 4s - loss: 0.5037 - acc: 0.8200 - val_loss: 1.0674 - val_acc: 0.6807
Epoch 8/15
 - 4s - loss: 0.4050 - acc: 0.8626 - val_loss: 1.0223 - val_acc: 0.6863
Epoch 9/15
 - 4s - loss: 0.2952 - acc: 0.8968 - val_loss: 0.9045 - val_acc: 0.7120
Epoch 10/15
 - 4s - loss: 0.2314 - acc: 0.9217 - val_loss: 0.8574 - val_acc: 0.7326
Epoch 11/15
 - 4s - loss: 0.1778 - acc: 0.9436 - val_loss: 0.8752 - val_acc: 0.7270
Epoch 12/15
 - 4s - loss: 0.1475 - acc: 0.9524 - val_loss: 0.8299 - val_acc: 0.7355
Epoch 13/15
 - 4s - loss: 0.1089 - acc: 0.9657 - val_loss: 0.8034 - val_acc: 0.7491
Epoch 14/15
 - 4s - loss: 0.1047 - acc: 0.9666 - val_loss: 0.8172 - val_acc: 0.7463
Epoch 15/15
 - 4s - loss: 0.0749 - acc: 0.9774 - val_loss: 0.8511 - val_acc: 0.7313


               precision    recall  f1-score   support

          0       0.75      0.61      0.67       319
          1       0.63      0.74      0.68       389
          2       0.74      0.54      0.62       394
          3       0.49      0.76      0.60       392
          4       0.60      0.70      0.64       385
          5       0.79      0.57      0.66       395
          6       0.73      0.76      0.74       390
          7       0.83      0.74      0.78       396
          8       0.86      0.88      0.87       398
          9       0.95      0.78      0.86       397
         10       0.93      0.93      0.93       399
         11       0.92      0.77      0.84       396
         12       0.55      0.72      0.62       393
         13       0.76      0.85      0.80       396
         14       0.86      0.83      0.84       394
         15       0.91      0.73      0.81       398
         16       0.75      0.65      0.70       364
         17       0.95      0.86      0.90       376
         18       0.60      0.49      0.54       310
         19       0.37      0.60      0.46       251
```

```
avg / total       0.76      0.73      0.74      7532
```

Hierarchical Attention Networks



Recurrent Convolutional Neural Networks (RCNN)

Recurrent Convolutional Neural Networks (RCNN) is also used for text classification. The main idea of this technique is capturing contextual information with the recurrent structure and constructing the representation of text using a convolutional neural network. This architecture is a combination of RNN and CNN to use advantages of both technique in a model.

import packages:

```
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from keras.layers import Embedding
from keras.layers import GRU
from keras.layers import Conv1D, MaxPooling1D
from keras.datasets import imdb
from sklearn.datasets import fetch_20newsgroups
import numpy as np
from sklearn import metrics
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
```

Convert text to word embedding (Using GloVe):

```
def loadData_Tokenizer(X_train, X_test,MAX_NB_WORDS=75000,MAX_SEQUENCE_LENGTH=500):
    np.random.seed(7)
    text = np.concatenate((X_train, X_test), axis=0)
    text = np.array(text)
    tokenizer = Tokenizer(num_words=MAX_NB_WORDS)
    tokenizer.fit_on_texts(text)
    sequences = tokenizer.texts_to_sequences(text)
    word_index = tokenizer.word_index
    text = pad_sequences(sequences, maxlen=MAX_SEQUENCE_LENGTH)
    print('Found %s unique tokens.' % len(word_index))
    indices = np.arange(text.shape[0])
    # np.random.shuffle(indices)
    text = text[indices]
    print(text.shape)
    X_train = text[0:len(X_train), ]
    X_test = text[len(X_train):, ]
    embeddings_index = {}
                                                                     f                 =
open("C:\\Users\\kamran\\Documents\\GitHub\\RMDL\\Examples\\Glove\\glove.6B.50d.txt",
encoding="utf8")
    for line in f:
        values = line.split()
        word = values[0]
        try:
            coefs = np.asarray(values[1:], dtype='float32')
        except:
            pass
        embeddings_index[word] = coefs
    f.close()
    print('Total %s word vectors.' % len(embeddings_index))
    return (X_train, X_test, word_index,embeddings_index)
```

```
def         Build_Model_RCNN_Text(word_index,        embeddings_index,        nclasses,
MAX_SEQUENCE_LENGTH=500, EMBEDDING_DIM=50):

    kernel_size = 2
    filters = 256
    pool_size = 2
    gru_node = 256

    embedding_matrix = np.random.random((len(word_index) + 1, EMBEDDING_DIM))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            # words not found in embedding index will be all-zeros.
            if len(embedding_matrix[i]) !=len(embedding_vector):
                                          print("could  not  broadcast  input  array  from
shape",str(len(embedding_matrix[i])),
                                  "into shape",str(len(embedding_vector))," Please make
sure your"
                                     " EMBEDDING_DIM is equal to embedding_vector file
,GloVe,")
                exit(1)

            embedding_matrix[i] = embedding_vector



    model = Sequential()
    model.add(Embedding(len(word_index) + 1,
                                EMBEDDING_DIM,
                                weights=[embedding_matrix],
                                input_length=MAX_SEQUENCE_LENGTH,
                                trainable=True))
    model.add(Dropout(0.25))
    model.add(Conv1D(filters, kernel_size, activation='relu'))
    model.add(MaxPooling1D(pool_size=pool_size))
    model.add(Conv1D(filters, kernel_size, activation='relu'))
    model.add(MaxPooling1D(pool_size=pool_size))
    model.add(Conv1D(filters, kernel_size, activation='relu'))
    model.add(MaxPooling1D(pool_size=pool_size))
    model.add(Conv1D(filters, kernel_size, activation='relu'))
    model.add(MaxPooling1D(pool_size=pool_size))
    model.add(LSTM(gru_node, return_sequences=True, recurrent_dropout=0.2))
    model.add(LSTM(gru_node, return_sequences=True, recurrent_dropout=0.2))
    model.add(LSTM(gru_node, return_sequences=True, recurrent_dropout=0.2))
    model.add(LSTM(gru_node, recurrent_dropout=0.2))
    model.add(Dense(1024,activation='relu'))
    model.add(Dense(nclasses))
    model.add(Activation('softmax'))

    model.compile(loss='sparse_categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

    return model
```

```
newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')
X_train = newsgroups_train.data
X_test = newsgroups_test.data
y_train = newsgroups_train.target
y_test = newsgroups_test.target

X_train_Glove,X_test_Glove,                word_index,embeddings_index                =
loadData_Tokenizer(X_train,X_test)
```

Run RCNN :

```
model_RCNN = Build_Model_CNN_Text(word_index,embeddings_index, 20)



model_RCNN.summary()

model_RCNN.fit(X_train_Glove, y_train,
                              validation_data=(X_test_Glove, y_test),
                              epochs=15,
                              batch_size=128,
                              verbose=2)

predicted = model_RCNN.predict(X_test_Glove)

predicted = np.argmax(predicted, axis=1)
print(metrics.classification_report(y_test, predicted))
```

summary of the model:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 500, 50)           8960500
_________________________________________________________________
dropout_1 (Dropout)          (None, 500, 50)           0
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 499, 256)          25856
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 249, 256)          0
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 248, 256)          131328
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 124, 256)          0
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 123, 256)          131328
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 61, 256)           0
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 60, 256)           131328
_________________________________________________________________
max_pooling1d_4 (MaxPooling1 (None, 30, 256)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 30, 256)           525312
_________________________________________________________________
lstm_2 (LSTM)                (None, 30, 256)           525312
_________________________________________________________________
lstm_3 (LSTM)                (None, 30, 256)           525312
_________________________________________________________________
lstm_4 (LSTM)                (None, 256)               525312
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              263168
_________________________________________________________________
dense_2 (Dense)              (None, 20)                20500
_________________________________________________________________
activation_1 (Activation)    (None, 20)                0
=================================================================
Total params: 11,765,256
Trainable params: 11,765,256
Non-trainable params: 0
_________________________________________________________________
```

Output:

```
Train on 11314 samples, validate on 7532 samples
Epoch 1/15
 - 28s - loss: 2.6624 - acc: 0.1081 - val_loss: 2.3012 - val_acc: 0.1753
Epoch 2/15
 - 22s - loss: 2.1142 - acc: 0.2224 - val_loss: 1.9168 - val_acc: 0.2669
Epoch 3/15
 - 22s - loss: 1.7465 - acc: 0.3290 - val_loss: 1.8257 - val_acc: 0.3412
Epoch 4/15
 - 22s - loss: 1.4730 - acc: 0.4356 - val_loss: 1.5433 - val_acc: 0.4436
Epoch 5/15
 - 22s - loss: 1.1800 - acc: 0.5556 - val_loss: 1.2973 - val_acc: 0.5467
Epoch 6/15
 - 22s - loss: 0.9910 - acc: 0.6281 - val_loss: 1.2530 - val_acc: 0.5797
Epoch 7/15
 - 22s - loss: 0.8581 - acc: 0.6854 - val_loss: 1.1522 - val_acc: 0.6281
Epoch 8/15
 - 22s - loss: 0.7058 - acc: 0.7428 - val_loss: 1.2385 - val_acc: 0.6033
Epoch 9/15
 - 22s - loss: 0.6792 - acc: 0.7515 - val_loss: 1.0200 - val_acc: 0.6775
Epoch 10/15
 - 22s - loss: 0.5782 - acc: 0.7948 - val_loss: 1.0961 - val_acc: 0.6577
Epoch 11/15
 - 23s - loss: 0.4674 - acc: 0.8341 - val_loss: 1.0866 - val_acc: 0.6924
Epoch 12/15
 - 23s - loss: 0.4284 - acc: 0.8512 - val_loss: 0.9880 - val_acc: 0.7096
Epoch 13/15
 - 22s - loss: 0.3883 - acc: 0.8670 - val_loss: 1.0190 - val_acc: 0.7151
Epoch 14/15
 - 22s - loss: 0.3334 - acc: 0.8874 - val_loss: 1.0025 - val_acc: 0.7232
Epoch 15/15
 - 22s - loss: 0.2857 - acc: 0.9038 - val_loss: 1.0123 - val_acc: 0.7331


             precision    recall  f1-score   support

          0       0.64      0.73      0.68       319
          1       0.45      0.83      0.58       389
          2       0.81      0.64      0.71       394
          3       0.64      0.57      0.61       392
          4       0.55      0.78      0.64       385
          5       0.77      0.52      0.62       395
          6       0.84      0.77      0.80       390
          7       0.87      0.79      0.83       396
          8       0.85      0.90      0.87       398
          9       0.98      0.84      0.90       397
         10       0.93      0.96      0.95       399
         11       0.92      0.79      0.85       396
         12       0.59      0.53      0.56       393
         13       0.82      0.82      0.82       396
         14       0.84      0.84      0.84       394
         15       0.83      0.89      0.86       398
         16       0.68      0.86      0.76       364
         17       0.97      0.86      0.91       376
         18       0.66      0.50      0.57       310
         19       0.53      0.31      0.40       251
```

```
avg / total       0.77      0.75      0.75      7532
```

Random Multimodel Deep Learning (RMDL)

Referenced paper : RMDL: Random Multimodel Deep Learning for Classification

A new ensemble, deep learning approach for classification. Deep learning models have achieved state-of-the-art results across many domains. RMDL solves the problem of finding the best deep learning structure and architecture while simultaneously improving robustness and accuracy through ensembles of different deep learning architectures. RDMLs can accept a variety of data as input including text, video, images, and symbols.

RMDL

Random Multimodel Deep Learning (RDML) architecture for classification. RMDL includes 3 Random models, oneDNN classifier at left, one Deep CNN classifier at middle, and one Deep RNN classifier at right (each unit could be LSTMor GRU).

Installation

There are pip and git for RMDL installation:

Using pip

```
pip install RMDL
```

Using git

```
git clone --recursive https://github.com/kk7nc/RMDL.git
```

The primary requirements for this package are Python 3 with Tensorflow. The requirements.txt file contains a listing of the required Python packages; to install all requirements, run the following:

```
pip -r install requirements.txt
```

Or

```
pip3  install -r requirements.txt
```

Or:

```
conda install --file requirements.txt
```

Documentation:

The exponential growth in the number of complex datasets every year requires more enhancement in machine learning methods to provide robust and accurate data classification. Lately, deep learning approaches are achieving better results compared to previous machine learning algorithms on tasks like image classification, natural language processing, face recognition, and etc. The success of these deep learning algorithms rely on their capacity to model complex and non-linear relationships within the data. However, finding suitable structures for these models has been a challenge for researchers. This paper introduces Random Multimodel Deep Learning (RMDL): a new ensemble, deep learning approach for classification. RMDL aims to solve the problem of finding the best deep learning architecture while simultaneously improving the robustness and accuracy through ensembles of multiple deep learning architectures. In short, RMDL trains multiple models of Deep Neural Network (DNN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) in parallel and combines their results to produce better result of any of those models individually. To create these models, each deep learning model has been constructed in a random fashion regarding the number of layers and nodes in their neural network structure. The resulting RDML model can be used in various domains such as text, video, images, and symbolic. In this Project, we describe RMDL model in depth and show the results for image and text classification as well as face recognition. For image classification, we compared our model with some of the available baselines using MNIST and CIFAR-10 datasets. Similarly, we used four datasets namely, WOS, Reuters, IMDB, and 20newsgroup and compared our results with available baselines. Web of Science (WOS) has been collected by authors and consists of three sets~(small, medium and large set). Lastly, we used ORL dataset to compare the performance of our approach with other face recognition methods. These test results show that RDML model consistently outperform standard methods over a broad range of data types and classification problems.

Hierarchical Deep Learning for Text (HDLTex)

Refrenced paper : HDLTex: Hierarchical Deep Learning for Text Classification

HDLTex

Documentation:

Increasingly large document collections require improved information processing methods for searching, retrieving, and organizing text documents. Central to these information processing methods is document classification, which has become an important task supervised learning aims to solve. Recently, the performance of traditional supervised classifiers has degraded as the number of documents has increased. This exponential growth of document volume has also increated the number of categories. This paper approaches this problem differently from current document classification methods that view the problem as multi-class classification. Instead we perform hierarchical classification using an approach we call Hierarchical Deep Learning for Text classification (HDLTex). HDLTex employs stacks of deep learning architectures to provide hierarchical understanding of the documents.

Comparison Text Classification Algorithms

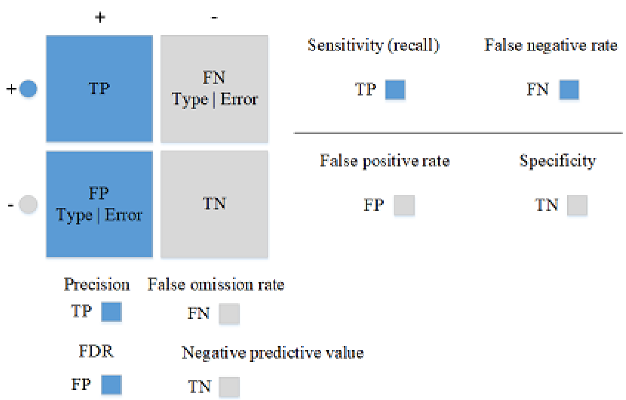
Model	Advantages	Disadvantages

Rocchio Algorithm	• Easy to implement • Computationally is very cheap • Relevance feedback mechanism (benefits to ranking documents as not relevant)	• The user can only retrieve a few relevant documents • Rocchio often misclassifies the type for multimodal class • This techniques is not very robust • linear combination in this algorithm is not good for multi-class datasets
Boosting and Bagging	• Improves the stability and accuracy (takes the advantage of ensemble learning where in multiple weak learner outperform a single strong learner.) • Reducing variance which helps to avoid overfitting problems.	• Computational complexity • loss of interpretability (if the number of models is hight, understanding the model is very difficult) • Requires careful tuning of different hyper-parameters.
Logistic Regression	• Easy to implement • does not require too many computational resources • it does not require input features to be scaled (pre-processing) • It does not require any tuning	• it cannot solve non-linear problems • prediction requires that each data point be independent • attempting to predict outcomes based on a set of independent variables
Naive Bayes Classifier	• It works very well with text data • Easy to implement • Fast in comparing to other algorithms	• A strong assumption about the shape of the data distribution • limited by data scarcity for which any possible value in feature space, a likelihood value must be estimated by a frequentist
K-Nearest Neighbor	• Effective for text datasets • non-parametric • More local characteristics of text or document are considered • Naturally handles multi-class datasets	• computational of this model is very expensive • diffcult to find optimal value of k • Constraint for large search problem to find nearest neighbors • Finding a meaningful distance function is difficult for text datasets
Support Vector Machine (SVM)	• SVM can model non-linear decision boundaries • Performs similarly to logistic regression when linear separation • Robust against overfitting problems~(especially for text dataset due to high-dimensional space)	• lack of transparency in results caused by a high number of dimensions (especially for text data). • Choosing an efficient kernel function is difficult (Susceptible to overfitting/training issues depending on kernel) • Memory complexity
Decision Tree	• Can easily handle qualitative (categorical) features • Works well with decision boundaries parellel to the feature axis • Decision tree is a very fast algorithm for both learning and prediction	• Issues with diagonal decision boundaries • Can be easily overfit • extremely sensitive to small perturbations in the data • Problems with out-of-sample prediction
Conditional Random Field (CRF)	• Its feature design is flexible • Since CRF computes the conditional probability of global optimal output nodes, it overcomes the drawbacks of label bias • Combining the advantages of classification and graphical modeling which combining the ability to compactly model multivariate data	• High computational complexity of the training step • this algorithm does not perform with unknown words • Problem about online learning (It makes it very difficult to re-train the model when newer data becomes available.)

Random Forest	• **Ensembles of decision trees are very fast to train in comparison to other techniques** • **Reduced variance (relative to regular trees)** • **Not require preparation and pre-processing of the input data**	• **Quite slow to create predictions once trained** • **more trees in forest increases time complexity in the prediction step** • **Not as easy to visually interpret** • **Overfitting can easily occur** • **Need to choose the number of trees at forest**
Deep Learning	• **Flexible with features design (Reduces the need for feature engineering, one of the most time-consuming parts of machine learning practice.)** • **Architecture that can be adapted to new problems** • **Can deal with complex input-output mappings** • **Can easily handle online learning (It makes it very easy to re-train the model when newer data becomes available.)** • **Parallel processing capability (It can perform more than one job at the same time)**	• **Requires a large amount of data (if you only have small sample text data, deep learning is unlikely to outperform other approaches.** • **Is extremely computationally expensive to train.** • **Model Interpretability is most important problem of deep learning~(Deep learning in most of the time is black-box)** • **Finding an efficient architecture and structure is still the main challenge of this technique**

Evaluation

F1 Score



Matthew correlation coefficient (MCC)

Compute the Matthews correlation coefficient (MCC)

The Matthews correlation coefficient is used in machine learning as a measure of the quality of binary (two-class) classification problems. It takes into account of true and false positives and negatives and is generally regarded as a balanced measure which can be used even if the classes are of very different sizes. The MCC is in essence a correlation coefficient value between -1 and +1. A coefficient of +1 represents a perfect prediction, 0 an average random prediction and -1 an inverse prediction. The statistic is also known as the phi coefficient.

```
from sklearn.metrics import matthews_corrcoef
y_true = [+1, +1, +1, -1]
y_pred = [+1, -1, +1, +1]
matthews_corrcoef(y_true, y_pred)
```

Receiver operating characteristics (ROC)

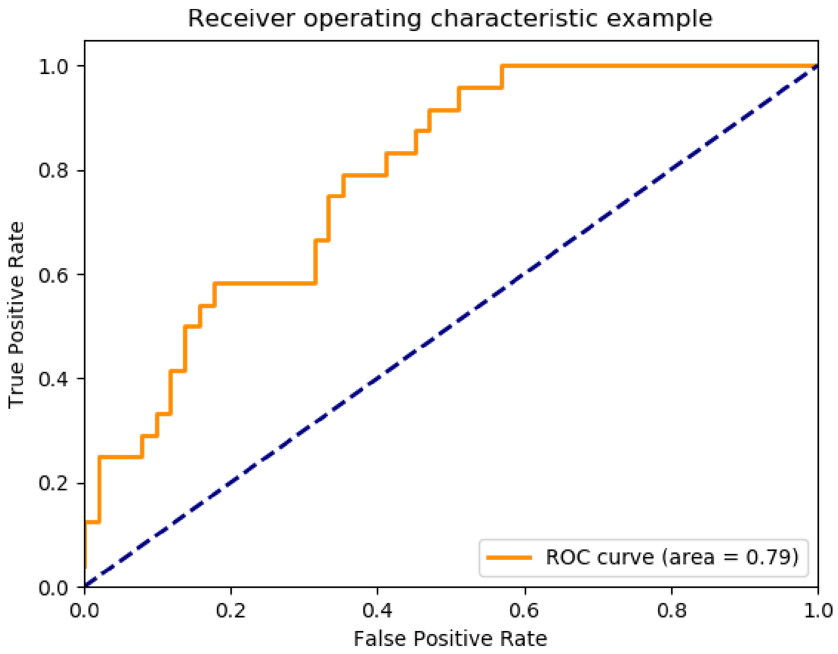
ROC curves are typically used in binary classification to study the output of a classifier. In order to extend ROC curve and ROC area to multi-class or multi-label classification, it is necessary to binarize the output. One ROC curve can be drawn per label, but one can also draw a ROC curve by considering each element of the label indicator matrix as a binary prediction (micro-averaging).

Another evaluation measure for multi-class classification is macro-averaging, which gives equal weight to the classification of each label. [sources]

```
import numpy as np
import matplotlib.pyplot as plt
from itertools import cycle

from sklearn import svm, datasets
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy import interp

# Import some data to play with
iris = datasets.load_iris()
X = iris.data
y = iris.target

# Binarize the output
y = label_binarize(y, classes=[0, 1, 2])
n_classes = y.shape[1]

# Add noisy features to make the problem harder
random_state = np.random.RandomState(0)
n_samples, n_features = X.shape
X = np.c_[X, random_state.randn(n_samples, 200 * n_features)]

# shuffle and split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.5,
                                                    random_state=0)

# Learn to predict each class against the other
classifier = OneVsRestClassifier(svm.SVC(kernel='linear', probability=True,
                                 random_state=random_state))
y_score = classifier.fit(X_train, y_train).decision_function(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```

Plot of a ROC curve for a specific class

```
plt.figure()
lw = 2
plt.plot(fpr[2], tpr[2], color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc[2])
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



Area Under Curve (AUC)

Area under ROC curve (AUC) is a summary metric that measures the entire area underneath the ROC curve. AUC holds helpful properties, such as increased sensitivity in the analysis of variance (ANOVA) tests, independence of decision threshold, invariance to a priori class probability and the indication of how well negative and positive classes are regarding decision index.

```
import numpy as np
from sklearn import metrics
fpr, tpr, thresholds = metrics.roc_curve(y, pred, pos_label=2)
metrics.auc(fpr, tpr)
```

Text and Document Datasets

IMDB

- IMDB Dataset

Dataset of 25,000 movies reviews from IMDB, labeled by sentiment (positive/negative). Reviews have been preprocessed, and each review is encoded as a sequence of word indexes (integers). For convenience, words are indexed by overall frequency in the dataset, so that for instance the integer "3" encodes the 3rd most frequent word in the data. This allows for quick filtering operations, such as "only consider the top 10,000 most common words, but eliminate the top 20 most common words".

As a convention, "0" does not stand for a specific word, but instead is used to encode any unknown word.

```
from keras.datasets import imdb

(x_train, y_train), (x_test, y_test) = imdb.load_data(path="imdb.npz",
                                                      num_words=None,
                                                      skip_top=0,
                                                      maxlen=None,
                                                      seed=113,
                                                      start_char=1,
                                                      oov_char=2,
                                                      index_from=3)
```

Reuters-21578

- Reters-21578 Dataset

Dataset of 11,228 newswires from Reuters, labeled over 46 topics. As with the IMDB dataset, each wire is encoded as a sequence of word indexes (same conventions).

```
from keras.datasets import reuters

(x_train, y_train), (x_test, y_test) = reuters.load_data(path="reuters.npz",
                                                         num_words=None,
                                                         skip_top=0,
                                                         maxlen=None,
                                                         test_split=0.2,
                                                         seed=113,
                                                         start_char=1,
                                                         oov_char=2,
                                                         index_from=3)
```

20Newsgroups

- 20Newsgroups Dataset

The 20 newsgroups dataset comprises around 18000 newsgroups posts on 20 topics split in two subsets: one for training (or development) and the other one for testing (or for performance evaluation). The split between the train and test set is based upon messages posted before and after a specific date.

This module contains two loaders. The first one, sklearn.datasets.fetch_20newsgroups, returns a list of the raw texts that can be fed to text feature extractors, such as sklearn.feature_extraction.text.CountVectorizer with custom parameters so as to extract feature vectors. The second one, sklearn.datasets.fetch_20newsgroups_vectorized, returns ready-to-use features, i.e., it is not necessary to use a feature extractor.

```
from sklearn.datasets import fetch_20newsgroups
newsgroups_train = fetch_20newsgroups(subset='train')

from pprint import pprint
pprint(list(newsgroups_train.target_names))

['alt.atheism',
 'comp.graphics',
 'comp.os.ms-windows.misc',
 'comp.sys.ibm.pc.hardware',
 'comp.sys.mac.hardware',
 'comp.windows.x',
 'misc.forsale',
 'rec.autos',
 'rec.motorcycles',
 'rec.sport.baseball',
 'rec.sport.hockey',
 'sci.crypt',
 'sci.electronics',
 'sci.med',
 'sci.space',
 'soc.religion.christian',
 'talk.politics.guns',
 'talk.politics.mideast',
 'talk.politics.misc',
 'talk.religion.misc']
```

Web of Science Dataset

Description of Dataset:

Here are three datasets which include WOS-11967, WOS-46985, and WOS-5736 Each folder contains:

- X.txt
- Y.txt
- YL1.txt
- YL2.txt

X is input data that include text sequences Y is target value YL1 is the target value of level one (parent label) YL2 is the target value of level one (child label)

Meta-data: This folder contains on data file as the following attribute: Y1 Y2 Y Domain area keywords Abstract

The abstract is input data that include text sequences of 46,985 published paper Y is target value YL1 is the target value of level one (parent label) YL2 is the target value of level one (child label) Domain is the major domain which includes 7 labels: {Computer Science, Electrical Engineering, Psychology, Mechanical Engineering, Civil Engineering, Medical Science, biochemistry} area is subdomain or area of the paper, such as CS-> computer graphics which contain 134 labels. keywords: is authors keyword of the papers

- Web of Science Dataset WOS-11967

This dataset contains 11,967 documents with 35 categories which include 7 parents categories.

- Web of Science Dataset WOS-46985

This dataset contains 46,985 documents with 134 categories which include 7 parents categories.

- Web of Science Dataset WOS-5736

This dataset contains 5,736 documents with 11 categories which include 3 parents categories.

Referenced paper: HDLTex: Hierarchical Deep Learning for Text Classification