

In [0]:

```
## Reading Economics Papers
```

In [1]:

```
## Read the economics papers from 2016 to 2018 and store it in a file
import urllib
url = 'http://export.arxiv.org/oai2?verb=ListRecords&set=econ&from=2016-01-01&until=2018-11-31&metadataPrefi
x=arXiv'
data = urllib.request.urlopen(url).read()

ee = open('eco1', 'wb')
ee.write(data)
```

Out[1]:

1372062

In [0]:

```
## Extract the title and abstract from papers - Read from finance1 to finance2

!xml_grep 'title|abstract' eco1 > eco2.txt
```

In [0]:

```
## Remove Junk lines , here we remove first 3 lines and last 3 lines which are not necessary
!cat eco2.txt | tail -n +4 | head -n -3 > eco3.txt
```

In [5]:

```
## Reading packages for Text classification
from sklearn import model_selection, preprocessing, linear_model, naive_bayes, metrics, svm
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn import decomposition, ensemble

import pandas, numpy, string
from keras.preprocessing import text, sequence
from keras import layers, models, optimizers
from nltk import word_tokenize
from nltk.corpus import stopwords
import sklearn
#import sklearn_crfsuite
#from sklearn_crfsuite import scorers
#from sklearn_crfsuite import metrics
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.decomposition import TruncatedSVD
from sklearn.metrics import accuracy_score
from sklearn import metrics
```

Using TensorFlow backend.

In [6]:

```
## Stopwords import and removal
import nltk
from nltk.corpus import stopwords

nltk.download('stopwords')
stopwords = set(stopwords.words('english'))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
```

In [7]:

```
# load the dataset # dataset contains combined labels and text from all training papers
data = open('labeled_sentences (1).txt').read()[:-2]
labels, texts = [], []
for i, line in enumerate(data.split("\n")):
    content = line.split()
    #print(content)
    labels.append(content[0])
    filtered_sentence = [w.lower() for w in content[1:] if not w in stopwords]
    texts.append(filtered_sentence)

# create a dataframe using texts and labels
trainDF = pandas.DataFrame()
trainDF['text'] = texts
trainDF['label'] = labels
print(trainDF['label'].unique())
trainDF.head(2)

['MISC' 'AIMX' 'OWNX' 'CONT' 'BASE']
```

Out[7]:

	text	label
0	[minimum, description, length, principle, onli...	MISC
1	[underlying, model, class, discrete,, total, e...	MISC

In [0]:

```
## Used the obtained dataset for training
train_x, valid1_x, train_y, valid1_y = model_selection.train_test_split(trainDF['text'], trainDF['label'], te
st_size=0)
```

In [9]:

```
## Convert from list to string
tempp = []

for item in train_x:
    tempp.append(" ".join(item))
#print(len(train_x))

#tempp1=[]
#for item1 in valid_x:
#    tempp1.append(" ".join(item1))

#print(len(tempp1))

temp=[]
temp_len=0
for item2 in texts:
    temp.append(" ".join(item2))
    temp_len = temp_len+len(texts)
print(len(temp))
print(temp_len)
print(type(temp))
```

```
18627
346965129
<class 'list'>
```

In [0]:

```
# create a count vectorizer object
count_vect = CountVectorizer(analyzer='word', token_pattern=r'\w{1,}')
count_vect.fit(temp)

# transform the training and validation data using count vectorizer object
xtrain_count = count_vect.transform(tempp)
```

In [0]:

```
## Create a classifier
import csv
trainDF2 = pandas.DataFrame()

def train_model(classifier, feature_vector_train, label, feature_vector_valid, is_neural_net=False):
    # fit the training dataset on the classifier
    #std_clf = make_pipeline(StandardScaler(with_mean=False), TruncatedSVD(100), MultinomialNB())
    #std_clf.fit(feature_vector_train, label)
    classifier.fit(feature_vector_train, label)

    # predict the labels on validation dataset
    #predictions = classifier.predict(feature_vector_valid)
    predictions = classifier.predict(feature_vector_valid)
    return predictions
    #tt = classifier.predict(feature_vector_valid)
    #labels3 = classifier.predict(feature_vector_valid)

    #trainDF2['labels'] = labels3
    #trainDF2['text']= valid_x
    #print(trainDF2)
```

In [12]:

```
## Read title and abstracts and loop through them
import re
global_list = []
title_list = []

test = open("eco3.txt", 'r').read().split("</abstract>")
#print(test[1])
for idx,i in enumerate(test):
    title = re.findall(r"(?<=<title>).*(?<=</title>)",i.replace("\n",""))
    #print(title)
    abstract = re.findall(r"(?<=<abstract>).*",i.replace("\n",""))
    #print(abstract[0].replace("\n",""))
    nlist = re.split(r"(?:(?<=[^i]\.)|\.(?<=[^e]))",abstract[0].replace("'", "").replace('\n', ''))
    #temp_abs = re.sub(r"((?<=[^i]\.)|\.(?<=[^e]))", "\n", abstract[0])
    #print(abstract)
    #temp_str = temp_abs.split("\n")
    #print(temp_str[0])
    #print(nlist[1])
    global_list.append(nlist)
    title_list.append(title)
    #print(global_list)

    if idx > 50:
        #print(global_list)
        break
    #print(abstract[0])
    #nlist = re.split(r"(?:(?<=[^i]\.)|\.(?<=[^e]))", str(abstract))

    #print(nlist[1])

    #tempp1 = []
    '''
    for idx, item1 in enumerate(nlist):

        if idx > 1 :
            break;
            print(item1)
            tempp1.append(" ".join(item1))
            #print(tempp1)

        xvalid_count = count_vect.transform(tempp1)
        for item in nlist:
            print(item)
            valid_x = item
            #accuracy = train_model(naive_bayes.MultinomialNB(), xtrain_count, train_y, xvalid_count)

    '''
    #print(global_list[0])
    #print(global_list[1])
    #print(global_list[2])
    #for idx, item1 in enumerate(global_list) :
    # if idx > 1:
    #     break
    #     print(item1)
    #     #tempp1.append(" ".join(item1))
    #     #xvalid_count = count_vect.transform(tempp1)
    #     #accuracy = train_model(naive_bayes.MultinomialNB(), xtrain_count, train_y, xvalid_count)
```

```
/usr/lib/python3.6/re.py:212: FutureWarning: split() requires a non-empty pattern match.
    return _compile(pattern, flags).split(string, maxsplit)
```

In [13]:

```
## Print triples from data

#print(global_list[1])
for idx, (item, title) in enumerate(zip(global_list, title_list)):

    #print(item)
    valid_x = item
    xvalid_count = count_vect.transform(valid_x)
    accuracy = train_model(linear_model.LogisticRegression(), xtrain_count, train_y, xvalid_count)
    #print("\n\n")
    if idx>1:
        break

    title_id = hash(str(title))
    abstract_id = hash(str(item))
    line1 = "<https://w3id.org/skg/articles/" + str(title_id) + "> <http://xmlns.com/foaf/0.1/name>" + "'" + "
".join(title) + "'" + "."
    line2 = "<https://w3id.org/skg/articles/" + str(title_id) + "> <http://purl.org/dc/terms/abstract> <http:/
/purl.org/dc/terms/abstract/" + str(abstract_id)+ ">"
    line3 = "<https://w3id.org/skg/articles/" + str(abstract_id) + "><http://purl.org/dc/terms/abstract/text>"
+ "'" + " ".join(item) + "'"
    print(line1,line2,line3,sep ="\n")
    for acc,element in zip(accuracy,item):
        print('<http://purl.org/dc/terms/abstract/{> <http://purl.org/dc/terms/abstract/" + str(acc) + ">" + "'" + str(element) + "'" )
```

<<https://w3id.org/skg/articles/8094898672661697709>> <<http://xmlns.com/foaf/0.1/name>>"Quantile and Probability Curves Without Crossing".

<<https://w3id.org/skg/articles/8094898672661697709>> <<http://purl.org/dc/terms/abstract>> <<http://purl.org/dc/terms/abstract/-7751916543779414938>>

<<https://w3id.org/skg/articles/-7751916543779414938>><<http://purl.org/dc/terms/abstract/text>>"

This paper proposes a method to address the longstanding problem of lack of monotonicity in estimation of conditional and structural quantile functions, also known as the quantile crossing problem. The method consists in sorting or monotone rearranging the original estimated non-monotone curve into a monotone rearranged curve. We show that the rearranged curve is closer to the true quantile curve in finite samples than the original curve, establish a functional delta method for rearrangement-related operators, and derive functional limit theory for the entire rearranged curve and its functionals. We also establish validity of the bootstrap for estimating the limit law of the entire rearranged curve and its functionals. Our limit results are generic in that they apply to every estimator of a monotone econometric function, provided that the estimator satisfies a functional central limit theorem and the function satisfies some smoothness conditions. Consequently, our results apply to estimation of other econometric functions with monotonicity restrictions, such as demand, production, distribution, and structural distribution functions. We illustrate the results with an application to estimation of structural quantile functions using data on Vietnam veteran status and earnings."

<<http://purl.org/dc/terms/abstract/OWNX>> " This paper proposes a method to address the longstanding problem of lack of monotonicity in estimation of conditional and structural quantile functions, also known as the quantile crossing problem"

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<<http://purl.org/dc/terms/abstract/MISC>> " Consequently, our results apply to estimation of other econometric functions with monotonicity restrictions, such as demand, production, distribution, and structural distribution functions"

<<http://purl.org/dc/terms/abstract/OWNX>> " We illustrate the results with an application to estimation of structural quantile functions using data on Vietnam veteran status and earnings."

<<https://w3id.org/skg/articles/-8455937720046133964>> <<http://xmlns.com/foaf/0.1/name>>"Improving Estimates of Monotone Functions by Rearrangement".

<<https://w3id.org/skg/articles/-8455937720046133964>> <<http://purl.org/dc/terms/abstract>> <<http://purl.org/dc/terms/abstract/-3755805548760784824>>

<<https://w3id.org/skg/articles/-3755805548760784824>><<http://purl.org/dc/terms/abstract/text>>"

Suppose that a target function is monotonic, namely, weakly increasing, and an original estimate of the target function is available, which is not weakly increasing. Many common estimation methods used in statistics produce such estimates. We show that these estimates can always be improved with no harm using rearrangement techniques: The rearrangement methods, univariate and multivariate, transform the original estimate to a monotonic estimate, and the resulting estimate is closer to the true curve in common metrics than the original estimate. We illustrate the results with a computational example and an empirical example dealing with age-height growth charts."

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