

# 447final

December 4, 2018

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import sys
from html.parser import HTMLParser
from html.entities import name2codepoint
sns.set(color_codes=True)
import warnings
warnings.filterwarnings("ignore")
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
LA = np.linalg

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from collections import defaultdict
from gensim.models.word2vec import Word2Vec
import re
%matplotlib inline

[nltk_data] Downloading package stopwords to
[nltk_data]    /Users/chd415/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!

In [2]: # load training data text
def load_data(filename):
    load_file = pd.read_csv(filename, delimiter=',', header=0,
                             dtype={'name':str, 'lvl1':str, 'lvl2':str, 'lvl3':str, 'description':str, 'price':float, 'type':str})
    load_file.columns = ['id', 'name', 'lvl1', 'lvl2', 'lvl3', 'description', 'price', 'type']
    load_file.duplicated(subset=None, keep='first')
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load_file.set_index('id', inplace = True)
load_file.head()
return load_file
#print(len(train_file))
def load_label(filename):
    load_label = pd.read_csv(filename,delimiter=',', header=0)
    load_label.columns = ['id', 'score']
    load_label.duplicated(subset=None, keep='first')
    load_label.set_index('id', inplace = True)
    return load_label

```

In [3]: '''

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def map_method(column):
    values = []
    indexs = []
    mapping = {}
    index = 0
    for count in range(len(train_file)):
        value = train_file.get_value(count+1,column)
        if value in values and value != np.nan:
            continue
        values.append(value)
        indexs.append(len(values))
    for j in range(len(indexs)):
        mapping[values[j]] = indexs[j]
    mapping[np.nan] = 0.0
    return mapping
#train_file['lvl3'] = train_file['lvl3'].str.lower().replace('[^\w]+', ' ', regex=True)
#mapping_lvl3 = map_method('lvl3')
#print(mapping_lvl3)
'''

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class MultiColumnLabelEncoder:
    def __init__(self,columns = None):
        self.columns = columns # array of column names to encode

    def fit(self,X,y=None):
        return self # not relevant here

    def transform(self,X):
        '''
        Transforms columns of X specified in self.columns using
        LabelEncoder(). If no columns specified, transforms all
        columns in X.
        '''
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:

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        output[col] = LabelEncoder().fit_transform(output[col])
    else:
        for colname,col in output.iteritems():
            output[colname] = LabelEncoder().fit_transform(col)
    return output

def fit_transform(self,X,y=None):
    return self.fit(X,y).transform(X)

In [4]: def text_embedding(column):
    temp_X = column.astype(str)
    stop = set(stopwords.words('english'))
    temp = []
    snow = nltk.stem.SnowballStemmer('english')

    for sentence in temp_X:
        words = [snow.stem(word) for word in sentence.split(' ') if word not in stopwo
        temp.append(sentence)

    count_vect = CountVectorizer(max_features=10000)
    bow_data = count_vect.fit_transform(temp)

    final_tf = temp
    tf_idf = TfidfVectorizer(max_features=10000)
    tf_data = tf_idf.fit_transform(final_tf)
    w2v_data = temp
    splitted = []
    for row in w2v_data:
        splitted.append([word for word in row.split()])    #splitting words

    train_w2v = Word2Vec(splitted,min_count=1,size=50, workers=4)
    avg_data = []
    for row in splitted:
        vec = np.zeros(50, dtype=float)
        count = 0
        for word in row:
            try:
                vec += train_w2v[word]
                count += 1
            except:
                pass
        if (count == 0):
            avg_data.append(vec)
        else:
            avg_data.append(vec/count)
    # avg_data.append(vec)

    return avg_data

```

```

In [ ]: '''
        #test cell
        temp = load_data('train_data.csv')
        temp['description'] = temp['description'].str.lower()
        description_X = temp.description.str.lower().replace('<.*?>', '', regex=True).replace('['
        '''

In [ ]: '''
        #test cell
        def test_embedding(column):
            temp_X = column.astype(str)
            stop = set(stopwords.words('english'))
            temp = []
            snow = nltk.stem.SnowballStemmer('english')

            for sentence in temp_X:
                words = [snow.stem(word) for word in sentence.split(' ') if word not in stopwo
                temp.append(sentence)

            count_vect = CountVectorizer(max_features=5000)
            bow_data = count_vect.fit_transform(temp)

            final_tf = temp
            tf_idf = TfidfVectorizer(ngram_range=(1,2), stop_words = 'english', max_features=500
            tf_data = tf_idf.fit_transform(final_tf)
            w2v_data = temp
            splitted = []
            for row in w2v_data:
                splitted.append([word for word in row.split()])      #splitting words

            train_w2v = Word2Vec(splitted, min_count=5, size=50, workers=4)
            avg_data = []
            for row in splitted:
                vec = np.zeros(50, dtype=float)
                count = 0
                for word in row:
                    try:
                        vec += train_w2v[word]
                        count += 1
                    except:
                        pass
                if (count == 0):
                    avg_data.append(vec)
                else:
                    avg_data.append(vec/count)
            #
            avg_data.append(vec)

            tf_w_data = []

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tf_data = tf_data.toarray()
i = 0
for row in splitted:
    vec = [0 for i in range(50)]

    temp_tfidf = []
    for val in tf_data[i]:
        if val != 0:
            temp_tfidf.append(val)

    count = 0
    tf_idf_sum = 0
    for word in row:
        try:
            count += 1
            tf_idf_sum = tf_idf_sum + temp_tfidf[count-1]
            vec += (temp_tfidf[count-1] * train_w2v[word])
        except:
            pass
    if (tf_idf_sum == 0):
        tf_w_data.append(vec)
    else:
        tf_w_data.append(vec/tf_idf_sum)
#         vec = float(1/tf_idf_sum) * vec
#         tf_w_data.append(vec)
    i = i + 1

    return tf_w_data
'''

```

```

In [ ]: '''
#test cell
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer

temp['description'] = test_embedding(description_X)
temp.description.head()
#tfidf_n = TfidfVectorizer(ngram_range=(1,2),stop_words = 'english')
'''

```

```

In [5]: def clean_data(filename):

    filename['lv11'] = filename['lv11'].str.lower().replace('[^a-zA-Z]+',' ',regex=True)
    filename['lv12'] = filename['lv12'].str.lower().replace('[^\w]+',' ',regex=True)
    filename['lv13'] = filename['lv13'].str.lower().replace('[^\w]+',' ',regex=True)
    filename['description'] = filename['description'].str.lower()
    filename['name'] = filename['name'].str.lower()

```

```

'''

mapping_lvl1 = map_method('lvl1')
mapping_lvl2 = map_method('lvl2')
mapping_lvl3 = map_method('lvl3')

filename['lvl1'] = filename['lvl1'].map(mapping_lvl1)
filename['lvl2'] = filename['lvl2'].map(mapping_lvl2)
filename['lvl3'] = filename['lvl3'].map(mapping_lvl3)

'''

#clean up data for lvl 1&2&3
temp = filename.drop(['price', 'description', 'name', 'type'], axis=1)
outfile = MultiColumnLabelEncoder(columns = ['lvl1', 'lvl2', 'lvl3']).fit_transform(temp)
enc = preprocessing.OneHotEncoder()
enc.fit(outfile)
outfile = enc.transform(outfile).toarray()

#normalize price
maxp = filename.price.max()
valuethred = 1000.
filename['price'] = filename['price'].clip(lower=0., upper=valuethred)
#filename['price'] = filename['price'].clip(lower=0., upper=valuethred).div(valuethred)
#hist = train_file['price'].hist(bins=10)
#maxp
ld = filename.price.as_matrix(columns=None).tolist()
outfile = np.column_stack((outfile, ld))

#clean up type
mapping_type = {'international':1., 'local':2., np.nan:0.}
filename['type'] = filename['type'].map(mapping_type)
le = filename.type.as_matrix(columns=None).tolist()
outfile = np.column_stack((outfile, le))

#clean up text
description_X = filename.description.str.lower().replace('<li>', 'final ', regex=True)
count_description = description_X.str.count('final').fillna(0).tolist()
outfile = np.column_stack((outfile, count_description))

description_X = filename.description.str.lower().replace('final ', '', regex=True)
filename['description'] = text_embedding(description_X)

lg = filename.description.as_matrix(columns=None).tolist()
lg_array = np.vstack( lg )

U, s, Vh = LA.svd(lg_array, full_matrices=False)
assert np.allclose(lg_array, np.dot(U, np.dot(np.diag(s), Vh)))
s_new = s[:8]

```

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U_new = U[:, :8]
new_lg = np.dot(U_new, np.diag(s_new))
lg_min = np.min(new_lg)
lg_out = new_lg - (lg_min-2)*np.ones_like(new_lg.size)
outfile = np.column_stack((outfile,lg_out))

name_X = filename.name.str.lower().replace('<.*?>','',regex=True).replace('[^\w\s]')
filename['name'] = text_embedding(name_X)

lf = filename.name.as_matrix(columns=None).tolist()
lf_array = np.vstack( lf )

Uf, sf, Vhf = LA.svd(lf_array, full_matrices=False)
assert np.allclose(lf_array, np.dot(Uf, np.dot(np.diag(sf), Vhf)))
sf_new = sf[:8]
Uf_new = Uf[:, :8]
new_lf = np.dot(Uf_new, np.diag(sf_new))
lf_min = np.min(new_lf)
lf_out = new_lf - (lf_min-2)*np.ones_like(new_lf.size)
outfile = np.column_stack((outfile,lf_out))

return outfile

```

```

In [ ]: '''
        train_file = pd.read_csv('train_data.csv',delimiter=',', header=0, nrows=10)
        train_file.columns = ['id', 'name', 'lvl1', 'lvl2', 'lvl3', 'description', 'price', 'type']
        description_X = train_file.description.str.lower().replace('<li>','final ',regex=True)
        count_description = description_X.str.count('final')
        description_X = train_file.description.str.lower().replace('final ', '',regex=True)
        print(np.shape(count_description))
        '''

```

```

In [6]: train_file = load_data('train_data.csv')
        test_file = load_data('test_data.csv')
        combined_file = pd.concat([train_file,test_file])
        cleaned_train = clean_data(combined_file)
        train_score = load_label('train_label.csv')
        np.shape(cleaned_train)

```

Out[6]: (36283, 270)

```

In [ ]: '''
        # test cell
        cleaned_train['description'] = temp['description']
        '''

```

```
In [7]: cleaned_train
        #print(mapping_lvl1)
```

```
Out [7]: array([[ 0.          ,  0.          ,  0.          , ..., 10.13324131,
                  11.99554897, 11.35688418],
                [ 0.          ,  1.          ,  0.          , ..., 11.9036486 ,
                  9.82575646, 10.58128699],
                [ 0.          ,  0.          ,  0.          , ..., 11.73378475,
                  11.62101979, 11.51830028],
                ...,
                [ 0.          ,  0.          ,  0.          , ..., 12.33374908,
                  11.35996205, 11.5136934 ],
                [ 0.          ,  0.          ,  0.          , ..., 11.17770531,
                  11.97945511, 11.61931454],
                [ 0.          ,  0.          ,  0.          , ..., 10.76861269,
                  11.21852384, 11.04587675]])
```

```
In [8]: '''
```

```
def rearrange(cleaned_data):
    la = cleaned_data.lvl1.as_matrix(columns=None).tolist()
    lb = cleaned_data.lvl2.as_matrix(columns=None).tolist()
    lc = cleaned_data.lvl3.as_matrix(columns=None).tolist()

    X = la
    X = np.column_stack((X, lb))
    X = np.column_stack((X, lc))

    enc = preprocessing.OneHotEncoder()
    enc.fit(X)
    X = enc.transform(X).toarray()

    ld = cleaned_data.price.as_matrix(columns=None).tolist()
    le = cleaned_data.type.as_matrix(columns=None).tolist()

    X = np.column_stack((X, ld))
    X = np.column_stack((X, le))

    lf = cleaned_data.name.as_matrix(columns=None).tolist()
    lg = cleaned_data.description.as_matrix(columns=None).tolist()
    lg_array = np.vstack( lg )
    lf_array = np.vstack( lf )

    U, s, Vh = LA.svd(lg_array, full_matrices=False)
    assert np.allclose(lg_array, np.dot(U, np.dot(np.diag(s), Vh)))

    # only use U \cdot s
```



```

#     s[8:] = 0.
#     new_lg = np.dot(U, np.dot(np.diag(s), Vh))
#     s_new = s[:5]
#     U_new = U[:, :5]
#     new_lg = np.dot(U_new, np.diag(s_new))
#     lg_min = np.min(new_lg)
#     lg_out = new_lg - (lg_min-2)*np.ones_like(new_lg.size)

Uf, sf, Vhf = LA.svd(lf_array, full_matrices=False)
assert np.allclose(lf_array, np.dot(Uf, np.dot(np.diag(sf), Vhf)))

#     sf[5:] = 0.
#     new_lf = np.dot(Uf, np.dot(np.diag(sf), Vhf))
#     sf_new = sf[:5]
#     Uf_new = Uf[:, :5]
#     new_lf = np.dot(Uf_new, np.diag(sf_new))
#     lf_min = np.min(new_lf)
#     lf_out = new_lf - (lf_min-2)*np.ones_like(new_lf.size)

X = np.column_stack((X, lf_out))
X = np.column_stack((X, lg_out))
X = X.tolist()

return X, lf_min, lg_min
'''

#print(len(X))
X = cleaned_train#rearrange(cleaned_train)
print(np.shape(np.array(X)))
Y = train_score.score.as_matrix(columns=None).tolist()
X[137,253]

```

(36283, 270)

Out[8]: 0.0

```

In [9]: X = cleaned_train[:18141]
        XX = cleaned_train[18141:]
        Y = train_score.score.as_matrix(columns=None).tolist()
        print(np.size(Y))
        print(np.shape(X))
        print(np.shape(XX))

```

18141

(18141, 270)

(18142, 270)

```
In [10]: from sklearn.utils import shuffle
X, Y = shuffle(X, Y)
from sklearn.model_selection import train_test_split
X_train, X_validation, y_train, y_validation = train_test_split(X, Y, test_size=0.20,

from keras.preprocessing import sequence
maxlen = 270
X_train = sequence.pad_sequences(X_train, maxlen=maxlen, dtype='float32')
X_validation = sequence.pad_sequences(X_validation, maxlen=maxlen, dtype='float32')
#X_train = np.any(np.isnan(X_train))
#X_train = np.all(np.isfinite(X_train))
print(X_train[1400].size)
```

Using TensorFlow backend.

270

```
In [11]: import os
import time
from sklearn import metrics
from sklearn import preprocessing
import numpy as np
import pandas as pd
import random
import math
import warnings
warnings.filterwarnings("ignore")

from matplotlib import pyplot as plt

from sklearn import preprocessing
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import SelectPercentile
from sklearn.feature_selection import chi2

from sklearn import linear_model
from sklearn.naive_bayes import MultinomialNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.svm import SVC
```

```

from sklearn.grid_search import GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier

from sklearn.ensemble import BaggingClassifier

from sklearn.model_selection import cross_val_score

In [12]: # Linear Regression Classifier
def linear_regression_classifier(train_x, train_y):
    model = linear_model.LinearRegression()
    model.fit(train_x, train_y)
    return model

# Multinomial Naive Bayes Classifier
def naive_bayes_classifier(train_x, train_y):
    model = MultinomialNB()

    param_grid = {'alpha': [math.pow(10,-i) for i in range(11)]}
    grid_search = GridSearchCV(model, param_grid, n_jobs = 1, verbose=1)
    grid_search.fit(train_x, train_y)
    best_parameters = grid_search.best_estimator_.get_params()

    model = MultinomialNB(alpha = best_parameters['alpha'])
    model.fit(train_x, train_y)
    return model

# KNN Classifier
def knn_classifier(train_x, train_y):
    model = KNeighborsClassifier()

    param_grid = {'n_neighbors': list(range(1,21))}
    grid_search = GridSearchCV(model, param_grid, n_jobs = 1, verbose=1)
    grid_search.fit(train_x, train_y)
    best_parameters = grid_search.best_estimator_.get_params()

    model = KNeighborsClassifier(n_neighbors = best_parameters['n_neighbors'], algorithm='brute')

    bagging = BaggingClassifier(model, max_samples=0.5, max_features=1 )
    bagging.fit(train_x, train_y)
    return bagging

# Logistic Regression Classifier
def logistic_regression_classifier(train_x, train_y):
    model = LogisticRegression(penalty='l2')
    model.fit(train_x, train_y)
    return model

```

*# Random Forest Classifier*

```
def random_forest_classifier(train_x, train_y):  
    model = RandomForestClassifier()  
  
    param_grid = {'n_estimators': list(range(1,21))}  
    grid_search = GridSearchCV(model, param_grid, n_jobs = 1, verbose=1)  
    grid_search.fit(train_x, train_y)  
    best_parameters = grid_search.best_estimator_.get_params()  
  
    model = RandomForestClassifier(n_estimators = best_parameters['n_estimators'])  
  
    model.fit(train_x, train_y)  
    return model
```

*# Decision Tree Classifier*

```
def decision_tree_classifier(train_x, train_y):  
    model = tree.DecisionTreeClassifier()  
    model.fit(train_x, train_y)  
  
    bagging = BaggingClassifier(model, max_samples=0.5, max_features=1 )  
    bagging.fit(train_x, train_y)  
    return bagging
```

*# GBDT(Gradient Boosting Decision Tree) Classifier*

```
def gradient_boosting_classifier(train_x, train_y):  
    model = GradientBoostingClassifier()  
  
    model = RandomForestClassifier()  
  
    param_grid = {'n_estimators': list(range(100,300,10))}  
    grid_search = GridSearchCV(model, param_grid, n_jobs = 1, verbose=1)  
    grid_search.fit(train_x, train_y)  
    best_parameters = grid_search.best_estimator_.get_params()  
  
    model = RandomForestClassifier(n_estimators = best_parameters['n_estimators'])  
  
    model.fit(train_x, train_y)  
    return model
```

*# SVM Classifier*

```
def svm_classifier(train_x, train_y):  
    model = SVC(kernel='linear', probability=True)  
    model.fit(train_x, train_y)  
    return model
```

```

# SVM Classifier using cross validation
def svm_cross_validation(train_x, train_y):
    model = SVC(kernel='linear', probability=True)
    param_grid = {'C': [1e-3, 1e-2, 1e-1, 1, 10, 100, 1000], 'gamma': [0.001, 0.0001]}
    grid_search = GridSearchCV(model, param_grid, n_jobs = 1, verbose=1)
    grid_search.fit(train_x, train_y)
    best_parameters = grid_search.best_estimator_.get_params()
    #for para, val in best_parameters.items():
        #print para, val
    model = SVC(kernel='rbf', C=best_parameters['C'], gamma=best_parameters['gamma'],
    model.fit(train_x, train_y)
    return model

def feature_select(x,y):
    clf = ExtraTreesClassifier()
    clf = clf.fit(x, y)
    model = SelectFromModel(clf, prefit=True)
    return model

```

In [13]: # just for my own record

```

if __name__ == '__main__':
    thresh = 0.5
    # model_save_file = "/home/jason/datamining/model/models"
    # model_save = {}
    # result_save_file = '/home/jason/datamining/result/results'

    test_classifiers = ['KNN', 'LR', 'RF', 'DT', 'GBC']
    classifiers = {
        'KNN': knn_classifier,
        'LR': logistic_regression_classifier,
        'RF': random_forest_classifier,
        'DT': decision_tree_classifier,
        'GBC': gradient_boosting_classifier
    }

    print('reading training and testing data...')
    #X_train, X_validation, y_train, y_validation
    select_model = feature_select(X_train, y_train)
    X_train = select_model.transform(X_train)
    X_validation = select_model.transform(X_validation)

    result = []

    for classifier in test_classifiers:
        print('***** %s *****' % classifier)

```

```

start_time = time.time()
model = classifiers[classifier](X_train, y_train)
print('training took %fs!' % (time.time() - start_time))
predict = model.predict(X_validation)

precision = metrics.precision_score(y_validation, predict)
recall = metrics.recall_score(y_validation, predict)
print('precision: %.2f%%, recall: %.2f%%' % (100 * precision, 100 * recall))
accuracy = metrics.accuracy_score(y_validation, predict)
print('accuracy: %.2f%%' % (100 * accuracy))

scores = cross_val_score(model, X_train, y_train)
print(scores)

reading training and testing data...
***** KNN *****
Fitting 3 folds for each of 20 candidates, totalling 60 fits

[Parallel(n_jobs=1)]: Done 60 out of 60 | elapsed: 16.6s finished

training took 16.900737s!
precision: 69.16%, recall: 100.00%
accuracy: 69.17%
[0.6920215 0.69588588 0.69051065]
***** LR *****
training took 0.241711s!
precision: 77.36%, recall: 90.43%
accuracy: 75.09%
[0.72219926 0.7366136 0.73433947]
***** RF *****
Fitting 3 folds for each of 20 candidates, totalling 60 fits

[Parallel(n_jobs=1)]: Done 60 out of 60 | elapsed: 19.7s finished

training took 21.534177s!
precision: 79.11%, recall: 89.36%
accuracy: 76.33%
[0.73770153 0.7506719 0.74260906]
***** DT *****
training took 0.650436s!
precision: 71.19%, recall: 92.07%
accuracy: 68.75%
[0.68561389 0.66694232 0.68658259]
***** GBC *****
Fitting 3 folds for each of 20 candidates, totalling 60 fits

```

```
[Parallel(n_jobs=1)]: Done 60 out of 60 | elapsed: 6.4min finished
```

```
training took 410.052062s!  
precision: 79.57%, recall: 90.35%  
accuracy: 77.29%  
[0.75010335 0.76431673 0.76121563]
```

```
In [14]: X_train  
        #X_train, y_train = X,Y
```

```
Out[14]: array([[ 0.        ,  1.        ,  0.        , ..., 11.774629, 11.737314,  
                11.739768],  
               [ 0.        ,  0.        ,  0.        , ..., 11.737541, 12.21775 ,  
                11.256157],  
               [ 1.        ,  0.        ,  0.        , ..., 11.562332, 11.451252,  
                11.531164],  
               ...,  
               [ 0.        ,  0.        ,  1.        , ..., 11.248144, 11.919338,  
                12.642514],  
               [ 0.        ,  1.        ,  0.        , ..., 11.222754, 11.798913,  
                11.439027],  
               [ 0.        ,  1.        ,  0.        , ..., 11.568027, 11.701103,  
                11.861883]], dtype=float32)
```

```
In [15]: #test cnn model
```

```
from __future__ import print_function  
  
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 LSTM  
from keras.layers import Conv1D, MaxPooling1D  
from keras.datasets import imdb  
  
# Embedding  
max_features = 15000  
maxlen = 270  
embedding_size = 128  
  
# Convolution  
kernel_size = 5  
filters = 64  
pool_size = 3  
  
# LSTM
```

```

lstm_output_size = 70

# Training
batch_size = 30
epochs = 5

'''
Note:
batch_size is highly sensitive.
Only 2 epochs are needed as the dataset is very small.
'''

print('Loading data...')
#X_train, X_validation, y_train, y_validation
#(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

#X_train = np.asarray(np.abs(X))
X_train = np.asarray(np.abs(X_train))
X_validation = np.asarray(np.abs(X_validation))
print(len(X_train), 'train sequences')
print(len(X_validation), 'test sequences')

print('Pad sequences (samples x time)')
X_train = sequence.pad_sequences(X_train, maxlen=maxlen, padding='post')
X_validation = sequence.pad_sequences(X_validation, maxlen=maxlen, padding='post')
print('x_train shape:', X_train.shape)
print('x_test shape:', X_validation.shape)

print('Build model...')

cnnmodel = Sequential()
cnnmodel.add(Embedding(max_features, embedding_size, input_length=maxlen))
#model.add(Dense(32, activation='relu', input_dim=100))
cnnmodel.add(Dropout(0.5))
cnnmodel.add(Conv1D(filters,
                    kernel_size,
                    padding='valid',
                    activation='relu',
                    strides=1))
cnnmodel.add(MaxPooling1D(pool_size=pool_size))
cnnmodel.add(LSTM(lstm_output_size))
cnnmodel.add(Dense(1))
cnnmodel.add(Activation('sigmoid'))

cnnmodel.compile(loss='binary_crossentropy',
                optimizer='adam',
                metrics=['accuracy'])

```



```
Loading data...
14512 train sequences
3629 test sequences
Pad sequences (samples x time)
x_train shape: (14512, 270)
x_test shape: (3629, 270)
Build model...
```

```
In [16]: X_train = cleaned_train[:18141]
        X_test = cleaned_train[18141:]
        y_train = train_score.score.as_matrix(columns=None).tolist()

In [17]: if __name__ == '__main__':
        thresh = 0.5
        # model_save_file = "/home/jason/datamining/model/models"
        # model_save = {}
        # result_save_file = '/home/jason/datamining/result/results'

        test_classifiers = ['LR','RF','GBC']
        classifiers = {
            'LR':logistic_regression_classifier,
            'RF':random_forest_classifier,
            'GBC':gradient_boosting_classifier
        }

        print('reading training and testing data...')
        #X_train, X_validation, y_train, y_validation
        # X_test = rearrange(Xt)
        # X_test = Xt
        select_model = feature_select(X_train, y_train)
        X_train = select_model.transform(X_train)
        X_test = select_model.transform(X_test)

        result = []

        start_time = time.time()
        model = classifiers['LR'](X_train, y_train)
        print('training took %fs!' % (time.time() - start_time))
        Y_predict_lr = model.predict_proba(X_test)[:,:1]
        print('predict finished')

        model = classifiers['RF'](X_train, y_train)
        print('training took %fs!' % (time.time() - start_time))
        Y_predict_rf = model.predict_proba(X_test)[:,:1]
        print('predict finished')

        model = classifiers['GBC'](X_train, y_train)
```

```

print('training took %fs!' % (time.time() - start_time))
Y_predict_gbc = model.predict_proba(X_test)[: ,1]
print('predict finished')

```

```

# for classifier in test_classifiers:
#     print('***** %s *****' % classifier)
#     start_time = time.time()
#     model = classifiers[classifier](X_train, y_train)
#     print('training took %fs!' % (time.time() - start_time))
#     Y_predict = model.predict_proba(X_test)[: ,1]
#     print('predict finished')

```

reading training and testing data...

training took 0.241209s!

predict finished

Fitting 3 folds for each of 20 candidates, totalling 60 fits

[Parallel(n\_jobs=1)]: Done 60 out of 60 | elapsed: 25.5s finished

training took 27.739618s!

predict finished

Fitting 3 folds for each of 20 candidates, totalling 60 fits

[Parallel(n\_jobs=1)]: Done 60 out of 60 | elapsed: 8.2min finished

training took 546.078951s!

predict finished

In [18]: *#cnn test*

```

X_train = cleaned_train[:18141]
X_test = cleaned_train[18141:]
y_train = train_score.score.as_matrix(columns=None).tolist()
X_train = np.asarray(X_train)
X_train = sequence.pad_sequences(X_train, maxlen=maxlen, padding='post')
#X_test = np.asarray(Xt)
X_test = sequence.pad_sequences(X_test, maxlen=maxlen, padding='post')

```

```

cnnmodel.fit(X_train, y_train, batch_size=128, epochs=5)

```

```

Y_predict_cnn = cnnmodel.predict(X_test, verbose=0)

```

```

Y_predict_cnn = np.squeeze(Y_predict_cnn, axis=1)

```

```

Epoch 1/5
18141/18141 [=====] - 60s 3ms/step - loss: 0.5846 - acc: 0.6992
Epoch 2/5
18141/18141 [=====] - 59s 3ms/step - loss: 0.5381 - acc: 0.7351
Epoch 3/5
18141/18141 [=====] - 59s 3ms/step - loss: 0.5243 - acc: 0.7417
Epoch 4/5
18141/18141 [=====] - 62s 3ms/step - loss: 0.5139 - acc: 0.7487
Epoch 5/5
18141/18141 [=====] - 65s 4ms/step - loss: 0.5042 - acc: 0.7539

```

```

In [19]: #nn train
X_train = cleaned_train[:18141]
X_test = cleaned_train[18141:]
y_train = train_score.score.as_matrix(columns=None).tolist()
X_array = np.asarray(X_train)
Y_array = np.asarray(y_train)
Xtest_array = np.asarray(X_test)
import warnings
warnings.filterwarnings("ignore")
# Create your first MLP in Keras
from keras.models import Sequential
from keras.layers import Dense

# fix random seed for reproducibility
np.random.seed(7)

# split into input (X) and output (Y) variables
X = X_array
Y = Y_array
# create model
nnmodel = Sequential()
nnmodel.add(Dense(100, input_dim=270, activation='relu'))
nnmodel.add(Dense(100, activation='relu'))
nnmodel.add(Dense(100, activation='relu'))
nnmodel.add(Dense(100, activation='relu'))
nnmodel.add(Dense(1, activation='sigmoid'))
# Compile model
nnmodel.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# Fit the model
nnmodel.fit(X, Y, epochs=25, batch_size=150)
# evaluate the model
scores = nnmodel.evaluate(X, Y)
print("\ns: %.2f%%" % (nnmodel.metrics_names[1], scores[1]*100))
Y_predict_nn = nnmodel.predict(Xtest_array, verbose=0)
Y_predict_nn = np.squeeze(Y_predict_nn, axis=1)

```

Epoch 1/25  
18141/18141 [=====] - 1s 59us/step - loss: 0.6737 - acc: 0.6873  
Epoch 2/25  
18141/18141 [=====] - 0s 26us/step - loss: 0.5794 - acc: 0.7171  
Epoch 3/25  
18141/18141 [=====] - 0s 22us/step - loss: 0.5597 - acc: 0.7253  
Epoch 4/25  
18141/18141 [=====] - 0s 22us/step - loss: 0.5516 - acc: 0.7259  
Epoch 5/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5565 - acc: 0.7264  
Epoch 6/25  
18141/18141 [=====] - 0s 22us/step - loss: 0.5491 - acc: 0.7297  
Epoch 7/25  
18141/18141 [=====] - 1s 29us/step - loss: 0.5310 - acc: 0.7361  
Epoch 8/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5338 - acc: 0.7349  
Epoch 9/25  
18141/18141 [=====] - 0s 26us/step - loss: 0.5247 - acc: 0.7377  
Epoch 10/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5242 - acc: 0.7415  
Epoch 11/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5275 - acc: 0.7386  
Epoch 12/25  
18141/18141 [=====] - 1s 29us/step - loss: 0.5212 - acc: 0.7438  
Epoch 13/25  
18141/18141 [=====] - 0s 24us/step - loss: 0.5219 - acc: 0.7452  
Epoch 14/25  
18141/18141 [=====] - 0s 26us/step - loss: 0.5212 - acc: 0.7422  
Epoch 15/25  
18141/18141 [=====] - 0s 22us/step - loss: 0.5218 - acc: 0.7409  
Epoch 16/25  
18141/18141 [=====] - 0s 22us/step - loss: 0.5178 - acc: 0.7452  
Epoch 17/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5130 - acc: 0.7465  
Epoch 18/25  
18141/18141 [=====] - 1s 28us/step - loss: 0.5088 - acc: 0.7495  
Epoch 19/25  
18141/18141 [=====] - 0s 27us/step - loss: 0.5174 - acc: 0.7449  
Epoch 20/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5054 - acc: 0.7480  
Epoch 21/25  
18141/18141 [=====] - 0s 23us/step - loss: 0.5094 - acc: 0.7462  
Epoch 22/25  
18141/18141 [=====] - 0s 24us/step - loss: 0.5045 - acc: 0.7511  
Epoch 23/25  
18141/18141 [=====] - 0s 25us/step - loss: 0.4998 - acc: 0.7534  
Epoch 24/25  
18141/18141 [=====] - 0s 25us/step - loss: 0.5001 - acc: 0.7516

```
Epoch 25/25
18141/18141 [=====] - 0s 25us/step - loss: 0.4994 - acc: 0.7551
18141/18141 [=====] - 1s 28us/step
```

acc: 75.64%

```
In [20]: Y_predict_nn
```

```
Out[20]: array([0.8579925 , 0.94041866, 0.8313853 , ..., 0.70595163, 0.50523454,
                0.61891323], dtype=float32)
```

```
In [21]: Y_predict_cnn
```

```
Out[21]: array([0.8295582 , 0.78621113, 0.6645141 , ..., 0.64757854, 0.41389206,
                0.569912  ], dtype=float32)
```

```
In [22]: Y_predict_lr
```

```
Out[22]: array([0.73480094, 0.67819865, 0.68934352, ..., 0.62148617, 0.41585488,
                0.49107215])
```

```
In [23]: Y_predict_rf
```

```
Out[23]: array([0.77777778, 0.83333333, 0.61111111, ..., 0.66666667, 0.27777778,
                0.72222222])
```

```
In [24]: Y_predict_gbc
```

```
Out[24]: array([0.68636364, 0.79545455, 0.71818182, ..., 0.68636364, 0.52272727,
                0.58636364])
```

```
In [25]: Y_predict = []
```

```
    for i in range(len(Y_predict_rf)):
        Y_predict.append(( Y_predict_rf[i] + Y_predict_gbc[i] + Y_predict_cnn[i] + Y_pred
```

```
In [31]: Y_predict
```

```
Out[31]: [0.7879230195223683,
          0.8388544181079576,
          0.7062980920377404,
          0.943190951750736,
          0.768477741034344,
          0.7789613797508105,
          0.49860520630773875,
          0.7843875995790115,
          0.7212234910690423,
          0.7845466396122267,
          0.8631969074709247,
          0.3807709932026237,
```

0.6003489641830174,  
0.40475087120677483,  
0.8834678248323575,  
0.2311255061265194,  
0.873183729010399,  
0.6564867117489227,  
0.8245094442307347,  
0.5769025559527705,  
0.9085451350970701,  
0.8365589516632485,  
0.8573541283005416,  
0.8478584218506862,  
0.9570992681113156,  
0.6973043681997242,  
0.7669518869633627,  
0.9678706323558635,  
0.8102602714239949,  
0.9404498155670937,  
0.8150021161394889,  
0.7075678125926943,  
0.8056072395558309,  
0.6466429714602653,  
0.720919211645319,  
0.45648324354128406,  
0.6798729751748268,  
0.9523854328827425,  
0.5096632492963714,  
0.8012050654852029,  
0.5585386865367793,  
0.8966844571961297,  
0.9577842205762863,  
0.6449160896166406,  
0.5598847478327125,  
0.8654995611821762,  
0.7667021310690678,  
0.31053749369551437,  
0.9412690380606988,  
0.6922423969314556,  
0.6682960966018715,  
0.8878353593927442,  
0.7403141237569577,  
0.5666097553390446,  
0.34242223821806184,  
0.5745137103579261,  
0.5056084916597665,  
0.8443176256887841,  
0.31077154433034887,  
0.652228018490955,

0.7001406736747183,  
0.5219168139377026,  
0.40930632921782406,  
0.656459810562206,  
0.3910168477983186,  
0.9005869375936912,  
0.6207800335956342,  
0.8155419999300831,  
0.7215054362410247,  
0.674287120471097,  
0.4946316438792932,  
0.44189750848695486,  
0.38850753680624145,  
0.670125709790172,  
0.8459431837604503,  
0.456926736356032,  
0.649020043858374,  
0.6364261954119711,  
0.35317333382789534,  
0.49661802042915365,  
0.5756961399557614,  
0.3289054932768899,  
0.2922133699661553,  
0.5969380459099105,  
0.6982537371642662,  
0.6672041084880781,  
0.9109541324051944,  
0.38655630711353184,  
0.9205146239562468,  
0.7611620288605642,  
0.847835368550185,  
0.7250494646002548,  
0.6386729278347709,  
0.8814101485591946,  
0.9426997240143593,  
0.8593327081865735,  
0.8854973321009164,  
0.761613302670344,  
0.8395708713567618,  
0.7394665759320211,  
0.8789345564866307,  
0.9001224914584497,  
0.7608284189243509,  
0.890749600379154,  
0.8078777135020554,  
0.8980867635120044,  
0.6896643446852462,  
0.9010148370506788,

0.5399896084359198,  
0.9436106944626028,  
0.7173233939240677,  
0.5830297254853778,  
0.910392844135111,  
0.840965419947499,  
0.7943909067698199,  
0.6443230259900141,  
0.2854903297592895,  
0.7789211454114529,  
0.5589566548063297,  
0.47925539472789475,  
0.7434961258461981,  
0.8142665823601714,  
0.6737935066524179,  
0.32949335013676173,  
0.7789133901848937,  
0.8469757748974693,  
0.8763380272520913,  
0.5939704627099663,  
0.534669560449894,  
0.8890788649970836,  
0.9061540941999416,  
0.8587573018639979,  
0.6894106894129455,  
0.42708793359272407,  
0.9092364098387535,  
0.7932932148979168,  
0.9141534354048546,  
0.8778116136488288,  
0.31902512615979317,  
0.5606782776689289,  
0.799687826181903,  
0.5312301490945046,  
0.8372125069300334,  
0.6845006552910564,  
0.7081792589389917,  
0.42824005556076467,  
0.8511270585084202,  
0.8249551722196617,  
0.8076245030068387,  
0.9575832835652611,  
0.8483461627755502,  
0.6348126131928329,  
0.4342086132728692,  
0.910660274432163,  
0.7441339467812066,  
0.5487191449813169,



0.9428483106873252,  
0.6458503601828007,  
0.6478715577510872,  
0.6748445736037361,  
0.6227878210821537,  
0.47721030353897753,  
0.38173084201836827,  
0.5624694144936523,  
0.4064605542204597,  
0.42283884106260355,  
0.7142826438552201,  
0.25735870097773245,  
0.300363426979142,  
0.8148475043701403,  
0.7483688134737689,  
0.18327714607420592,  
0.187424812940034,  
0.5018928777238335,  
0.8774436646940732,  
0.7461095380060601,  
0.5821547227074402,  
0.7574544534237698,  
0.9182699016248337,  
0.4044226799348388,  
0.9030570583813118,  
0.9534332047809254,  
0.6053482233273862,  
0.8338723847059288,  
0.6746717732663107,  
0.4710536087101156,  
0.7165282924668958,  
0.5253831539792244,  
0.5434089610672961,  
0.5374659979584241,  
0.4923096076707647,  
0.9242050391556036,  
0.7847563390779977,  
0.9297017475270262,  
0.24365215433968437,  
0.8239973632675228,  
0.8743608000001521,  
0.7637416302254706,  
0.8781491487917273,  
0.5730877148834141,  
0.4451484339857342,  
0.8534584199238305,  
0.8504844195312924,  
0.9633799940347672,

0.8727364252613048,  
0.5896017647752858,  
0.7880152231515056,  
0.7866893572638733,  
0.6372686437585138,  
0.557448315635474,  
0.5232809077308636,  
0.6768979428392468,  
0.41333027170463044,  
0.6733820088885047,  
0.3901863222471391,  
0.37588769712231374,  
0.6202792083073144,  
0.6115061372819574,  
0.9277016359146195,  
0.7874259028470878,  
0.5903055927970193,  
0.674875012612102,  
0.5501333484745989,  
0.8095936993757884,  
0.7760574921514048,  
0.8920446934724094,  
0.7165780002420599,  
0.7187719467613432,  
0.8814212735253151,  
0.5807313810845818,  
0.3672774839130315,  
0.3771320255717846,  
0.7178939505056902,  
0.23993113250518688,  
0.8084332549511785,  
0.6688980896665593,  
0.5472185995843676,  
0.4059818581649751,  
0.4196123341117242,  
0.48654953126955514,  
0.48960989256097814,  
0.8181980276348615,  
0.6550325908444145,  
0.4042796959178616,  
0.26801735141662636,  
0.32224028688864875,  
0.792819875689468,  
0.5036875356929471,  
0.41166821430728895,  
0.9129034184446239,  
0.6911988183103427,  
0.682110450574846,

0.8094428915267039,  
0.7789399079903208,  
0.8764303402166174,  
0.8697151045907627,  
0.8709752200227795,  
0.8973718220236325,  
0.8913357615470886,  
0.7886683804519249,  
0.9222270407459953,  
0.3868860996281258,  
0.8841624048322139,  
0.93529912693934,  
0.7465166455567485,  
0.42523248632146854,  
0.9372259506974557,  
0.9483359392243202,  
0.8820688567077271,  
0.7292473619935489,  
0.7551258529376502,  
0.6753964922644875,  
0.866395427933847,  
0.9497094652869484,  
0.7964538020919067,  
0.9300987685268576,  
0.9003800843099151,  
0.4278203835391035,  
0.9267455072414995,  
0.47436560932735,  
0.8086494818781361,  
0.7873489572845325,  
0.8615791296116029,  
0.7466026792923609,  
0.689918143219418,  
0.6607753328602723,  
0.4456969882653217,  
0.749690659268938,  
0.7708888434099429,  
0.734322137934993,  
0.5580578808230583,  
0.7534403522207279,  
0.5241464212837845,  
0.8705191810022701,  
0.42413503350031495,  
0.35287840304651646,  
0.6580460749641813,  
0.7663515042777014,  
0.6625641684339504,  
0.5929596339211319,

0.32459908910471985,  
0.889376096924146,  
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0.3573729398124146,  
0.387807725896739,  
0.6822845463499878,  
0.8120342117668402,  
0.6132718926126307,  
0.5349965954669799,  
0.6653914597299364,  
0.2882020725520572,  
0.7743458351703605,  
0.7350094733515171,  
0.6838421782760908,  
0.7569975134700235,  
0.4411341812273469,  
0.7142410216909466,  
0.6375649080131993,  
0.6912523763348357,  
0.36259249076247213,  
0.6160562602257488,  
0.43535042019805525,  
0.6808919955985715,  
0.7052298425725012,  
0.6327057378159628,  
0.7820889674051843,  
0.45044085926780797,  
0.6856062317285875,  
0.5227355614455059,  
0.7840680001058964,  
0.7814689537792494,  
0.8521055931093717,  
0.8143975616404504,  
0.8166510367634321,  
0.5592338114374815,  
0.8636048674583435,  
0.46555604450028354,

```

0.8021451380818782,
0.5838297293041692,
0.9007595030948369,
0.751490477088726,
0.9144833569875871,
0.5356153687142362,
0.8782710076582552,
0.3201451778110832,
0.8058657756357481,
0.6573308645775824,
0.7995697505245305,
0.9229980880262876,
0.9121274190719681,
0.8425156342561799,
0.8987830066921735,
0.4438310125861505,
0.8963282037865032,
0.7028695393993397,
0.867933125929399,
0.7304127310562616,
0.578213436404864,
0.3260228379733032,
0.8932427215154725,
0.9148329760390099,
0.5005388915839821,
0.8016761651544859,
0.8241777198483246,
0.8153525488846229,
...]
```

```

In [37]: Y_predict_temp = []
         for i in range(len(Y_predict_rf)):
             Y_predict_temp.append((Y_predict_rf[i] + Y_predict_gbc[i]) / 2.0)
```

```

In [40]: Y_predict_temp
```

```

In [35]: temp_score = load_label('submission.csv')
         submit_score = temp_score
         submit_score['score'] = Y_predict
         submit_score.to_csv('predict_result_cnn.csv')
```

```

In [41]: temp_score = load_label('submission.csv')
         submit_score = temp_score
         submit_score['score'] = Y_predict_temp
         submit_score.to_csv('predict_result_ncnn.csv')
```

```

In [ ]: table = pd.pivot_table(train_file, values = 'price', index=['lv11', 'lv12', 'lv13'], column
         table
```