stack-rnn-arima-xgb

September 29, 2021

[1]:
```
import tensorflow as tf
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
import seaborn as sns
import pandas as pd
import autoencoder
import model
from datetime import datetime
from datetime import timedelta
sns.set()
```

0.1 Deep Feed-forward Auto-Encoder Neural Network to reduce dimension + Deep Recurrent Neural Network + ARIMA + Extreme Boosting Gradient Regressor

0.1.1 Our target is Close market

[2]:
```
google = pd.read_csv('GOOG.csv')
eur_myr = pd.read_csv('eur-myr.csv')
usd_myr = pd.read_csv('usd-myr.csv')
oil = pd.read_csv('oil.csv')
```

[3]:
```
google['oil_price'] = oil['Price']
google['oil_open'] = oil['Open']
google['oil_high'] = oil['High']
google['oil_low'] = oil['Low']
google['eur_myr'] = eur_myr['Unnamed: 1']
google['usd_myr'] = usd_myr['Unnamed: 1']
```

[4]:
```
date_ori = pd.to_datetime(google.iloc[:, 0]).tolist()
google.head()
```

[4]:
```
         Date        Open        High         Low       Close   Adj Close  \
0  2017-10-02  959.979980  962.539978  947.840027  953.270020  953.270020
1  2017-10-03  954.000000  958.000000  949.140015  957.789978  957.789978
2  2017-10-04  957.000000  960.390015  950.690002  951.679993  951.679993
3  2017-10-05  955.489990  970.909973  955.179993  969.960022  969.960022
4  2017-10-06  966.700012  979.460022  963.359985  978.890015  978.890015

    Volume oil_price oil_open oil_high oil_low  eur_myr  usd_myr
0  1283400     54.27    54.26    54.39   54.22   4.9260    4.226
1   888300     54.24    54.59    55.22   53.89   4.9232    4.232
2   952400     54.38    54.08    54.85   53.93   4.9255    4.231
3  1213800     54.15    54.16    54.46   53.75   4.9239    4.238
4  1173900     53.90    52.80    54.20   52.25   4.9251    4.241
```

[5]:
```python
minmax = MinMaxScaler().fit(google.iloc[:, 4].values.reshape((-1,1)))
df_log = MinMaxScaler().fit_transform(google.iloc[:, 1:].astype('float32'))
df_log = pd.DataFrame(df_log)
df_log.head()
```

[5]:
```
         0         1         2         3         4         5         6  \
0  0.094605  0.050227  0.000000  0.021539  0.021539  0.092326  0.978389
1  0.000000  0.000000  0.018810  0.082769  0.082769  0.000000  0.972495
2  0.047461  0.026441  0.041238  0.000000  0.000000  0.014979  1.000000
3  0.023572  0.142825  0.106207  0.247630  0.247630  0.076062  0.954813
4  0.200918  0.237416  0.224569  0.368600  0.368600  0.066738  0.905698

         7         8         9        10        11
0  0.938202  0.847145  1.000000  0.033373  0.523804
1  1.000000  1.000000  0.935547  0.000000  0.714279
2  0.904495  0.931860  0.943359  0.027411  0.682536
3  0.919476  0.860036  0.908203  0.008343  0.904755
4  0.664794  0.812155  0.615234  0.022643  1.000000
```

[6]:
```python
thought_vector = autoencoder.reducedimension(df_log.values, 4, 0.001, 128, 100)
```

```
epoch: 10 loss: 0.272533 time: 0.0006597042083740234
epoch: 20 loss: 0.272347 time: 0.0007002353668212891
epoch: 30 loss: 0.272032 time: 0.0006601810455322266
epoch: 40 loss: 0.271498 time: 0.0006575584411621094
epoch: 50 loss: 0.270591 time: 0.0006284713745117188
epoch: 60 loss: 0.26905 time: 0.0006418228149414062
epoch: 70 loss: 0.266411 time: 0.0006747245788574219
epoch: 80 loss: 0.261816 time: 0.0007426738739013672
epoch: 90 loss: 0.253563 time: 0.0006310939788818359
epoch: 100 loss: 0.238662 time: 0.0006124973297119141
```

[7]:
```python
thought_vector.shape
```

[7]: (23, 4)

[8]:
```
num_layers = 1
size_layer = 128
timestamp = 5
epoch = 500
dropout_rate = 0.1
```

[9]:
```
tf.reset_default_graph()
modelnn = model.Model(0.01, num_layers, thought_vector.shape[1], size_layer, 1,␣
 ↪dropout_rate)
sess = tf.InteractiveSession()
sess.run(tf.global_variables_initializer())
for i in range(epoch):
    init_value = np.zeros((1, num_layers * 2 * size_layer))
    total_loss = 0
    for k in range(0, (thought_vector.shape[0] // timestamp) * timestamp,␣
 ↪timestamp):
        batch_x = np.expand_dims(thought_vector[k: k + timestamp, :], axis = 0)
        batch_y = df_log.values[k + 1: k + timestamp + 1, 3].reshape([-1, 1])
        last_state, _, loss = sess.run([modelnn.last_state,
                                        modelnn.optimizer,
                                        modelnn.cost], feed_dict={modelnn.X:␣
 ↪batch_x,
                                                                  modelnn.Y:␣
 ↪batch_y,
                                                                  modelnn.
 ↪hidden_layer: init_value})
        init_value = last_state
        total_loss += loss
    total_loss /= (thought_vector.shape[0] // timestamp)
    if (i + 1) % 100 == 0:
        print('epoch:', i + 1, 'avg loss:', total_loss)
```

```
WARNING:tensorflow:<tensorflow.python.ops.rnn_cell_impl.LSTMCell object at
0x7ff23c502128>: Using a concatenated state is slower and will soon be
deprecated.  Use state_is_tuple=True.
epoch: 100 avg loss: 0.226264208555
epoch: 200 avg loss: 0.0964816752821
epoch: 300 avg loss: 0.0767136435024
epoch: 400 avg loss: 0.0496228779666
epoch: 500 avg loss: 0.0471770029981
```

[10]:
```
output_predict = np.zeros(((thought_vector.shape[0] // timestamp) * timestamp,␣
 ↪1))
init_value = np.zeros((1, num_layers * 2 * size_layer))
```

```
for k in range(0, (thought_vector.shape[0] // timestamp) * timestamp,␣
↪timestamp):
    out_logits, last_state = sess.run([modelnn.logits, modelnn.last_state],␣
↪feed_dict = {modelnn.X:np.expand_dims(thought_vector[k: k + timestamp, :],␣
↪axis = 0),
                                        modelnn.hidden_layer: init_value})
    init_value = last_state
    output_predict[k: k + timestamp, :] = out_logits
```

[11]:
```
print('Mean Square Error:', np.mean(np.square(output_predict[:, 0] - df_log.
↪iloc[1: (thought_vector.shape[0] // timestamp) * timestamp + 1, 0].values)))
```

```
Mean Square Error: 0.0510127100734
```

Import ARIMA model using stats model

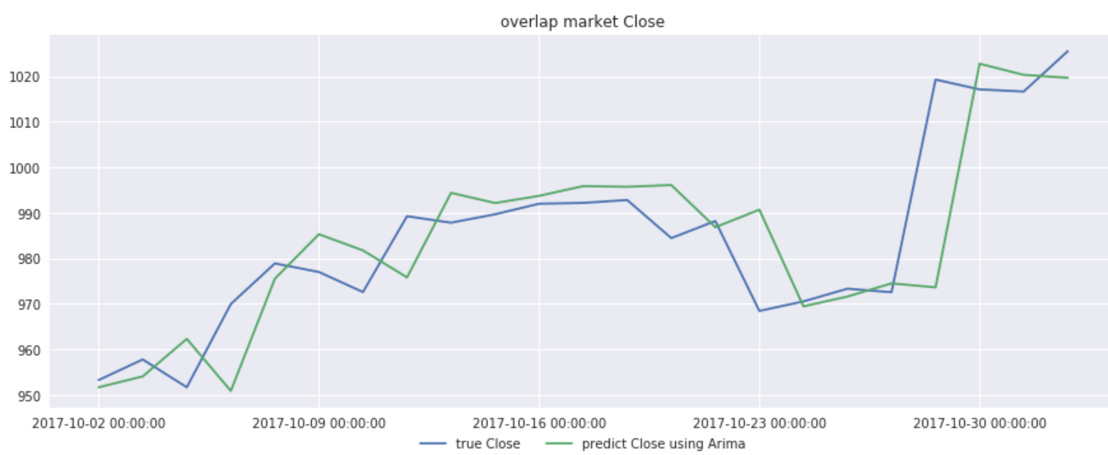
[12]:
```
import statsmodels.api as sm
from itertools import product
from scipy import stats

Qs = range(0, 1)
qs = range(0, 2)
Ps = range(0, 2)
ps = range(0, 2)
D=1
parameters = product(ps, qs, Ps, Qs)
parameters_list = list(parameters)
best_aic = float("inf")
for param in parameters_list:
    try:
        arima=sm.tsa.statespace.SARIMAX(df_log.iloc[:,3].values,␣
↪order=(param[0], D, param[1]), seasonal_order=(param[2], D, param[3], 1)).
↪fit(disp=-1)
    except:
        continue
    aic = arima.aic
    if aic < best_aic and aic:
        best_arima = arima
        best_aic = aic

best_aic
```

```
/usr/local/lib/python3.5/dist-packages/statsmodels/compat/pandas.py:56:
FutureWarning: The pandas.core.datetools module is deprecated and will be
removed in a future version. Please use the pandas.tseries module instead.
  from pandas.core import datetools
```

[12]: -7.7935465732797873

[13]:
```
def reverse_close(array):
    return minmax.inverse_transform(array.reshape((-1,1))).reshape((-1))
```

[14]:
```
pred_arima = best_arima.predict()
x_range = np.arange(df_log.shape[0])
fig = plt.figure(figsize = (15,6))
ax = plt.subplot(111)
ax.plot(x_range, reverse_close(df_log.iloc[:,3].values), label = 'true Close')
ax.plot(x_range, reverse_close(pred_arima), label = 'predict Close using Arima')
box = ax.get_position()
ax.set_position([box.x0, box.y0 + box.height * 0.1, box.width, box.height * 0.
 ↪9])
ax.legend(loc = 'upper center', bbox_to_anchor= (0.5, -0.05), fancybox = True,␣
 ↪shadow = True, ncol = 5)
plt.xticks(x_range[::5], date_ori[::5])
plt.title('overlap market Close')
plt.show()
```

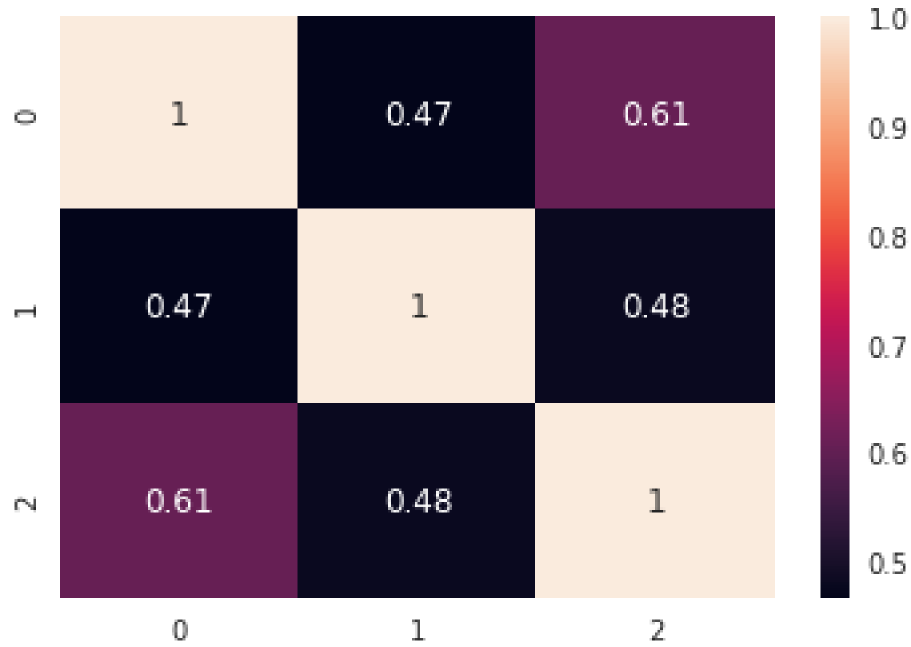


[15]:
```
boundary = (thought_vector.shape[0] // timestamp) * timestamp
stack_predict = np.vstack([pred_arima[:boundary], output_predict.
 ↪reshape((-1))]).T
```

[16]:
```
where_below_0 = np.where(stack_predict < 0)
where_higher_1 = np.where(stack_predict > 1)
stack_predict[where_below_0[0], where_below_0[1]] = 0
stack_predict[where_higher_1[0], where_higher_1[1]] = 1
```

[17]:
```
corr_df = pd.DataFrame(np.hstack([stack_predict, df_log.values[:boundary, 3].
 ↪reshape((-1,1))]))
```

[18]:
```
sns.heatmap(corr_df.corr(), annot= True)
plt.show()
```



ARIMA able to predict data that correlate 0.61 originally from original Close

Deep Recurrent Neural Network able to predict data that correlate 0.48 originally from original Close

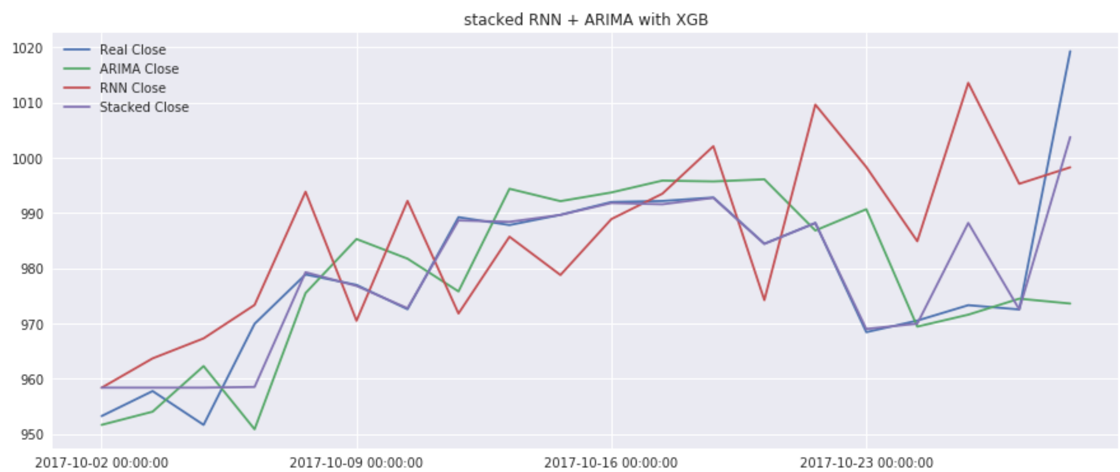
[19]:
```
params_xgd = {
    'max_depth': 7,
    'objective': 'reg:logistic',
    'learning_rate': 0.05,
    'n_estimators': 10000
    }
train_Y = df_log.values[:boundary, 3]
clf = xgb.XGBRegressor(**params_xgd)
clf.fit(stack_predict,train_Y, eval_set=[(stack_predict,train_Y)],
        eval_metric='rmse', early_stopping_rounds=20, verbose=False)
```

[19]:
```
XGBRegressor(base_score=0.5, colsample_bylevel=1, colsample_bytree=1, gamma=0,
       learning_rate=0.05, max_delta_step=0, max_depth=7,
       min_child_weight=1, missing=None, n_estimators=10000, nthread=-1,
       objective='reg:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1)
```

[20]:
```
stacked = clf.predict(stack_predict)
```

[25]:

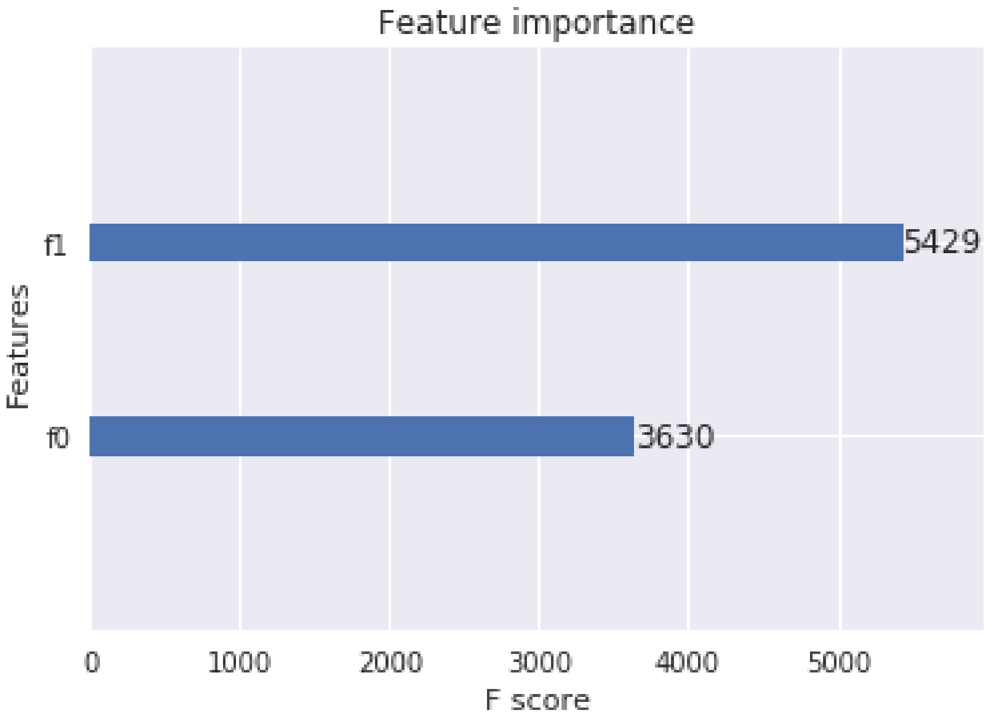
```
plt.figure(figsize = (15,6))
x_range = np.arange(boundary)
plt.plot(x_range, reverse_close(train_Y), label = 'Real Close')
plt.plot(x_range, reverse_close(pred_arima[:boundary]), label = 'ARIMA Close')
plt.plot(x_range, reverse_close(output_predict), label = 'RNN Close')
plt.plot(x_range, reverse_close(stacked), label = 'Stacked Close')
plt.legend()
plt.xticks(x_range[::5], date_ori[:boundary][::5])
plt.title('stacked RNN + ARIMA with XGB')
plt.show()
```



1 Pretty insane i can say!

[26]:

```
from xgboost import plot_importance
plot_importance(clf)
plt.show()
```



1.1 Arima is more important than RNN