

market_features

December 11, 2019

https://github.com/QuantCS109/TrumpTweets/blob/master/notebooks_features/market_features.ipynb

1 Overview

This notebook uses cleans and aggregates futures market data file 'futures.csv'

We will use the notebook to create market predictors & perform some EDA used in our report(Boxplot, Correlation Matrix, etc.)

```
[1]: import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.model_selection import train_test_split
```

```
[2]: # create futures dataframe
futures_df = pd.read_csv('../data/input_data/futures.csv')
```

```
[3]: # quick check of df
display(futures_df.head())
display(futures_df.shape)
display(futures_df.dtypes)

assets_key = futures_df['symbol'].unique()
display(len(futures_df['name'].unique()))

# display(len(assets_name))
display(futures_df['name'].unique())
```

	Unnamed: 0		name	symbol	\
0	472	CBOT 10-year US Treasury Note Futures #1 (TY1)		TY	
1	473	CBOT 10-year US Treasury Note Futures #1 (TY1)		TY	
2	474	CBOT 10-year US Treasury Note Futures #1 (TY1)		TY	
3	475	CBOT 10-year US Treasury Note Futures #1 (TY1)		TY	
4	476	CBOT 10-year US Treasury Note Futures #1 (TY1)		TY	

	date	open	high	low	settle	volume
0	2015-11-16	123.125000	123.125000	122.812500	122.859375	910514
1	2015-11-17	122.921875	123.031250	122.500000	122.921875	1042810
2	2015-11-18	122.875000	122.968750	122.609375	122.843750	861285
3	2015-11-19	122.796875	123.078125	122.734375	122.968750	939993
4	2015-11-20	122.921875	123.140625	122.828125	122.859375	916842

(13052, 9)

```

Unnamed: 0      int64
name            object
symbol          object
date            object
open            float64
high            float64
low             float64
settle          float64
volume          int64
dtype: object

```

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```

array(['CBOT 10-year US Treasury Note Futures #1 (TY1)',
      'CBOT 30-year US Treasury Bond Futures #1 (US1)',
      'CBOT Corn Futures #2 (C2)', 'CBOT Soybeans Futures #2 (S2)',
      'CBOT Wheat Futures #2 (W2)',
      'CME Canadian Dollar CAD Futures #1 (CD1)',
      'CME Euro FX Futures #1 (EC1)',
      'CME Japanese Yen JPY Futures #1 (JY1)',
      'CME Mexican Peso Futures #1 (MP1)',
      'CME NASDAQ 100 Index Mini Futures #1 (NQ1)',
      'CME S&P 500 Index E-Mini Futures #1 (ES1)',
      'NYMEX Gold Futures #1 (GC1)',
      'NYMEX WTI Crude Oil Futures #1 (CL1)'], dtype=object)

```

```

[4]: # drop reduntant column
futures_df = futures_df.drop(['Unnamed: 0'],axis=1)
display(futures_df.head())

```

	name	symbol	date	\
0	CBOT 10-year US Treasury Note Futures #1 (TY1)	TY	2015-11-16	
1	CBOT 10-year US Treasury Note Futures #1 (TY1)	TY	2015-11-17	
2	CBOT 10-year US Treasury Note Futures #1 (TY1)	TY	2015-11-18	
3	CBOT 10-year US Treasury Note Futures #1 (TY1)	TY	2015-11-19	
4	CBOT 10-year US Treasury Note Futures #1 (TY1)	TY	2015-11-20	

	open	high	low	settle	volume
0	123.125000	123.125000	122.812500	122.859375	910514
1	122.921875	123.031250	122.500000	122.921875	1042810
2	122.875000	122.968750	122.609375	122.843750	861285
3	122.796875	123.078125	122.734375	122.968750	939993
4	122.921875	123.140625	122.828125	122.859375	916842

```
[5]: # to keep new names in case we need them
new_names = []
key_names = futures_df['name'].unique()

for name in key_names:
    clean_name = name[0:name.find('#')]
    new_names.append(clean_name)

symbol_names = {}
for i in range(len(key_names)):
    symbol_names[assets_key[i]] = new_names[i]
print(symbol_names)
```

```
{'TY': 'CBOT 10-year US Treasury Note Futures ', 'US': 'CBOT 30-year US Treasury
Bond Futures ', 'C': 'CBOT Corn Futures ', 'S': 'CBOT Soybeans Futures ', 'W':
'CBOT Wheat Futures ', 'CD': 'CME Canadian Dollar CAD Futures ', 'EC': 'CME Euro
FX Futures ', 'JY': 'CME Japanese Yen JPY Futures ', 'MP': 'CME Mexican Peso
Futures ', 'NQ': 'CME NASDAQ 100 Index Mini Futures ', 'ES': 'CME S&P 500 Index
E-Mini Futures ', 'GC': 'NYMEX Gold Futures ', 'CL': 'NYMEX WTI Crude Oil
Futures '}
```

```
[6]: # to initialize new dict of lists
assets_list = futures_df['symbol'].unique()

col_dict = {inst:[key for key in futures_df.columns if re.match(r"{}_+".
    ↳format(inst),key) ]
             for inst in assets_list}

new_col_dict = {inst:[key for key in futures_df.columns if re.match(r"{}_+".
    ↳format(inst),key) ]
                for inst in assets_list}
```

```
[7]: # to create new column names by asset info
asset_info = ['open', 'high', 'low', 'settle', 'volume']
print(len(col_dict))

for key in new_col_dict:
    new_col_names = []
    for info in asset_info:
```

```

        new_col_names.append(f'{key}_{info}')
    new_col_dict[key] = new_col_names
    col_dict[key] = asset_info

print(new_col_dict)

```

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```

{'TY': ['TY_open', 'TY_high', 'TY_low', 'TY_settle', 'TY_volume'], 'US':
['US_open', 'US_high', 'US_low', 'US_settle', 'US_volume'], 'C': ['C_open',
'C_high', 'C_low', 'C_settle', 'C_volume'], 'S': ['S_open', 'S_high', 'S_low',
'S_settle', 'S_volume'], 'W': ['W_open', 'W_high', 'W_low', 'W_settle',
'W_volume'], 'CD': ['CD_open', 'CD_high', 'CD_low', 'CD_settle', 'CD_volume'],
'EC': ['EC_open', 'EC_high', 'EC_low', 'EC_settle', 'EC_volume'], 'JY':
['JY_open', 'JY_high', 'JY_low', 'JY_settle', 'JY_volume'], 'MP': ['MP_open',
'MP_high', 'MP_low', 'MP_settle', 'MP_volume'], 'NQ': ['NQ_open', 'NQ_high',
'NQ_low', 'NQ_settle', 'NQ_volume'], 'ES': ['ES_open', 'ES_high', 'ES_low',
'ES_settle', 'ES_volume'], 'GC': ['GC_open', 'GC_high', 'GC_low', 'GC_settle',
'GC_volume'], 'CL': ['CL_open', 'CL_high', 'CL_low', 'CL_settle', 'CL_volume']}

```

```

[8]: # to modify original dataframe with new columns renamed
futures_chg = futures_df.copy()
for key_new, value_new in new_col_dict.items():
    for key_old, value_old in col_dict.items():
        if key_new == key_old and len(value_new) == len(value_old):
            for i in range(len(value_new)):
                futures_chg[value_new[i]] =
↪futures_chg[value_old[i]][(futures_chg['symbol'] == key_new)]

```

```

[9]: # to create list of df with each data and merge
df_list = []
for key, values in new_col_dict.items():
    if 'date' in values:
        values = values
    else:
        values.append('date')

    df_name = f'df_{key}'
    df_name = pd.DataFrame(futures_chg[values].dropna())
    df_name.set_index('date', inplace = True)
    df_name.index = pd.to_datetime(df_name.index)
    df_list.append(df_name)

# merge all individual asset df into a single final
df_merged = pd.concat(df_list, join='outer', axis=1).dropna()

```

```

[10]: # check shape of new dataframe
display(df_merged.shape)

```

```
display(df_merged.columns)
```

```
(1004, 65)
```

```
Index(['TY_open', 'TY_high', 'TY_low', 'TY_settle', 'TY_volume', 'US_open',  
      'US_high', 'US_low', 'US_settle', 'US_volume', 'C_open', 'C_high',  
      'C_low', 'C_settle', 'C_volume', 'S_open', 'S_high', 'S_low',  
      'S_settle', 'S_volume', 'W_open', 'W_high', 'W_low', 'W_settle',  
      'W_volume', 'CD_open', 'CD_high', 'CD_low', 'CD_settle', 'CD_volume',  
      'EC_open', 'EC_high', 'EC_low', 'EC_settle', 'EC_volume', 'JY_open',  
      'JY_high', 'JY_low', 'JY_settle', 'JY_volume', 'MP_open', 'MP_high',  
      'MP_low', 'MP_settle', 'MP_volume', 'NQ_open', 'NQ_high', 'NQ_low',  
      'NQ_settle', 'NQ_volume', 'ES_open', 'ES_high', 'ES_low', 'ES_settle',  
      'ES_volume', 'GC_open', 'GC_high', 'GC_low', 'GC_settle', 'GC_volume',  
      'CL_open', 'CL_high', 'CL_low', 'CL_settle', 'CL_volume'],  
      dtype='object')
```

```
[11]: # create new df to add changes  
df_chg = df_merged.copy()
```

```
[12]: # to group keys for new columns  
settle_list = [value[3] for value in new_col_dict.values()]  
  
chg_list = []  
for key in new_col_dict:  
    chg_list.append(f'{key}_chg')  
  
# info to calculate chg  
chg_dict = {}  
for i in range(len(settle_list)):  
    chg_dict[chg_list[i]] = settle_list[i]  
print(chg_dict)
```

```
{'TY_chg': 'TY_settle', 'US_chg': 'US_settle', 'C_chg': 'C_settle', 'S_chg':  
'S_settle', 'W_chg': 'W_settle', 'CD_chg': 'CD_settle', 'EC_chg': 'EC_settle',  
'JY_chg': 'JY_settle', 'MP_chg': 'MP_settle', 'NQ_chg': 'NQ_settle', 'ES_chg':  
'ES_settle', 'GC_chg': 'GC_settle', 'CL_chg': 'CL_settle'}
```

```
[13]: # to calculate daily returns  
start = 0  
end = 1  
for new_col, col in chg_dict.items():  
    df_chg[new_col] = ((df_chg[col].shift(-end) - df_chg[col].shift(-start)) /  
↳ df_chg[col].shift(-start))*100
```

```
[14]: # check calculated returns make sense
```

```
display(df_chg['ES_settle'][:5])
display(df_chg['ES_chg'][:5])
display(df_chg['ES_chg'].head())
display(df_chg['CL_chg'].max())
```

```
date
2015-11-16    2033.25
2015-11-17    2034.25
2015-11-18    2065.00
2015-11-19    2064.50
2015-11-20    2074.00
Name: ES_settle, dtype: float64
```

```
date
2015-11-16    0.049182
2015-11-17    1.511614
2015-11-18   -0.024213
2015-11-19    0.460160
2015-11-20   -0.216972
Name: ES_chg, dtype: float64
```

```
date
2015-11-16    0.049182
2015-11-17    1.511614
2015-11-18   -0.024213
2015-11-19    0.460160
2015-11-20   -0.216972
Name: ES_chg, dtype: float64
```

```
14.356074425392187
```

```
[15]: # correlation matrix for train set
```

```
corr = df_chg[['TY_chg',
               'US_chg', 'C_chg', 'S_chg', 'W_chg', 'CD_chg', 'EC_chg', 'JY_chg',
               'MP_chg', 'NQ_chg', 'ES_chg', 'GC_chg', 'CL_chg']].
    ↪corr(method='spearman')

train_chg, test_chg = train_test_split(df_chg[['TY_chg', 'US_chg', 'C_chg',
    ↪'S_chg',
    ↪'W_chg', 'CD_chg', 'EC_chg',
    ↪'JY_chg',
    ↪'MP_chg', 'NQ_chg', 'ES_chg',
    ↪'GC_chg',
```

```

                                'CL_chg']], test_size=0.2,
    shuffle=False)
display(corr)

corr_train = train_chg[['TY_chg', 'US_chg', 'C_chg', 'S_chg',
                        'W_chg', 'CD_chg', 'EC_chg', 'JY_chg',
                        'MP_chg', 'NQ_chg', 'ES_chg', 'GC_chg', 'CL_chg']]
corr(method='spearman')

```

	TY_chg	US_chg	C_chg	S_chg	W_chg	CD_chg	EC_chg	\
TY_chg	1.000000	0.929813	-0.037894	-0.033128	-0.009360	-0.029599	0.185025	
US_chg	0.929813	1.000000	-0.021297	-0.017051	-0.001817	-0.066555	0.137872	
C_chg	-0.037894	-0.021297	1.000000	0.590967	0.635705	0.123561	0.031685	
S_chg	-0.033128	-0.017051	0.590967	1.000000	0.377231	0.165789	0.081151	
W_chg	-0.009360	-0.001817	0.635705	0.377231	1.000000	0.154748	0.085512	
CD_chg	-0.029599	-0.066555	0.123561	0.165789	0.154748	1.000000	0.386823	
EC_chg	0.185025	0.137872	0.031685	0.081151	0.085512	0.386823	1.000000	
JY_chg	0.615694	0.546382	-0.000670	0.003932	0.010033	0.114173	0.428219	
MP_chg	-0.052900	-0.067062	0.103884	0.180698	0.090852	0.466071	0.204817	
NQ_chg	-0.253752	-0.223282	0.050750	0.112248	0.031669	0.237212	-0.027786	
ES_chg	-0.334398	-0.307023	0.058807	0.133042	0.046745	0.311372	-0.017914	
GC_chg	0.427560	0.407059	0.017868	0.058155	0.046955	0.259988	0.457338	
CL_chg	-0.210198	-0.214595	0.096303	0.101937	0.113049	0.432394	0.049678	

	JY_chg	MP_chg	NQ_chg	ES_chg	GC_chg	CL_chg
TY_chg	0.615694	-0.052900	-0.253752	-0.334398	0.427560	-0.210198
US_chg	0.546382	-0.067062	-0.223282	-0.307023	0.407059	-0.214595
C_chg	-0.000670	0.103884	0.050750	0.058807	0.017868	0.096303
S_chg	0.003932	0.180698	0.112248	0.133042	0.058155	0.101937
W_chg	0.010033	0.090852	0.031669	0.046745	0.046955	0.113049
CD_chg	0.114173	0.466071	0.237212	0.311372	0.259988	0.432394
EC_chg	0.428219	0.204817	-0.027786	-0.017914	0.457338	0.049678
JY_chg	1.000000	-0.026159	-0.295784	-0.341942	0.529157	-0.129834
MP_chg	-0.026159	1.000000	0.309020	0.376872	0.094373	0.239515
NQ_chg	-0.295784	0.309020	1.000000	0.885055	-0.104344	0.208172
ES_chg	-0.341942	0.376872	0.885055	1.000000	-0.113819	0.305280
GC_chg	0.529157	0.094373	-0.104344	-0.113819	1.000000	0.024639
CL_chg	-0.129834	0.239515	0.208172	0.305280	0.024639	1.000000

```

[16]: # correlation heatmap
fig, ax = plt.subplots(1, 1, figsize=(18,14))
# to hide right side
mask = np.triu(corr_train.corr())

sns.set(font_scale=1.25)

```

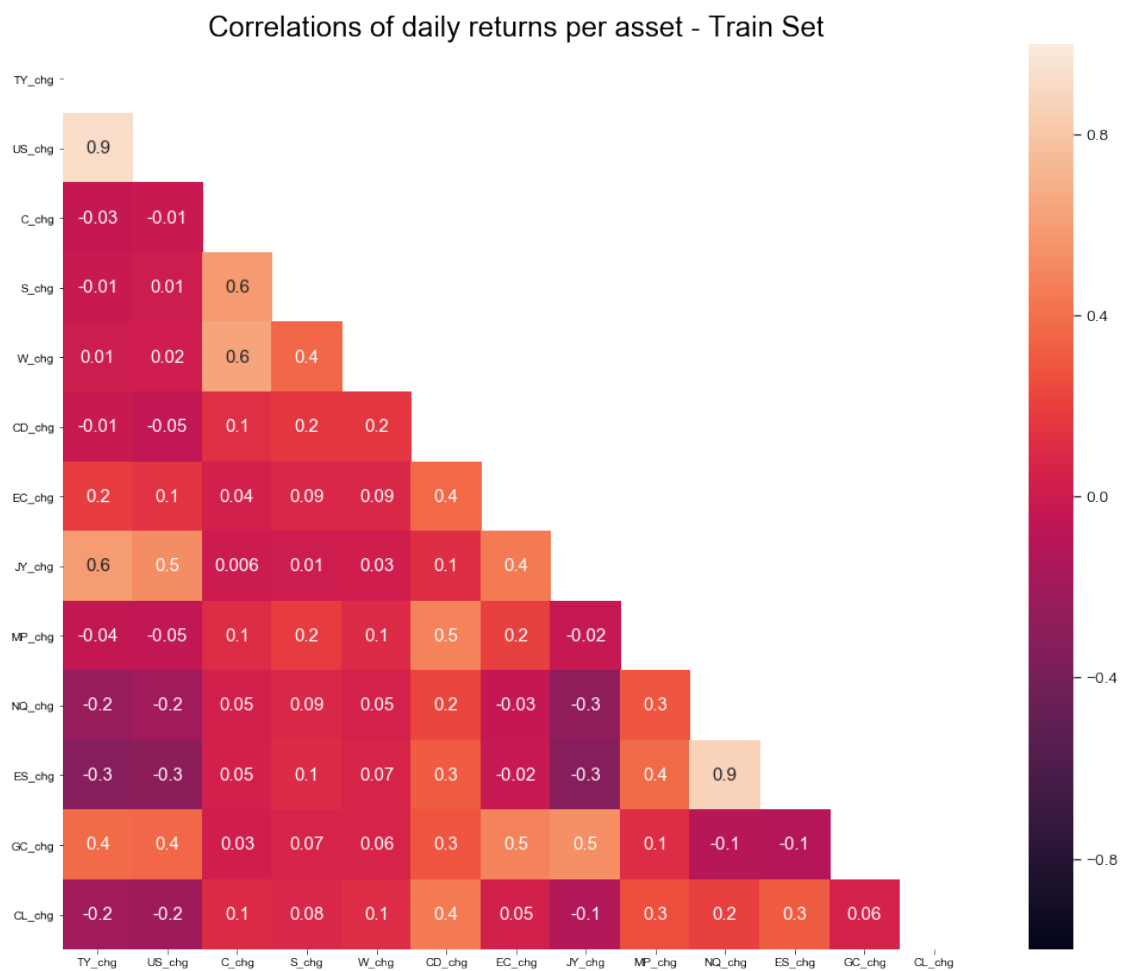
```

sns.heatmap(corr_train, annot=True, square=True, fmt='.01', vmin=-1, vmax=1,
            mask=mask)

b, t = plt.ylim()
b += 0.5 # add 0.5 to the bottom ylim value
t -= 0.5 # subtract 0.5 from the top ylim value
plt.ylim(b, t)
# set plot & labels
ax.set_yticklabels(labels=corr_train.columns, rotation=1)
ax.set_title("Correlations of daily returns per asset - Train Set", fontsize=24)

plt.show()

```



```

[17]: # boxplot for daily returns
df_chgs = df_chg.dropna()
df_chgs.index = pd.to_datetime(df_chgs.index)
labels = new_col_dict.keys()

```



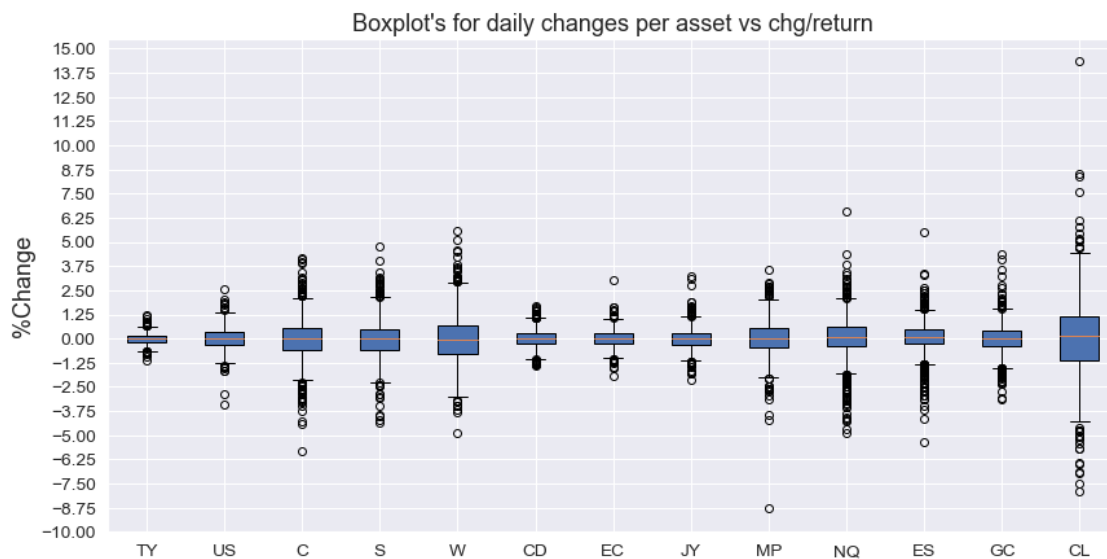
```

box_plot_data = [df_chgs.TY_chg, df_chgs.US_chg, df_chgs.C_chg, df_chgs.S_chg,
                 df_chgs.W_chg, df_chgs.CD_chg, df_chgs.EC_chg, df_chgs.JY_chg,
                 df_chgs.MP_chg, df_chgs.NQ_chg, df_chgs.ES_chg, df_chgs.GC_chg,
                 df_chgs.CL_chg]

fig, ax = plt.subplots(1, 1, figsize=(14,7))

ax.boxplot(box_plot_data, patch_artist=True, labels=labels)
ax.set_title("Boxplot's for daily changes per asset vs chg/return", fontsize=18)
ax.set_ylabel('%Change', fontsize=18)
plt.yticks(np.arange(-10, 15.25, step=1.25))
plt.show()

```



```

[18]: # to see top 5 up/down potential outliers
for asset_chg in chg_list:
    # for outliers print
    chg_q3 = np.percentile(df_chgs[asset_chg], 75)
    chg_q1 = np.percentile(df_chgs[asset_chg], 25)
    chg_iqr = chg_q3 - chg_q1
    outliers_up = pd.DataFrame(df_chgs[asset_chg].loc[(df_chgs[asset_chg] >
    ↪ (chg_q3 + chg_iqr*1.5))])

    outliers_down = pd.DataFrame(df_chgs[asset_chg].loc[(df_chgs[asset_chg] <
    ↪ (chg_q1 - chg_iqr*1.5))])

    if len(outliers_up) > 5:
        print(outliers_up.sort_values(by=[asset_chg], ascending=False)[0:5])

```

```

else:
    print(outliers_up.sort_values(by=[asset_chg], ascending=False))

print()

if len(outliers_down) > 5:
    print(outliers_down.sort_values(by=[asset_chg], ascending=True)[0:5])
else:
    print(outliers_down.sort_values(by=[asset_chg], ascending=True))
print()

```

	TY_chg
date	
2016-06-23	1.220554
2018-05-25	1.166105
2019-07-31	0.988166
2016-06-02	0.860691
2019-01-02	0.784413

	TY_chg
date	
2016-11-08	-1.150410
2015-12-02	-0.949247
2016-05-17	-0.808724
2016-02-11	-0.752336
2019-09-04	-0.744153

	US_chg
date	
2016-06-23	2.529064
2016-06-24	2.029043
2016-02-05	1.883598
2018-05-25	1.837741
2016-02-01	1.724881

	US_chg
date	
2016-11-08	-3.401078
2015-12-02	-2.846975
2015-12-28	-1.673734
2016-05-17	-1.650165
2017-02-28	-1.553271

	C_chg
date	
2019-10-10	4.150702

2019-09-27	4.104235
2019-05-24	3.992954
2019-05-29	3.909348
2019-05-23	3.400121

	C_chg
date	
2019-08-09	-5.837712
2016-06-20	-4.428698
2019-03-28	-4.313001
2019-06-27	-3.776683
2019-10-09	-3.452528

	S_chg
date	
2016-05-09	4.764903
2018-07-05	4.012589
2019-05-13	3.401760
2019-09-11	3.192383
2018-10-31	3.111702

	S_chg
date	
2016-07-01	-4.316682
2018-08-09	-4.185351
2016-07-06	-4.020598
2017-07-12	-3.915789
2016-07-29	-3.444654

	W_chg
date	
2018-07-24	5.579399
2019-03-11	5.104782
2019-05-29	4.536680
2017-06-29	4.519341
2017-06-30	4.250641

	W_chg
date	
2019-08-09	-4.911591
2016-04-21	-3.811734
2017-07-12	-3.654604
2018-06-29	-3.508772
2018-07-10	-3.462051

	CD_chg
date	
2016-02-02	1.676400

2017-11-30	1.603257
2016-01-20	1.519131
2017-07-11	1.475170
2016-03-15	1.440262

	CD_chg
date	
2017-01-17	-1.365735
2016-05-02	-1.355431
2015-12-16	-1.349073
2016-06-23	-1.294051
2016-01-14	-1.250966

	EC_chg
date	
2015-12-02	3.054289
2016-03-09	1.639960
2016-06-02	1.611437
2016-02-02	1.478370
2017-04-21	1.413166

	EC_chg
date	
2016-06-23	-1.910336
2018-06-13	-1.515275
2015-12-16	-1.485066
2016-12-07	-1.259348
2018-08-09	-1.196931

	JY_chg
date	
2016-06-23	3.246625
2016-07-28	3.117164
2016-04-27	2.749549
2016-06-02	1.912375
2016-02-02	1.877416

	JY_chg
date	
2016-07-08	-2.136953
2016-04-21	-1.808851
2016-07-11	-1.785286
2016-01-28	-1.765703
2016-11-29	-1.651203

	MP_chg
date	
2016-02-16	3.530778

2016-11-14	2.885345
2017-03-02	2.814885
2017-02-17	2.722590
2017-03-14	2.691318

	MP_chg
date	
2016-11-08	-8.775779
2016-11-09	-4.208754
2016-06-23	-3.971756
2018-10-26	-3.152873
2019-05-30	-2.916831

	NQ_chg
date	
2018-12-24	6.590186
2019-01-03	4.358276
2018-10-15	3.863304
2018-02-05	3.396755
2018-03-23	3.267876

	NQ_chg
date	
2018-10-09	-4.893986
2018-02-02	-4.707494
2016-06-23	-4.280447
2018-10-23	-4.198750
2018-12-20	-4.157395

	ES_chg
date	
2018-12-24	5.491821
2019-01-03	3.394999
2018-02-05	3.280865
2016-01-28	2.626667
2016-02-29	2.521118

	ES_chg
date	
2018-02-02	-5.349129
2016-06-23	-4.118480
2018-10-09	-3.694136
2019-08-02	-3.492334
2018-12-03	-3.172057

	GC_chg
date	
2016-06-23	4.371867

2016-02-10	4.114462
2019-06-19	3.532349
2016-02-05	3.200382
2018-10-10	2.781166

	GC_chg
date	
2016-11-10	-3.114136
2016-10-03	-3.075383
2016-12-14	-2.720051
2016-02-12	-2.332187
2015-12-16	-2.314500

	CL_chg
date	
2019-09-13	14.356074
2016-11-29	8.523993
2018-12-24	8.405467
2016-02-11	7.558282
2016-01-21	6.092533

	CL_chg
date	
2019-07-31	-7.922656
2018-11-21	-7.492436
2018-12-17	-6.980803
2018-11-12	-6.878650
2018-12-21	-6.516184

```
[19]: # to create new predictors names
vol_list = ['TY_volume', 'US_volume', 'C_volume', 'S_volume',
            'W_volume', 'CD_volume', 'EC_volume', 'JY_volume',
            'MP_volume', 'NQ_volume', 'ES_volume', 'GC_volume', 'CL_volume']

vol_chg_dict = {inst:[key for key in futures_df.columns if re.match(r"{}_+".
    ↪format(inst),key) ]
                for inst in assets_list}

for key in vol_chg_dict:
    new_col_avg = f'{key}_volume_avg'
    new_col_op_cl = f'{key}_OP_v_CL'
    vol_chg_dict[key] = [new_col_avg, new_col_op_cl]
```

```
[20]: # new df to create predictors
df_new_pred = df_chg.copy()
```

```

start = -1
end = 0

count = 0
for col, new_col in vol_chg_dict.items():
    df_new_pred[new_col[0]] = df_new_pred[vol_list[count]].rolling(5,
    ↪min_periods=1).mean()
    df_new_pred[f'{col}_volume_chg'] = ((df_new_pred[new_col[0]].shift(-end) -
    ↪df_new_pred[new_col[0]].shift(-start)
    ↪) / df_new_pred[new_col[0]].
    ↪shift(-start))*100
    df_new_pred[new_col[1]] = (df_new_pred[f'{col}_open'].shift(-end) -
    ↪df_new_pred[f'{col}_settle'].shift(-start))
    df_new_pred[f'{col}_opening'] = [('up' if op_v_cl > 0 else ('down' if
    ↪op_v_cl < 0 else 'unch'))
    ↪for op_v_cl in df_new_pred[new_col[1]]]

    count +=1

```

```

[21]: # validate new feature make sense
display(df_new_pred[['TY_volume', 'TY_volume_avg',
    ↪'TY_volume_chg', 'TY_OP_v_CL', 'TY_opening', 'TY_chg']].head())

```

	TY_volume	TY_volume_avg	TY_volume_chg	TY_OP_v_CL	TY_opening	\
date						
2015-11-16	910514.0	910514.0	NaN	NaN	unch	
2015-11-17	1042810.0	976662.0	7.264908	0.062500	up	
2015-11-18	861285.0	938203.0	-3.937800	-0.046875	down	
2015-11-19	939993.0	938650.5	0.047698	-0.046875	down	
2015-11-20	916842.0	934288.8	-0.464678	-0.046875	down	

	TY_chg
date	
2015-11-16	0.050871
2015-11-17	-0.063557
2015-11-18	0.101755
2015-11-19	-0.088945
2015-11-20	0.114460

```

[22]: # new df for adj predictors
temp_cols = vol_chg_dict.values()

df_preds = df_new_pred.copy()

for cols in temp_cols:
    df_preds = df_preds.drop(cols, axis=1)

```

```
df_preds = df_preds.drop(df_merged.columns, axis=1)
display(df_preds.head())
```

	TY_chg	US_chg	C_chg	S_chg	W_chg	CD_chg	\
date							
2015-11-16	0.050871	0.435680	0.145773	0.410034	-1.058201	0.130796	
2015-11-17	-0.063557	0.000000	0.000000	-0.408359	-0.200535	-0.143688	
2015-11-18	0.101755	0.616438	0.436681	0.217077	0.837240	0.327033	
2015-11-19	-0.088945	-0.181529	-0.048309	-0.240674	-0.365327	-0.365082	
2015-11-20	0.114460	0.363719	0.579990	0.554885	1.166667	-0.222469	

	EC_chg	JY_chg	MP_chg	NQ_chg	...	MP_volume_chg	\
date					...		
2015-11-16	-0.248181	-0.112918	0.263745	0.205101	...	NaN	
2015-11-17	-0.017159	-0.113045	0.060704	1.742416	...	-9.487984	
2015-11-18	0.737944	0.520598	1.071790	0.154751	...	-1.474846	
2015-11-19	-0.681431	0.016888	0.720288	0.607746	...	14.791535	
2015-11-20	-0.248714	0.005628	-0.198649	-0.281560	...	1.550716	

	MP_opening	NQ_volume_chg	NQ_opening	ES_volume_chg	ES_opening	\
date						
2015-11-16	unch	NaN	unch	NaN	unch	
2015-11-17	up	-2.480323	up	-2.869230	up	
2015-11-18	up	-4.076211	up	-2.553725	up	
2015-11-19	up	-4.872332	down	-5.156960	down	
2015-11-20	down	-5.892286	down	13.056758	down	

	GC_volume_chg	GC_opening	CL_volume_chg	CL_opening
date				
2015-11-16	NaN	unch	NaN	unch
2015-11-17	8.504745	down	-10.880246	up
2015-11-18	-3.044936	up	7.026649	up
2015-11-19	2.525782	up	7.071820	up
2015-11-20	-14.641963	up	4.785334	up

[5 rows x 39 columns]

```
[23]: # dummies for opening
df_preds = pd.get_dummies(df_preds, columns=['TY_opening', 'US_opening',
                                             'C_opening', 'S_opening',
                                             'W_opening', 'CD_opening',
                                             'EC_opening', 'JY_opening',
                                             'MP_opening', 'NQ_opening',
                                             'ES_opening',
                                             'GC_opening', 'CL_opening'])
```



```
[24]: display(df_preds.tail())
```

	TY_chg	US_chg	C_chg	S_chg	W_chg	CD_chg	\
date							
2019-11-04	-0.506451	-0.999412	-0.444727	-0.420499	0.774818	-0.065742	
2019-11-05	0.315113	0.692795	-1.021059	-0.686197	0.240269	-0.197355	
2019-11-06	-0.724900	-1.454688	-1.031593	0.850385	-0.814957	0.013183	
2019-11-07	0.000000	-0.159585	0.716612	-0.500659	-0.579990	-0.349305	
2019-11-08	NaN	NaN	NaN	NaN	NaN	NaN	

	EC_chg	JY_chg	MP_chg	NQ_chg	...	NQ_opening_up	\
date					...		
2019-11-04	-0.573605	-0.552756	-0.096544	-0.060859	...	1	
2019-11-05	0.027043	0.261566	0.231929	-0.042627	...	1	
2019-11-06	-0.216284	-0.369585	0.250675	0.283286	...	0	
2019-11-07	-0.216753	0.147291	0.153876	0.325011	...	1	
2019-11-08	NaN	NaN	NaN	NaN	...	0	

	ES_opening_down	ES_opening_unch	ES_opening_up	GC_opening_down	\
date					
2019-11-04		0	0	1	0
2019-11-05		0	0	1	0
2019-11-06		1	0	0	0
2019-11-07		0	0	1	1
2019-11-08		0	0	1	0

	GC_opening_unch	GC_opening_up	CL_opening_down	CL_opening_unch	\
date					
2019-11-04	0	1	0	0	
2019-11-05	0	1	0	0	
2019-11-06	0	1	0	0	
2019-11-07	0	0	0	1	
2019-11-08	0	1	1	0	

	CL_opening_up
date	
2019-11-04	1
2019-11-05	1
2019-11-06	1
2019-11-07	0
2019-11-08	0

[5 rows x 65 columns]

```
[25]: # clean nan & only predictos
df_preds = df_preds.dropna()
```

```
df_preds = df_preds.drop(columns=['TY_chg', 'US_chg', 'C_chg',
                                   'S_chg', 'W_chg', 'CD_chg',
                                   'EC_chg', 'JY_chg', 'MP_chg',
                                   'NQ_chg', 'ES_chg', 'GC_chg',
                                   'CL_chg'], axis=1)
```

```
[26]: display(df_preds.head())
      display(df_preds.tail())
```

	TY_volume_chg	US_volume_chg	C_volume_chg	S_volume_chg	\
date					
2015-11-17	7.264908	15.490918	24.506945	-0.360762	
2015-11-18	-3.937800	-2.338013	14.887758	48.598815	
2015-11-19	0.047698	28.648659	1.152503	2.666122	
2015-11-20	-0.464678	-2.639304	-1.979218	6.434186	
2015-11-23	15.506875	10.638416	4.286497	14.352737	

	W_volume_chg	CD_volume_chg	EC_volume_chg	JY_volume_chg	\
date					
2015-11-17	110.707511	-1.582925	2.775035	-25.097245	
2015-11-18	7.521267	2.253567	3.006541	8.761078	
2015-11-19	0.050234	0.956822	8.022800	-8.684613	
2015-11-20	-6.863598	7.343141	1.632575	-9.503479	
2015-11-23	15.793635	5.520806	3.223812	-17.977841	

	MP_volume_chg	NQ_volume_chg	...	NQ_opening_up	ES_opening_down	\
date			...			
2015-11-17	-9.487984	-2.480323	...	1	0	
2015-11-18	-1.474846	-4.076211	...	1	0	
2015-11-19	14.791535	-4.872332	...	0	1	
2015-11-20	1.550716	-5.892286	...	0	1	
2015-11-23	-3.448337	-10.153613	...	0	0	

	ES_opening_unch	ES_opening_up	GC_opening_down	GC_opening_unch	\
date					
2015-11-17	0	1	1	0	
2015-11-18	0	1	0	0	
2015-11-19	0	0	0	0	
2015-11-20	0	0	0	0	
2015-11-23	0	1	1	0	

	GC_opening_up	CL_opening_down	CL_opening_unch	CL_opening_up
date				
2015-11-17	0	0	0	1
2015-11-18	1	0	0	1
2015-11-19	1	0	0	1
2015-11-20	1	0	0	1

2015-11-23	0	1	0	0
------------	---	---	---	---

[5 rows x 52 columns]

	TY_volume_chg	US_volume_chg	C_volume_chg	S_volume_chg	\
date					
2019-11-01	5.444218	3.559422	2.346276	-7.204511	
2019-11-04	-0.249927	0.744727	8.269223	-2.750233	
2019-11-05	9.582721	7.085331	2.704347	-11.998904	
2019-11-06	0.769120	0.529222	4.371096	-3.834591	
2019-11-07	5.457695	4.377160	12.496372	1.452101	

	W_volume_chg	CD_volume_chg	EC_volume_chg	JY_volume_chg	\
date					
2019-11-01	6.994584	5.248811	8.418831	8.156451	
2019-11-04	-3.320639	-1.795057	6.518063	0.180374	
2019-11-05	2.290130	-1.928930	4.955569	9.126471	
2019-11-06	15.326201	-21.129020	-7.754343	-0.602006	
2019-11-07	18.185768	-6.346015	-2.141936	2.863428	

	MP_volume_chg	NQ_volume_chg	...	NQ_opening_up	ES_opening_down	\
date			...			
2019-11-01	6.478965	0.135277	...	1	0	
2019-11-04	1.368208	0.815442	...	1	0	
2019-11-05	0.091712	-2.284713	...	1	0	
2019-11-06	-6.454871	-3.647642	...	0	1	
2019-11-07	-5.892271	-4.716510	...	1	0	

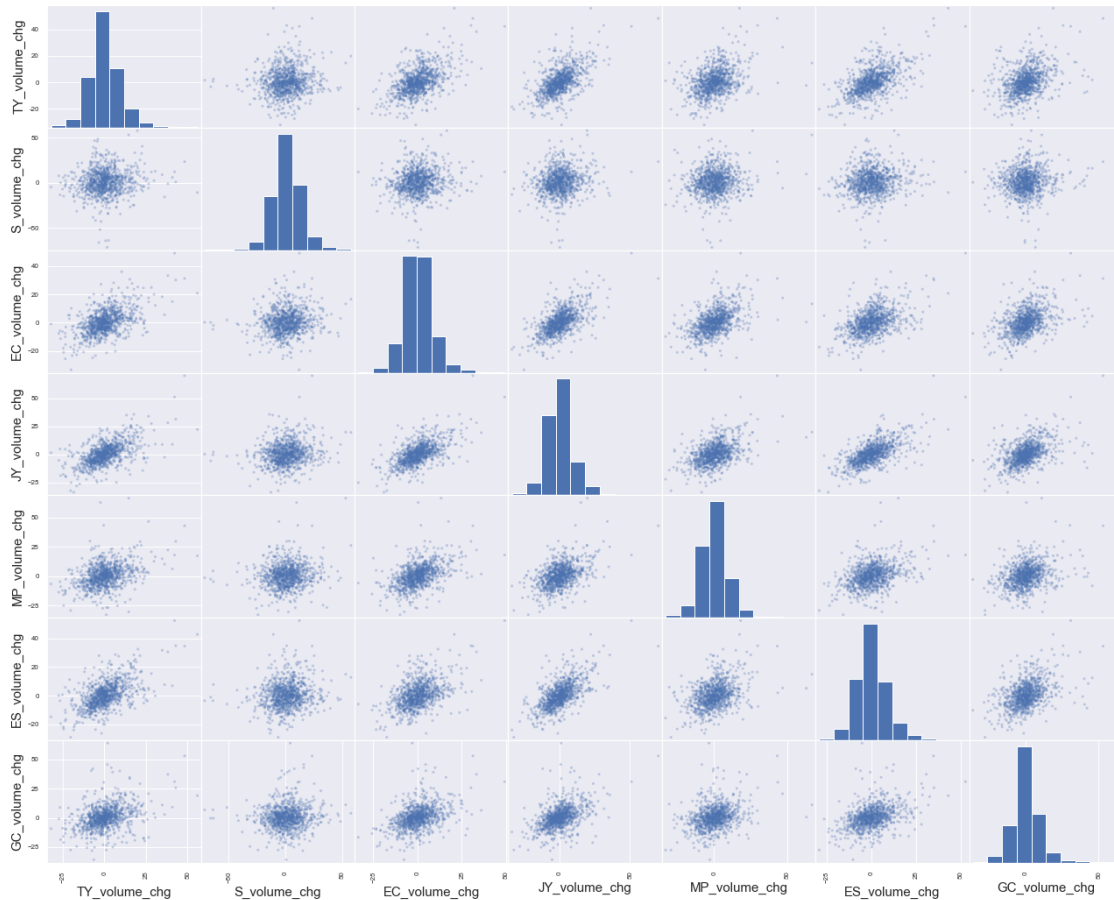
	ES_opening_unch	ES_opening_up	GC_opening_down	GC_opening_unch	\
date					
2019-11-01	0	1	0	0	
2019-11-04	0	1	0	0	
2019-11-05	0	1	0	0	
2019-11-06	0	0	0	0	
2019-11-07	0	1	1	0	

	GC_opening_up	CL_opening_down	CL_opening_unch	CL_opening_up
date				
2019-11-01	1	1	0	0
2019-11-04	1	0	0	1
2019-11-05	1	0	0	1
2019-11-06	1	0	0	1
2019-11-07	0	0	1	0

[5 rows x 52 columns]

```
[27]: # scatter_matrix for some volume predictors
cor_columns = ['TY_volume_chg', 'S_volume_chg', 'EC_volume_chg', 'JY_volume_chg',
               'MP_volume_chg', 'ES_volume_chg', 'GC_volume_chg']

scatter_matrix(df_preds.loc[:, cor_columns] , figsize = (22,18), alpha=0.3);
```



```
[28]: # create csv_file of only predictors
df_preds.to_csv('../data/features/market_features.csv')
```

```
[ ]:
```