US Dollar Index

October 8, 2019

```
In [1]: import pandas as pd
        import numpy as np; np.random.seed(0)
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.metrics import mean_squared_error, r2_score
        import matplotlib.pyplot as plt
        import seaborn as sns
        import sys

        feature_files = ['SP500', 'Gold', 'WTI', 'US10Y', 'DAX', 'FTSE', 'Nikkei',
                         'Shanghai', 'USD_HKD']
        target_file = 'DXY'
```

In order to predict US Dollar Index, **I choose the following features: S&P 500 Index(SP500), Gold Price (Gold), Crude Oil WTI(WTI), US 10-Year Bond Yield(US10Y), the German Stock Index(DAX), the UK Stock Index(FTSE), the Japan Stock Index(Nikkei), the China Stock Index(Shanghai) and the price of USD to HKD currency(USD_HKD).** I use the historical data from 01/01/2005 to 08/02/2019. Each indicator contains closing , open, high, and low prices.

```
In [2]: for n, f in enumerate([target_file]+feature_files):
            df_tmp = pd.read_csv(f+'.csv', sep = ',', thousands = ',', header = 0,
                                 index_col = 0)
            df_tmp = df_tmp.drop('Change %', axis = 1)
            try:
                df_tmp = df_tmp.drop('Vol.', axis = 1)
            except:
                pass
            df_tmp.index = pd.to_datetime(df_tmp.index)
            df_tmp.columns = ['Price-'+f, 'Open-'+f, 'high-'+f, 'low-'+f]
            if n == 0:
                df = df_tmp
            else:
                df = df.join(df_tmp)
```

By using for loop, we can combine all dataset into one. Since every feature file has columns of price, open, high, and low, I add the name of each feature file at the end.

```
In [3]: df = df.interpolate(method='linear')
        df = df.iloc[::-1]
```

There are some missing value in the dataset, so I use interpolation to replace the missing values. Replacing missing value is not necessary in Random Forest model.

```
In [4]: def timeseries_to_array(df_v, history_steps = 5):
            for n in range(df_v.shape[0]-history_steps):
                step_features = df_v.iloc[n:n+history_steps,:].values.flatten().reshape((1,-1)
                step_target = df_v.iloc[n+history_steps, 0]
                if n == 0:
                    feature_array = step_features
                    target_array = [step_target]
                else:
                    feature_array = np.concatenate((feature_array, step_features), axis = 0)
                    target_array.append(step_target)
            return feature_array, np.array(target_array)
```

This part is to set up the function of autoregression. It uses the observations from previous 5 days as input to predict the value for next day. It reads the original observation, flattens all observations, and concatenates them together.

0.0.1 Prediction of Gold price with Random Forest Model

```
In [5]: print('df.shape', df.shape)
        x_train, y_train = timeseries_to_array(df.iloc[:-50,:], 5)
        x_test, y_test = timeseries_to_array(df.iloc[-50:,:], 5)
        print('x_train.shape', x_train.shape)
        print('y_train.shape', y_train.shape)
        print('x_test.shape', x_test.shape)
        print('y_test.shape', y_test.shape)
```

```
df.shape (3781, 40)
x_train.shape (3726, 200)
y_train.shape (3726,)
x_test.shape (45, 200)
y_test.shape (45,)
```

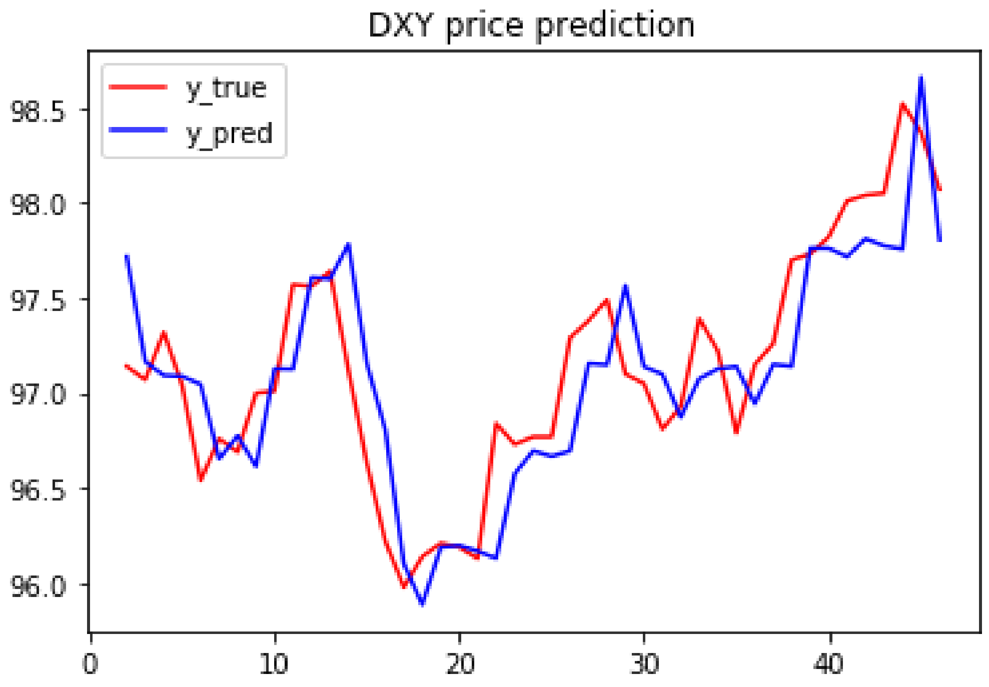
The target is to predict the US Dollar Index. The first column is our target, and the rest columns are features.The original data set has 40 columns and 3781 rows. Base on the concept of autoregression, I uses observations from previous 5 steps as input to predict the value at the next step. So in the traing set and test set, there are total of 200 features (40 x 5 days). I use the data to predict the latest 50 days of US Dollar Index.

```
In [6]: model = RandomForestRegressor(n_estimators = 100, max_depth = 10,
                                      max_features = 1.0, verbose = 0)
        model.fit(x_train, y_train)

        y_pred = model.predict(x_test)
        print('mse root:', round(np.sqrt(np.mean(np.square(y_test-y_pred))),3))
        print('r2_score:', r2_score(y_test, y_pred))
```

```
mse root: 0.337
r2_score: 0.6918892773215379
```

R-squared is a statistical measure of how close the data are to the fitted regression line. The R-Squared is 0.71, which shows the fitting is not bad.

```
In [7]: plt.figure(0)
        plt.plot(list(range(2,len(y_pred)+2)), y_test,'r',
                 list(range(2,len(y_pred)+2)), y_pred, 'b')
        #plt.xticks(ticks = np.arange(2,27,2))
        plt.legend(['y_true', 'y_pred'])
        plt.title(target_file+' price prediction')
        plt.savefig('predict.png')
```



Overfitting???This graph shows the trend of prediction and the real data. The performance is really good.

0.0.2 Prediction of Gold price by Year

```
In [8]: df.index=pd.to_datetime(df.index)
        df['year']=df.index.year


        for v in range(2005,2020):
            df_v=df.loc[df.loc[:,'year']==v, :]
            df_v=df_v.drop(columns=['year'])
            feature_v, target_v =  timeseries_to_array(df_v, history_steps = 5)
            print('df_%s:' %v, 'shape:', feature_v.shape, target_v.shape)
            model = RandomForestRegressor(n_estimators = 100, max_depth = 5,
                                          max_features = 0.7, verbose = 0)
            model.fit(feature_v, target_v)
            y_pred = model.predict(feature_v)
            print('r2_score:', round(r2_score(target_v, y_pred),3))
            print('mse root:', round(np.sqrt(np.mean(np.square(target_v-y_pred))),3))
```

```
df_2005: shape: (250, 200) (250,)
r2_score: 0.993
mse root: 0.252
df_2006: shape: (247, 200) (247,)
r2_score: 0.991
mse root: 0.207
df_2007: shape: (248, 200) (248,)
r2_score: 0.998
mse root: 0.142
df_2008: shape: (254, 200) (254,)
r2_score: 0.996
mse root: 0.32
df_2009: shape: (256, 200) (256,)
r2_score: 0.995
mse root: 0.301
df_2010: shape: (255, 200) (255,)
r2_score: 0.991
mse root: 0.266
df_2011: shape: (255, 200) (255,)
r2_score: 0.982
mse root: 0.258
df_2012: shape: (256, 200) (256,)
r2_score: 0.983
mse root: 0.18
df_2013: shape: (256, 200) (256,)
r2_score: 0.981
mse root: 0.178
df_2014: shape: (256, 200) (256,)
r2_score: 0.998
mse root: 0.138
df_2015: shape: (256, 200) (256,)
r2_score: 0.965
mse root: 0.344
df_2016: shape: (256, 200) (256,)
r2_score: 0.989
mse root: 0.251
df_2017: shape: (256, 200) (256,)
r2_score: 0.996
```

```
mse root: 0.209
df_2018: shape: (256, 200) (256,)
r2_score: 0.994
mse root: 0.2
df_2019: shape: (149, 200) (149,)
r2_score: 0.963
mse root: 0.136
```

According to the result, most years fit really well.

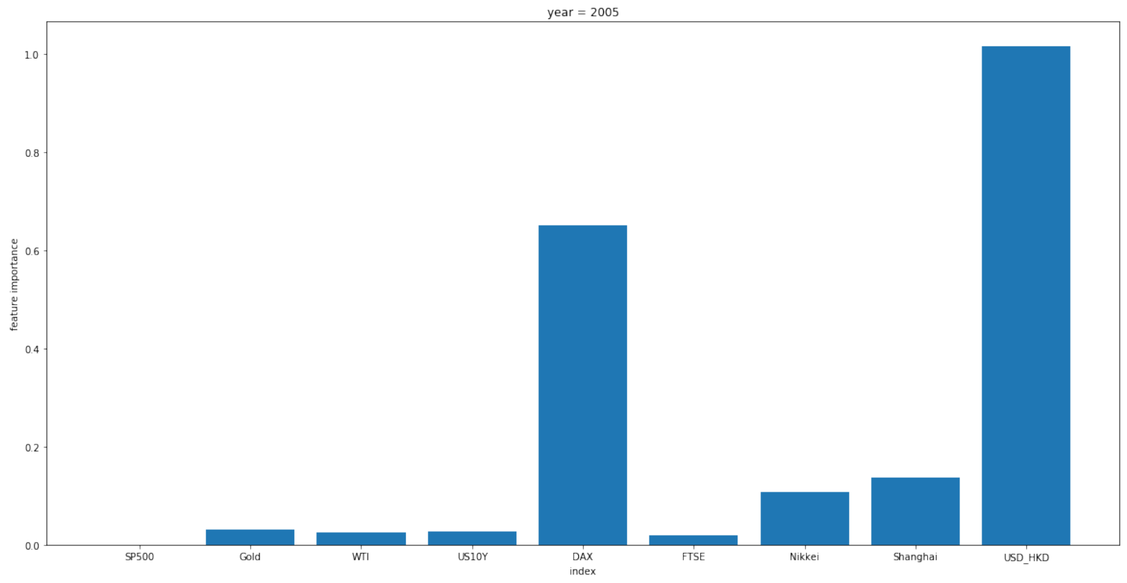
0.0.3 Analysis of Feature Importancy by Year

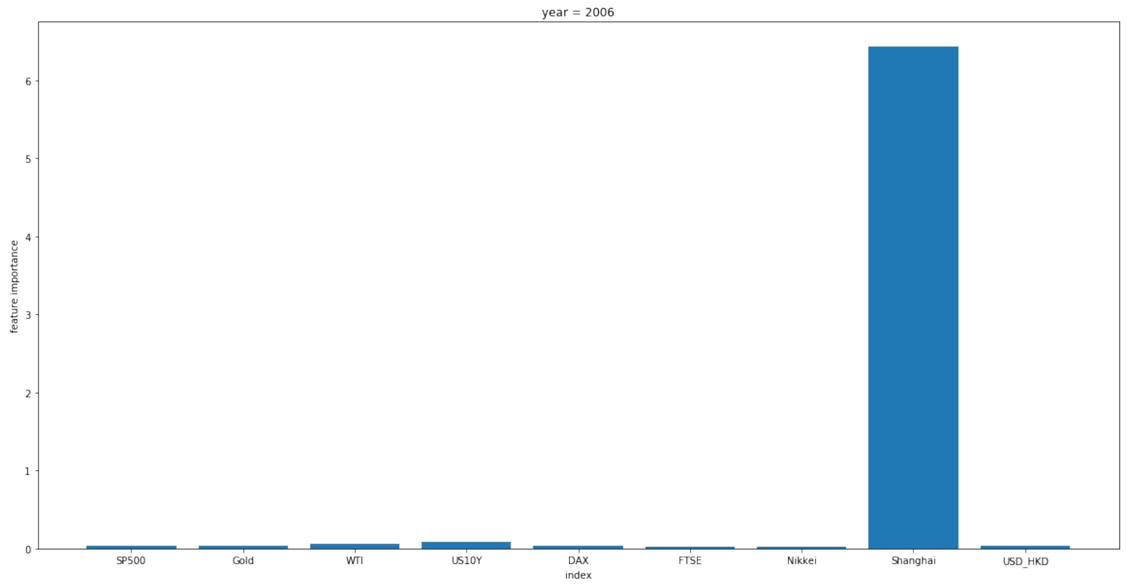
```
In [9]: df.index=pd.to_datetime(df.index)
        df['year']=df.index.year
        print(df.shape)
```

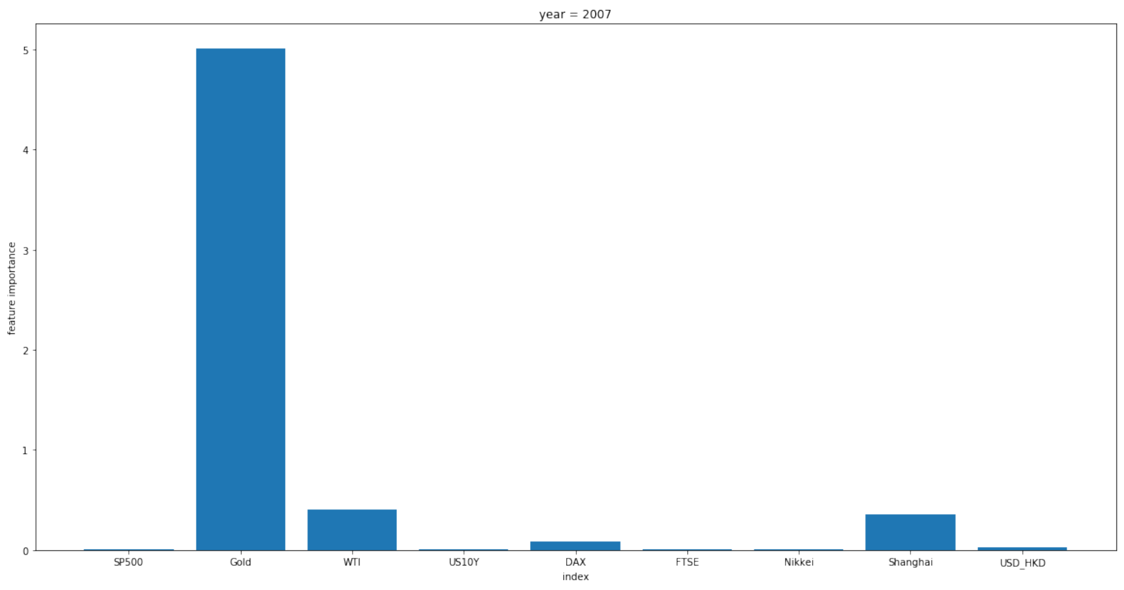
```
(3781, 41)
```

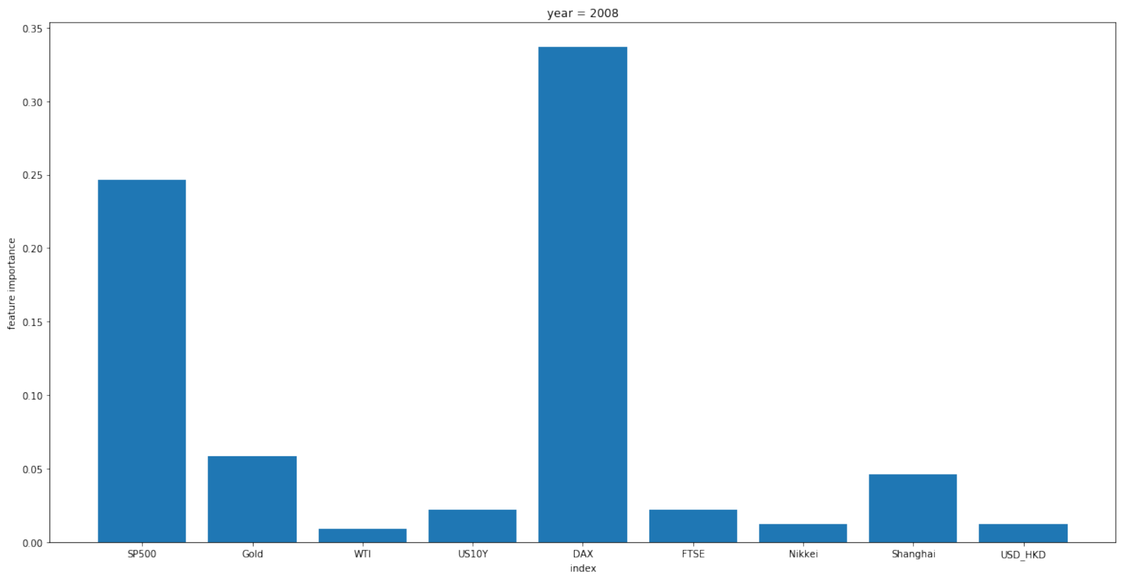
```
In [10]: for v in range(2005,2020):
             df_v=df.loc[df.loc[:,'year']==v, :]
             df_v=df_v.drop(columns=['year'])
             feature_v, target_v =  timeseries_to_array(df_v, history_steps = 5)
             model = RandomForestRegressor(n_estimators = 100, max_depth = 10,
                                           max_features = 0.7, oob_score = True, verbose = 0)
             model.fit(feature_v, target_v)
             y_pred = model.predict(feature_v)

             #feature importance
             FIP = np.zeros((len(feature_files+[target_file])*4*5,))
             for n in range(10):
                 FIP = FIP + model.feature_importances_
             FIP_10 = FIP / 10

             n_index=len(feature_files+[target_file])
             history_steps = 5
             FIP_by_index = np.zeros((n_index,))
             for n in range(n_index):
                 for m in range(history_steps):
                     FIP_by_index[n] = FIP_by_index[n]+ np.sum(
                         FIP[ m*n_index*4 + (n)*4: m*n_index*4 + (n+1)*4])

             plt.figure(figsize=(20, 10))
             plt.bar(feature_files, FIP_by_index[1:]
                    )
             plt.title('year = '+str(v))
             plt.xlabel('index')
```

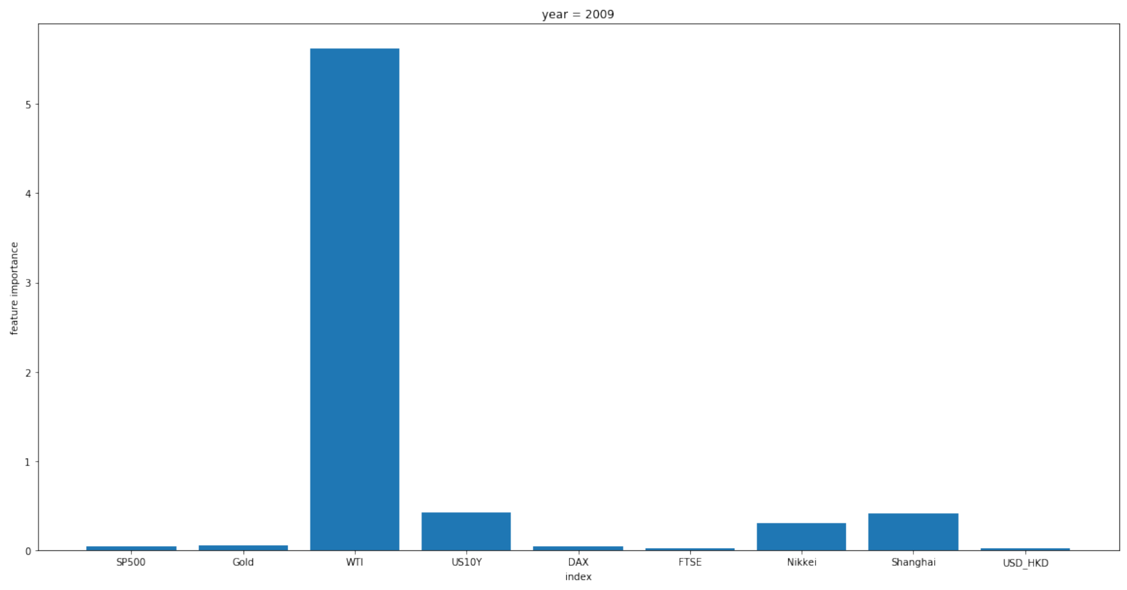
```
        plt.ylabel('feature importance')
    plt.show()
```

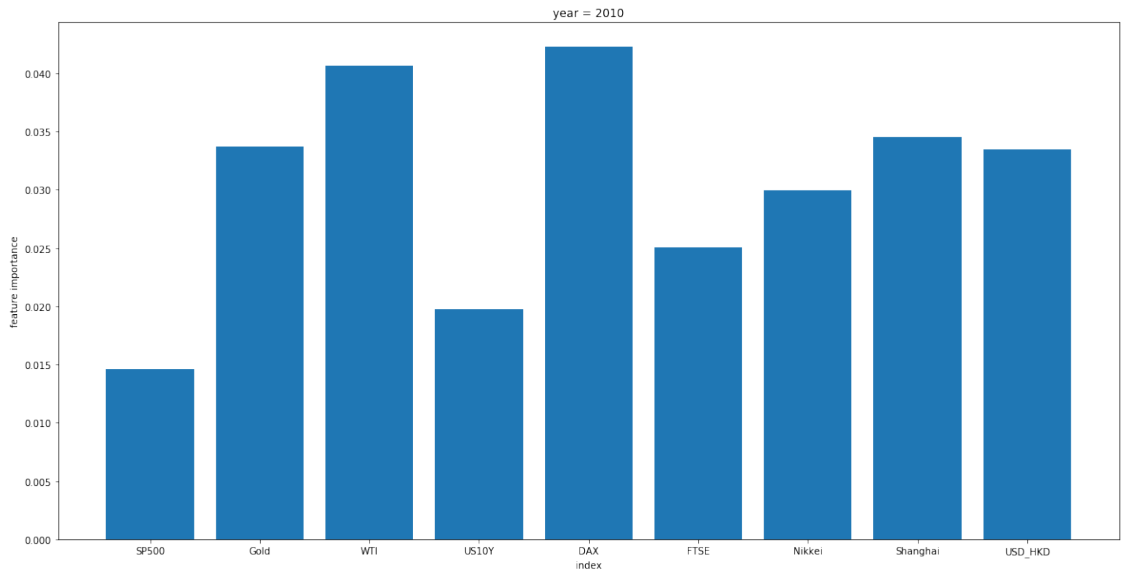


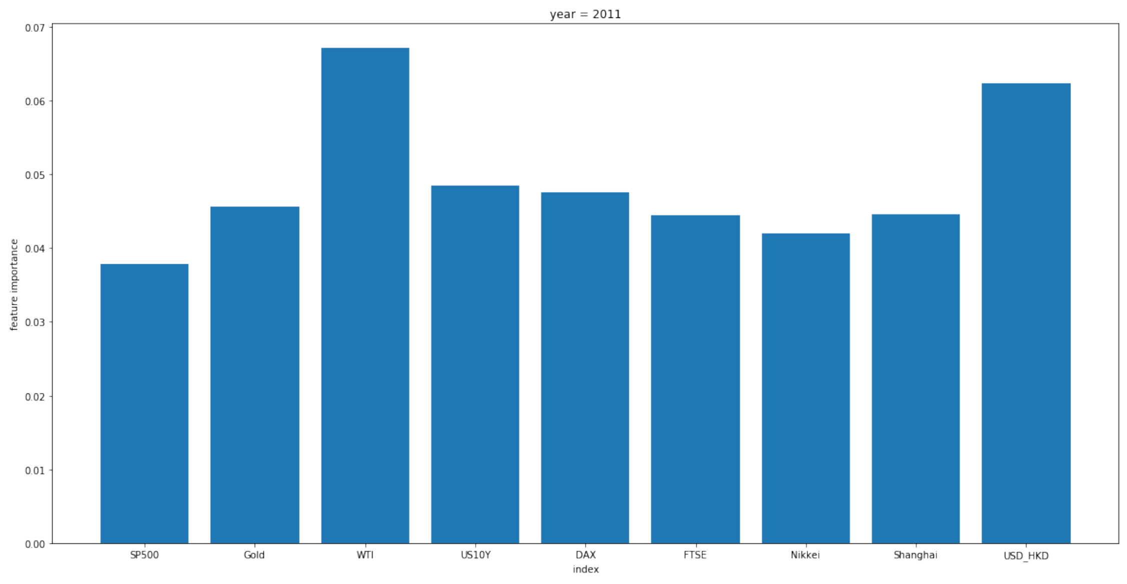


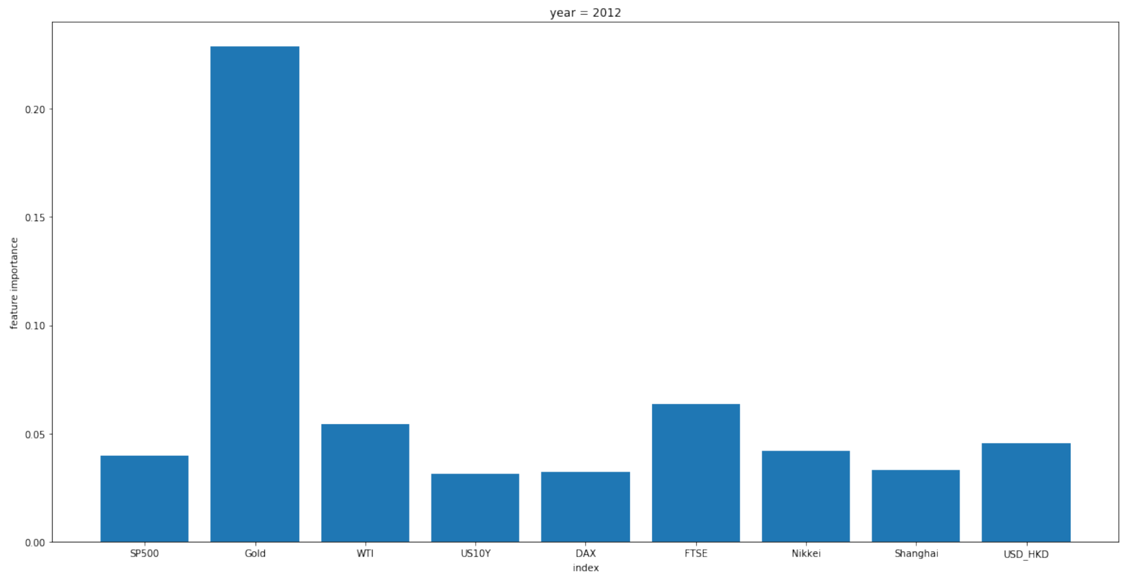

year = 2007
feature importance
index
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
0
1
2
3
4
5

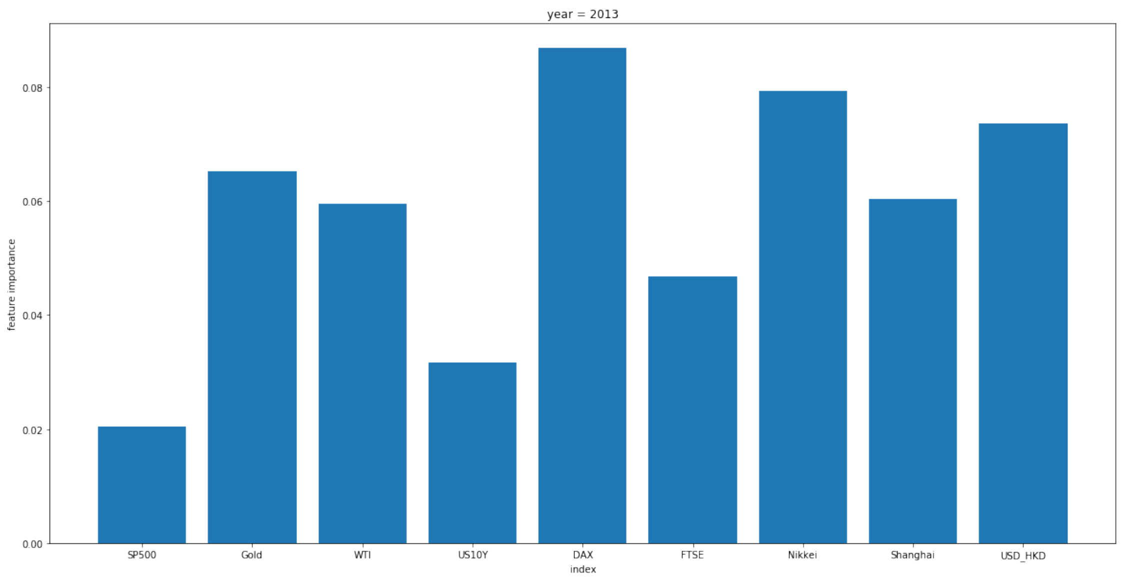

year = 2008
feature importance
index
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35

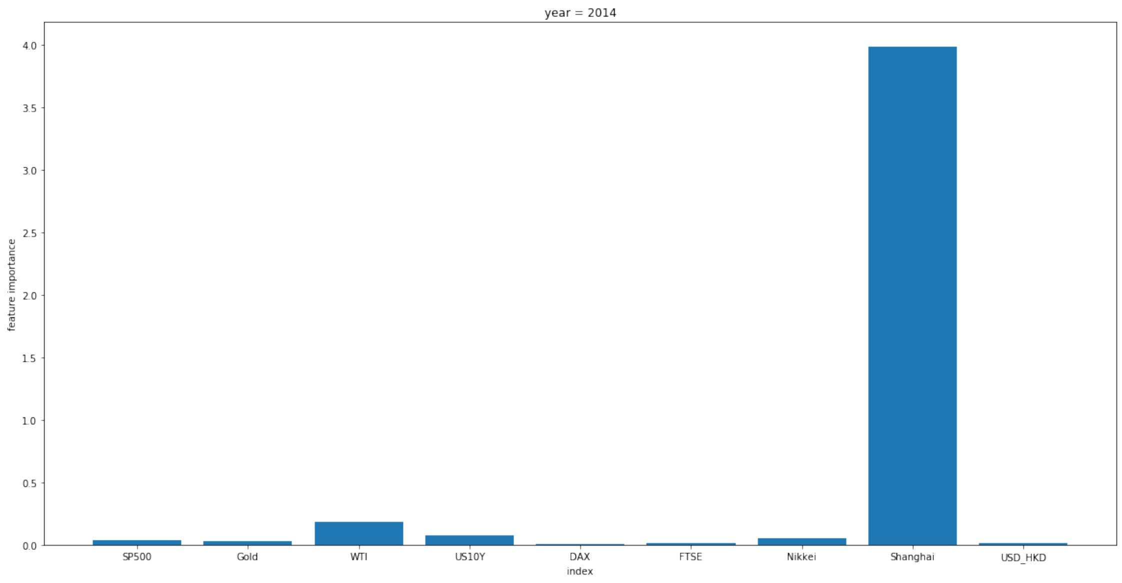

year = 2009
feature importance
0
1
2
3
4
5
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index

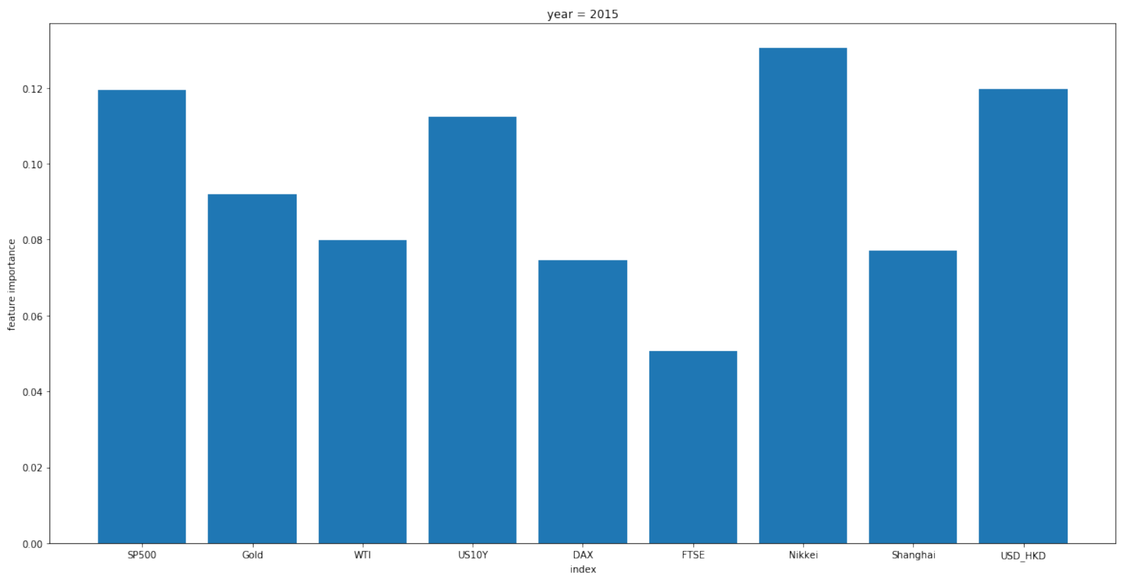

year = 2010
feature importance
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0.040
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index

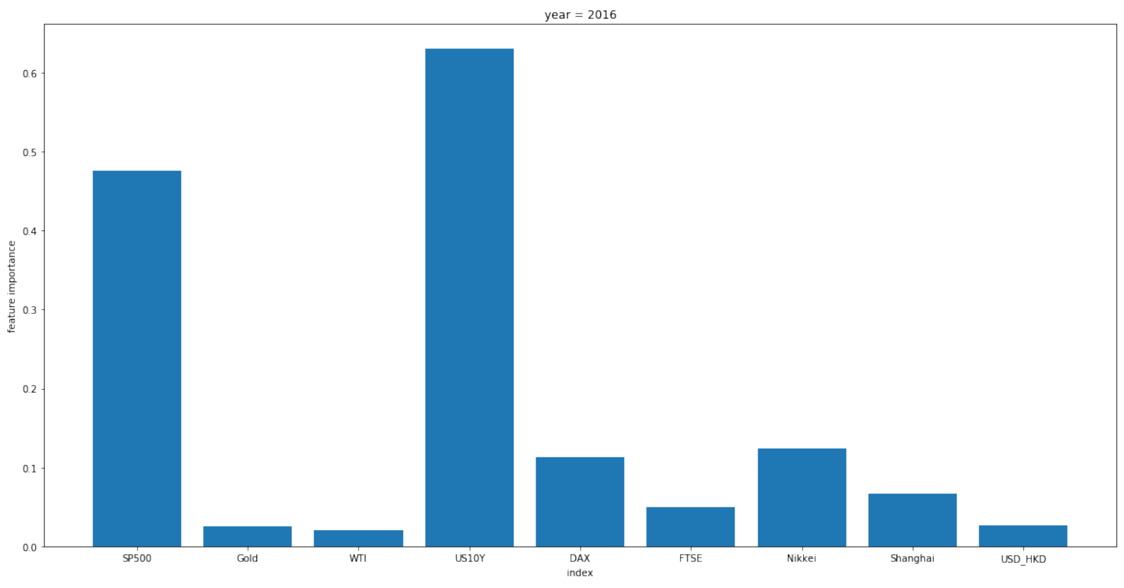

year = 2011
feature importance
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index

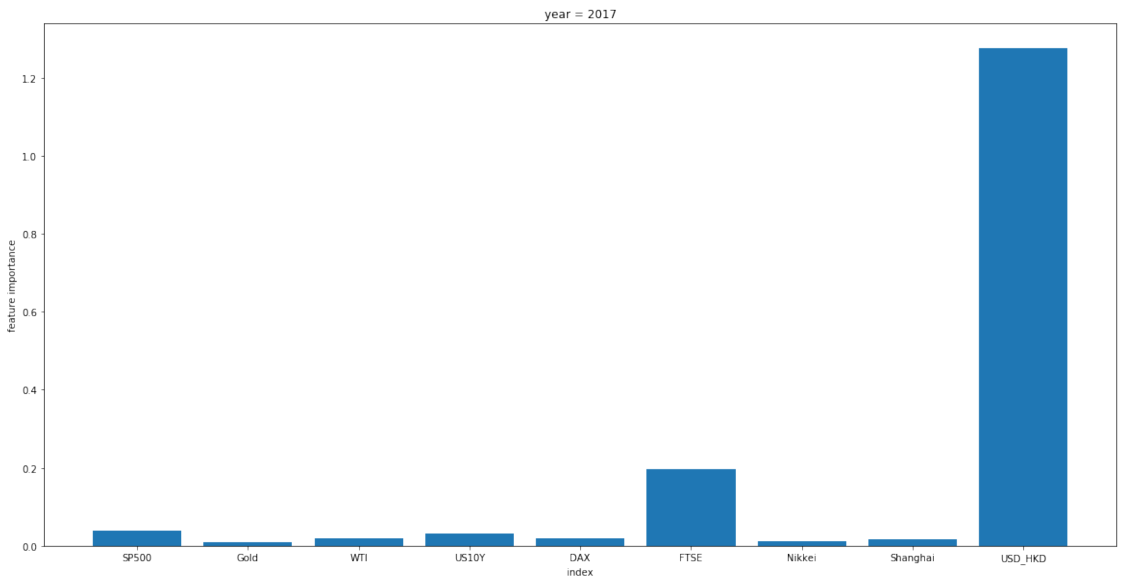

year = 2012
feature importance
0.00
0.05
0.10
0.15
0.20
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index

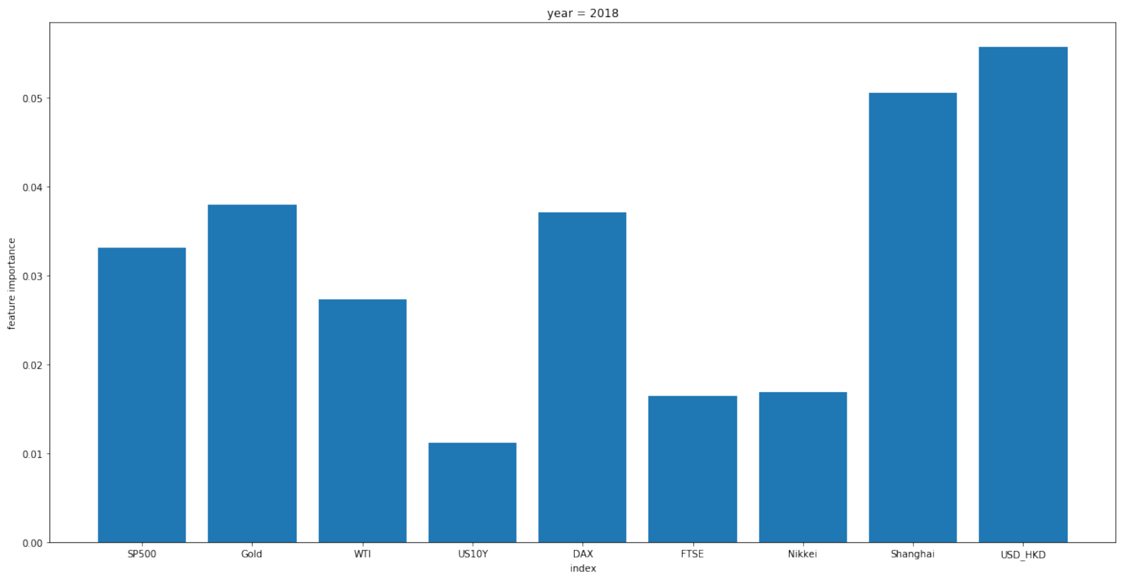

year = 2013
feature importance
0.00
0.02
0.04
0.06
0.08
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index

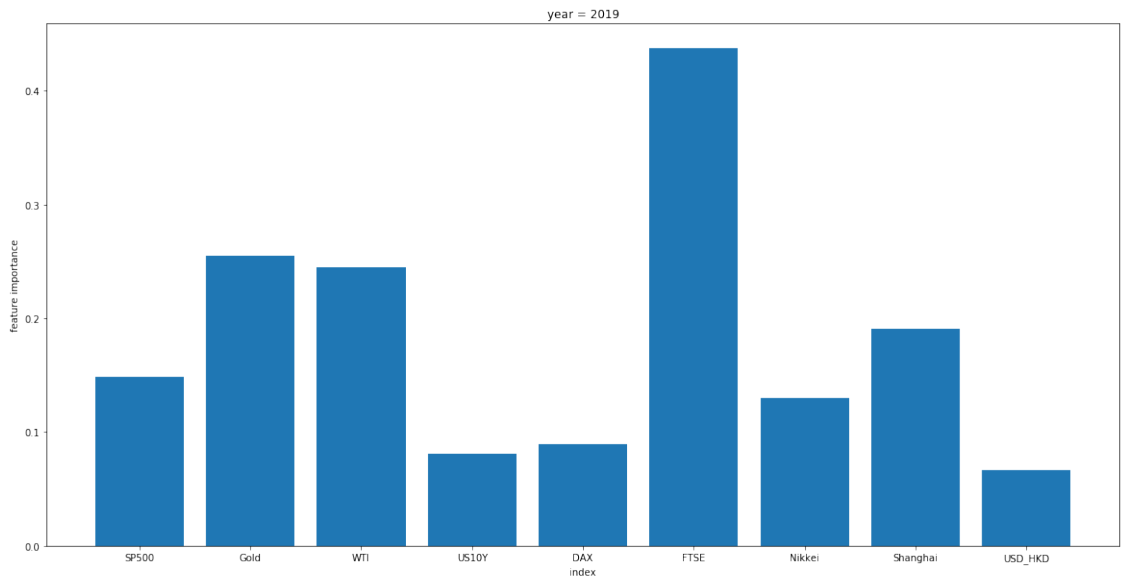

year = 2014
feature importance
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index


year = 2015
feature importance
0.00
0.02
0.04
0.06
0.08
0.10
0.12
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index


year = 2016
feature importance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
index


year = 2017
feature importance
index
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
0.0
0.2
0.4
0.6
0.8
1.0
1.2


year = 2018
feature importance
index
SP500
Gold
WTI
US10Y
DAX
FTSE
Nikkei
Shanghai
USD_HKD
0.00
0.01
0.02
0.03
0.04
0.05



From these 15 graphs, the importancy of features changes in different year. For example, the German stock index,DAX, is the most important features in 2005. But, in 2014, the China stock index, Shanghai, becomes the most important feature. There is no features that has strong effect in 2019. So this analysis gives us a big picture about how feature importancies changing with years and help us to make investment strategy.