

```
In [1]: # This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input direct

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserved as output when you cre
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

/kaggle/input/usaids-final-submission/submission\_format.csv  
/kaggle/input/usaids-final-submission/contraceptive\_logistics\_data.csv  
/kaggle/input/usaidsfinalsubmission/service\_delivery\_site\_data.csv

```
In [2]: %matplotlib inline
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
import seaborn as sns
import matplotlib.pyplot as plt
import time

from sklearn.model_selection import train_test_split, GridSearchCV
import matplotlib.pyplot as plt
from xgboost import XGBRegressor
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import mean_squared_error
from math import sqrt
```

```
In [3]: train=pd.read_csv('../input/usaaid-final-submission/contraceptive_logistics_data.csv')
sub = pd.read_csv('../input/usaaid-final-submission/submission_format.csv')
test = pd.read_csv('../input/usaaid-final-submission/submission_format.csv')
sd=pd.read_csv('../input/usaaidfinalsubmission/service_delivery_site_data.csv')
```

```
In [4]: train.columns
```

```
Out[4]: Index(['year', 'month', 'region', 'district', 'site_code', 'product_code',
              'stock_initial', 'stock_received', 'stock_distributed',
              'stock_adjustment', 'stock_end', 'average_monthly_consumption',
              'stock_stockout_days', 'stock_ordered'],
              dtype='object')
```

```
In [5]: test.columns
```

```
Out[5]: Index(['year', 'month', 'site_code', 'product_code', 'predicted_value'], dtype='object')
```

```
In [6]: test.head()
```

```
Out[6]:
```

	year	month	site_code	product_code	predicted_value
0	2019	10	C4001	AS27134	0
1	2019	10	C4001	AS27132	0
2	2019	10	C4001	AS27000	0
3	2019	10	C4001	AS27137	0
4	2019	10	C4001	AS27138	0

```
In [7]: sd.columns
```

```
Out[7]: Index(['site_code', 'site_type', 'site_region', 'site_district',
              'site_latitude', 'site_longitude'],
              dtype='object')
```

```
In [8]: #drop columns in the training data that are not useful for builing the model
train.drop(columns={'stock_initial', 'stock_received', 'stock_adjustment',
                  'stock_end', 'average_monthly_consumption',
                  'stock_stockout_days', 'stock_ordered'}, inplace=True)
```

```
In [9]: test.drop(['predicted_value'], axis =1, inplace = True)
```

```
In [10]: test.head()
```

```
Out[10]:
```

	year	month	site_code	product_code
0	2019	10	C4001	AS27134
1	2019	10	C4001	AS27132
2	2019	10	C4001	AS27000
3	2019	10	C4001	AS27137
4	2019	10	C4001	AS27138

```
In [11]: test.dtypes
```

```
Out[11]: year          int64
month          int64
site_code      object
product_code    object
dtype: object
```

```
In [12]: test=pd.merge(test,sd,on='site_code',how='left') #Merge test data with service delivery site data
test.rename(columns={'site_region':'region','site_district':'district'},inplace=True)
test=test[['year', 'month', 'region','district','site_code', 'product_code']]
```

```
In [13]: train.head(2).append(test.head(2))
```

```
Out[13]:
```

	year	month	region	district	site_code	product_code	stock_distributed
0	2019	1	INDENIE-DJUABLIN	ABENGOUROU	C4001	AS27134	21.0
1	2019	1	INDENIE-DJUABLIN	ABENGOUROU	C4001	AS27132	3.0
0	2019	10	INDENIE-DJUABLIN	ABENGOUROU	C4001	AS27134	NaN
1	2019	10	INDENIE-DJUABLIN	ABENGOUROU	C4001	AS27132	NaN

```
In [14]: train['train_or_test']='train'
test['train_or_test']='test'
df=pd.concat([train,test])
```

```
In [15]: #Label encode region, district, site_code and product_code so its values can be accepted by the model
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for col in ['region', 'district', 'site_code', 'product_code']:
    df[col]= df[col].astype('str')
    df[col]= le.fit_transform(df[col])
```

```
In [16]: train=df.loc[df.train_or_test.isin(['train'])]
test=df.loc[df.train_or_test.isin(['test'])]
train.drop(columns={'train_or_test'},axis=1,inplace=True)
test.drop(columns={'train_or_test'},axis=1,inplace=True)
```

/opt/conda/lib/python3.7/site-packages/pandas/core/frame.py:4164: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy) ([https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy))  
errors=errors,

```
In [17]: train.head()
```

```
Out[17]:
```

	year	month	region	district	site_code	product_code	stock_distributed
0	2019	1	11	0	119	5	21.0
1	2019	1	11	0	119	3	3.0
2	2019	1	11	0	119	2	22.0
3	2019	1	11	0	119	6	0.0
4	2019	1	11	0	119	7	2.0

```
In [18]: train.year.unique()
```

```
Out[18]: array([2019, 2018, 2017, 2016])
```

```
In [19]: test.head()
```

```
Out[19]:
```

	year	month	region	district	site_code	product_code	stock_distributed
0	2019	10	11	0	119	5	NaN
1	2019	10	11	0	119	3	NaN
2	2019	10	11	0	119	2	NaN
3	2019	10	11	0	119	6	NaN
4	2019	10	11	0	119	7	NaN

```
In [20]: test.year.unique()
```

```
Out[20]: array([2019])
```

```
In [21]: #convert product code in both train and test data from numerical variable to categorical variable
train['product_code'] = train['product_code'].astype('category')
test['product_code'] = test['product_code'].astype('category')
```

/opt/conda/lib/python3.7/site-packages/ipykernel\_launcher.py:2: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy) ([https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy))

/opt/conda/lib/python3.7/site-packages/ipykernel\_launcher.py:3: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy) ([https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy))

This is separate from the ipykernel package so we can avoid doing imports until

```
In [22]: train = pd.get_dummies(train, drop_first = True)
test = pd.get_dummies(test, drop_first = True)
```

In [23]: `train.columns`

Out[23]: Index(['year', 'month', 'region', 'district', 'site\_code', 'stock\_distributed',  
 'product\_code\_1', 'product\_code\_2', 'product\_code\_3', 'product\_code\_4',  
 'product\_code\_5', 'product\_code\_6', 'product\_code\_7', 'product\_code\_8',  
 'product\_code\_9', 'product\_code\_10'],  
 dtype='object')

In [24]: `test.columns`

Out[24]: Index(['year', 'month', 'region', 'district', 'site\_code', 'stock\_distributed',  
 'product\_code\_1', 'product\_code\_2', 'product\_code\_3', 'product\_code\_4',  
 'product\_code\_5', 'product\_code\_6', 'product\_code\_7', 'product\_code\_8',  
 'product\_code\_9', 'product\_code\_10'],  
 dtype='object')

In [25]: `train.columns`

Out[25]: Index(['year', 'month', 'region', 'district', 'site\_code', 'stock\_distributed',  
 'product\_code\_1', 'product\_code\_2', 'product\_code\_3', 'product\_code\_4',  
 'product\_code\_5', 'product\_code\_6', 'product\_code\_7', 'product\_code\_8',  
 'product\_code\_9', 'product\_code\_10'],  
 dtype='object')

In [26]: *#both test and submission data have the same number of records after data preprocessing*  
`len(test), len(sub)`

Out[26]: (3115, 3115)

In [27]: `train.head()`

Out[27]:

	year	month	region	district	site_code	stock_distributed	product_code_1	product_code_2	product_code_3	product_code_4	product
0	2019	1	11	0	119	21.0	0	0	0	0	
1	2019	1	11	0	119	3.0	0	0	1	0	
2	2019	1	11	0	119	22.0	0	1	0	0	
3	2019	1	11	0	119	0.0	0	0	0	0	
4	2019	1	11	0	119	2.0	0	0	0	0	

In [28]: `test.head()`

Out[28]:

	year	month	region	district	site_code	stock_distributed	product_code_1	product_code_2	product_code_3	product_code_4	product
0	2019	10	11	0	119	NaN	0	0	0	0	
1	2019	10	11	0	119	NaN	0	0	1	0	
2	2019	10	11	0	119	NaN	0	1	0	0	
3	2019	10	11	0	119	NaN	0	0	0	0	
4	2019	10	11	0	119	NaN	0	0	0	0	

In [29]: `train.corr()`

Out[29]:

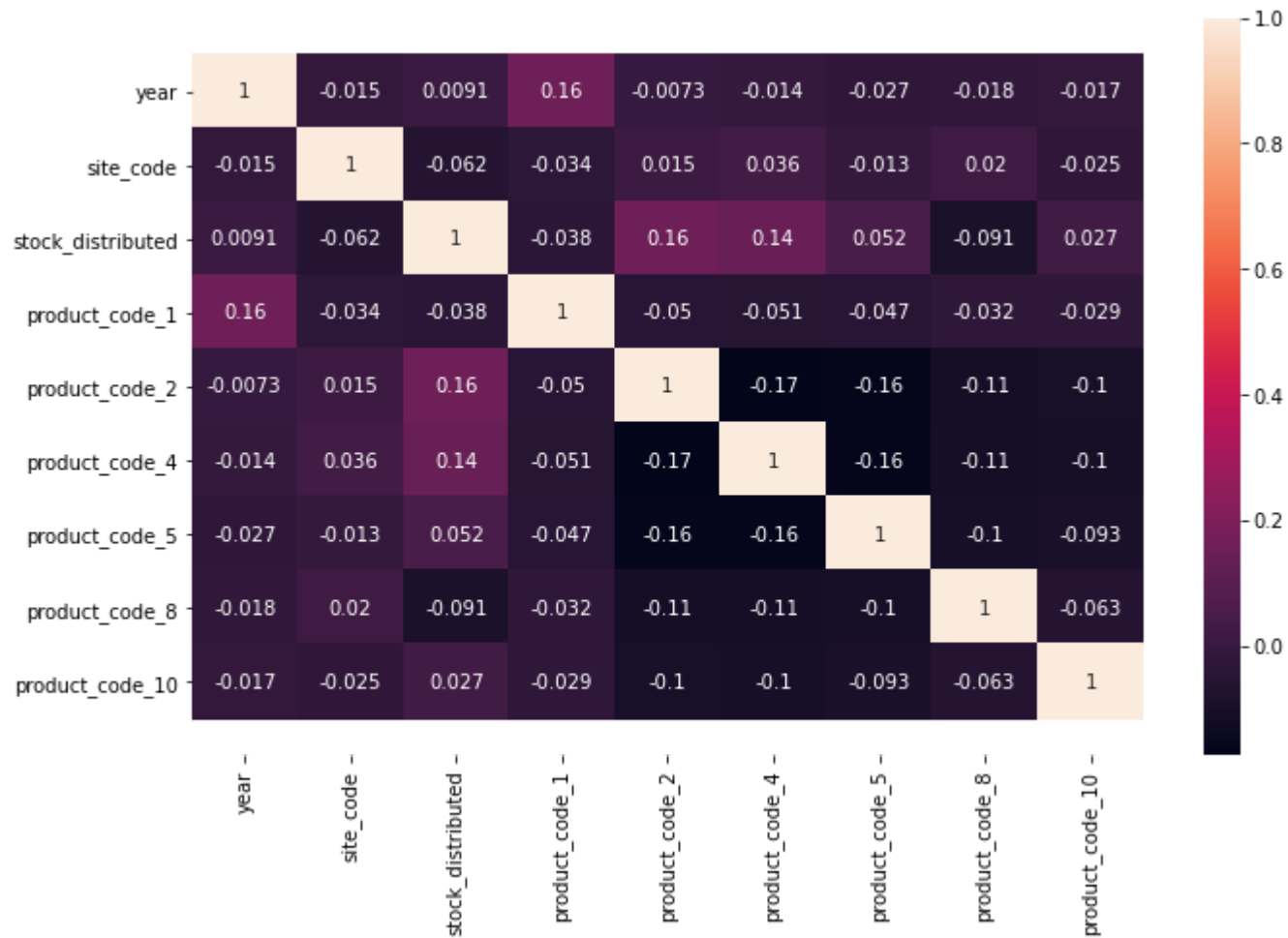
	year	month	region	district	site_code	stock_distributed	product_code_1	product_code_2	product_code_3	product_code_4	product
year	1.000000	-0.191016	-0.028990	-0.016426	-0.015245	0.009055	0.156266	-0.007252	-0.011982	-0.013596	-0.027153
month	-0.191016	1.000000	-0.001431	0.001167	0.002958	0.004145	-0.009155	0.002897	0.000583	-0.002013	0.000126
region	-0.028990	-0.001431	1.000000	-0.009061	0.520614	-0.030530	-0.037977	0.005724	-0.013614	0.022181	-0.018690
district	-0.016426	0.001167	-0.009061	1.000000	0.094775	-0.025625	-0.004275	-0.020570	0.004507	-0.029640	-0.018258
site_code	-0.015245	0.002958	0.520614	0.094775	1.000000	-0.062439	-0.033595	0.014692	-0.011797	0.035514	-0.013000
stock_distributed	0.009055	0.004145	-0.030530	-0.025625	-0.062439	1.000000	-0.037728	0.158383	-0.088686	0.141248	0.052328
product_code_1	0.156266	-0.009155	-0.037977	-0.004275	-0.033595	-0.037728	1.000000	-0.049957	-0.045124	-0.050540	-0.046570
product_code_2	-0.007252	0.002897	0.005724	-0.020570	0.014692	0.158383	-0.049957	1.000000	-0.155510	-0.174176	-0.160493
product_code_3	-0.011982	0.000583	-0.013614	0.004507	-0.011797	-0.088686	-0.045124	-0.155510	1.000000	-0.157332	-0.144960
product_code_4	-0.013596	-0.002013	0.022181	-0.029640	0.035514	0.141248	-0.050540	-0.174176	-0.157332	1.000000	-0.141494
product_code_5	-0.027153	0.000126	-0.018690	-0.018258	-0.013000	0.052328	-0.046570	-0.160493	-0.144960	-0.141494	1.000000
product_code_6	0.006429	0.000730	0.015869	-0.001128	0.011098	-0.076418	-0.045441	-0.156601	-0.141494	-0.141494	-0.141494
product_code_7	0.044771	0.000397	-0.004848	0.007058	0.012047	-0.071193	-0.043440	-0.149707	-0.135221	-0.135221	-0.135221
product_code_8	-0.018397	-0.002231	0.049511	0.048489	0.019765	-0.090831	-0.031619	-0.108967	-0.098421	-0.098421	-0.098421
product_code_9	-0.003149	0.013983	-0.007973	0.028481	-0.021152	-0.075334	-0.025287	-0.087146	-0.078717	-0.078717	-0.078717
product_code_10	-0.017107	-0.002652	-0.016273	-0.010105	-0.024723	0.027305	-0.029015	-0.099994	-0.090303	-0.090303	-0.090303

```
In [30]: #a further dropping of variables that are not useful to the model due to multicollinearity effect  
train.drop(columns = ['month', 'district', 'region', 'product_code_6', 'product_code_3', 'product_code_7', 'prod  
test.drop(columns = ['month', 'district', 'region', 'product_code_6', 'product_code_3', 'product_code_7', 'produ
```



```
In [31]: corr = train.corr()
fig, ax = plt.subplots()
fig.set_size_inches(11, 7)
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, annot = True, ax = ax)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[31]: (9.5, -0.5)



```
In [32]: #this code takes care of invalid zeros in cases where stock_distributed for a contraceptive product at a service
train['stock_distributed'] = np.where(train['stock_distributed'] == 0, train['stock_distributed'].median(),
                                     train['stock_distributed'])
```

```
In [33]: #split the data into 60% training set and 40% validation set
X=train.drop(columns={'stock_distributed'})
y=train.loc[:,['stock_distributed']]
del test['stock_distributed']

train_X, valid_X, train_y, valid_y = train_test_split(X, y, test_size=0.4, random_state=15)
```

```
In [34]: #Define the model
my_model = XGBRegressor()
```

```
In [35]: ##Hyper Parameter Optimization
booster = ['gbtree', 'gblinear']
base_score = [0.25, 0.5, 0.75, 1]
eta = [0.01, 0.015, 0.025, 0.05, 0.1]
gamma = [0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0]
n_estimators = [100, 500, 900, 1100, 1500]
max_depth = [2, 3, 5, 10, 15]
min_child_weight = [1, 3, 5, 7]
subsample = [0.6, 0.7, 0.8, 0.9, 1.0]
colsample_bytree = [0.6, 0.7, 0.8, 0.9, 1.0]
reg_lambda = [0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 1.0]
reg_alpha = [0, 0.1, 0.5, 1.0, 1.5]
booster = ['gbtree', 'gblinear']
learning_rate = [0.05, 0.1, 0.15, 0.20]
min_child_weight = [1, 2, 3, 4]

#Define the grid of hyperparameters to search
hyperparameter_grid = {
    'n_estimators': n_estimators,
    'max_depth': max_depth,
    'learning_rate': learning_rate,
    'min_child_weight': min_child_weight,
    'booster': booster,
    'base_score': base_score
}
```

```
In [36]: #Set up the random search with 4-fold cross validation
random_cv = RandomizedSearchCV(estimator=my_model, param_distributions = hyperparameter_grid,
                               cv = 5, n_iter = 50,
                               scoring = 'neg_mean_absolute_error', n_jobs = 4,
                               verbose = 5,
                               return_train_score = True,
                               random_state = 42)
```

```
In [37]: #fit the model
random_cv.fit(train_X, train_y)
```

Fitting 5 folds for each of 50 candidates, totalling 250 fits

[Parallel(n\_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.

[Parallel(n\_jobs=4)]: Done 10 tasks | elapsed: 25.8s

/opt/conda/lib/python3.7/site-packages/joblib/externals/loky/process\_executor.py:706: UserWarning: A worker stopped while some jobs were given to the executor. This can be caused by a too short worker timeout or by a memory leak.

"timeout or by a memory leak.", UserWarning

[Parallel(n\_jobs=4)]: Done 64 tasks | elapsed: 4.6min

[Parallel(n\_jobs=4)]: Done 154 tasks | elapsed: 7.8min

[Parallel(n\_jobs=4)]: Done 250 out of 250 | elapsed: 11.4min finished

```
Out[37]: RandomizedSearchCV(cv=5,
                             estimator=XGBRegressor(base_score=None, booster=None,
                                                    colsample_bylevel=None,
                                                    colsample_bynode=None,
                                                    colsample_bytree=None, gamma=None,
                                                    gpu_id=None, importance_type='gain',
                                                    interaction_constraints=None,
                                                    learning_rate=None,
                                                    max_delta_step=None, max_depth=None,
                                                    min_child_weight=None, missing=nan,
                                                    monotone_constraints=None,
                                                    n_estimators=100, n...
                                                    validate_parameters=None,
                                                    verbosity=None),
                             n_iter=50, n_jobs=4,
                             param_distributions={'base_score': [0.25, 0.5, 0.75, 1],
                                                  'booster': ['gbtree', 'gblinear'],
                                                  'learning_rate': [0.05, 0.1, 0.15, 0.2],
                                                  'max_depth': [2, 3, 5, 10, 15],
                                                  'min_child_weight': [1, 2, 3, 4],
                                                  'n_estimators': [100, 500, 900, 1100,
                                                                1500]},
                             random_state=42, return_train_score=True,
                             scoring='neg_mean_absolute_error', verbose=5)
```

```
In [38]: random_cv.best_estimator_
```

```
Out[38]: XGBRegressor(base_score=1, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
                      importance_type='gain', interaction_constraints='',
                      learning_rate=0.1, max_delta_step=0, max_depth=15,
                      min_child_weight=1, missing=nan, monotone_constraints='()',
                      n_estimators=900, n_jobs=0, num_parallel_tree=1, random_state=0,
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
                      tree_method='exact', validate_parameters=1, verbosity=None)
```

```
In [39]: random_cv.best_params_
```

```
Out[39]: {'n_estimators': 900,
          'min_child_weight': 1,
          'max_depth': 15,
          'learning_rate': 0.1,
          'booster': 'gbtree',
          'base_score': 1}
```

In [40]: *#Apply Grid search to the best parameters from the Random search with a consideration of close values*

```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'booster': [random_cv.best_params_['booster']],
    'max_depth': [random_cv.best_params_['max_depth']],
    'learning_rate': [random_cv.best_params_['learning_rate']],
    'min_child_weight': [random_cv.best_params_['min_child_weight'],
                        random_cv.best_params_['min_child_weight']+2,
                        random_cv.best_params_['min_child_weight'] + 4],
    'base_score': [random_cv.best_params_['base_score'] + 2,
                  random_cv.best_params_['base_score'] + 1,
                  random_cv.best_params_['base_score'],
                  random_cv.best_params_['base_score'] + 3,
                  random_cv.best_params_['base_score'] + 5],
    'n_estimators': [random_cv.best_params_['n_estimators'] - 200, random_cv.best_params_['n_estimators'] - 100,
                    random_cv.best_params_['n_estimators'],
                    random_cv.best_params_['n_estimators'] + 100, random_cv.best_params_['n_estimators'] + 200]
}

print(param_grid)

{'booster': ['gbtree'], 'max_depth': [15], 'learning_rate': [0.1], 'min_child_weight': [1, 3, 5], 'base_score': [3, 2, 1, 4, 6], 'n_estimators': [700, 800, 900, 1000, 1100]}
```

```
In [41]: ##### Fit the grid_search to the data
my_model = XGBRegressor()
grid_search=GridSearchCV(estimator=my_model,param_grid=param_grid,cv=10,n_jobs=-1,verbose=2)
grid_search.fit(train_X,train_y)
```

Fitting 10 folds for each of 75 candidates, totalling 750 fits

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 33 tasks      | elapsed: 2.9min
[Parallel(n_jobs=-1)]: Done 154 tasks    | elapsed: 24.3min
[Parallel(n_jobs=-1)]: Done 357 tasks    | elapsed: 53.2min
[Parallel(n_jobs=-1)]: Done 640 tasks    | elapsed: 99.0min
[Parallel(n_jobs=-1)]: Done 750 out of 750 | elapsed: 119.6min finished
```

```
Out[41]: GridSearchCV(cv=10,
                    estimator=XGBRegressor(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None, max_delta_step=None,
                                           max_depth=None, min_child_weight=None,
                                           missing=nan, monotone_constraints=None,
                                           n_estimators=100, n_jobs...,
                                           num_parallel_tree=None, random_state=None,
                                           reg_alpha=None, reg_lambda=None,
                                           scale_pos_weight=None, subsample=None,
                                           tree_method=None, validate_parameters=None,
                                           verbosity=None),
                    n_jobs=-1,
                    param_grid={'base_score': [3, 2, 1, 4, 6], 'booster': ['gbtree'],
                                'learning_rate': [0.1], 'max_depth': [15],
                                'min_child_weight': [1, 3, 5],
                                'n_estimators': [700, 800, 900, 1000, 1100]},
                    verbose=2)
```

```
In [42]: grid_search.best_estimator_
```

```
Out[42]: XGBRegressor(base_score=4, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
                      importance_type='gain', interaction_constraints='',
                      learning_rate=0.1, max_delta_step=0, max_depth=15,
                      min_child_weight=1, missing=nan, monotone_constraints='()',
                      n_estimators=700, n_jobs=0, num_parallel_tree=1, random_state=0,
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
                      tree_method='exact', validate_parameters=1, verbosity=None)
```

```
In [43]: best_grid=grid_search.best_estimator_
```

```
In [44]: #The optimal grid search paramaters
         best_grid
```

```
Out[44]: XGBRegressor(base_score=4, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
                      importance_type='gain', interaction_constraints='',
                      learning_rate=0.1, max_delta_step=0, max_depth=15,
                      min_child_weight=1, missing=nan, monotone_constraints='()',
                      n_estimators=700, n_jobs=0, num_parallel_tree=1, random_state=0,
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
                      tree_method='exact', validate_parameters=1, verbosity=None)
```

```
In [45]: #prediction on the validation set
         valid_pred = best_grid.predict(valid_X)
```

```
In [46]: #RMSE score from fitting the model to the validation set
         rmse = sqrt(mean_squared_error(valid_y, valid_pred))

         print(rmse)
```

```
29.610726652402565
```

```
In [47]: #Predict stock distributed from OCT 2019 - DEC 2019
         pred = best_grid.predict(test)
```

```
In [48]: sub['predicted_value']=np.abs(pred)
```



```
In [49]: #Convert the predicted value to the nearest whole number  
sub['predicted_value'] = sub['predicted_value'].round()
```

```
In [50]: sub.to_csv('Fork of Third_Model.csv', index=False)
```