demo

June 2, 2024

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os

from sklearn.linear_model import ElasticNet
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
import joblib
from sklearn.metrics import r2_score

path = 'dataset'
trainPath = os.path.join(path, 'train.csv')
testPath = os.path.join(path, 'test.csv')
outPath = 'out'
modelPath = 'model'

train = pd.read_csv(trainPath)
test = pd.read_csv(testPath)
sample = pd.read_csv(os.path.join(path, 'sample_submission.csv'))

def outCsv(sample, fileName):
    sample.to_csv(os.path.join(outPath, fileName), index=False)

def outModel(model, fileName):
    joblib.dump(model, os.path.join(modelPath, fileName))
```

0.0.1

[ ]:
```
print(train.columns)
print(train.columns.shape)
feature = train.drop(columns=['id', 'FloodProbability']).columns
```

```
Index(['id', 'MonsoonIntensity', 'TopographyDrainage', 'RiverManagement',
       'Deforestation', 'Urbanization', 'ClimateChange', 'DamsQuality',
       'Siltation', 'AgriculturalPractices', 'Encroachments',
       'IneffectiveDisasterPreparedness', 'DrainageSystems',
       'CoastalVulnerability', 'Landslides', 'Watersheds',
```

```
       'DeterioratingInfrastructure', 'PopulationScore', 'WetlandLoss',
       'InadequatePlanning', 'PoliticalFactors', 'FloodProbability'],
      dtype='object')
(22,)
```

[ ]:
```
feature.shape
```

[ ]:
```
(20,)
```

[ ]:
```
print('train set null values: ', train.isnull().any().sum())
print('test set null values: ', test.isnull().any().sum())
```

```
train set null values:  0
test set null values:  0
```

[ ]:
```
print(train.shape)
print(test.shape)
```

```
(1117957, 22)
(745305, 21)
```

[ ]:
```
train.describe()
```

[ ]:

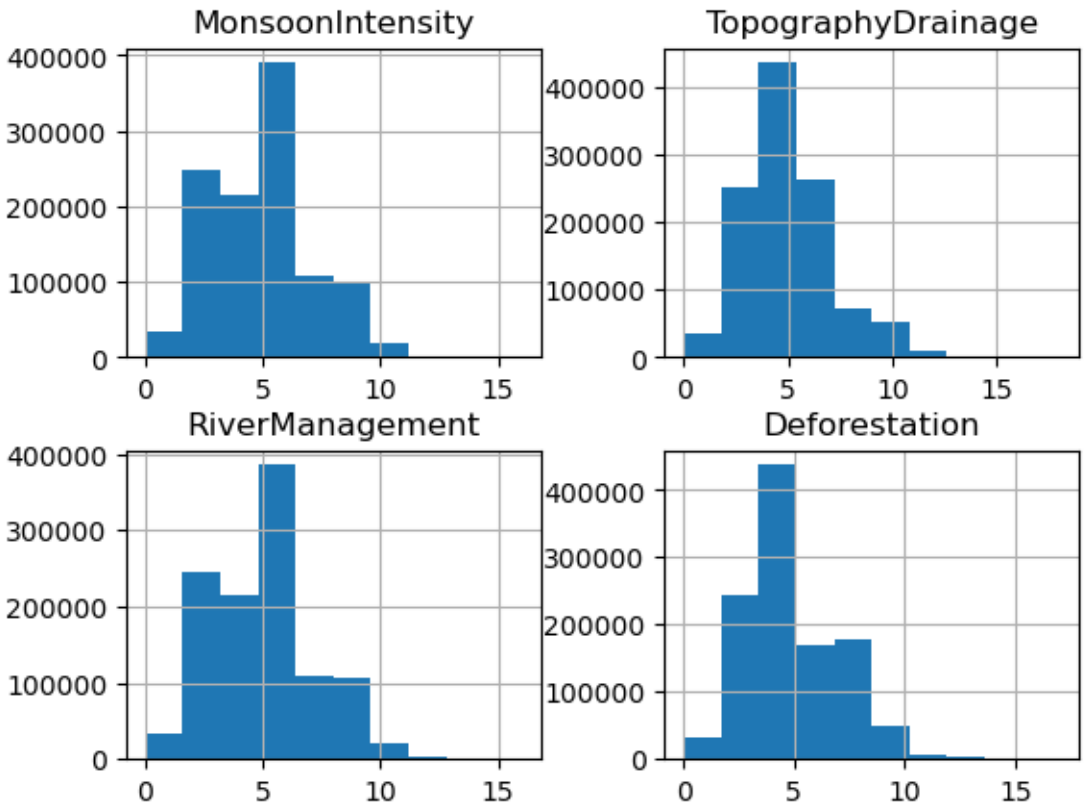
	id	MonsoonIntensity	TopographyDrainage	RiverManagement	\
count	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	
mean	5.589780e+05	4.921450e+00	4.926671e+00	4.955322e+00	
std	3.227265e+05	2.056387e+00	2.093879e+00	2.072186e+00	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	2.794890e+05	3.000000e+00	3.000000e+00	4.000000e+00	
50%	5.589780e+05	5.000000e+00	5.000000e+00	5.000000e+00	
75%	8.384670e+05	6.000000e+00	6.000000e+00	6.000000e+00	
max	1.117956e+06	1.600000e+01	1.800000e+01	1.600000e+01	

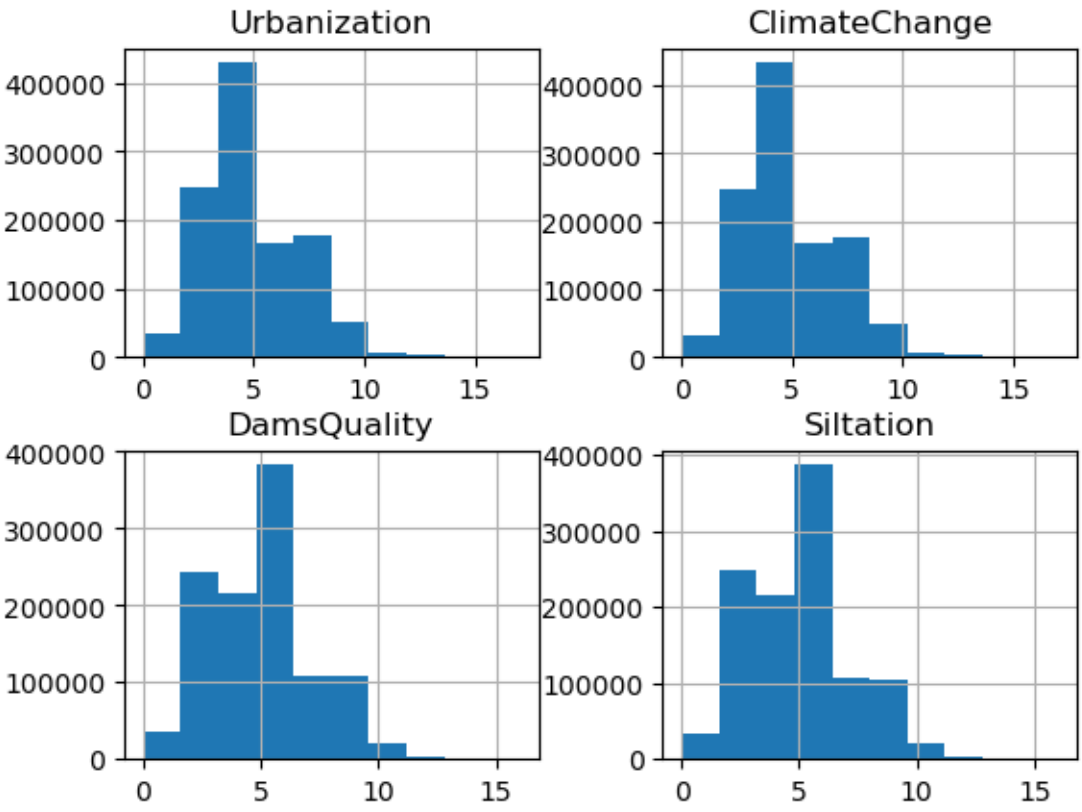
	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	\
count	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	
mean	4.942240e+00	4.942517e+00	4.934093e+00	4.955878e+00	4.927791e+00	
std	2.051689e+00	2.083391e+00	2.057742e+00	2.083063e+00	2.065992e+00	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	4.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	3.000000e+00	
50%	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	
75%	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	
max	1.700000e+01	1.700000e+01	1.700000e+01	1.600000e+01	1.600000e+01	

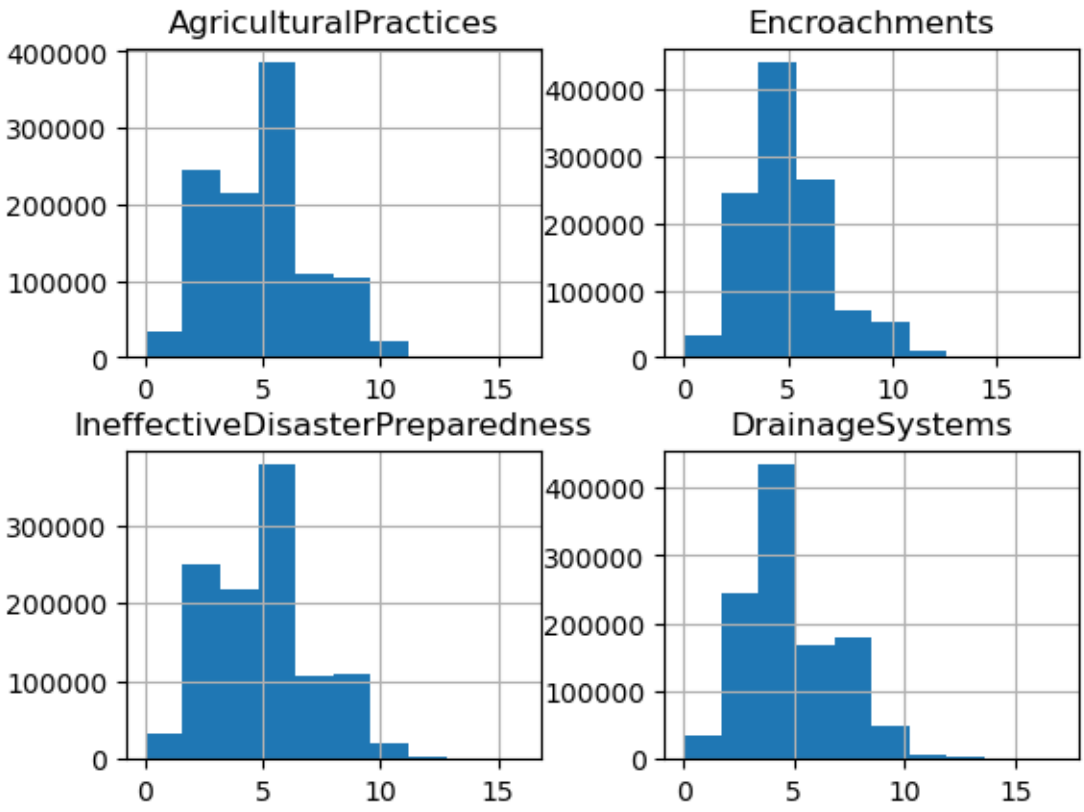
	AgriculturalPractices	…	DrainageSystems	CoastalVulnerability	\
count	1.117957e+06	…	1.117957e+06	1.117957e+06	
mean	4.942619e+00	…	4.946893e+00	4.953999e+00	
std	2.068545e+00	…	2.072333e+00	2.088899e+00	
min	0.000000e+00	…	0.000000e+00	0.000000e+00	
25%	3.000000e+00	…	4.000000e+00	3.000000e+00	

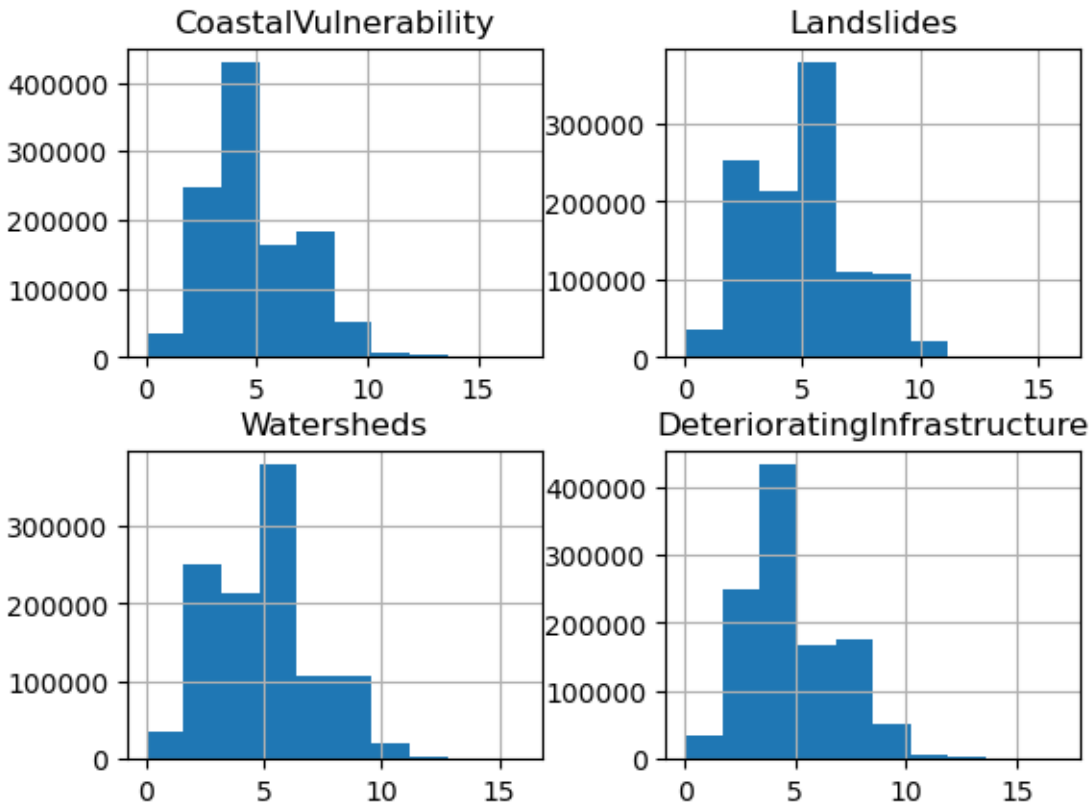
```
50%             5.000000e+00  …     5.000000e+00          5.000000e+00
75%             6.000000e+00  …     6.000000e+00          6.000000e+00
max             1.600000e+01  …     1.700000e+01          1.700000e+01

         Landslides    Watersheds  DeterioratingInfrastructure  \
count  1.117957e+06  1.117957e+06                 1.117957e+06
mean   4.931376e+00  4.929032e+00                 4.925907e+00
std    2.078287e+00  2.082395e+00                 2.064813e+00
min    0.000000e+00  0.000000e+00                 0.000000e+00
25%    3.000000e+00  3.000000e+00                 3.000000e+00
50%    5.000000e+00  5.000000e+00                 5.000000e+00
75%    6.000000e+00  6.000000e+00                 6.000000e+00
max    1.600000e+01  1.600000e+01                 1.700000e+01

       PopulationScore   WetlandLoss  InadequatePlanning  PoliticalFactors  \
count     1.117957e+06  1.117957e+06        1.117957e+06      1.117957e+06
mean      4.927520e+00  4.950859e+00        4.940587e+00      4.939004e+00
std       2.074176e+00  2.068696e+00        2.081123e+00      2.090350e+00
min       0.000000e+00  0.000000e+00        0.000000e+00      0.000000e+00
25%       3.000000e+00  4.000000e+00        3.000000e+00      3.000000e+00
50%       5.000000e+00  5.000000e+00        5.000000e+00      5.000000e+00
75%       6.000000e+00  6.000000e+00        6.000000e+00      6.000000e+00
max       1.800000e+01  1.900000e+01        1.600000e+01      1.600000e+01

       FloodProbability
count      1.117957e+06
mean       5.044803e-01
std        5.102610e-02
min        2.850000e-01
25%        4.700000e-01
50%        5.050000e-01
75%        5.400000e-01
max        7.250000e-01

[8 rows x 22 columns]
```

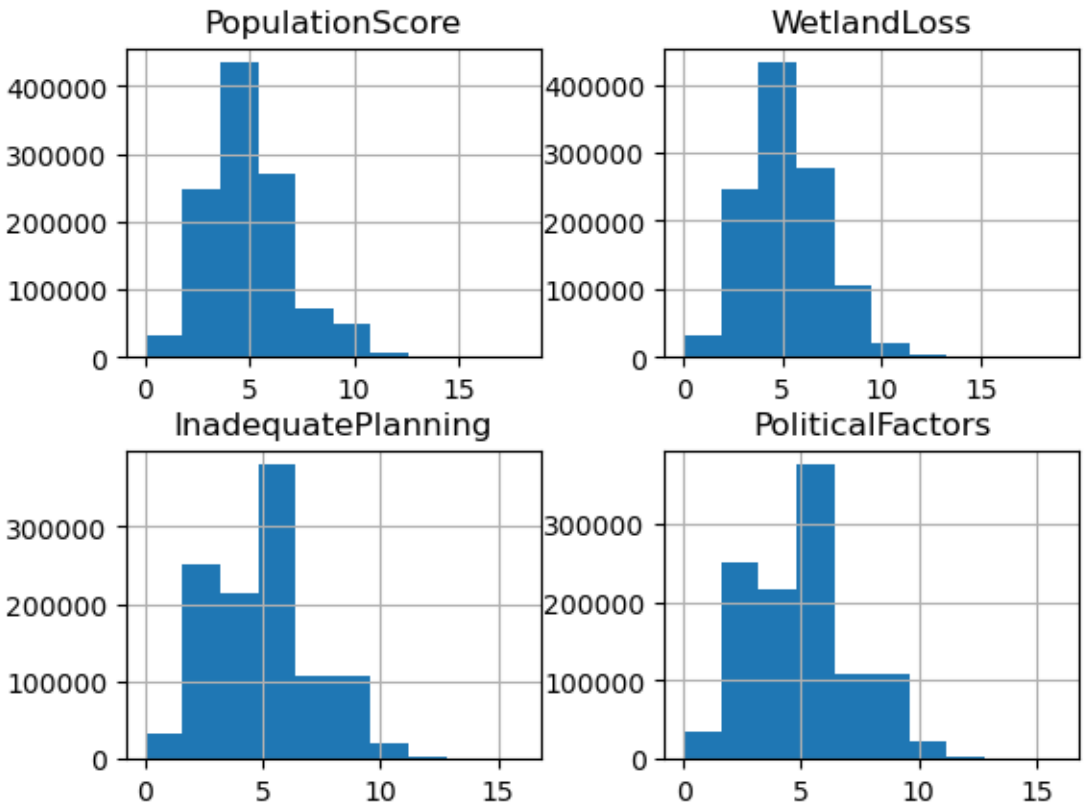
[ ]:
```python
for col in range(5):
    train[feature[ col*4: (col+1)*4 ]].hist()
    plt.savefig(os.path.join(outPath, f'hist_{col}'))
```


MonsoonIntensity
TopographyDrainage
RiverManagement
Deforestation
400000
300000
200000
100000
0
0
5
10
15


Urbanization
ClimateChange
DamsQuality
Siltation
400000
300000
200000
100000
0
0
5
10
15

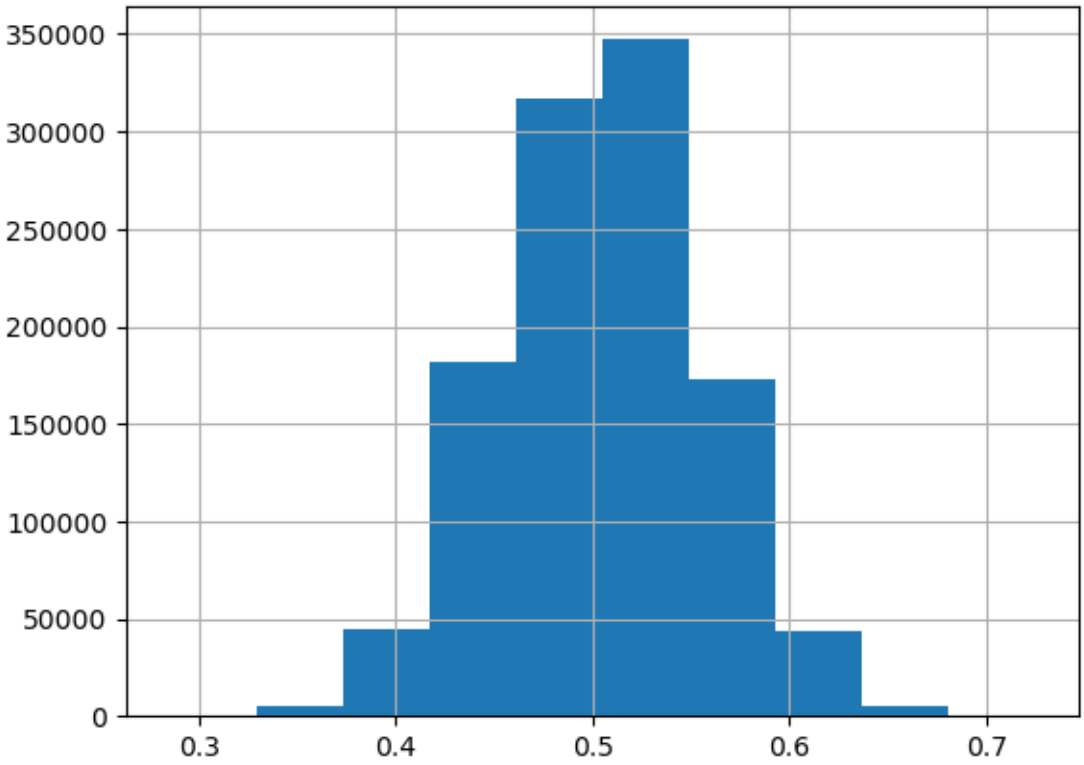

AgriculturalPractices
Encroachments
IneffectiveDisasterPreparedness
DrainageSystems
0
100000
200000
300000
400000
0
5
10
15


CoastalVulnerability
Landslides
Watersheds
DeterioratingInfrastructure
0
100000
200000
300000
400000
0
5
10
15



[ ]:
```
train['FloodProbability'].hist()
```

[ ]: <Axes: >



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[ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, StandardScaler

full_pipeline = Pipeline([
    ('stdScaler', StandardScaler()),
    ('minmaxScaler', MinMaxScaler())
])

X_train = full_pipeline.fit_transform(train[feature])
y_train = train['FloodProbability'].to_numpy()

X_test = full_pipeline.transform(test[feature])
```

0.0.3

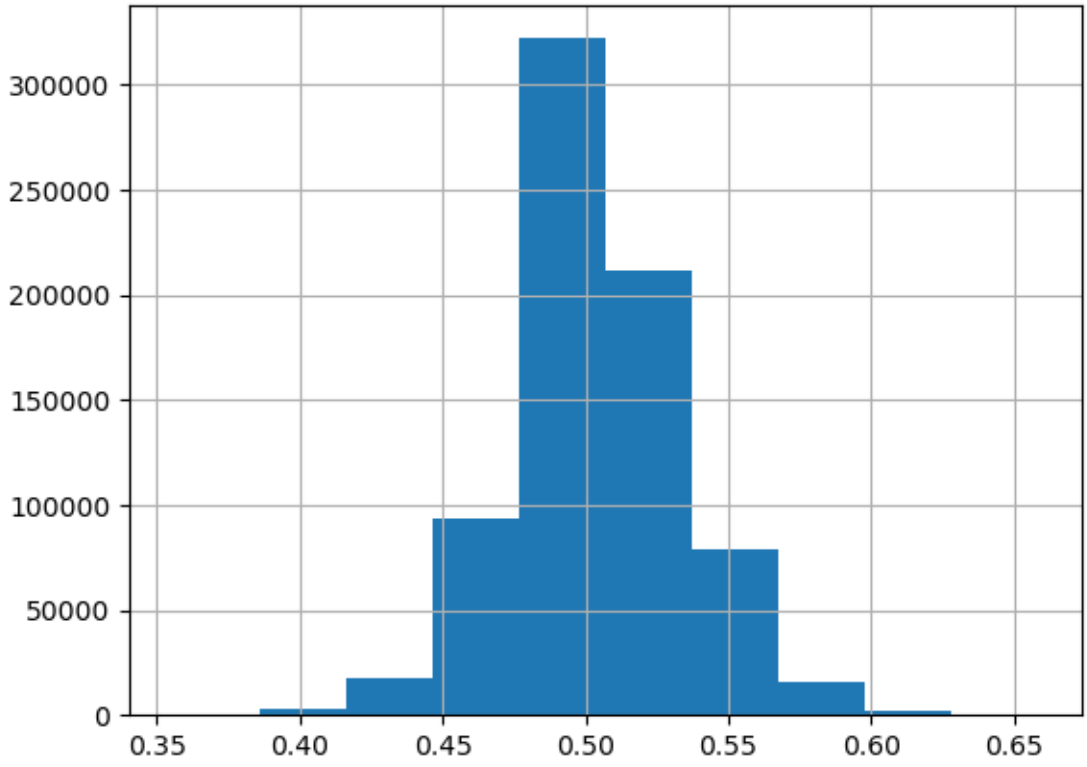
[ ]:
```
rf_model = RandomForestRegressor(n_estimators=200, max_depth=35, n_jobs=-1)

rf_model.fit(X_train, y_train)
```

[ ]:
```
y_pred_rf = rf_model.predict(X_test)
```

[ ]:
```
sample['FloodProbability'] = y_pred_rf
outCsv(sample, 'sample_randomForest.csv')
```

[ ]:
```
sample['FloodProbability'].hist()
```

[ ]: <Axes: >



0.66287 public score

[ ]:
```
param_grid_net = {
    'alpha': np.arange(0.1, 0.5, 0.1),
    'l1_ratio' : np.arange(0.1, 1, 0.1),
    'max_iter' : [500, 1000]
    }
scoreing = 'r2'

elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5)
```

```
gird_search_net = GridSearchCV(estimator=elastic_net, param_grid=param_grid_net,
                               scoring=scoreing, cv=3, verbose=True)
gird_search_net.fit(X_train, y_train)

print(gird_search_net.best_params_)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits
{'alpha': 0.1, 'l1_ratio': 0.1, 'max_iter': 500}
```

[ ]:
```
best_parm_net = gird_search_net.best_params_
elastic_net = ElasticNet(alpha=0,
                         l1_ratio=0.01)
elastic_net.fit(X_train, y_train)
```

```
d:\tool\Anconda\envs\ML\Lib\site-packages\sklearn\base.py:1151: UserWarning:
With alpha=0, this algorithm does not converge well. You are advised to use the
LinearRegression estimator
  return fit_method(estimator, *args, **kwargs)
d:\tool\Anconda\envs\ML\Lib\site-
packages\sklearn\linear_model\_coordinate_descent.py:628: UserWarning:
Coordinate descent with no regularization may lead to unexpected results and is
discouraged.
  model = cd_fast.enet_coordinate_descent(
d:\tool\Anconda\envs\ML\Lib\site-
packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.257e+02, tolerance: 2.911e-01 Linear regression models with null weight
for the l1 regularization term are more efficiently fitted using one of the
solvers implemented in sklearn.linear_model.Ridge/RidgeCV instead.
  model = cd_fast.enet_coordinate_descent(
```

[ ]:
```
ElasticNet(alpha=0, l1_ratio=0.01)
```

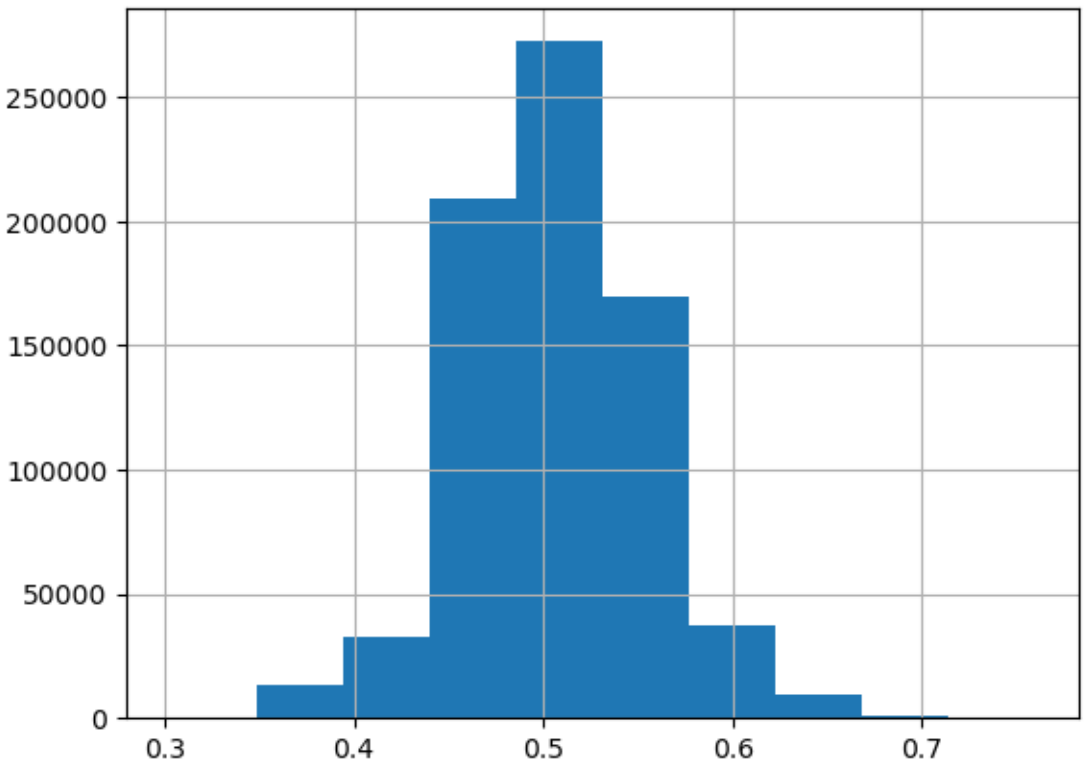
[ ]:
```
score_r2 = r2_score(y_train, elastic_net.predict(X_train),␣
 ↪multioutput='raw_values')
print(score_r2)
```

```
[0.84495011]
```

[ ]:
```
y_pred_net = elastic_net.predict(X_test)
```

[ ]:
```
sample['FloodProbability'] = y_pred_net
sample['FloodProbability'].hist()
```

[ ]:
```
<Axes: >
```



[ ]:
```
outCsv(sample, 'sample_Enet.csv')
```

l1_ratio　0 (　l2 penalty)

[ ]:
```
from sklearn.linear_model import Ridge

param_rg = {'alpha': np.arange(0.3, 1.11, 0.1),
            'solver': ['svd', 'cholesky', 'sag']}
scoreing = 'r2'

rg_model = Ridge()
grid_rg = GridSearchCV(rg_model, param_rg, scoring=scoreing, cv=5, n_jobs=4)
grid_rg.fit(X_train, y_train)

print(grid_rg.best_params_)
```

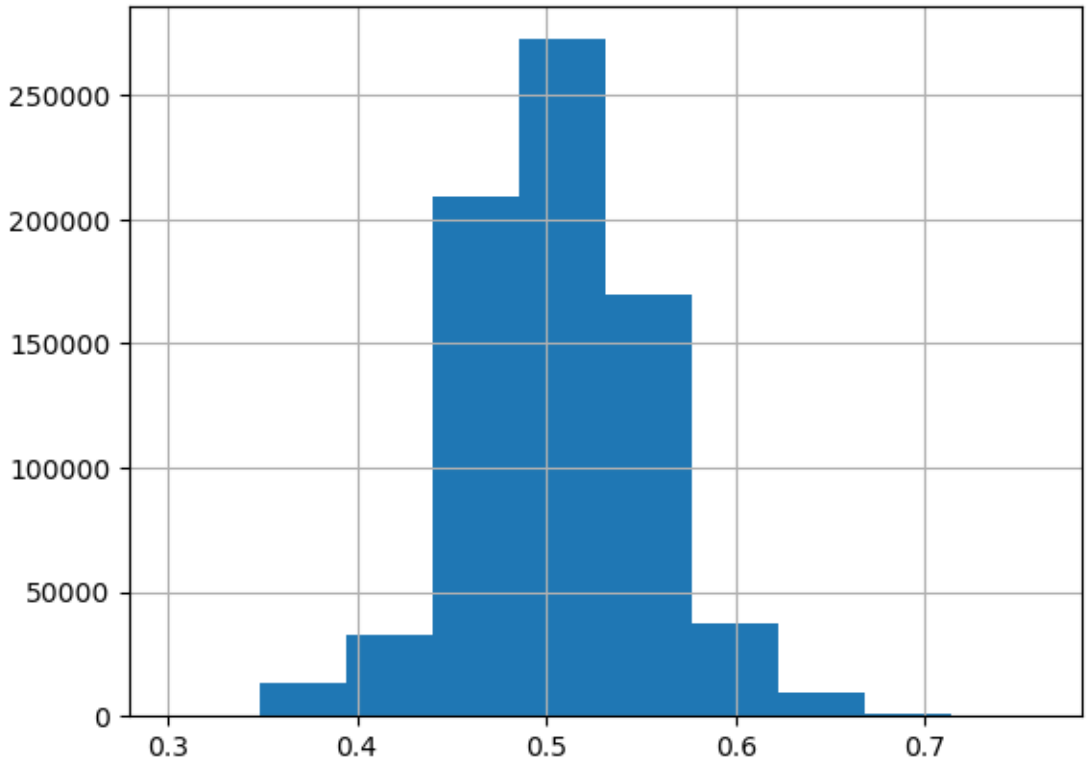
```
{'alpha': 1.0000000000000002, 'solver': 'sag'}
```

[ ]:
```
best_parm_rg = grid_rg.best_params_
rg_model = Ridge(alpha=best_parm_rg['alpha'], solver=best_parm_rg['solver'])
rg_model.fit(X_train, y_train)
print(r2_score(y_train, rg_model.predict(X_train)))
```

```
0.8449501006427806
```

[ ]:
```
y_pred_rg = rg_model.predict(X_test)
sample['FloodProbability'] = y_pred_rg

sample['FloodProbability'].hist()
```

[ ]: <Axes: >



[ ]:
```
outCsv(sample, 'sample_ridge.csv')
```

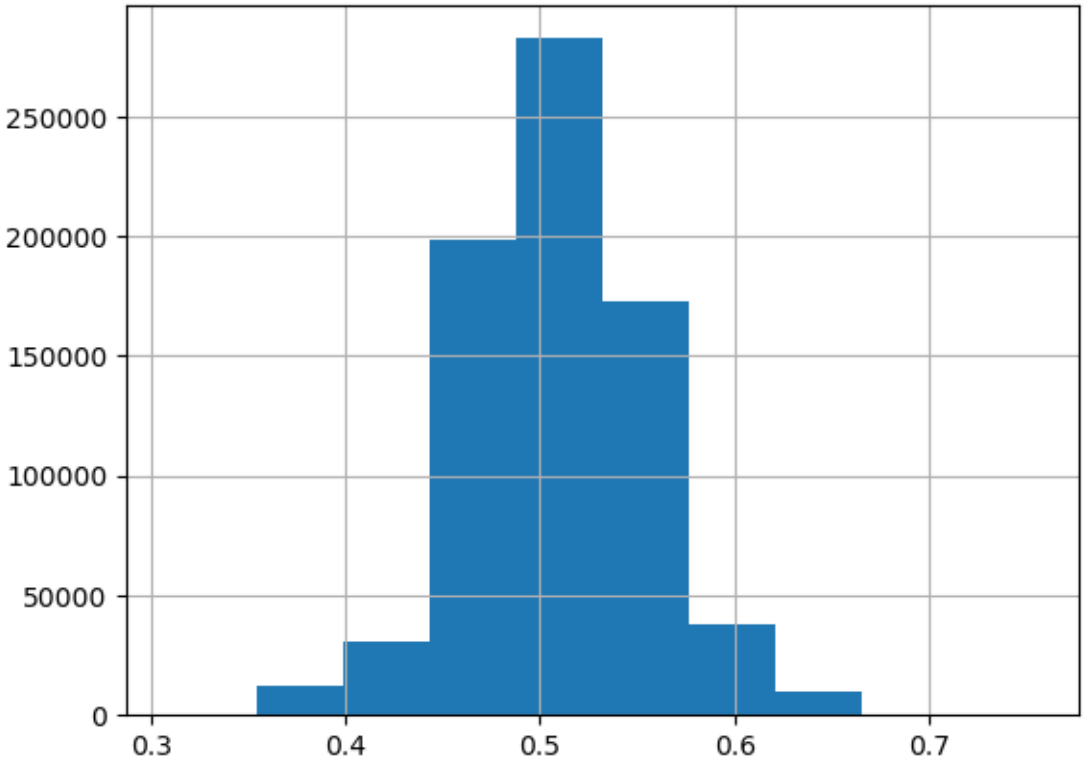
R2

AdaBoost

[ ]:
```
from sklearn.ensemble import AdaBoostRegressor

ada_reg = AdaBoostRegressor(
    rg_model, n_estimators=20,
    loss='linear', learning_rate=0.5)

ada_reg.fit(X_train, y_train)
print(r2_score(y_train, ada_reg.predict(X_train)))
y_pred_ada = ada_reg.predict(X_test)
```

```
0.8393886009765373
```

[ ]:
```
sample['FloodProbability'] = y_pred_ada
sample['FloodProbability'].hist()

outCsv(sample, 'sample_ada.csv')
```



[ ]:
```

```