600000 500000 400000 를 ³⁰⁰⁰⁰⁰ 200000 100000 140000 160000 180000 280000 200000 220000 240000 260000 In [8]: clf = make_pipeline(OneHotEncoder(handle_unknown='ignore') , DecisionTreeRegressor(max_features = 10)) clf.fit(X_train, np.ravel(y_train)) Pipeline(steps=[('onehotencoder', OneHotEncoder(handle_unknown='ignore')), Out[8]: ('decisiontreeregressor', DecisionTreeRegressor(max_features=10))]) In [9]: y pred = clf.predict(X test) In [10]: mean_squared_error(y_test, y_pred, squared=False) 75477.87745487913 Out[10]: In [11]: plt.figure(figsize = (8,6))out = pd.DataFrame(data = {"true":np.ravel(y_test), "pred":y_pred}) sns.scatterplot(x = "true", y = "pred", data = out) <AxesSubplot:xlabel='true', ylabel='pred'> Out[11]: 700000 600000 500000 400000 300000 200000 100000 140000 160000 180000 200000 220000 240000 260000 280000 true In [12]: clf = make pipeline(OneHotEncoder(handle unknown='ignore') , RandomForestRegressor(max features = 10)) clf.fit(X train, np.ravel(y train)) Pipeline(steps=[('onehotencoder', OneHotEncoder(handle unknown='ignore')), Out[12]: ('randomforestregressor', RandomForestRegressor(max features=10))]) In [13]: y pred = clf.predict(X test) In [14]: mean_squared_error(y_test, y_pred, squared=False) 49277.047616828866 Out[14]: In [15]: plt.figure(figsize = (8,6)) out = pd.DataFrame(data = {"true":np.ravel(y_test), "pred":y_pred}) sns.scatterplot(x = "true", y = "pred", data = out) <AxesSubplot:xlabel='true', ylabel='pred'> Out[15]: 350000 300000 250000 200000 150000 100000 140000 160000 240000 260000 280000 180000 200000 220000 In [16]: clf = make_pipeline(OneHotEncoder(handle_unknown='ignore') , xgb.XGBRegressor(n_estimators=1000, max_depth=6, e clf.fit(X train, np.ravel(y train)) Pipeline(steps=[('onehotencoder', OneHotEncoder(handle unknown='ignore')), Out[16]: ('xgbregressor', XGBRegressor(base score=0.5, booster='gbtree', callbacks=None, colsample bylevel=1, colsample bynode=1, colsample bytree=1, early stopping rounds=None, enable categorical=False, eta=0.03, eval metric=None, feature types=None, gamma=0, gpu id=-1, grow policy='depthwise', importance type=None, interaction constraints='', learning rate=0.0299999993, max bin=256, max cat threshold=64, max cat to onehot=4, max delta step=0, max depth=6, max leaves=0, min child weight=1, missing=nan, monotone constraints='()', n estimators=1000, n_jobs=-1, num_parallel_tree=1, predictor='auto', ...))]) In [17]: y pred = clf.predict(X test) In [18]: mean_squared_error(y_test, y_pred, squared=False) 74818.74364636105 Out[18]: In [19]: plt.figure(figsize = (8,6))out = pd.DataFrame(data = {"true":np.ravel(y_test), "pred":y_pred}) sns.scatterplot(x = "true", y = "pred", data = out) <AxesSubplot:xlabel='true', ylabel='pred'> Out[19]: 600000

In [1]:

In [2]:

In [3]:

In [4]:

Out[4]:

In [5]:

In [6]:

Out[6]:

In [7]:

Out[7]:

import pandas as pd import numpy as np

import seaborn as sns

import xgboost as xgb

X train = train.iloc[:,:79] y train = train.iloc[:,79:] $X_{\text{test}} = \text{test.iloc}[:,:79]$ $y_{test} = test.iloc[:,79:]$

clf.fit(X train, np.ravel(y train))

y pred = clf.predict(X test)

plt.figure(figsize = (8,6))

67444.2725850821

500000

400000

300000

200000

100000

140000

Problem 2

X = pkm.iloc[:,2:22]y = pkm.iloc[:,1:2]

In [20]:

In [21]:

In [22]:

In [23]:

Out[23]:

In [24]:

In [25]:

160000

Parameters tuned for XGBoost are in the code.

clf.fit(X_train, np.ravel(y_train))

print(confusion matrix(y test, y pred))

4 0

1 0

0 0

0 0 0

0

0

0 0

0

0 0 1 0 3

0

0 0 0 2 0 0

1 0 0 0 0 0

0 0

0 13

0 0

 $[\hspace{.08cm} 0 \hspace{.08cm} 0 \hspace{.08cm} 0 \hspace{.08cm} 1 \hspace{.08cm} 0 \hspace{.08cm} 2 \hspace{.08cm} 3 \hspace{.08cm}] \hspace{.08cm}]$ precision recall f1-score

0.89

0.50

0.29

0.29

0.27

0.75

0.00

0.14

0.74

0.40

0.50

0.18 0.22

1.00

0.30

0

2 0 0 0

1 0 0 0 0 0 0 0 1

1 0 1 0 0 0 1 0 0 0 1

0 0 0 0 0 0 0 0 0

0.80

0.60

0.44

0.17

0.25

1.00

0.47

1.00

0.81

0.83

0.47

0.55

clf.fit(X_train, np.ravel(y_train))

print(confusion_matrix(y_test, y_pred))

0 3 0 0 0 1 0 0 0

0 0 4 0 0 0 0 0 0 0 0 0 3 1 0 0 0 0

0 0 0 0 3 0 0 0 1

0 0 1 0 0 8 0 0 0 0 0 1 0 0 0 0 0 0

0 0 0 0 0 0 0 5 2

0 0 0 0 0 0 0 13

0 0 0 0 0 0 0 0

0 0 1 0 0 0 0 0 1

0 0 2 0 0 3 0 0 0

0 0 0 0 0 0 0 2 0

0 0 0 0 0 1 0 1

0

0

1

precision recall f1-score support

0 0 0 1 0 0 0 0 0 0 0 1 0 0 3 0 41

 0.67
 0.20
 0.31

 1.00
 0.38
 0.55

 0.40
 0.57
 0.47

 1.00
 0.43
 0.60

 0.75
 0.27
 0.40

 0.47
 0.67
 0.55

 0.00
 0.00
 0.00

 0.62
 0.71
 0.67

 0.76
 1.00
 0.87

 1.00
 0.09
 0.17

 0.00
 0.00
 0.00

 0.50
 0.69
 0.58

 1.00
 0.17
 0.29

 0.43
 0.60
 0.50

 0.43
 0.33
 0.38

0.33

0.91

0.47

0.59

warn prf(average, modifier, msg start, len(result))

_warn_prf(average, modifier, msg_start, len(result))

_warn_prf(average, modifier, msg_start, len(result))

y_train_x = le.fit_transform(np.ravel(y_train)) y_test_x = le.fit_transform(np.ravel(y_test))

0.78 1.00 0.67 0.20

0.43

0.61

0.61

0.64

parameter to control this behavior.

parameter to control this behavior.

` parameter to control this behavior.

0.50 0.43 0.61 0.91

0 4

0.88

0.31

0.38

0.46

0.73

0.59

0.47

0.55

0 0 1

[0 2 0 0 0 0 4 0 0 0 0 3 0 1]

y pred = clf.predict(X test)

0.29

0.00

y pred = clf.predict(X test)

0

0 4 0 1 0

0 0 0 0 3

0 0 0 0 0

0 2 3 2 0

3 1

0 1

0 0

0 0

0 0

0 1

Ground Normal

Ghost

Water

Bug

Rock

Ice Poison

Grass

Fire Electric

Dark

Dragon

Fairy

Steel

Flying

accuracy macro avg

weighted avg

In [26]:

In [27]:

In [28]:

0 1

0

0

0

0

3

0

0

0

Ground

Normal

Ghost

Water Fighting

Bug

Rock

Ice

Poison Grass

Fire

Dark

Dragon

Steel

Fairy

Flying

accuracy

macro avg

weighted avg

In [29]:

In [30]:

Out[30]:

In [31]:

In [32]:

Electric

Psychic

0 1

Psychic

Fighting

0 1

0 1

0 1

0 1

0 1

0 1

0 1

0 1

Γ 2

0 1

0 1

[2

0 1 0 1 0 0

2 1 0 1 0

1 2 0 1 0

1 0 0 9 0

0 0 0 0 0 0 0 1 2

1 0 0 0 0

0 0 0 0 0 0

0 0 0 2 0 0 0

180000

pkm = pd.read csv("pokemon.csv", index col = "Number")

200000

true

220000

240000

Random Forest are less drastic which leads to a better RMSE Score but removing outlier points could increase the score.

X train, X test, y train, y test = train test split(X, y, test size = 0.30, random state = 42)

clf = make pipeline(OneHotEncoder(handle unknown='ignore') , DecisionTreeClassifier())

('decisiontreeclassifier', DecisionTreeClassifier())])

print(classification_report(y_test, y_pred, target_names=y_train.Type_1.unique()))

0 0 0 0.1

> 1 0 1]

1 0

1 0 01

1

0 0

0 0

0 1

3 3 1 0 0]

2 2 1 1 01

0 0 2 3 0]

support

18

10

8

7

7

11

12

1

7

13

11

5

35

12

10 9

7

34

217

217

217

0 0 01

0 0 3 2

0 0 01

01

01

01

01

1]

1]

0 0

0 0

0 1

1 2

4 0 0 01

0

3

0 1

2

Pipeline(steps=[('onehotencoder', OneHotEncoder(handle_unknown='ignore')),

0 2 0

1 0 0

0 0 0

0 2 16

1 2

1 1

0

1

0 0

0

0.84

0.40

0.47

0.21

0.27

0.43

0.58

0.00

0.25

0.90

0.78

0.50

0.40

0.50

Pipeline(steps=[('onehotencoder', OneHotEncoder(handle unknown='ignore')),

clf = make pipeline(OneHotEncoder(handle unknown='ignore') , RandomForestClassifier())

('randomforestclassifier', RandomForestClassifier())])

print(classification_report(y_test, y_pred, target_names=y_train.Type_1.unique()))

0 0 1 0 0 0 0 31

0 0 1 0 0 1 0 1

0 0 3 0 0 0 0 01

0 0 3 0 2 0 0 2]

0 0 3 0 0 0 0 01

0 0 0 0 0 0 0 01

0 0 24 0 1 0 0 51

0 0 2 2 2 1 0 1]

0 0 2 0 6 0 0 01

0 0 0 0 0 0 0]

0 0 0 0 0 0 0]

0 0 0 2 1]

0 0 0 0 21

18

10

8

7

7

11 12

1

13

11 5

35

12

10

9

7

34

217

217

217

colsample bylevel=1, colsample bynode=1,

learning rate=0.0299999993, max bin=256, max cat threshold=64, max cat to onehot=4, max delta step=0, max depth=6, max leaves=0,

enable categorical=False, eta=0.03,

gpu id=-1, grow policy='depthwise',

min child weight=1, missing=nan,

n jobs=-1, num parallel tree=1, objective='multi:softprob', ...))])

support

18

10

8

7

7

11

12

1

7

13

11

12

10

9 7

34

217

217

217

tsne fit = pd.DataFrame(data = {"tsne1":X embedded[:,0], "tsne2":X embedded[:,1], "Class":np.ravel(y.values)})

TSNE

20

Class

Grass Fire Water Bug

Normal Poison Electric Ground Fairy

Fighting Psychic Rock Ghost

lce Dragon Dark Steel Flying

40

plot = sns.scatterplot(x='tsne1', y='tsne2', data=tsne fit, hue='Class', ec=None).set(title='TSNE')

0

tsne1

0.78

0.35

0.67

0.45

0.60

0.74

0.55

0.81

0.00

0.00

0.56

0.35

0.32

0.50

0.40

0.79

0.58

0.47

0.56

X_embedded = TSNE(n_components=2, n_jobs = -1, random_state = 101).fit_transform(X_oh)

print(classification_report(y_test_x, y_pred, target_names=y_train.Type_1.unique()))

colsample bytree=1, early stopping rounds=None,

eval metric=None, feature types=None, gamma=0,

monotone constraints='()', n estimators=1000,

importance type=None, interaction constraints='',

 $\verb|C:\Users\matth\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: \ Undefined \texttt{MetricWarning: Prescription: MetricWarning: Prescription: MetricWarning: Prescription: MetricWarning: Prescription: MetricWarning: MetricWarning$ cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division

C:\Users\matth\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division

C:\Users\matth\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero division

7

0 0

0 0 0

0 0 0

0 0

0

2 0 3 1 0 1 260000

Good overall fit minus the outliers. The overal general trend of the dataset is preserved in each of the models. It seems like outliers in

280000

Problem 1

from sklearn import metrics import matplotlib.pyplot as plt

from sklearn.svm import LinearSVC

from sklearn.preprocessing import StandardScaler from sklearn.preprocessing import OneHotEncoder from sklearn.pipeline import make pipeline

from sklearn.metrics import mean squared error from sklearn.tree import DecisionTreeRegressor from sklearn.tree import DecisionTreeClassifier from sklearn.ensemble import RandomForestRegressor from sklearn.ensemble import RandomForestClassifier from sklearn.preprocessing import LabelEncoder

from sklearn.model selection import train test split

train = pd.read csv("train1.csv", index col = "Id") test = pd.read csv("test1.csv", index col = "Id")

mean_squared_error(y_test, y_pred, squared=False)

sns.scatterplot(x = "true", y = "pred", data = out)

<AxesSubplot:xlabel='true', ylabel='pred'>

from sklearn.metrics import classification report, confusion matrix

Pipeline(steps=[('onehotencoder', OneHotEncoder(handle unknown='ignore')),

out = pd.DataFrame(data = {"true":np.ravel(y_test), "pred":y_pred})

('linearsvc', LinearSVC(C=0.01, dual=False))])

clf = make pipeline(OneHotEncoder(handle unknown='ignore'), LinearSVC(C=0.01, penalty="12", dual=False, max ite

clf = make_pipeline(OneHotEncoder(handle_unknown='ignore'), xgb.XGBClassifier(n_estimators=1000, max_depth=6, e clf.fit(X_train, y_train_x) Pipeline(steps=[('onehotencoder', OneHotEncoder(handle unknown='ignore')), ('xgbclassifier', XGBClassifier(base score=0.5, booster='gbtree', callbacks=None,

y pred = clf.predict(X test)

print(confusion_matrix(y_test_x, y_pred))

[0 3 1 0 0 1 1 0 0 0 0 0 2 1 0 0 0 1][0 1 5 0 0 0 0 0 0 1 0 0 0 0 0 0 1] $[\ 0 \ 0 \ 0 \ 0 \ 0 \ 7 \ 0 \ 0 \ 0 \ 1 \ 0 \ 1 \ 0 \ 2 \ 0 \ 0 \ 0]$ $[\ 0 \ 0 \ 0 \ 2 \ 0 \ 0 \ 8 \ 0 \ 0 \ 0 \ 0 \ 2 \ 0 \ 0 \ 0 \ 0]$ $[\ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 3 \ 2 \ 0 \ 0 \ 0 \ 2 \ 0 \ 0 \ 0]$ [3 0 0 1 0 0 0 0 0 1 0 0 3 0 0 0 2 1][0 1 0 4 0 0 2 0 0 0 1 1 1 9 5 0 0 0 2][2 0 1 0 0 0 0 1 0 0 2 0 4 1 1 0 0] $[1 \quad 0 \quad 0 \quad 2 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 3 \quad 0 \quad 0]$ precision recall f1-score

le = LabelEncoder()

0.00 0.00 0.58 0.54 Electric 0.36 0.33 0.33 0.30 0.57 0.44 0.38 0.43 0.74 0.85 0.50 0.48 0.57 0.58 Model Performance is poor as there arent enough samples to train on. Some types are much rarer than others. Since a lot of pokemon overlap with their features, it is hard to accurately predict each pokemon's type. TSNE Below shows no Clustering so effectively there is no way to accuratly classify this data. from sklearn.manifold import TSNE plt.figure(figsize = (15,10))

enc = OneHotEncoder(handle unknown='ignore')

 $X ext{ oh } = enc.fit transform(X)$

plt.savefig("TSNE.jpg", dpi = 600)

0.70

0.43

0.33

1.00

0.88

0.62

0.00

0.75

0.68

0.00

0.71

Ground

Normal

Ghost

Water

Bug

Rock

Ice

Poison

Grass Fire

Dark Dragon

Steel

Fairv

Flying

accuracy

macro avq

weighted avg

plt.show()

30

20

10

-10

-20

-30

-40

-20

tsne2

In [33]:

In [34]:

Psychic

Fighting

0.89

0.30

0.62

0.71

0.43

0.64

0.43

1.00

0.00

0.67 0.64 0.00 0.00