```
import os
import urllib
import urllib.request
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import sklearn
from pandas.plotting import scatter_matrix
from google.colab import files
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import  SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import LabelEncoder
```

```
os.listdir()
```

```
['.config', 'test_scores.csv', 'sample_data']
```

```
data_location = 'test_scores.csv' #location of Data/csv file

def load_test_scores(data = data_location ):
  df = pd.read_csv(data_location)
  return df

df = load_test_scores()
```

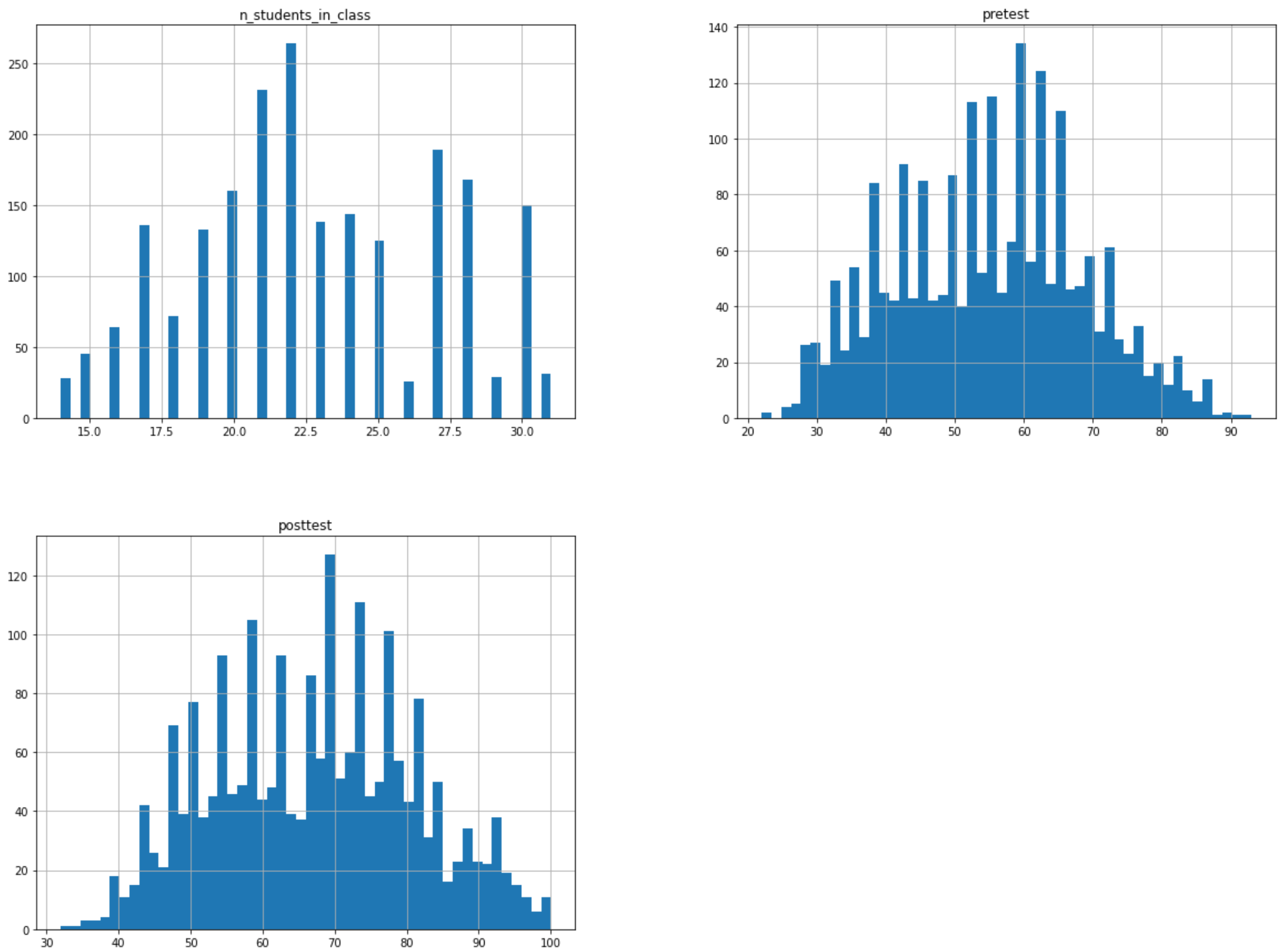
n_student refers to the number of students in this students class. We can change this column name to n_students_in_class.

```
df.rename(columns={"n_student":'n_students_in_class'} , inplace=True)
# df.drop(axis=1 , columns=['student_id'] , inplace=True )
```

```
df.isnull().sum()
```

```
school                0
school_setting        0
school_type           0
classroom             0
teaching_method       0
n_students_in_class   0
student_id            0
gender                0
lunch                 0
pretest               0
posttest              0
dtype: int64
```

```
%matplotlib inline
df.hist(bins=50 , figsize=(20,15) )
plt.show()
```



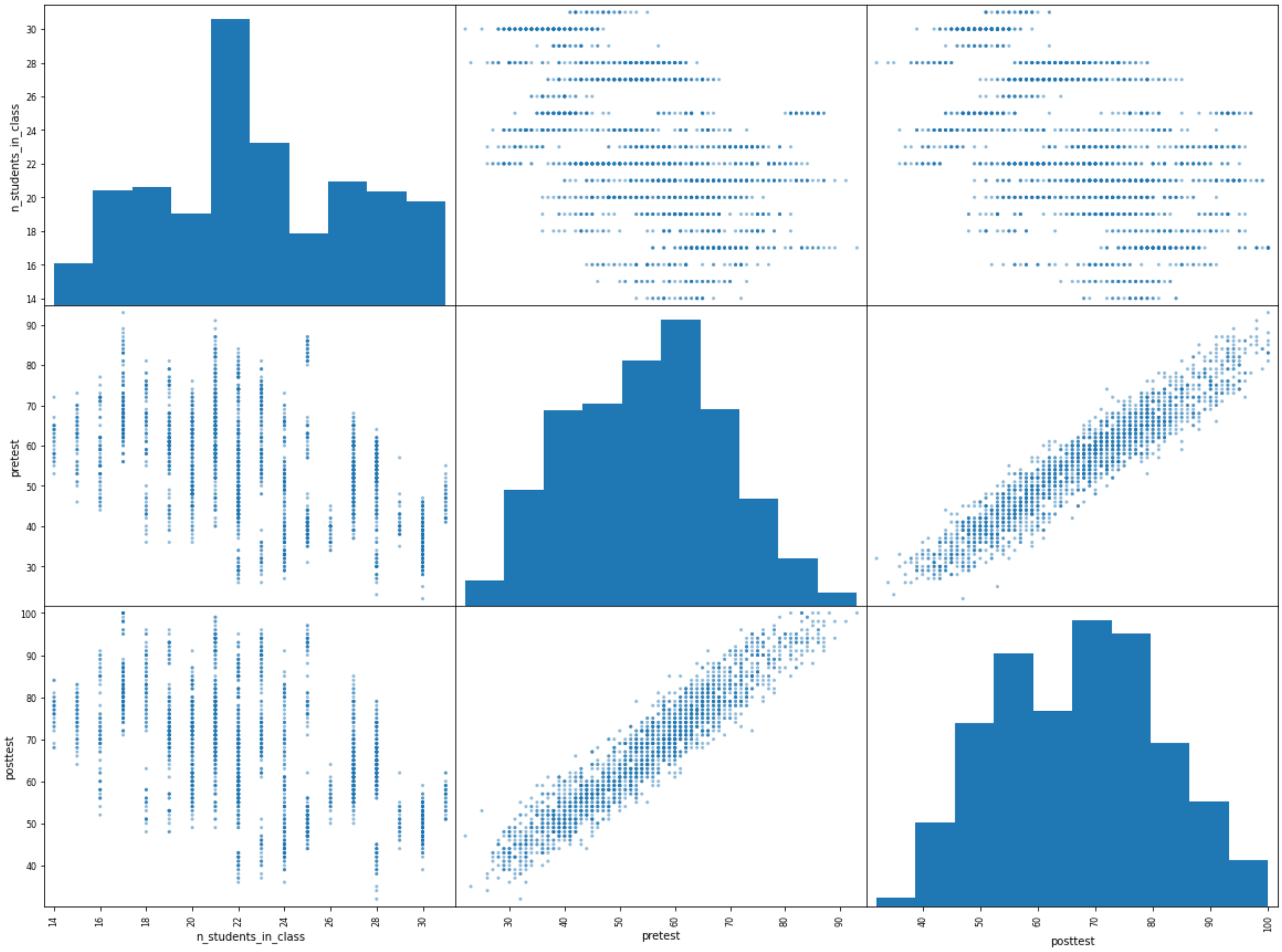
Let's get the pearson correlation between these features.

```
corr_matrix = df.corr()
corr_matrix['posttest'].sort_values(ascending=False)
```

```
posttest              1.000000
pretest               0.950884
n_students_in_class  -0.504886
Name: posttest, dtype: float64
```

The numbers above tell us that the pretest and posttest values are very closely and positively related. As for the n_students_in_class the correlation is negative but fairly strong.

```
%matplotlib inline
pd.plotting.scatter_matrix(df, figsize=(20,15) )
plt.show()
```



From the scatter plot above we can view the horizontal/vertical lines in any plot related to n_students_in_class. This can give us an indication that maybe we should turn this column into a categorical variable where the number of n_students_in_class relates to the category.

OR

We can actually drop the n_students_in_class columns. This is because we already have a column called classroom. Since all the classrooms with the same name have the same number of students in them, the n_students_in_class can be droppped.

```
def convert_column_to_cat(df , column_to_convert='n_students_in_class' , new_columi
  class_sizes = df.n_students_in_class.unique()
  try:
    for i in class_sizes:
      df.replace({column_to_convert : i} , str(i) , inplace=True)
    if df.loc[:,column_to_convert].dtype == 'O':
        print(" {}'s data converted to Object type".format(column_to_convert))
  except Exception as e:
    print(e)

# convert_column_to_cat(df)
```

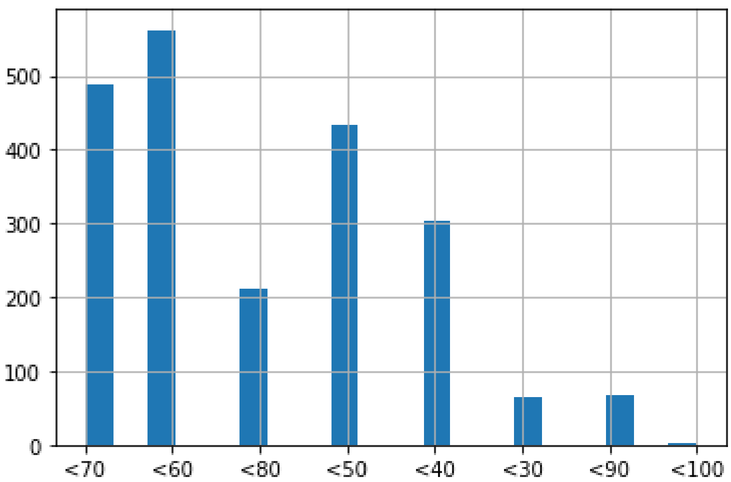
```
# cond = df.n_students_in_class ==20.0
# only_20_perclassroom = df[cond]
# only_20_perclassroom.classroom.unique()
```

```
df.drop('n_students_in_class', inplace=True , axis=1)
# df.columns
```

Now we are going to have to split our dataset into a train set and a test set. Based on the Pearson Correlation Coefficient, the pretest scores are a very strong indicator of the posttest scores. Hence we shall use Stratified Shuffling to split our dataset. That way our model will be trained on data with a distribution is similar to that of actual data.

```
model_this_distribution = pd.cut(df['pretest'],bins=[0 , 30. , 40. , 50. , 60. , 7(
labels = ['<30' , '<40','<50','<60','<70','<80','<90' , '<100'])

%matplotlib inline
model_this_distribution.hist(grid=True, bins=20, rwidth=0.9)
plt.show()
```



```
split = StratifiedShuffleSplit(n_splits=1,test_size=0.2,random_state=42)
for train,test in split.split(df , model_this_distribution):
  strat_train_set = df.loc[train]
  strat_test_set = df.loc[test]
```

Data Transformation

Handling Numerical Null values

To handle null values, we shall use the mean strategy.

Handling Categorical Columns

Columns to encode :

1. gender
2. school_type
3. teaching_method
4. lunch(Whether the student qualifies for reduced/free lunch or not)
5. school_setting

For items 1-4 the values are binary so we can drop each column from the 2 columns produced when each one of the 4 columns are encoded. For school_settings column we wouldnt need to do this

```
OneHotEncoder_Instance = OneHotEncoder()
df_Encoded = OneHotEncoder_Instance.fit_transform(df[['gender' , 'school_type' , 't
df_Encoded = pd.DataFrame.sparse.from_spmatrix(df_Encoded ).drop(axis=1 , columns=[
```

```
df_Encoded
```

	gender	school_type	teaching_method	lunch	Rural	Suburban	Urban
0	0.0	0.0	1.0	0.0	0.0	0.0	1.0

This set of code above works well. We shall incorporate this into a custom transformer.

```
class HotEncodingCleaner(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
      df = pd.DataFrame.sparse.from_spmatrix(X )
      df.drop(axis=1 , columns=[0,2,4,6]  , inplace=True)

      return df
```

```
categorical_attributes = ['gender' , 'school_type' , 'teaching_method' , 'lunch' ,
Ordinal_encoding_attributes = ['school' , 'classroom']
num_attributes = ['pretest' , 'posttest' ]


cat_pipeline = Pipeline([

        ("cat", OneHotEncoder()),
        ('custom' , HotEncodingCleaner())
    ])

Ordinal_pipeline = Pipeline([
        ('ordinal' ,  OrdinalEncoder()),
    ])

full_pipeline = ColumnTransformer( [
        ("cat_pipeline", cat_pipeline,  categorical_attributes ),
        ("Ordinal_pipeline", Ordinal_pipeline , Ordinal_encoding_attributes),
        ('imputer', SimpleImputer(strategy="mean") , num_attributes ),
    ] , remainder='passthrough')
```

Now we shall apply this full pipeline to our stratified_train_set and then we will make the transformed DataFrame more intuitive.

We will also isolate the input data and the labels.

```
strat_train_treated = full_pipeline.fit_transform(strat_train_set)
strat_train_treated_df = pd.DataFrame(strat_train_treated , columns=['gender' , 'sc
strat_train_treated_prepared  = strat_train_treated_df.drop(columns=['posttest' ,
strat_train_treated_labels  = strat_train_treated_df.loc[:,['posttest']]
```

Visualizing our Input and Labels for the training set.

```
print(strat_train_treated_prepared,'\n',strat_train_treated_labels)
```

```
     gender school_type teaching_method lunch  ... Urban school classroom pre
0         0           1               0     0  ...     0     21        81
1         1           1               1     1  ...     1      8         3
2         0           0               0     0  ...     0     17        43
3         1           1               1     1  ...     0      6        44
4         0           1               1     1  ...     0     13        40
...     ...         ...             ...   ...  ...   ...    ...       ...
1701      1           1               0     0  ...     0     16        54
1702      0           1               1     1  ...     0     11        12
1703      1           1               1     0  ...     0     13        87
1704      1           0               1     1  ...     0     18        50
1705      0           0               1     0  ...     1      2        62

[1706 rows x 10 columns]
      posttest
0           94
1           58
2           85
3           60
4           72
...        ...
1701        95
1702        55
1703        66
1704        60
1705        79

[1706 rows x 1 columns]
```

```
forest_reg = RandomForestRegressor(n_estimators=100, random_state=42)
forest_reg.fit(strat_train_treated_prepared , strat_train_treated_labels)
predictions_train_set = forest_reg.predict(strat_train_treated_prepared)
forestreg_rmse_train = np.sqrt(mean_squared_error(strat_train_treated_labels , pred
print('The RMSE on the training set is {}'.format(forestreg_rmse_train))
```

```
The RMSE on the training set is 1.673026573143772
```

Decent RMSE on the training set, lets see how this model performs on our test set.

```
strat_test_treated = full_pipeline.transform(strat_test_set)
strat_test_treated_df = pd.DataFrame(strat_test_treated , columns=['gender' , 'scho
strat_test_treated_prepared  = strat_test_treated_df.drop(columns=['student_id' ,
strat_test_treated_labels  = strat_test_treated_df.loc[:,['posttest']]
```

Visualizing our Input and Labels for the test set.

```
print(strat_test_treated_prepared , '\n' , strat_test_treated_labels )
```

```
     gender school_type teaching_method lunch  ... Urban school classroom pret
0         0           0               1     1  ...     1      0        96
1         1           0               0     1  ...     1     10         8
2         0           1               0     1  ...     0      6        55
3         0           1               1     1  ...     0      6        95
4         0           0               1     1  ...     1     10         9
```

```
..      ...          ...               ...    ...   ...    ...     ...         ...
422       1            0                 0      0   ...      1       9          25
423       1            0                 0      1   ...      1      10           8
424       1            1                 1      0   ...      0      19          13
425       0            0                 1      1   ...      0       1          80
426       0            0                 1      0   ...      0      17          21

[427 rows x 10 columns]
     posttest
0          65
1          62
2          76
3          65
4          53
..        ...
422        89
423        57
424        51
425        77
426        72

[427 rows x 1 columns]
```

```
predictions_test_set = forest_reg.predict(strat_test_treated_prepared)
forestreg_rmse_test = np.sqrt(mean_squared_error(strat_test_treated_labels , predic
print('The RMSE on the test set is {}'.format(forestreg_rmse_test))
```

```
The RMSE on the test set is 3.351896223717534
```

A RMSE of 3.37(3 s.f) is fairly decent. However, RMSE alone may not be a good enough metric to evaluate our model's accuracy. For this we can use K-fold cross-validation.

Evaluating using K-fold cross-validation

In K-fold cross validation we split the training set randomly into K number of folds of equal size or thereabout.(K is set as cv in the cross_val_score Instance) Then we train and evaluate our lin_regressor 10 times. Each time, we pick 9 of the folds to train the lin_regressor on and then test it on the fold we did not pick.

For cross-validation, Scikit-Learn expects a utility function(greater is better) instead of a cost function(smaller is better). root_mean_squared_error is a cost function so its value will be negative when calculated by the cross-validator. Hence, scoring="neg_root_mean_squared_error". As shown below there is a simple workaround.

```
def scores_breakdown(scores_Linear , name=''): #A simple function to evaluate our l
  scores_mean = scores_Linear.mean()
  scores_std = scores_Linear.std()
  print('Mean and Standard deviation of the k-fold scores of the {} set is {} and ·
```

```
cross_val_score_train = cross_val_score(forest_reg, strat_train_treated_prepared ,
cross_val_score_train = -cross_val_score_train
```

```
scores_breakdown(cross_val_score_train , name='train')
```

```
    Mean and Standard deviation of the k-fold scores of the train set is 3.280603
```

```
cross_val_score_test = cross_val_score(forest_reg, strat_test_treated_prepared , st
cross_val_score_test = -cross_val_score_test
scores_breakdown(cross_val_score_test , name='test')
```

```
    Mean and Standard deviation of the k-fold scores of the test set is 3.7413291
```

As shown above, the mean k-fold score of our training set isn't that great.

On a better note, the difference between our train and test set's mean k-fold score isn't too large. This means the algorithm hasn't overfitted to our training set.

Fine Tuning

We could manually fiddle with the hyperparameters of the Algorithm to give us a better model and thus better predictions.

For the RandomForest Algorithm these are the hyperparameters.

RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse', max_depth=None, max_features='auto',max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None, oob_score=False, random_state=42, verbose=0, warm_start=False))

Changing each one of these features manually would take alot of time, however we can use GridSearchCV to explore any combinations of the hyperparameters above and do CrossValidation to evaluate the model with a given set of hyperparameters.

```
param_grid = [
    # try 24 (2×3×4) combinations of hyperparameters
    {'bootstrap': [False,True], 'n_estimators': [30,45,50], 'max_features': [2, 4,
    # then try 12 (2×2×3) combinations with bootstrap set as False
    {'bootstrap': [False,True], 'n_estimators': [3, 10], 'max_features': [8,11 ,7 
  ]

forest_reg_GCSV = RandomForestRegressor(random_state=42)
# train across 5 folds, that's a total of (36)*5=180 rounds of training
RF_grid_search = GridSearchCV(forest_reg_GCSV, param_grid, cv=5,
                           scoring='neg_root_mean_squared_error',
                           return_train_score=True)
RF_grid_search.fit(strat_train_treated_prepared , strat_train_treated_labels)
```

```
    GridSearchCV(cv=5, error_score=nan,
                 estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,
                                                 criterion='mse', max_depth=None,
```

```
                                                                  max_features='auto',
                                                                  max_leaf_nodes=None,
                                                                  max_samples=None,
                                                                  min_impurity_decrease=0.0,
                                                                  min_impurity_split=None,
                                                                  min_samples_leaf=1,
                                                                  min_samples_split=2,
                                                                  min_weight_fraction_leaf=0.0,
                                                                  n_estimators=100, n_jobs=None,
                                                                  oob_score=False, random_state=42
                                                                  verbose=0, warm_start=False),
                 iid='deprecated', n_jobs=None,
                 param_grid=[{'bootstrap': [False, True],
                              'max_features': [2, 4, 6, 8],
                              'n_estimators': [30, 45, 50]},
                             {'bootstrap': [False, True],
                              'max_features': [8, 11, 7],
                              'n_estimators': [3, 10]}],
                 pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                 scoring='neg_root_mean_squared_error', verbose=0)
```

We can get the best combination of parameters,the best estimator and the best score from out RF_grid_search by follwing the steps below

```
print('Best Parameters are: {}, \nthe  best estimator is: {} \nand the best score i
```

```
    Best Parameters are: {'bootstrap': True, 'max_features': 4, 'n_estimators': 5
    the  best estimator is: RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, 
                          max_depth=None, max_features=4, max_leaf_nodes=None,
                          max_samples=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=1,
                          min_samples_split=2, min_weight_fraction_leaf=0.0,
                          n_estimators=50, n_jobs=None, oob_score=False,
                          random_state=42, verbose=0, warm_start=False)
    and the best score is: 3.1875340880567298
```

This approach is fine when we are exloring a handfull of combinations for our hyperparameters. To cast a wider net, we can use RandomizedSearchCV instead.

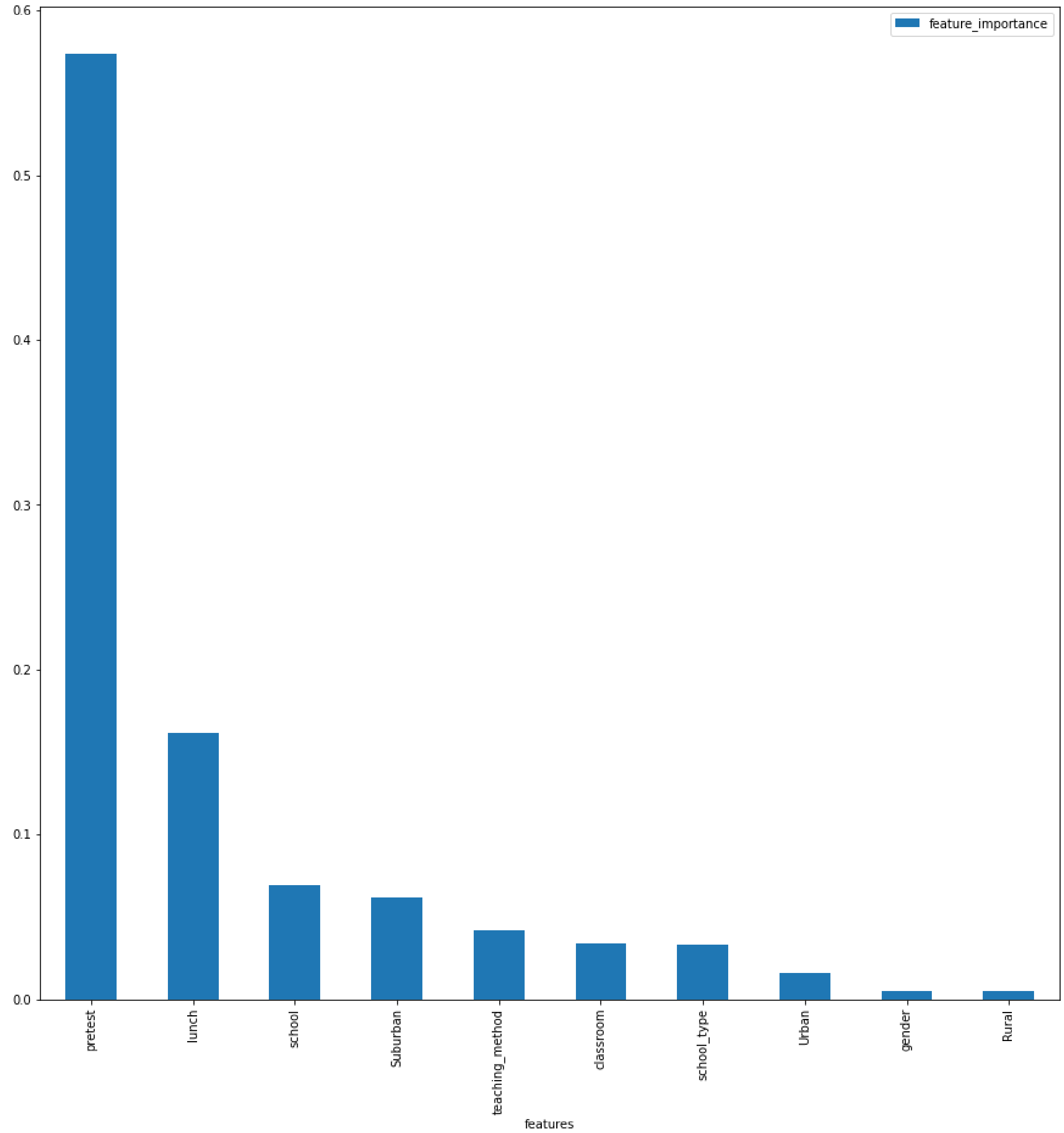
Analysing the model and its errors

The RandomForestRegressor can tell us the how important each feature is in the process of making accurate prediction.

```
relative_feature_importance = RF_grid_search.best_estimator_.feature_importances_.t
feature_dict = dict(zip(strat_train_treated_prepared.columns, relative_feature_impo
feature_dict = sorted(feature_dict.items(), key=lambda x: x[1] , reverse=True) #Sor
feature_dict_df = pd.DataFrame.from_dict(feature_dict )
feature_dict_df.rename(inplace=True , columns={0:'features' , 1:'feature_importance
```

```
%matplotlib inline
feature_dict_df.plot.bar(x='features' , y='feature_importance' , figsize=(15,15) )
```

```
feature_dict_df.plot.bar(x='features', y='feature_importance', figsize=(15,15))
plt.show()
```



To close this off, we shall now try our best model on our train and test set and see how it performs.

```
best_model = RF_grid_search.best_estimator_
```

```
cross_val_score_train = cross_val_score(best_model, strat_train_treated_prepared ,
cross_val_score_train = -cross_val_score_train
scores_breakdown(cross_val_score_train , name='train')
```

```
Mean and Standard deviation of the k-fold scores of the train set is 3.211105
```

```
cross_val_score_test = cross_val_score(best_model, strat_test_treated_prepared , st
cross_val_score_test = -cross_val_score_test
scores_breakdown(cross_val_score_test , name='test')
```

```
Mean and Standard deviation of the k-fold scores of the test set is 3.5747844
```

Let's visualize the discrepancy between our predicted and actual scores on both the train and test set.

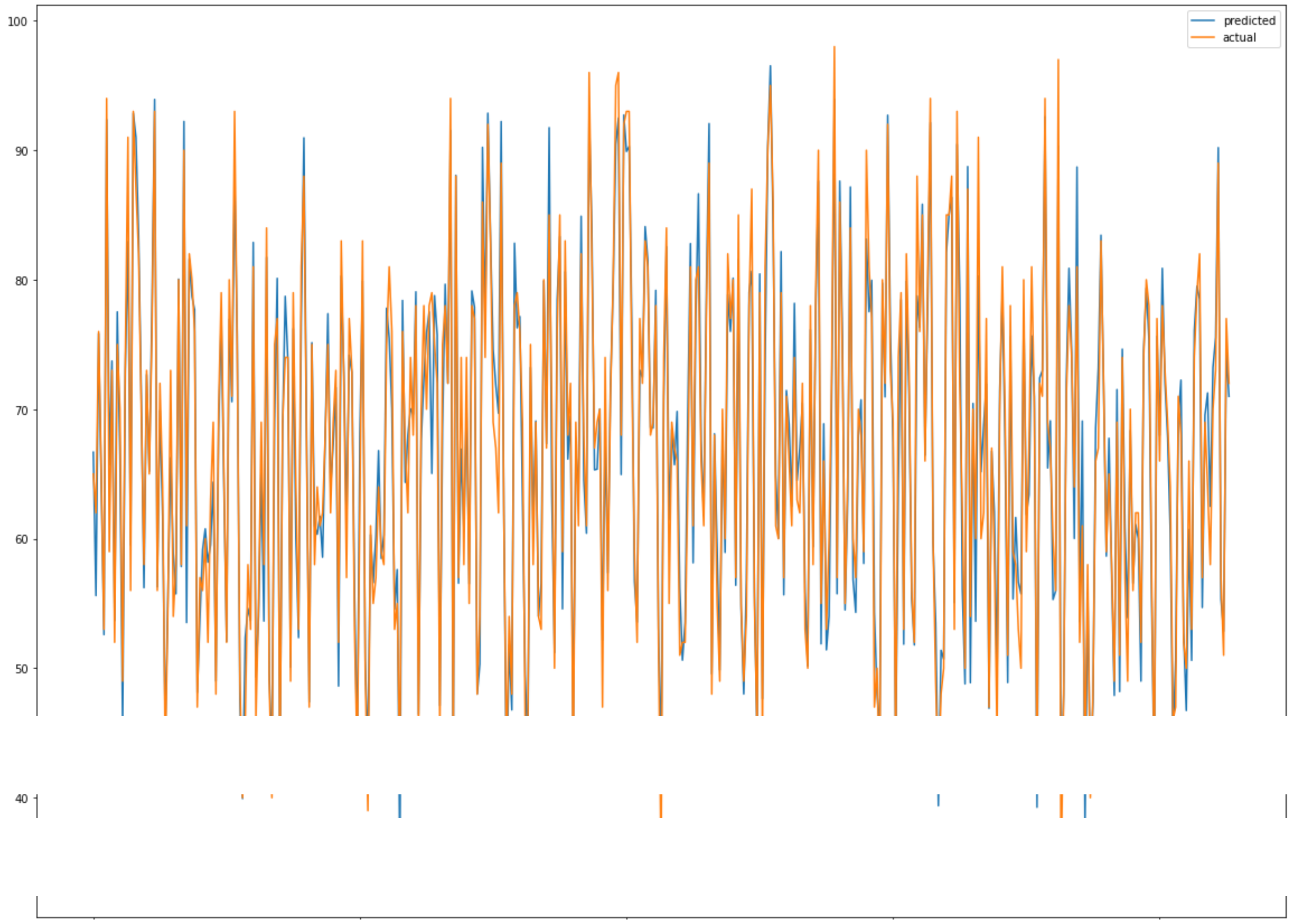
```
best_model = RF_grid_search.best_estimator_

predictions_train_set = best_model.predict(strat_train_treated_prepared)
train_labels = strat_train_treated_labels.iloc[:,0].astype('int')


predictions_test_set = best_model.predict(strat_test_treated_prepared)
test_labels = strat_test_treated_labels.iloc[:,0].astype('int')


def plot_comparison(predictions,labels , split_plots=False):
  data_dict_predictedvactual = {
      'predicted':predictions,
      'actual':labels
  }
  predictedvactual = pd.DataFrame.from_dict(data_dict_predictedvactual )
  %matplotlib inline
  predictedvactual.plot.line(figsize=(20,15) , subplots=split_plots)
  return plt.show()
```

```
plot_comparison(predictions_test_set ,test_labels )
```


predicted
actual
100
90
80
70
60
50
40

✓ 0s completed at 4:01 PM