Student Marks Predictor

In [1]:
```
import pandas as pd
```

In [2]:
```
student = pd.read_csv("data.csv")
```

In [3]:
```
student.head()
```

Out[3]:

	age	PT	ST	tut	heal	conc	marks
0	16	3	2	22	53	100	71
1	16	3	9	45	87	34	70
2	19	3	1	56	32	25	47
3	16	2	7	98	12	59	72
4	17	1	6	4	79	50	60

In [4]:
```
%matplotlib inline
```

In [5]:
```
student.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   age     1001 non-null   int64
 1   PT      1001 non-null   int64
 2   ST      1001 non-null   int64
 3   tut     1001 non-null   int64
 4   heal    1001 non-null   int64
 5   conc    1001 non-null   int64
 6   marks   1001 non-null   int64
dtypes: int64(7)
memory usage: 54.9 KB
```

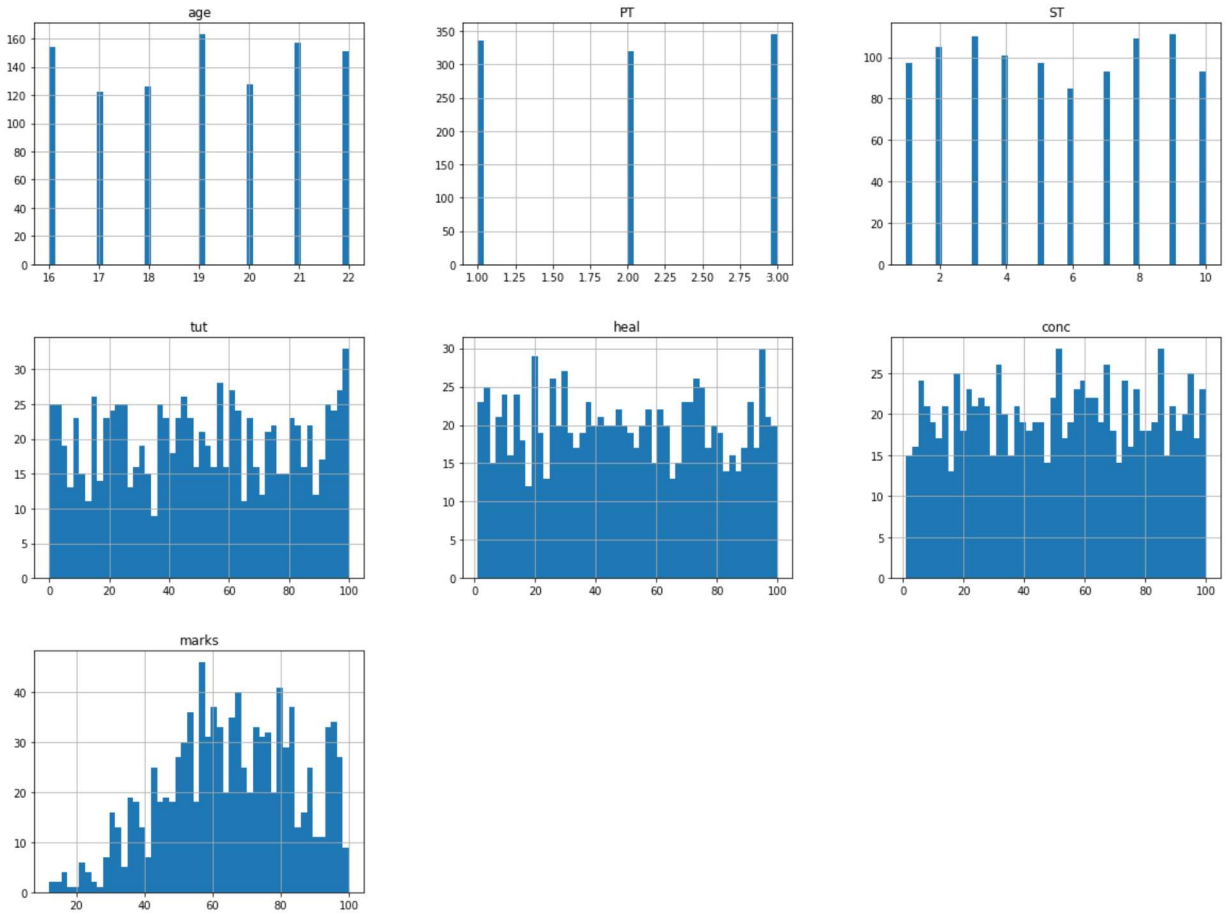
In [6]:
```
student.describe()
```

Out[6]:

	age	PT	ST	tut	heal	conc	marks
count	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000
mean	19.062937	2.008991	5.482517	50.310689	50.014985	51.131868	65.424575
std	2.027569	0.825178	2.888589	29.519458	29.087743	28.705585	19.383874
min	16.000000	1.000000	1.000000	0.000000	1.000000	1.000000	12.000000
25%	17.000000	1.000000	3.000000	24.000000	26.000000	26.000000	52.000000
50%	19.000000	2.000000	5.000000	50.000000	49.000000	52.000000	66.000000
75%	21.000000	3.000000	8.000000	76.000000	75.000000	76.000000	80.000000
max	22.000000	3.000000	10.000000	100.000000	100.000000	100.000000	100.000000

In [7]:
```
import matplotlib.pyplot as plt
student.hist(bins=50, figsize=(20,15))
```

Out[7]:
```
array([[<AxesSubplot:title={'center':'age'}>,
        <AxesSubplot:title={'center':'PT'}>,
        <AxesSubplot:title={'center':'ST'}>],
       [<AxesSubplot:title={'center':'tut'}>,
        <AxesSubplot:title={'center':'heal'}>,
        <AxesSubplot:title={'center':'conc'}>],
       [<AxesSubplot:title={'center':'marks'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



In [8]:
```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(student, test_size=0.2, random_state=42)
```

In [9]:
```
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(student, student['age']):
    strat_train_set = student.loc[train_index]
    strat_test_set = student.loc[test_index]
```

In [10]:
```
strat_train_set['age'].value_counts()
```

Out[10]:
```
19    130
21    125
16    123
22    121
20    102
18    101
17     98
Name: age, dtype: int64
```

In [11]:
```
strat_test_set['age'].value_counts()
```

Out[11]:
```
19    33
21    32
16    31
22    30
20    26
18    25
17    24
Name: age, dtype: int64
```

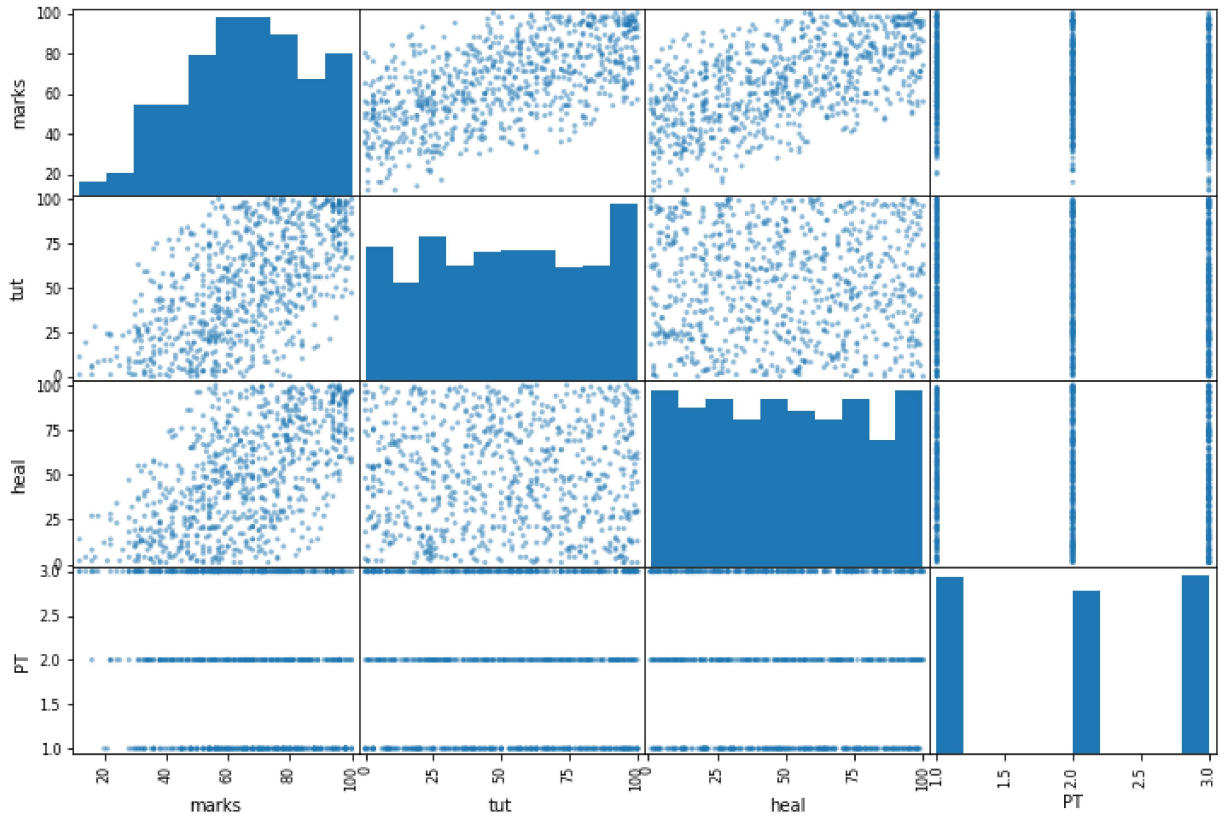
In [12]:
```
housing = strat_train_set.copy()
```

In [13]:
```
# Taking out insights
corr_matrix = student.corr()


# Tells us that if we increase a given value, then how much MEDV will be increase
# Strong positive coorelation means that if you increase a certain value then the
# Strong negative coorelation means that if you increase a certain value then the

corr_matrix['marks'].sort_values(ascending=False)
```

Out[13]:
```
marks    1.000000
tut      0.578737
heal     0.570704
conc     0.559649
ST       0.065329
age      0.048070
PT      -0.134217
Name: marks, dtype: float64
```

In [14]:
```
# Taking out insights by plotting
from pandas.plotting import scatter_matrix
attributes = ["marks", "tut", "heal", "PT"]
scatter_matrix(housing[attributes], figsize= (12, 8))
```

Out[14]:
```
array([[<AxesSubplot:xlabel='marks', ylabel='marks'>,
        <AxesSubplot:xlabel='tut', ylabel='marks'>,
        <AxesSubplot:xlabel='heal', ylabel='marks'>,
        <AxesSubplot:xlabel='PT', ylabel='marks'>],
       [<AxesSubplot:xlabel='marks', ylabel='tut'>,
        <AxesSubplot:xlabel='tut', ylabel='tut'>,
        <AxesSubplot:xlabel='heal', ylabel='tut'>,
        <AxesSubplot:xlabel='PT', ylabel='tut'>],
       [<AxesSubplot:xlabel='marks', ylabel='heal'>,
        <AxesSubplot:xlabel='tut', ylabel='heal'>,
        <AxesSubplot:xlabel='heal', ylabel='heal'>,
        <AxesSubplot:xlabel='PT', ylabel='heal'>],
       [<AxesSubplot:xlabel='marks', ylabel='PT'>,
        <AxesSubplot:xlabel='tut', ylabel='PT'>,
        <AxesSubplot:xlabel='heal', ylabel='PT'>,
        <AxesSubplot:xlabel='PT', ylabel='PT'>]], dtype=object)
```



In [15]:
```
student = strat_train_set.drop("marks", axis=1)
```

In [16]:
```
student_labels = strat_train_set["marks"].copy() # get train_sets marks
```

In [17]:
```
# Note a machine learning algorithm works perfectly when data is at the same scal
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    # .....add as many as you want in your pipline.
    ('std_scaler', StandardScaler()),
])
```

In [18]:
```
student_num_tr = my_pipeline.fit_transform(student)
```

In [19]:
```
student_num_tr.shape
```

Out[19]:
```
(800, 6)
```

In [20]:
```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeRegressor
model =  LinearRegression()
model.fit(student_num_tr, student_labels)
```

Out[20]:
```
LinearRegression()
```

In [21]:
```
some_data = student.iloc[:5]
# some_data = test_set.drop("marks", axis = 1)
```

In [22]:
```
some_labels = student_labels.iloc[0:5]
```

In [23]:
```
prepared_data = my_pipeline.transform(some_data)
```

In [24]:
```
model.predict(prepared_data)
```

Out[24]:
```
array([ 65.51277049,  54.03320197,  78.96053453, 119.78096552,
        34.46858732])
```

In [25]:
```
list(some_labels)
```

Out[25]:
```
[66, 54, 80, 98, 33]
```

In [26]:
```
from sklearn.metrics import mean_squared_error
import numpy as np
student_predictions = model.predict(student_num_tr)
mse = mean_squared_error(student_labels, student_predictions) # mse = Mean Square
rmse = np.sqrt(mse)
```

In [27]:
```
rmse
```

Out[27]:
```
2.522925978637198
```

In [28]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model, student_num_tr, student_labels, scoring="neg_mean
rmse_scores = np.sqrt(-scores)
```

In [29]:
```
rmse_scores # Errors are less as compared to linear Regressor Out 43
```

Out[29]:
```
array([3.84610145, 2.26804069, 1.53957906, 3.03861113, 2.75699856,
       2.1519924 , 1.84700329, 2.47461475, 2.96399275, 1.64138174])
```

In [30]:
```
def print_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard deviation: ", scores.std()) # std = standard deviation
```

In [31]:
```
print_scores(rmse_scores)
```

```
Scores:  [3.84610145 2.26804069 1.53957906 3.03861113 2.75699856 2.1519924
 1.84700329 2.47461475 2.96399275 1.64138174]
Mean:  2.4528315829474896
Standard deviation:  0.6799100826101739
```

In [32]:
```
from joblib import dump, load
dump(model, "Student.joblib")
```

Out[32]:
```
['Student.joblib']
```

In [33]:
```
X_test = strat_test_set.drop("marks", axis=1)
Y_test = strat_test_set["marks"].copy()
X_test_prepared = my_pipeline.transform(X_test)
final_predictions = model.predict(X_test_prepared)
final_mse= mean_squared_error(Y_test, final_predictions)
final_rmse = np.sqrt(final_mse)
j = 0
# perform conversion
for i in range(0, len(final_predictions)):
    final_predictions[i] = int(final_predictions[i])


print("Predictions: ", list(final_predictions))
print("Test data : ", list(Y_test))
```

```
Predictions:  [61.0, 82.0, 74.0, 93.0, 93.0, 75.0, 90.0, 85.0, 15.0, 54.0, 107.
0, 56.0, 69.0, 80.0, 64.0, 55.0, 48.0, 61.0, 95.0, 77.0, 55.0, 79.0, 55.0, 31.
0, 61.0, 82.0, 62.0, 78.0, 58.0, 76.0, 62.0, 71.0, 87.0, 82.0, 73.0, 98.0, 58.
0, 54.0, 82.0, 79.0, 75.0, 58.0, 63.0, 48.0, 22.0, 58.0, 39.0, 43.0, 68.0, 73.
0, 53.0, 63.0, 53.0, 55.0, 83.0, 67.0, 52.0, 32.0, 79.0, 36.0, 42.0, 53.0, 53.
0, 79.0, 54.0, 109.0, 54.0, 57.0, 50.0, 78.0, 43.0, 72.0, 64.0, 73.0, 91.0, 83.
0, 81.0, 56.0, 77.0, 77.0, 60.0, 62.0, 78.0, 81.0, 120.0, 72.0, 58.0, 72.0, 51.
0, 70.0, 43.0, 78.0, 69.0, 33.0, 56.0, 70.0, 50.0, 74.0, 40.0, 70.0, 65.0, 77.
0, 45.0, 52.0, 30.0, 81.0, 62.0, 83.0, 56.0, 65.0, 44.0, 67.0, 59.0, 28.0, 37.
0, 46.0, 92.0, 64.0, 42.0, 79.0, 51.0, 73.0, 75.0, 50.0, 59.0, 82.0, 58.0, 66.
0, 71.0, 61.0, 56.0, 61.0, 43.0, 53.0, 63.0, 103.0, 72.0, 26.0, 73.0, 86.0, 53.
0, 61.0, 39.0, 53.0, 60.0, 40.0, 65.0, 52.0, 44.0, 26.0, 80.0, 37.0, 72.0, 88.
0, 66.0, 73.0, 65.0, 82.0, 75.0, 68.0, 61.0, 57.0, 58.0, 87.0, 43.0, 91.0, 70.
0, 54.0, 48.0, 71.0, 77.0, 86.0, 78.0, 82.0, 72.0, 83.0, 53.0, 63.0, 73.0, 83.
0, 67.0, 62.0, 68.0, 50.0, 47.0, 66.0, 46.0, 47.0, 44.0, 58.0, 55.0, 55.0, 62.
0, 48.0, 75.0, 66.0, 90.0, 76.0, 58.0, 75.0, 54.0]
Test data :  [62, 84, 76, 96, 96, 77, 92, 87, 14, 55, 94, 56, 70, 82, 66, 55, 4
8, 62, 98, 79, 56, 81, 55, 30, 62, 85, 63, 80, 58, 78, 63, 72, 90, 84, 75, 96,
58, 55, 84, 81, 77, 59, 64, 48, 21, 59, 38, 43, 70, 74, 53, 64, 54, 56, 85, 68,
52, 30, 81, 36, 41, 54, 53, 81, 54, 94, 54, 57, 50, 80, 43, 74, 64, 75, 94, 85,
82, 56, 79, 79, 60, 63, 80, 83, 98, 73, 59, 73, 50, 72, 43, 80, 70, 32, 57, 72,
50, 76, 39, 71, 66, 78, 44, 52, 29, 84, 64, 85, 56, 66, 44, 68, 60, 27, 36, 47,
94, 65, 42, 82, 51, 75, 78, 50, 60, 84, 59, 68, 72, 61, 56, 61, 42, 54, 64, 96,
74, 24, 74, 88, 53, 62, 39, 53, 60, 40, 66, 52, 44, 24, 82, 37, 74, 90, 67, 75,
66, 84, 77, 70, 62, 58, 58, 89, 43, 95, 72, 54, 48, 73, 78, 88, 80, 84, 74, 85,
54, 64, 74, 85, 68, 63, 70, 51, 47, 68, 46, 47, 44, 58, 55, 56, 62, 48, 76, 68,
93, 79, 59, 76, 54]
```

In [34]:
```
final_rmse
```

Out[34]:
```
2.5449199150386614
```

In [35]:
```
prepared_data[0] # Taking a data for usage
```

Out[35]:
```
array([ 9.56315032e-01, -1.50893082e-03, -1.53990688e+00,  1.41234767e+00,
       -1.26198495e+00, -7.19800247e-02])
```

In [ ]:
```

```