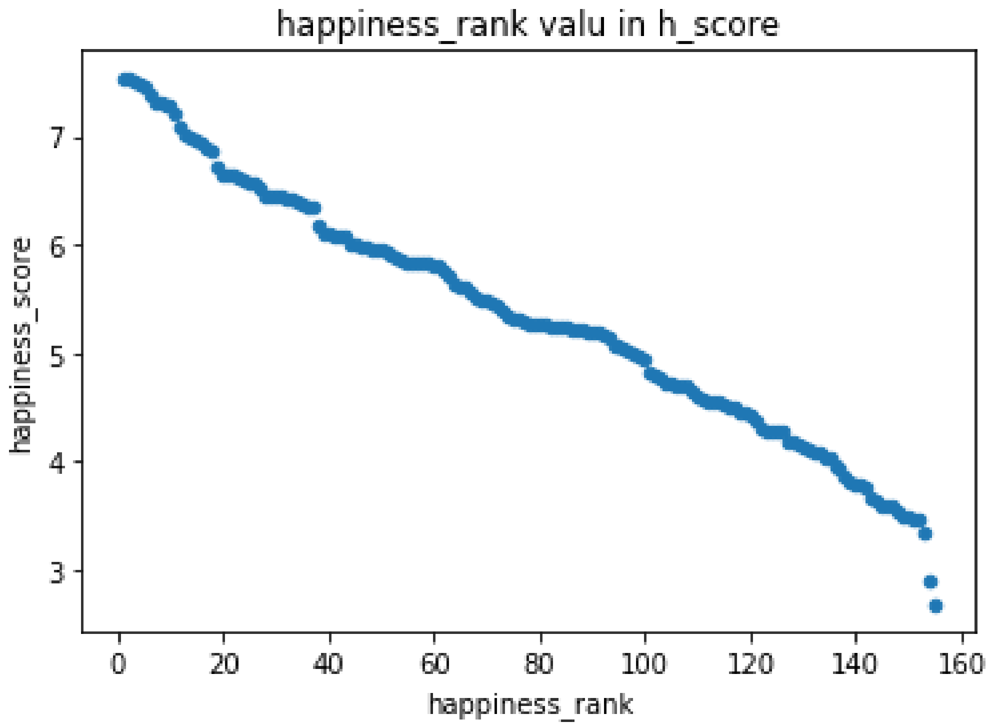
# l1p2 (3)

April 4, 2019

## 1 Q2.1

1. Use `matplotlib` to show scatterplots of each variable

```
In [238]: from matplotlib import pyplot as plt
          import numpy as np
          import pandas as pd
          import csv

          # you can also use pandas to load the data
          data = pd.read_csv('happiness.csv')

In [239]: colnames = pd.read_csv('happiness.csv', nrows=1).columns.tolist()
          print(colnames)

['country', 'happiness_rank', 'happiness_score', 'economy', 'family', 'health', 'freedom', 'ge

In [241]: #x = data.iloc[:, 1]
          #y = data.iloc[:, 2] can do with iloc
          #plt.scatter(x,y)
          data.plot.scatter(x='happiness_rank', y='happiness_score', title="happiness_rank valu
          plt.show()
```



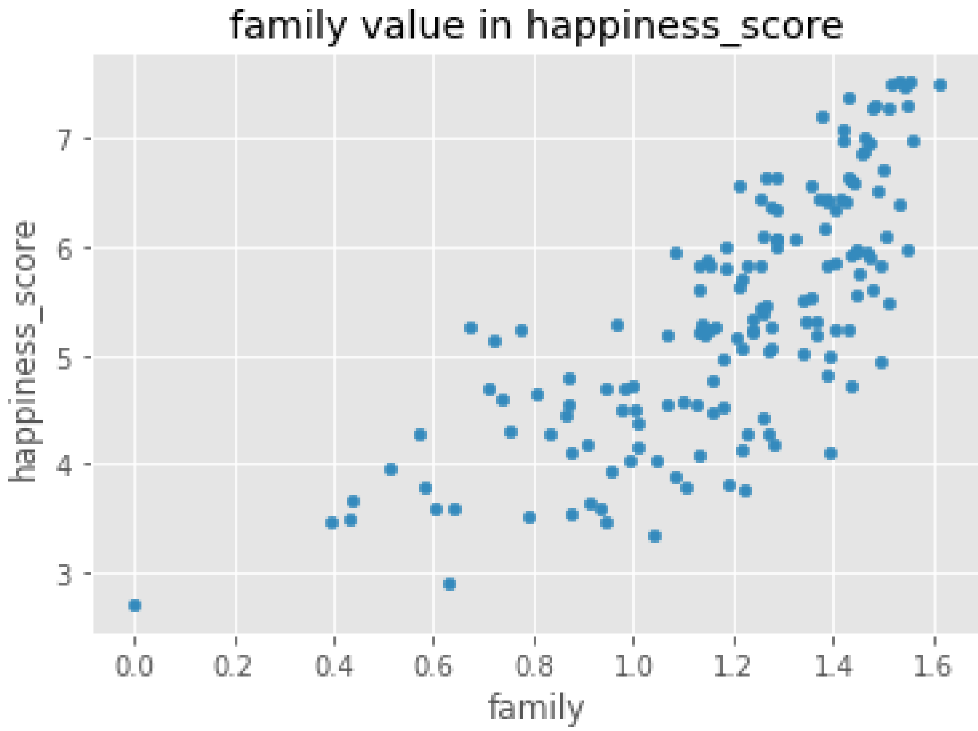

## 2 trend:

the above plot clearly show the linear trend h_score and h_rank are dependent with each other

```
In [133]: data.plot.scatter(x='economy', y='happiness_score', title="economy value in h_score")
          plt.show()
```

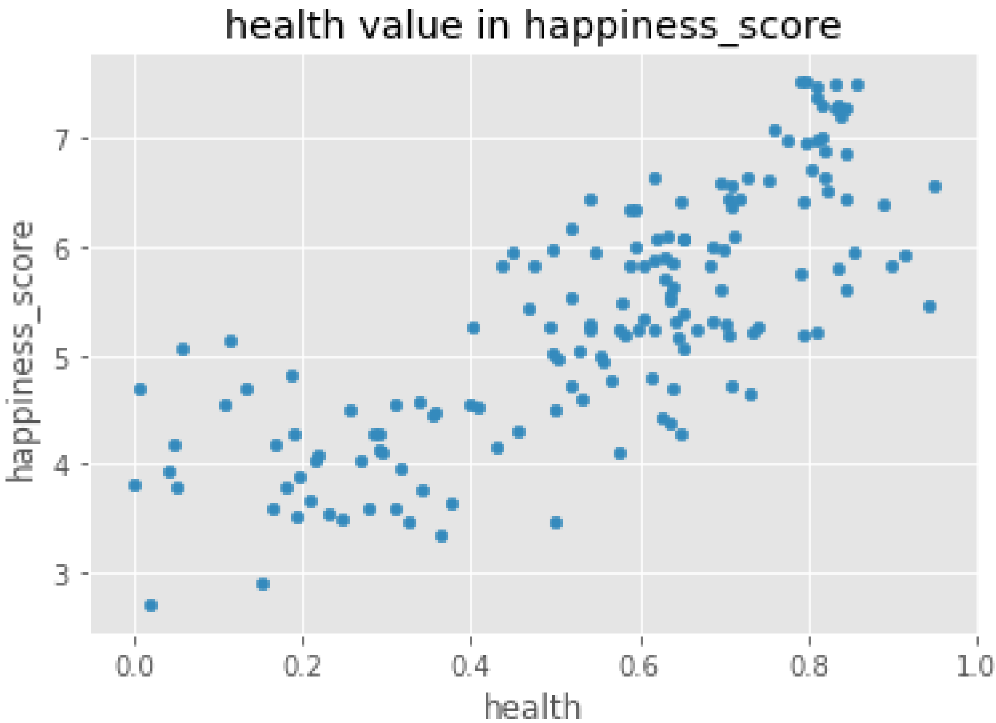

Trend:Clear linear growing trend with significant potential bias from the trendline.
Very probably important, though outliers may cause issues.

```
In [136]: data.plot.scatter(x='family', y='happiness_score', title="family value in happiness_s
          plt.show()
```




Trend:probably shows linear trend.

```
In [137]: data.plot.scatter(x='health', y='happiness_score', title="health value in happiness_s
          plt.show()
```




Trend: could be quadratic usefull for high happiness_score

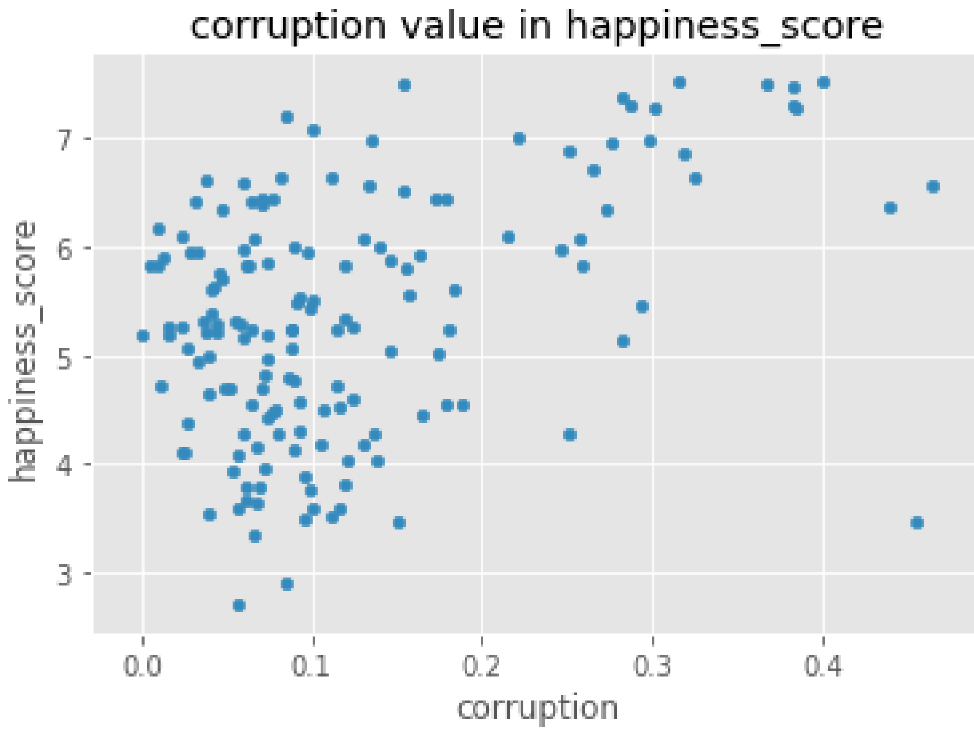
```
In [138]: data.plot.scatter(x='freedom', y='happiness_score', title="freedom value in happines
          plt.show()
```


Trend:it shows linear trend well having low freedom shows less h_score

```
In [139]: data.plot.scatter(x='generosity', y='happiness_score', title="generosity value in hap
          plt.show()
```

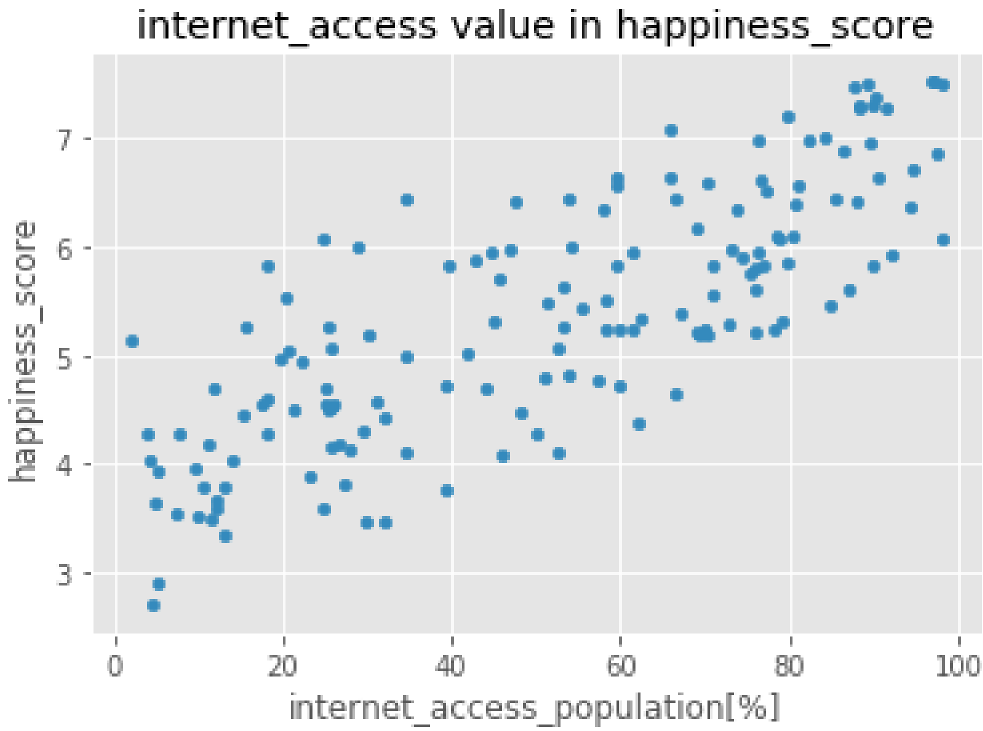

probably it shows exponential trend

```
In [140]: data.plot.scatter(x='corruption', y='happiness_score', title="corruption value in hap
          plt.show()
```



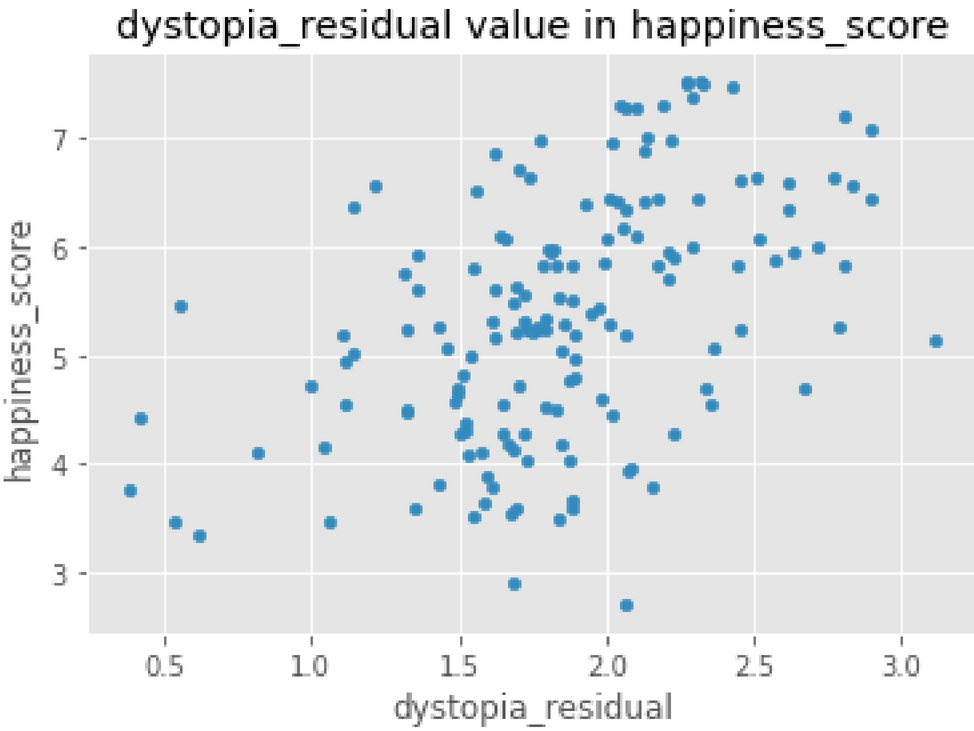

their is probably linear relation between h_score an cooruption,while corruption high their is h_score more

```
In [154]: data.plot.scatter(x='internet_access_population[%]', y='happiness_score', title="inte
          plt.show()
```



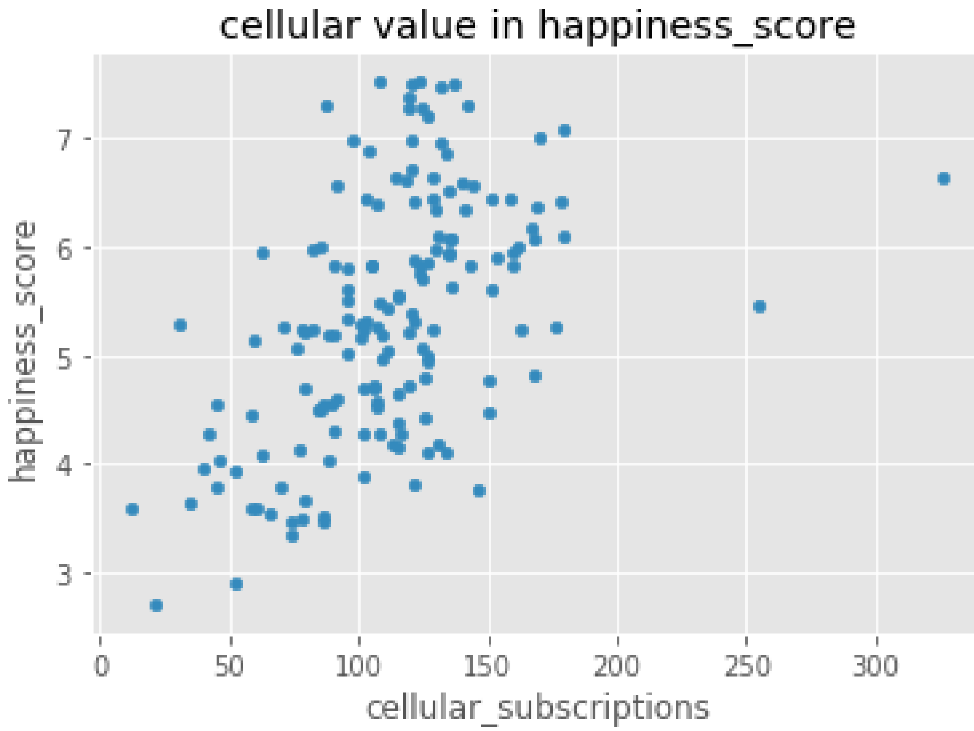

their is clear linear trend between h_score and internet_access.

```
In [141]: data.plot.scatter(x='dystopia_residual', y='happiness_score', title="dystopia_residua
          plt.show()
```



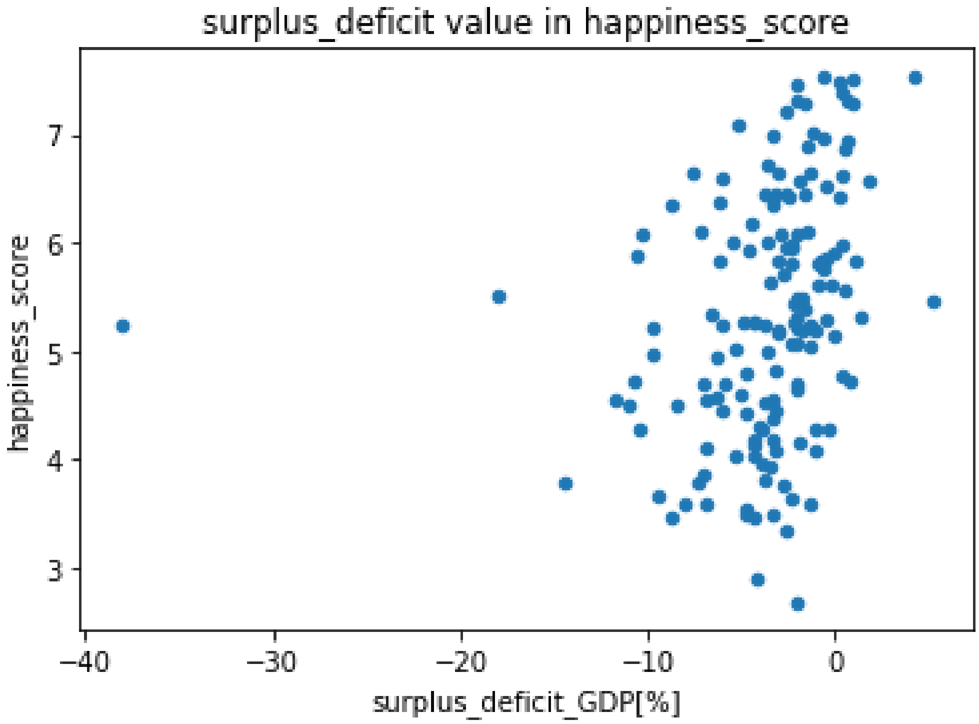

in this plot the quadratic trend shown

```
In [143]: data.plot.scatter(x='cellular_subscriptions', y='happiness_score', title="cellular va
          plt.show()
```




it probaly shows linear trend

```
In [221]: data.plot.scatter(x='surplus_deficit_GDP[%]', y='happiness_score', title="surplus_de
          plt.show()
```

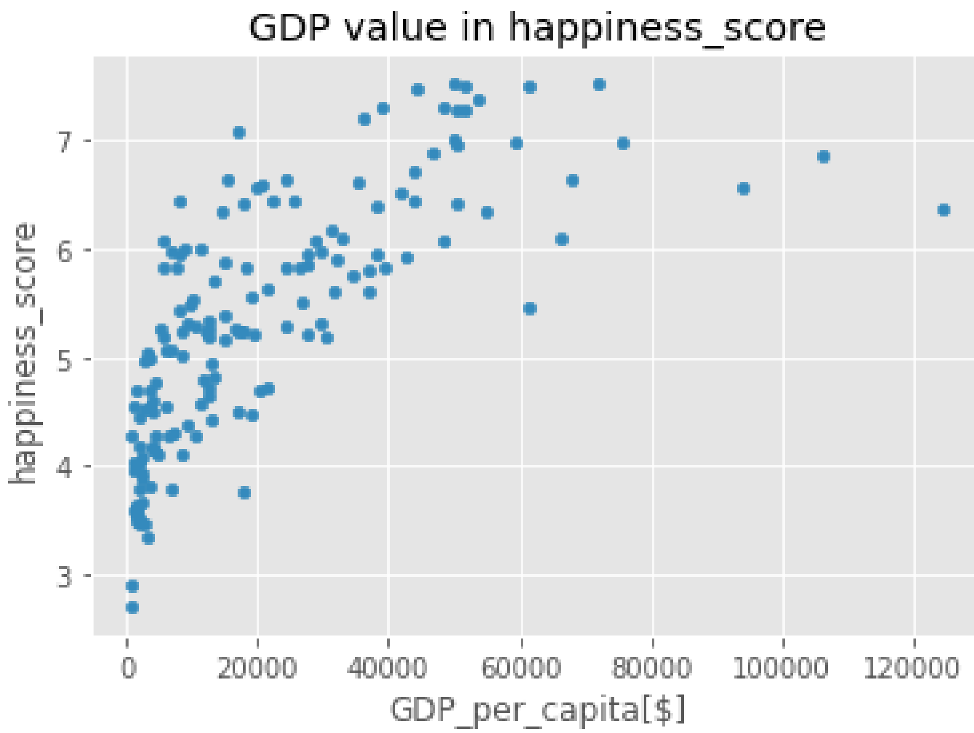



thier it shows a quadratic trend

```
In [220]: data.plot.scatter(x='familiy_income_gini_coeff', y='happiness_score', title="family_i
          plt.show()
```

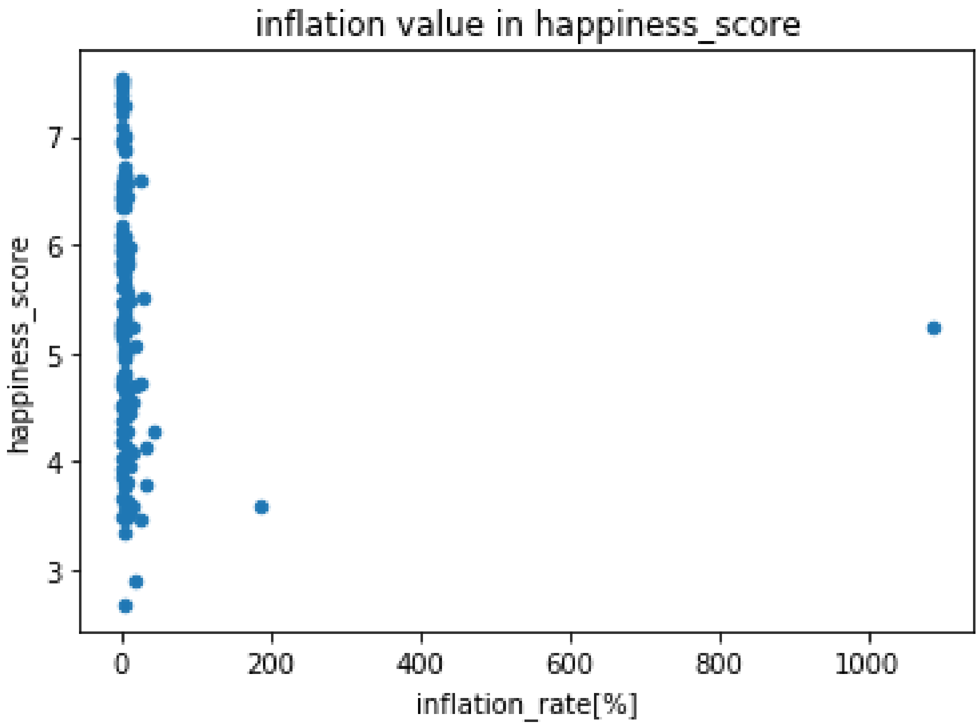
could be a quadratic trend

```
In [149]: data.plot.scatter(x='GDP_per_capita[$]', y='happiness_score', title="GDP value in hap
          plt.show()
```




Low GDP suggest logarithmic trend, but this trend rapidly disappears as the distance increases.

```
In [101]: data.plot.scatter(x='inflation_rate[%]', y='happiness_score', title="inflation value
          plt.show()
```




no clear trend.
Probably useless as there is no hint of a trend.

```
In [151]: data.plot.scatter(x='military_expenditures[%]', y='happiness_score', title="military_
          plt.show()
```


could be quadratic trend

```
In [153]: data.plot.scatter(x='population', y='happiness_score', title="population value in hap
          plt.show()
```


no trend is shown clear here

IMPORTANT FACTORS: Reasons moastly discussed at individual discription,the most clear factors that should give reasonably good result with the data is Happiness_rank,economy,family,freedom,internet access population slightly less usefull that can moastly be used for excluding score would be military_expenditure,gdp,family_income,surplus_deficit,cellular value,generocity probably useless are population,inflation,

## 3 Q2.2

Load data and set up packages

In [252]:
```
import numpy as np
import pandas as pd
from sklearn.kernel_ridge import KernelRidge
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RepeatedKFold
from matplotlib import pyplot as plt
from sklearn.preprocessing import Normalizer
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import scale
from sklearn import metrics
```

```
#from sklearn.preprocessing import Imputer

data = pd.read_csv('happiness.csv')


le = preprocessing.LabelEncoder()
data = data.apply(le.fit_transform)
#x = preprocessing.scale(data.iloc[:, 3:18])
#y = preprocessing.scale(data.iloc[:, 2])

normalizer = Normalizer().fit(data)
data = normalizer.transform(data)
print(data)
#print(x.shape)
```

```
[[0.22205601 0.         0.3202731  ... 0.01067577 0.02135154 0.08327101]
 [0.08238308 0.00222657 0.33175888 ... 0.01113285 0.04230482 0.0957425 ]
 [0.12578859 0.00441363 0.32660897 ... 0.00220682 0.07282497 0.        ]
 ...
 [0.44110763 0.49300265 0.00648688 ... 0.         0.12973754 0.41516012]
 [0.08890068 0.61826383 0.00404094 ... 0.         0.15759666 0.31115238]
 [0.09235783 0.54704252 0.         ... 0.         0.09235783 0.15629786]]
```

```
In [244]: missing_values = ["n/a", "na", "--"]
          data = pd.read_csv("happiness.csv", na_values=missing_values)
          print(data.isnull().sum())
```

```
country                          0
happiness_rank                   0
happiness_score                  0
economy                          0
family                           0
health                           0
freedom                          0
generosity                       0
corruption                       0
dystopia_residual                0
internet_access_population[%]    3
cellular_subscriptions           0
surplus_deficit_GDP[%]           0
familiy_income_gini_coeff       14
GDP_per_capita[$]                1
inflation_rate[%]                0
military_expenditures[%]        15
map_reference                    0
biggest_official_language        0
population                       0
```

```
dtype: int64
```

```
In [246]: #data.familiy_income_gini_coeff.head()
          data['familiy_income_gini_coeff'].fillna(((data['familiy_income_gini_coeff'].mean())
          data['military_expenditures[%]'].fillna(((data['military_expenditures[%]'].mean())),
          data['internet_access_population[%]'].fillna(((data['internet_access_population[%]']
```

dataset have missing values,above values is showing in which feature how many missing values was their.

Check the dataset for missing values and, if any are found, address them programmatically

```
In [289]: data = pd.read_csv('happiness.csv')
          le = preprocessing.LabelEncoder()
          data = data.apply(le.fit_transform)
          x = preprocessing.scale(data.iloc[:, 3:18].values)
          y = preprocessing.scale(data.iloc[:, 2].values)

          normalizer = Normalizer().fit(data)
          data = normalizer.transform(data)
          print(data)
```

```
[[0.22205601 0.         0.3202731  ... 0.01067577 0.02135154 0.08327101]
 [0.08238308 0.00222657 0.33175888 ... 0.01113285 0.04230482 0.0957425 ]
 [0.12578859 0.00441363 0.32660897 ... 0.00220682 0.07282497 0.        ]
 ...
 [0.44110763 0.49300265 0.00648688 ... 0.         0.12973754 0.41516012]
 [0.08890068 0.61826383 0.00404094 ... 0.         0.15759666 0.31115238]
 [0.09235783 0.54704252 0.         ... 0.         0.09235783 0.15629786]]
```

```
C:\Users\Srilu\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarn
  warnings.warn(msg, DataConversionWarning)
```

### 3.1 Linear model

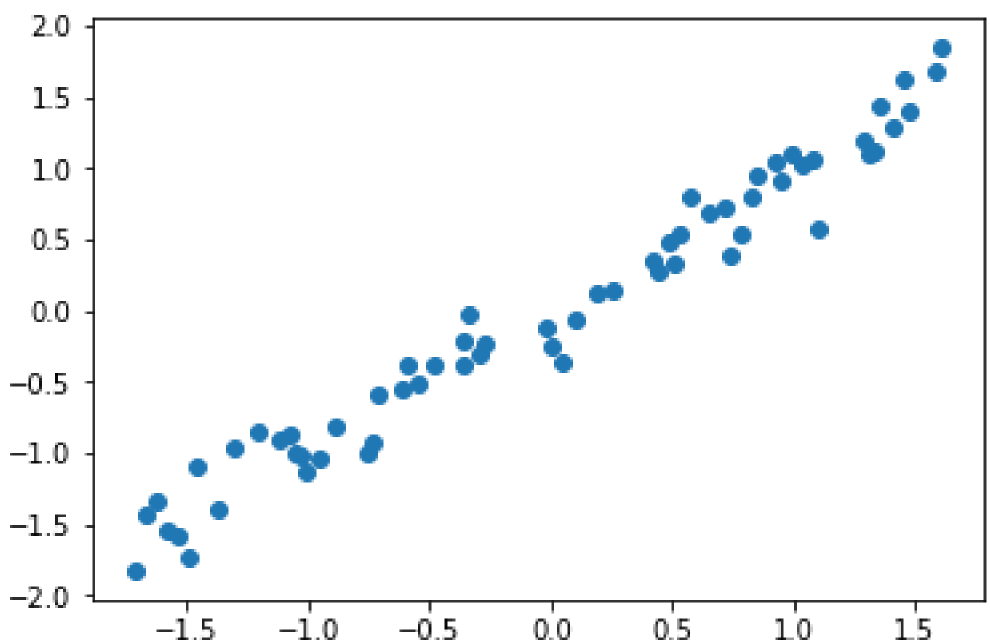
```
In [317]: model1 = KernelRidge(kernel='linear')

          #train data
          rkf = RepeatedKFold(n_splits=5, n_repeats=1, random_state=0)
          #for train_index, test_index in rkf.split(x):
              #print("train index:", train_index, "test_index", test_index)
          #    xTrain, xTest = x[train_index], x[test_index]
          #    yTrain, yTest = y[train_index], y[test_index]


          xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size=0.4, random_state = 
          #model fitting
```

```
print(xTrain.shape)
print(xTest.shape)
print(yTrain.shape)
print(yTest.shape)
lm.score(xTest,yTest)
#ypredictions = lm.fit(xTrain ,yTrain).predict(xTest)
```

```
(93, 15)
(62, 15)
(93,)
(62,)
```

In [324]:
```
lm = model1
lm.fit(xTrain,yTrain)
ypredictions = lm.predict(xTest)
data = pd.DataFrame({'actual':yTest, 'predicted': ypredictions})
data
plt.scatter(yTest,ypredictions)
```

Out[324]: <matplotlib.collections.PathCollection at 0x21e65ae03c8>




In [325]:
```
#calculating MSE and R2 score
mse_linear = metrics.mean_squared_error(yTest, ypredictions)
print('MSE = ',mse_linear)
score = cross_val_score(model1, x, y, scoring='r2', cv=rkf)
```

```
    print("cross:", score)
    score1 = cross_val_score(model1, x, y, scoring='r2', cv=rkf).mean()
    print("r2=", score1)
    #score_linear = metrics.r2_score(yTest, ypredictions)
    #print('r2 = ', score_linear)
```

```
MSE =  0.034685335649298855
cross: [0.95974719 0.96542273 0.94965564 0.95807237 0.93867103]
r2= 0.9543137913170767
```

the linear model has R2 value 0.954 which is impressive

### 3.2 Quadratic model

```
In [293]: model2 = KernelRidge(kernel = "polynomial", degree=2)
          ypredictions_kpolynomial = model2.fit(xTrain,yTrain).predict(xTest)
          #plt.scatter(yTest,ypredictions_kpolynomial)
          mse_poly = metrics.mean_squared_error(yTest, ypredictions_kpolynomial)
          print('MSE poly =', mse_poly)
          score = cross_val_score(model2, x, y, cv=rkf, scoring='r2')
          print("cross:", score)
          score2 = cross_val_score(model2, x, y, cv=rkf, scoring='r2').mean()
          print("r2:", score2)
```

```
MSE poly = 0.037429573741612314
cross: [0.95618397 0.97013646 0.95583916 0.96259831 0.943982  ]
r2: 0.9577479786097467
```

{text results here}

### 3.3 Gaussian model

```
In [294]: model3 = KernelRidge(kernel = "rbf", degree=1)
          ypredictions_rbf = model3.fit(xTrain,yTrain).predict(xTest)
          #plt.scatter(yTest,ypredictions_rbf)
          mse_rbf = metrics.mean_squared_error(yTest, ypredictions_rbf)
          print('MSE rbf =', mse_rbf)
          score = cross_val_score(model3, x, y, cv=rkf, scoring='r2')
          print("cross:", score)
          score3 = cross_val_score(model3, x, y, cv=rkf, scoring='r2').mean()
          print("cross:", score3)
```

```
MSE rbf = 0.09504262818613479
cross: [0.90468855 0.91405417 0.89591381 0.92238792 0.88106397]
cross: 0.9036216847196451
```

the R2score is 0.903 prettymuch equal to all models

### 3.4 Comparison

where as R2 score are pretty much similar,where as linear model is best fit preferable while MSE are taken into consideration