L01_intro

February 13, 2026

1 L01 - Intro

Code given:

[27]:
```
# To support both python 2 and python 3
from __future__ import division, print_function, unicode_literals

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# To plot pretty figures
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
plt.rcParams['axes.labelsize'] = 14
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12

# Where to save the figures
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "fundamentals"

def save_fig(fig_id, tight_layout=True):
    path = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID, fig_id + ".png")
    print("IGNORING: Saving figure", fig_id) # SWMAL: I've disabled saving of␣
 ↪figures
    #if tight_layout:
    #    plt.tight_layout()
    #plt.savefig(path, format='png', dpi=300)

# Ignore useless warnings (see SciPy issue #5998)
import warnings
warnings.filterwarnings(action="ignore", module="scipy", message="^internal␣
 ↪gelsd")
```

```python
print("OK")
```

```
OK
```

[28]:
```python
def prepare_country_stats(oecd_bli, gdp_per_capita):
    oecd_bli = oecd_bli[oecd_bli["INEQUALITY"]=="TOT"]
    oecd_bli = oecd_bli.pivot(index="Country", columns="Indicator",␣
 ↪values="Value")
    gdp_per_capita.rename(columns={"2015": "GDP per capita"}, inplace=True)
    gdp_per_capita.set_index("Country", inplace=True)
    full_country_stats = pd.merge(left=oecd_bli, right=gdp_per_capita,
                                  left_index=True, right_index=True)
    full_country_stats.sort_values(by="GDP per capita", inplace=True)
    remove_indices = [0, 1, 6, 8, 33, 34, 35]
    keep_indices = list(set(range(36)) - set(remove_indices))
    return full_country_stats[["GDP per capita", 'Life satisfaction']].
 ↪iloc[keep_indices]

print("OK")
```

```
OK
```

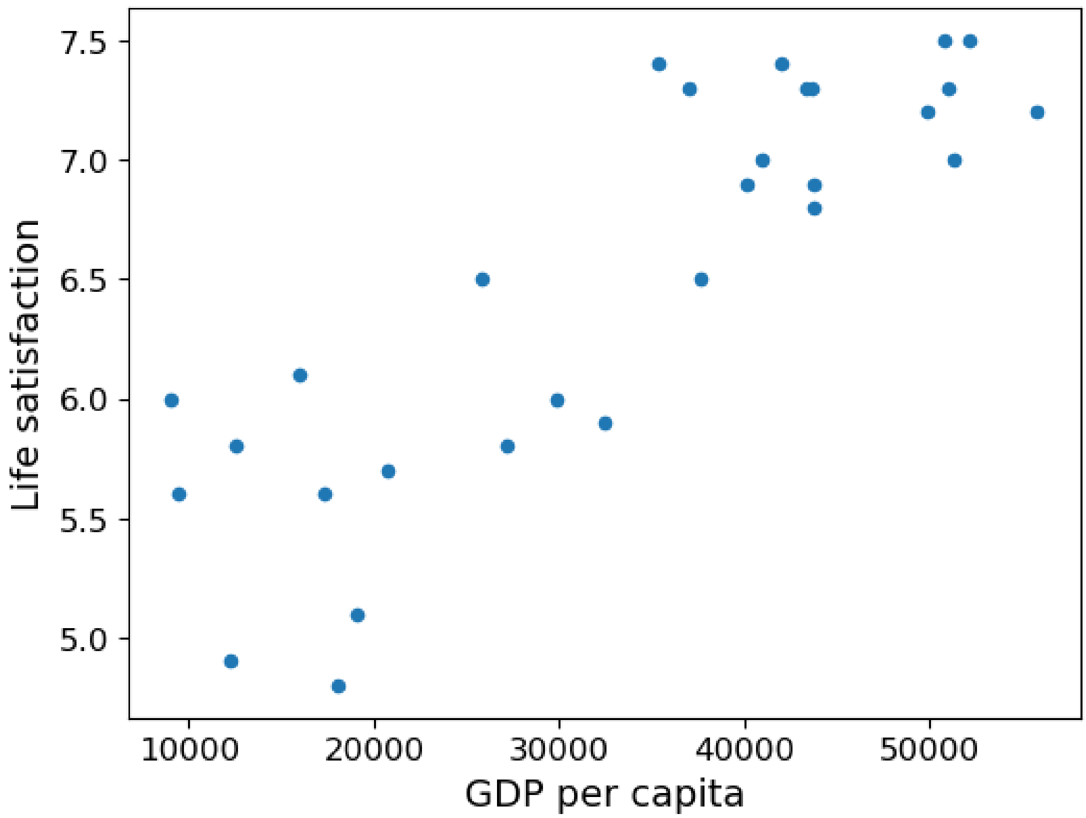
[29]:
```python
import os
# os.path.join handles the path
datapath = os.path.join("GITMAL", "datasets", "lifesat", "")

# This check ensures you are in the right place before loading data
if not os.path.exists(datapath):
    print(f"ERROR: Datapath not found at {os.path.abspath(datapath)}")
else:
    print(f"OK: Found datasets at {os.path.abspath(datapath)}")

# Run system command to verify files exist
! dir "{datapath}"
```

```
OK: Found datasets at c:\Users\bruger\Desktop\unii\6.sem\SWMAL\git-
rep\SWMALLER-1\01\GITMAL\datasets\lifesat
 Volume in drive C has no label.
 Volume Serial Number is 1E52-7239

 Directory of c:\Users\bruger\Desktop\unii\6.sem\SWMAL\git-
rep\SWMALLER-1\01\GITMAL\datasets\lifesat

11-02-2026  12:12    <DIR>          .
11-02-2026  12:12    <DIR>          ..
03-02-2026  14:25            36.323 gdp_per_capita.csv
03-02-2026  14:25               814 lifesat.csv
03-02-2026  14:25           405.467 oecd_bli_2015.csv
```

```
03-02-2026  14:25             4.405 README.md
               4 File(s)        447.009 bytes
               2 Dir(s)  290.290.335.744 bytes free
```

[30]:

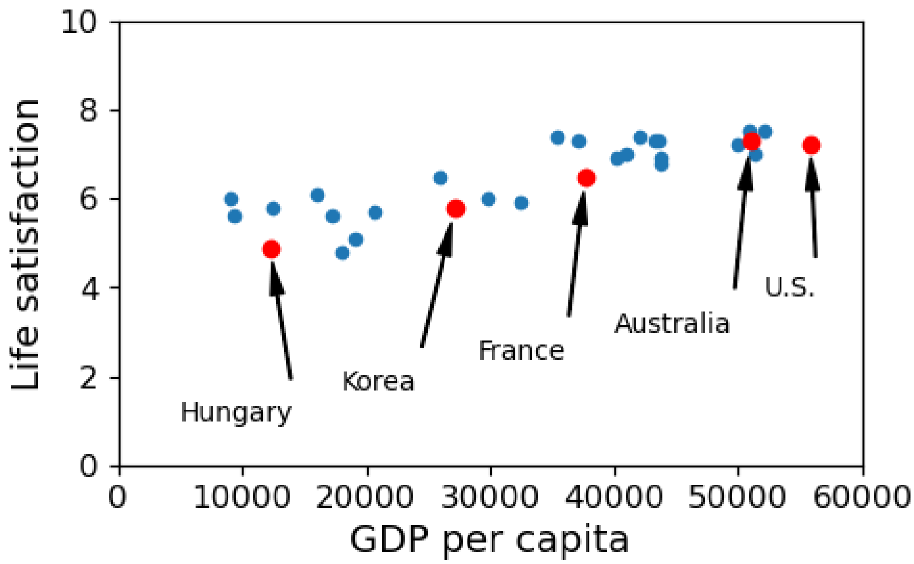
```python
# Code example
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model

# Load the data
try:
    oecd_bli = pd.read_csv(datapath + "oecd_bli_2015.csv", thousands=',')
    gdp_per_capita = pd.read_csv(datapath + "gdp_per_capita.
 ↪csv",thousands=',',delimiter='\t',
                             encoding='latin1', na_values="n/a")
except Exception as e:
    print(f"SWMAL NOTE: well, you need to have the 'datasets' dir in path,␣
 ↪please unzip 'datasets.zip' and make sure that its included in the␣
 ↪datapath='{datapath}' setting in the cell above..")
    raise e

# Prepare the data
country_stats = prepare_country_stats(oecd_bli, gdp_per_capita)
X = np.c_[country_stats["GDP per capita"]]
y = np.c_[country_stats["Life satisfaction"]]

# Visualize the data
country_stats.plot(kind='scatter', x="GDP per capita", y='Life satisfaction')
plt.show()

# Select a linear model
model = sklearn.linear_model.LinearRegression()

# Train the model
model.fit(X, y)

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita
y_pred = model.predict(X_new)
print(y_pred) # outputs [[ 5.96242338]]

print("OK")
```

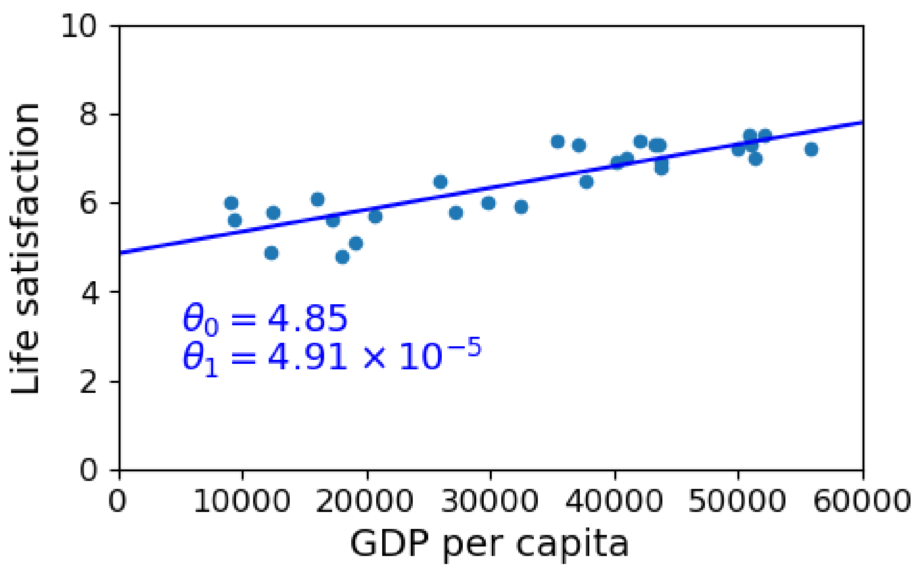



```
[[5.96242338]]
OK
```

[31]:
```
oecd_bli = pd.read_csv(datapath + "oecd_bli_2015.csv", thousands=',')
oecd_bli = oecd_bli[oecd_bli["INEQUALITY"]=="TOT"]
oecd_bli = oecd_bli.pivot(index="Country", columns="Indicator", values="Value")
#oecd_bli.head(2)

gdp_per_capita = pd.read_csv(datapath+"gdp_per_capita.csv", thousands=',',␣
 ↪delimiter='\t',
                             encoding='latin1', na_values="n/a")
gdp_per_capita.rename(columns={"2015": "GDP per capita"}, inplace=True)
gdp_per_capita.set_index("Country", inplace=True)
#gdp_per_capita.head(2)

full_country_stats = pd.merge(left=oecd_bli, right=gdp_per_capita,␣
 ↪left_index=True, right_index=True)
full_country_stats.sort_values(by="GDP per capita", inplace=True)
#full_country_stats

remove_indices = [0, 1, 6, 8, 33, 34, 35]
```

```python
keep_indices = list(set(range(36)) - set(remove_indices))

sample_data = full_country_stats[["GDP per capita", 'Life satisfaction']].iloc[keep_indices]
#missing_data = full_country_stats[["GDP per capita", 'Life satisfaction']].iloc[remove_indices]

sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(5,3))
plt.axis([0, 60000, 0, 10])
position_text = {
    "Hungary": (5000, 1),
    "Korea": (18000, 1.7),
    "France": (29000, 2.4),
    "Australia": (40000, 3.0),
    "United States": (52000, 3.8),
}
for country, pos_text in position_text.items():
    pos_data_x, pos_data_y = sample_data.loc[country]
    country = "U.S." if country == "United States" else country
    plt.annotate(country, xy=(pos_data_x, pos_data_y), xytext=pos_text,
            arrowprops=dict(facecolor='black', width=0.5, shrink=0.1, headwidth=5))
    plt.plot(pos_data_x, pos_data_y, "ro")
#save_fig('money_happy_scatterplot')
plt.show()

from sklearn import linear_model
lin1 = linear_model.LinearRegression()
Xsample = np.c_[sample_data["GDP per capita"]]
ysample = np.c_[sample_data["Life satisfaction"]]
lin1.fit(Xsample, ysample)

t0 = 4.8530528
t1 = 4.91154459e-05

sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(5,3))
plt.axis([0, 60000, 0, 10])
M=np.linspace(0, 60000, 1000)
plt.plot(M, t0 + t1*M, "b")
plt.text(5000, 3.1, r"$\theta_0 = 4.85$", fontsize=14, color="b")
plt.text(5000, 2.2, r"$\theta_1 = 4.91 \times 10^{-5}$", fontsize=14, color="b")
#save_fig('best_fit_model_plot')
plt.show()

print("OK")
```






```
OK
```

1.0.1 1.4.2. Qa) The parameters θ_0 and θ_1 and R^2 the Score

Finding the and is relatively simple in our notation, referencing https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html it is done by extracting .intercept and .coef

[32]:
```
 _0 = model.intercept_
 _1 = model.coef_
print(" _0 and  _1 are respectively",  _0,  _1)
```

```
 _0 and  _1 are respectively [4.8530528] [[4.91154459e-05]]
```

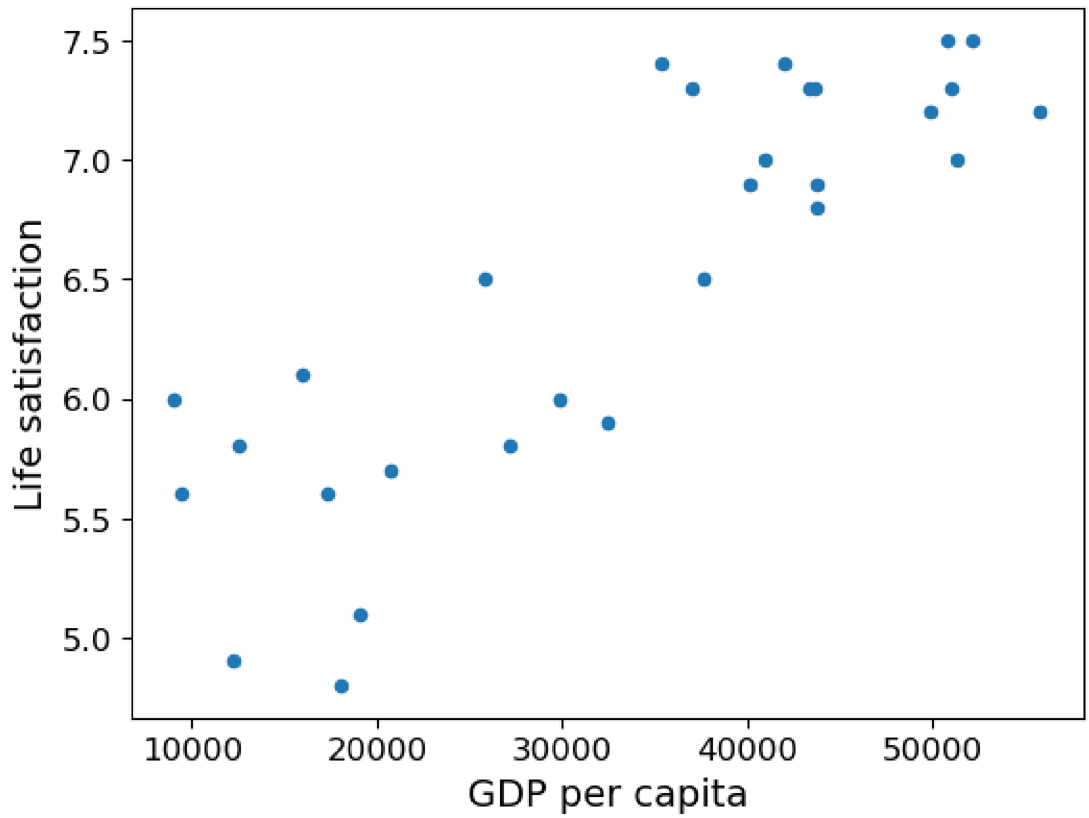
[33]:
```
R2 = model.score(X,y)
print("R2 is then extracted to be", R2)
```

```
R2 is then extracted to be 0.7344414355437031
```

1.0.2 Qb) Using k-Nearest Neighbors

[34]:
```
# Prepare the data
X = np.c_[country_stats["GDP per capita"]]
y = np.c_[country_stats["Life satisfaction"]]

print("X.shape=",X.shape)
print("y.shape=",y.shape)

# Visualize the data
country_stats.plot(kind='scatter', x="GDP per capita", y='Life satisfaction')
plt.show()

# Select and train a model

# TODO: add your code here..
knn = sklearn.neighbors.KNeighborsRegressor(n_neighbors=3)

# Train the model
knn.fit(X, y)

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita
y_pred = knn.predict(X_new)
print("y_pred =", y_pred)

knnscore = knn.score(X,y)
print("The nearest neighbour models score is", knnscore)
```

```
X.shape= (29, 1)
y.shape= (29, 1)
```




```
y_pred = [[5.76666667]]
The nearest neighbour models score is 0.8525732853499179
```

According to https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsRegressor.html the Knn model also returns the R^2 when calling model.score. We see that it is quite a bit better than that of the linear regressor.

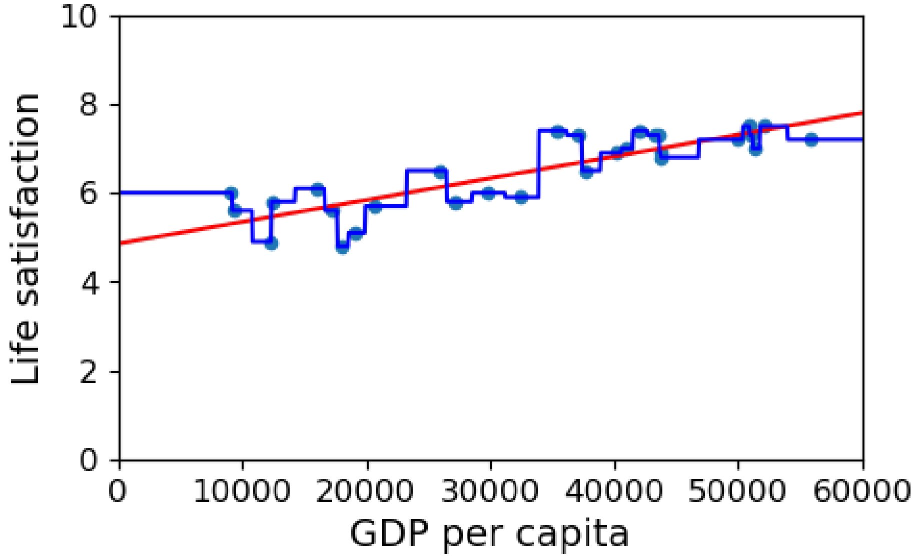
1.0.3 1.5.2. Qc) Tuning Parameter for k-Nearest Neighbors and A Sanity Check

[35]:
```python
knn= sklearn.neighbors.KNeighborsRegressor(n_neighbors=1)

# Train the model
knn.fit(X, y)

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita
y_pred = knn.predict(X_new)
print("y_pred =", y_pred)

knnscore = knn.score(X,y)
print("The nearest neighbour models score is", knnscore)
```

```python
sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction',␣
  ↪figsize=(5,3))
plt.axis([0, 60000, 0, 10])

# create  test matrix M, with the same dimensionality as X, and in the range [0;
  ↪60000]
m=np.linspace(0, 60000, 1000)
M=np.empty([m.shape[0],1])
M[:,0]=m

# from this test M data, predict the y values via the lin.reg. and k-nearest␣
  ↪models
y_pred_lin = model.predict(M)
y_pred_knn = knn.predict(M)

# use plt.plot to plot x-y into the sample_data plot..
plt.plot(m, y_pred_lin, "r")
plt.plot(m, y_pred_knn, "b")
print(X)
```

```
y_pred = [[5.7]]
The nearest neighbour models score is 1.0
[[ 9054.914]
 [ 9437.372]
 [12239.894]
 [12495.334]
 [15991.736]
 [17288.083]
 [18064.288]
 [19121.592]
 [20732.482]
 [25864.721]
 [27195.197]
 [29866.581]
 [32485.545]
 [35343.336]
 [37044.891]
 [37675.006]
 [40106.632]
 [40996.511]
 [41973.988]
 [43331.961]
 [43603.115]
 [43724.031]
 [43770.688]
 [49866.266]
```

```
[50854.583]
[50961.865]
[51350.744]
[52114.165]
[55805.204]]
```



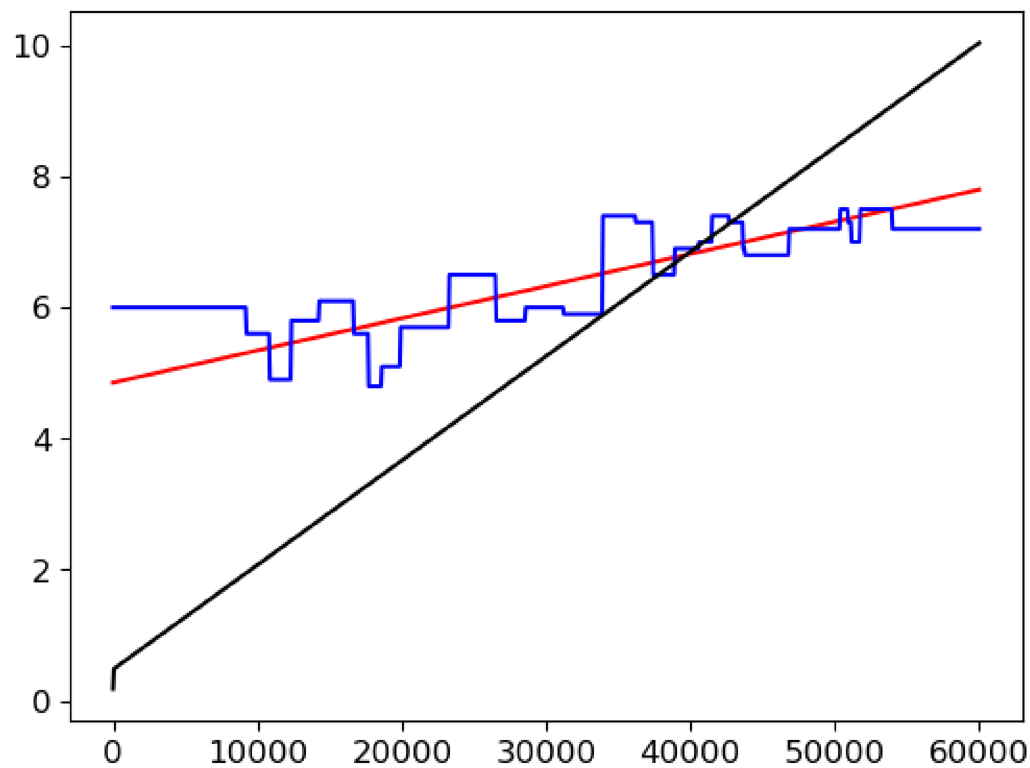
When initiated with n_neighbours = 1 we get a score of 1 which either indicates a perfect model (unlikely) or more likely the neighbour counted first is the point it self, leading to nothing but perfect predictions but no ability to predict the overall correlation. Furthermore we see that we have not split X and y into a test and train set indicating that we are using already known values to test how good the model is at predicting.

1.0.4 1.5.3. Qd) Trying out a Neural Networkfrom sklearn.neural_network import MLPRegressor

[36]:
```
from sklearn.neural_network import MLPRegressor

# Setup MLPRegressor
mlp = MLPRegressor( hidden_layer_sizes=(10,), solver='adam', activation='relu',␣
↪tol=1E-5, max_iter=100000, verbose=False)
mlp.fit(X, y.ravel())

# lets make a MLP regressor prediction and redo the plots
y_pred_mlp = mlp.predict(M)

plt.plot(m, y_pred_lin, "r")
plt.plot(m, y_pred_knn, "b")
plt.plot(m, y_pred_mlp, "k")
```

```
# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita
y_pred = mlp.predict(X_new)
print("y_pred =", y_pred)

nnscore = mlp.score(X,y)
print("The score for the nn is",nnscore)
```

```
y_pred = [4.07671125]
The score for the nn is -3.6741440524089137
```



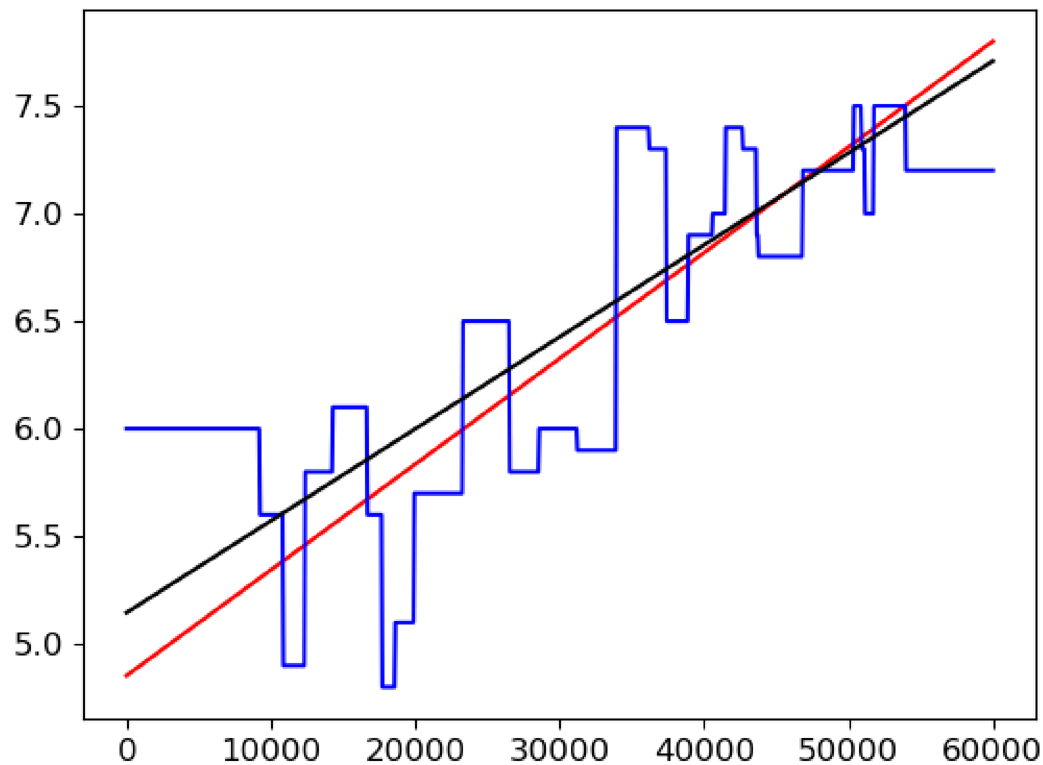
While the Neural network does return the R^2 value when .score is called it is clear that a score of order -10^3 is far from as good as the others, this might stem from the fact that this dataset is not very suitable for the MLP model, at least not without some adjustement.

1.0.5 1.5.4. Qe) Neural Network with pre-scaling

[37]:
```
from sklearn.neural_network import MLPRegressor
# lets scale the data to something more suitable for the MLP using the
 ↪MinMaxsclaer from sklearn
from sklearn.preprocessing import MinMaxScaler
```

```
# Initialize the scaler
scaler = MinMaxScaler()

X_scaled = scaler.fit_transform(X)

# Setup MLPRegressor
mlp = MLPRegressor( hidden_layer_sizes=(10,), solver='adam', activation='relu',␣
 ↪tol=1E-5, max_iter=100000, verbose=False)
mlp.fit(X_scaled, y.ravel())

# lets make a MLP regressor prediction and redo the plots
M_scaled = scaler.fit_transform(M)
y_pred_mlp = mlp.predict(M_scaled)

plt.plot(m, y_pred_lin, "r")
plt.plot(m, y_pred_knn, "b")
plt.plot(m, y_pred_mlp, "k")

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita

# Scale
X_new_scaled = scaler.transform(X_new)
y_pred = mlp.predict(X_new_scaled)

print(f"Scaled input: {X_new_scaled}")
print("y_pred =", y_pred)

nnscore = mlp.score(X_scaled,y)
print("The new score for the nn is",nnscore)
```

```
Scaled input: [[0.37645]]
y_pred = [6.11008679]
The new score for the nn is 0.7242636173560772
```



We see that when the data is properly scaled to what the model might expect the R^2 is much better (closer to 1) while it does not fit as well as the other two models, it is better. Wierdly linear though.