handson-ml2 (/github/ageron/handson-ml2/tree/master)
/
01_the_machine_learning_landscape.ipynb (/github/ageron/handson-ml2/tree/master/01_the_machine_learning_landscape.ipynb)

Chapter 1 – The Machine Learning landscape

This is the code used to generate some of the figures in chapter 1.

Open in Colab (https://colab.research.google.com/github/ageron/handson-ml2/blob/master/01_the_machine_learning_landscape.ipynb) Open in Kaggle (https://kaggle.com/kernels/welcome?src=https://github.com/ageron/handson-ml2/blob/master/01_the_machine_learning_landscape.ipynb)

Code example 1-1

Although Python 2.x may work, it is deprecated so we strongly recommend you use Python 3 instead.

In [1]:
```
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)
```

In [2]:
```
# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"
```

This function just merges the OECD's life satisfaction data and the IMF's GDP per capita data. It's a bit too long and boring and it's not specific to Machine Learning, which is why I left it out of the book.

In [3]:
```
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]
```

The code in the book expects the data files to be located in the current directory. I just tweaked it here to fetch the files in `datasets/lifesat` .

In [4]:
```
import os
datapath = os.path.join("datasets", "lifesat", "")
```

In [5]:
```
# To plot pretty figures directly within Jupyter
%matplotlib inline
import matplotlib as mpl
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

In [6]:
```
# Download the data
import urllib.request
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
os.makedirs(datapath, exist_ok=True)
for filename in ("oecd_bli_2015.csv", "gdp_per_capita.csv"):
    print("Downloading", filename)
    url = DOWNLOAD_ROOT + "datasets/lifesat/" + filename
    urllib.request.urlretrieve(url, datapath + filename)
```

```
Downloading oecd_bli_2015.csv
Downloading gdp_per_capita.csv
```

In [7]:
```
# Code example
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model

# Load the data
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")

# 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
print(model.predict(X_new)) # outputs [[ 5.96242338]]
```

```
[[5.96242338]]
```

Replacing the Linear Regression model with k-Nearest Neighbors (in this example, k = 3) regression in the previous code is as simple as replacing these two lines:

```
import sklearn.linear_model
model = sklearn.linear_model.LinearRegression()
```

with these two:

```
import sklearn.neighbors
model = sklearn.neighbors.KNeighborsRegressor(n_neighbors=3)
```

In [8]:

```
# Select a 3-Nearest Neighbors regression model
import sklearn.neighbors
model1 = sklearn.neighbors.KNeighborsRegressor(n_neighbors=3)

# Train the model
model1.fit(X,y)

# Make a prediction for Cyprus
print(model1.predict(X_new)) # outputs [[5.76666667]]
```

```
[[5.76666667]]
```

In [ ]:

In [ ]:

In [ ]:

Note: you can ignore the rest of this notebook, it just generates many of the figures in chapter 1.

In [ ]:

In [ ]:

In [ ]:

Create a function to save the figures.

In [9]:

```
# Where to save the figures
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "fundamentals"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

Make this notebook's output stable across runs:

In [10]:

```
np.random.seed(42)
```

Load and prepare Life satisfaction data

If you want, you can get fresh data from the OECD's website. Download the CSV from http://stats.oecd.org/index.aspx?DataSetCode=BLI (http://stats.oecd.org/index.aspx?DataSetCode=BLI) and save it to `datasets/lifesat/` .

In [11]:

```
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)
```

Out[11]:

Indicator	Air pollution	Assault rate	Consultation on rule-making	Dwellings without basic facilities	Educational attainment	Employees working very long hours	Employment rate	Homicide rate	Household net adjusted disposable income	I
Country										
Australia	13.0	2.1	10.5	1.1	76.0	14.02	72.0	0.8	31588.0	
Austria	27.0	3.4	7.1	1.0	83.0	7.61	72.0	0.4	31173.0	

2 rows × 24 columns

In [12]:
```
oecd_bli["Life satisfaction"].head()
```

Out[12]:
```
Country
Australia    7.3
Austria      6.9
Belgium      6.9
Brazil       7.0
Canada       7.3
Name: Life satisfaction, dtype: float64
```

Load and prepare GDP per capita data

Just like above, you can update the GDP per capita data if you want. Just download data from http://goo.gl/j1MSKe (http://goo.gl/j1MSKe) (=> imf.org) and save it to `datasets/lifesat/` .

In [13]:
```
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)
```

Out[13]:

	Subject Descriptor	Units	Scale	Country/Series-specific Notes	GDP per capita	Estimates Start After
Country						
Afghanistan	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	599.994	2013.0
Albania	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	3995.383	2010.0

In [14]:
```
full_country_stats = pd.merge(left=oecd_bli, right=gdp_per_capita, left_index=True, right_index=Tru
full_country_stats.sort_values(by="GDP per capita", inplace=True)
full_country_stats
```

Out[14]:

Country	Air pollution	Assault rate	Consultation on rule-making	Dwellings without basic facilities	Educational attainment	Employees working very long hours	Employment rate	Homicide rate	Househol ne adjuste disposabl incom
Brazil	18.0	7.9	4.0	6.7	45.0	10.41	67.0	25.5	11664.
Mexico	30.0	12.8	9.0	4.2	37.0	28.83	61.0	23.4	13085.
Russia	15.0	3.8	2.5	15.1	94.0	0.16	69.0	12.8	19292.
Turkey	35.0	5.0	5.5	12.7	34.0	40.86	50.0	1.2	14095.
Hungary	15.0	3.6	7.9	4.8	82.0	3.19	58.0	1.3	15442.
Poland	33.0	1.4	10.8	3.2	90.0	7.41	60.0	0.9	17852.
Chile	46.0	6.9	2.0	9.4	57.0	15.42	62.0	4.4	14533.
Slovak Republic	13.0	3.0	6.6	0.6	92.0	7.02	60.0	1.2	17503.
Czech Republic	16.0	2.8	6.8	0.9	92.0	6.98	68.0	0.8	18404.

Country	Air pollution	Assault rate	Consultation on rule-making	Dwellings without basic facilities	Educational attainment	Employees working very long hours	Employment rate	Homicide rate	Household net adjusted disposable income
Estonia	9.0	5.5	3.3	8.1	90.0	3.30	68.0	4.8	15167.
Greece	27.0	3.7	6.5	0.7	68.0	6.16	49.0	1.6	18575.
Portugal	18.0	5.7	6.5	0.9	38.0	9.62	61.0	1.1	20086.
Slovenia	26.0	3.9	10.3	0.5	85.0	5.63	63.0	0.4	19326.
Spain	24.0	4.2	7.3	0.1	55.0	5.89	56.0	0.6	22477.
Korea	30.0	2.1	10.4	4.2	82.0	18.72	64.0	1.1	19510.
Italy	21.0	4.7	5.0	1.1	57.0	3.66	56.0	0.7	25166.
Japan	24.0	1.4	7.3	6.4	94.0	22.26	72.0	0.3	26111.
Israel	21.0	6.4	2.5	3.7	85.0	16.03	67.0	2.3	22104.

Country	Air pollution	Assault rate	Consultation on rule-making	Dwellings without basic facilities	Educational attainment	Employees working very long hours	Employment rate	Homicide rate	Household net adjusted disposable income
New Zealand	11.0	2.2	10.3	0.2	74.0	13.87	73.0	1.2	23815.
France	12.0	5.0	3.5	0.5	73.0	8.15	64.0	0.6	28799.
Belgium	21.0	6.6	4.5	2.0	72.0	4.57	62.0	1.1	28307.
Germany	16.0	3.6	4.5	0.1	86.0	5.25	73.0	0.5	31252.
Finland	15.0	2.4	9.0	0.6	85.0	3.58	69.0	1.4	27927.
Canada	15.0	1.3	10.5	0.2	89.0	3.94	72.0	1.5	29365.
Netherlands	30.0	4.9	6.1	0.0	73.0	0.45	74.0	0.9	27888.
Austria	27.0	3.4	7.1	1.0	83.0	7.61	72.0	0.4	31173.
United Kingdom	13.0	1.9	11.5	0.2	78.0	12.70	71.0	0.3	27029.

Country	Air pollution	Assault rate	Consultation on rule-making	Dwellings without basic facilities	Educational attainment	Employees working very long hours	Employment rate	Homicide rate	Household net adjusted disposable income
Sweden	10.0	5.1	10.9	0.0	88.0	1.13	74.0	0.7	29185.
Iceland	18.0	2.7	5.1	0.4	71.0	12.25	82.0	0.3	23965.
Australia	13.0	2.1	10.5	1.1	76.0	14.02	72.0	0.8	31588.
Ireland	13.0	2.6	9.0	0.2	75.0	4.20	60.0	0.8	23917.
Denmark	15.0	3.9	7.0	0.9	78.0	2.03	73.0	0.3	26491.
United States	18.0	1.5	8.3	0.1	89.0	11.30	67.0	5.2	41355.
Norway	16.0	3.3	8.1	0.3	82.0	2.82	75.0	0.6	33492.
Switzerland	20.0	4.2	8.4	0.0	86.0	6.72	80.0	0.5	33491.
Luxembourg	12.0	4.3	6.0	0.1	78.0	3.47	66.0	0.4	38951.

36 rows × 30 columns

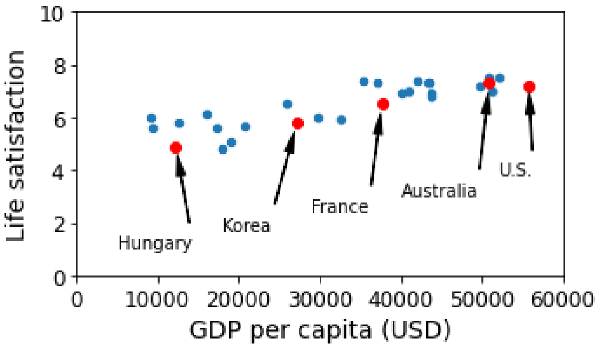
In [15]:
```
full_country_stats[["GDP per capita", 'Life satisfaction']].loc["United States"]
```

Out[15]:
```
GDP per capita       55805.204
Life satisfaction        7.200
Name: United States, dtype: float64
```

In [16]:
```
remove_indices = [0, 1, 6, 8, 33, 34, 35]
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]
```

In [17]:
```
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")
plt.xlabel("GDP per capita (USD)")
save_fig('money_happy_scatterplot')
plt.show()
```

```
Saving figure money_happy_scatterplot
```



In [18]:
```
sample_data.to_csv(os.path.join("datasets", "lifesat", "lifesat.csv"))
```

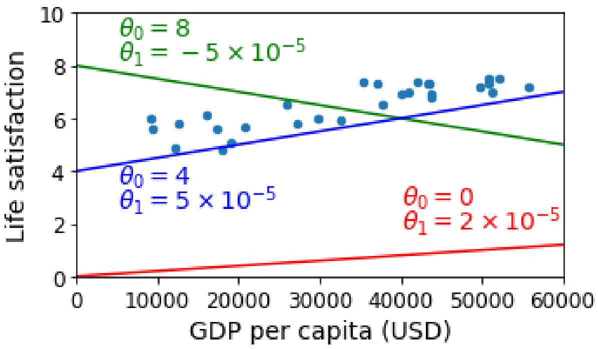
In [19]:
```
sample_data.loc[list(position_text.keys())]
```

Out[19]:

	GDP per capita	Life satisfaction
Country		
Hungary	12239.894	4.9
Korea	27195.197	5.8
France	37675.006	6.5
Australia	50961.865	7.3
United States	55805.204	7.2

In [20]:
```
import numpy as np

sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(5,3))
plt.xlabel("GDP per capita (USD)")
plt.axis([0, 60000, 0, 10])
X=np.linspace(0, 60000, 1000)
plt.plot(X, 2*X/100000, "r")
plt.text(40000, 2.7, r"$\theta_0 = 0$", fontsize=14, color="r")
plt.text(40000, 1.8, r"$\theta_1 = 2 \times 10^{-5}$", fontsize=14, color="r")
plt.plot(X, 8 - 5*X/100000, "g")
plt.text(5000, 9.1, r"$\theta_0 = 8$", fontsize=14, color="g")
plt.text(5000, 8.2, r"$\theta_1 = -5 \times 10^{-5}$", fontsize=14, color="g")
plt.plot(X, 4 + 5*X/100000, "b")
plt.text(5000, 3.5, r"$\theta_0 = 4$", fontsize=14, color="b")
plt.text(5000, 2.6, r"$\theta_1 = 5 \times 10^{-5}$", fontsize=14, color="b")
save_fig('tweaking_model_params_plot')
plt.show()
```

```
Saving figure tweaking_model_params_plot
```

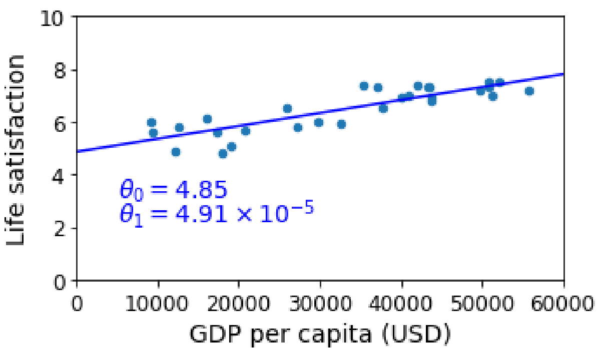


In [21]:
```
from sklearn import linear_model
lin1 = linear_model.LinearRegression()
Xsample = np.c_[sample_data["GDP per capita"]]
ysample = np.c_[sample_data["Life satisfaction"]]
lin1.fit(Xsample, ysample)
t0, t1 = lin1.intercept_[0], lin1.coef_[0][0]
t0, t1
```

Out[21]:
```
(4.853052800266436, 4.911544589158484e-05)
```

In [22]:
```
sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(5,3))
plt.xlabel("GDP per capita (USD)")
plt.axis([0, 60000, 0, 10])
X=np.linspace(0, 60000, 1000)
plt.plot(X, t0 + t1*X, "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()
```

```
Saving figure best_fit_model_plot
```



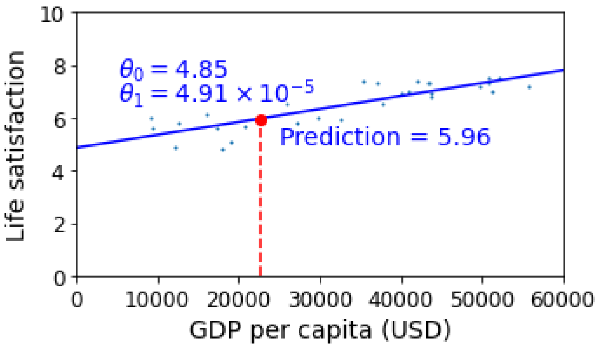
In [23]:
```
cyprus_gdp_per_capita = gdp_per_capita.loc["Cyprus"]["GDP per capita"]
print(cyprus_gdp_per_capita)
cyprus_predicted_life_satisfaction = lin1.predict([[cyprus_gdp_per_capita]])[0][0]
cyprus_predicted_life_satisfaction
```

```
22587.49
```

Out[23]: `5.96244744318815`

In [24]:
```
sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(5,3), s=1)
plt.xlabel("GDP per capita (USD)")
X=np.linspace(0, 60000, 1000)
plt.plot(X, t0 + t1*X, "b")
plt.axis([0, 60000, 0, 10])
plt.text(5000, 7.5, r"$\theta_0 = 4.85$", fontsize=14, color="b")
plt.text(5000, 6.6, r"$\theta_1 = 4.91 \times 10^{-5}$", fontsize=14, color="b")
plt.plot([cyprus_gdp_per_capita, cyprus_gdp_per_capita], [0, cyprus_predicted_life_satisfaction], "
plt.text(25000, 5.0, r"Prediction = 5.96", fontsize=14, color="b")
plt.plot(cyprus_gdp_per_capita, cyprus_predicted_life_satisfaction, "ro")
save_fig('cyprus_prediction_plot')
plt.show()
```

```
Saving figure cyprus_prediction_plot
```



In [25]:
```
sample_data[7:10]
```

Out[25]:

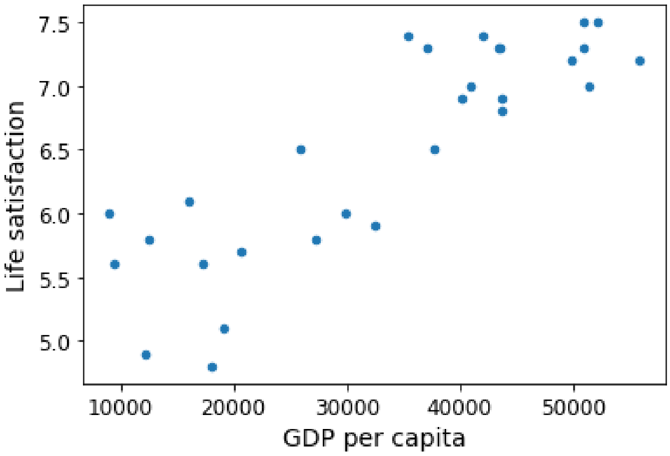
Country	GDP per capita	Life satisfaction
Portugal	19121.592	5.1
Slovenia	20732.482	5.7
Spain	25864.721	6.5

In [26]:
```
(5.1+5.7+6.5)/3
```

Out[26]: `5.766666666666667`

In [27]:
```
backup = oecd_bli, gdp_per_capita

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]
```

In [28]:
```
# Code example
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model

# Load the data
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")

# 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
print(model.predict(X_new)) # outputs [[ 5.96242338]]
```




```
[[5.96242338]]
```

In [29]:
```
oecd_bli, gdp_per_capita = backup
```

In [30]:
```
missing_data
```

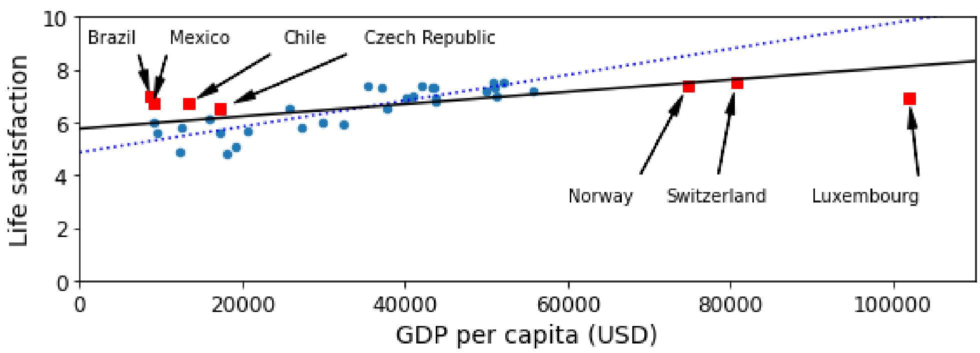
Out[30]:

Country	GDP per capita	Life satisfaction
Brazil	8669.998	7.0
Mexico	9009.280	6.7
Chile	13340.905	6.7
Czech Republic	17256.918	6.5
Norway	74822.106	7.4
Switzerland	80675.308	7.5
Luxembourg	101994.093	6.9

In [31]:
```
position_text2 = {
    "Brazil": (1000, 9.0),
    "Mexico": (11000, 9.0),
    "Chile": (25000, 9.0),
    "Czech Republic": (35000, 9.0),
    "Norway": (60000, 3),
    "Switzerland": (72000, 3.0),
    "Luxembourg": (90000, 3.0),
}
```

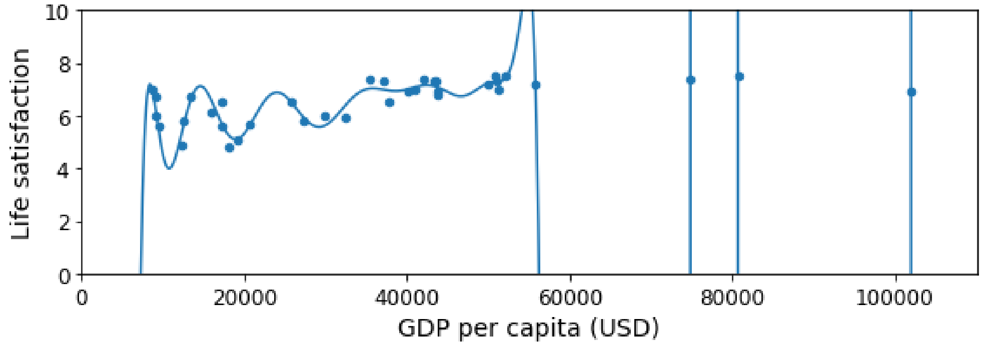
In [32]:
```
sample_data.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(8,3))
plt.axis([0, 110000, 0, 10])

for country, pos_text in position_text2.items():
    pos_data_x, pos_data_y = missing_data.loc[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, "rs")

X=np.linspace(0, 110000, 1000)
plt.plot(X, t0 + t1*X, "b:")

lin_reg_full = linear_model.LinearRegression()
Xfull = np.c_[full_country_stats["GDP per capita"]]
yfull = np.c_[full_country_stats["Life satisfaction"]]
lin_reg_full.fit(Xfull, yfull)

t0full, t1full = lin_reg_full.intercept_[0], lin_reg_full.coef_[0][0]
X = np.linspace(0, 110000, 1000)
plt.plot(X, t0full + t1full * X, "k")
plt.xlabel("GDP per capita (USD)")

save_fig('representative_training_data_scatterplot')
plt.show()
```

```
Saving figure representative_training_data_scatterplot
```



In [33]:
```
full_country_stats.plot(kind='scatter', x="GDP per capita", y='Life satisfaction', figsize=(8,3))
plt.axis([0, 110000, 0, 10])

from sklearn import preprocessing
from sklearn import pipeline

poly = preprocessing.PolynomialFeatures(degree=30, include_bias=False)
scaler = preprocessing.StandardScaler()
lin_reg2 = linear_model.LinearRegression()

pipeline_reg = pipeline.Pipeline([('poly', poly), ('scal', scaler), ('lin', lin_reg2)])
pipeline_reg.fit(Xfull, yfull)
curve = pipeline_reg.predict(X[:, np.newaxis])
plt.plot(X, curve)
plt.xlabel("GDP per capita (USD)")
save_fig('overfitting_model_plot')
plt.show()
```

```
Saving figure overfitting_model_plot
```



In [34]:
```
full_country_stats.loc[[c for c in full_country_stats.index if "W" in c.upper()]]["Life satisfactic
```

Out[34]:
```
Country
New Zealand    7.3
Sweden         7.2
Norway         7.4
Switzerland    7.5
Name: Life satisfaction, dtype: float64
```

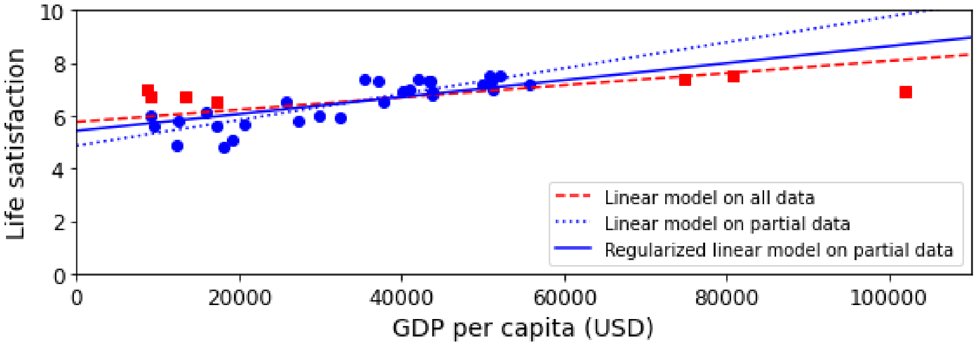
In [35]:
```
gdp_per_capita.loc[[c for c in gdp_per_capita.index if "W" in c.upper()]].head()
```

Out[35]:

Country	Subject Descriptor	Units	Scale	Country/Series-specific Notes	GDP per capita	Estimates Start After
Botswana	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	6040.957	2008.0
Kuwait	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	29363.027	2014.0
Malawi	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	354.275	2011.0
New Zealand	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	37044.891	2015.0
Norway	Gross domestic product per capita, current prices	U.S. dollars	Units	See notes for: Gross domestic product, curren...	74822.106	2015.0

In [36]:
```
plt.figure(figsize=(8,3))

plt.xlabel("GDP per capita")
plt.ylabel('Life satisfaction')

plt.plot(list(sample_data["GDP per capita"]), list(sample_data["Life satisfaction"]), "bo")
plt.plot(list(missing_data["GDP per capita"]), list(missing_data["Life satisfaction"]), "rs")

X = np.linspace(0, 110000, 1000)
plt.plot(X, t0full + t1full * X, "r--", label="Linear model on all data")
plt.plot(X, t0 + t1*X, "b:", label="Linear model on partial data")

ridge = linear_model.Ridge(alpha=10**9.5)
Xsample = np.c_[sample_data["GDP per capita"]]
ysample = np.c_[sample_data["Life satisfaction"]]
ridge.fit(Xsample, ysample)
t0ridge, t1ridge = ridge.intercept_[0], ridge.coef_[0][0]
plt.plot(X, t0ridge + t1ridge * X, "b", label="Regularized linear model on partial data")

plt.legend(loc="lower right")
plt.axis([0, 110000, 0, 10])
plt.xlabel("GDP per capita (USD)")
save_fig('ridge_model_plot')
plt.show()
```

```
Saving figure ridge_model_plot
```


Life satisfaction
GDP per capita (USD)
Linear model on all data
Linear model on partial data
Regularized linear model on partial data
0
2
4
6
8
10
0
20000
40000
60000
80000
100000

```
In [ ]:
```