# Data Science Fundamentals 5

Basic introduction on how to perform typical machine learning tasks with Python.

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# Solutions to Part 1.

In [0]:
```
from sklearn import linear_model

from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split
from sklearn import metrics

from matplotlib import  pyplot as plt
import numpy as np
import os
from imageio import imread
import pandas as pd
from time import time as timer

import tensorflow as tf

%matplotlib inline
from matplotlib import animation
from IPython.display import HTML
```

In [2]:
```
if not os.path.exists('data'):
    path = os.path.abspath('.')+'/colab_material.tgz'
    tf.keras.utils.get_file(path, 'https://github.com/neworldemancer/DSF
5/raw/master/colab_material.tgz')
    !tar -xvzf colab_material.tgz > /dev/null 2>&1
```

```
Downloading data from https://github.com/neworldemancer/DSF5/raw/master/c
olab_material.tgz
98304/96847 [==============================] - 0s 0us/step
```

# Datasets

In this course we will use several synthetic and real-world datasets to ilustrate the behavior of the models and excercise our skills.

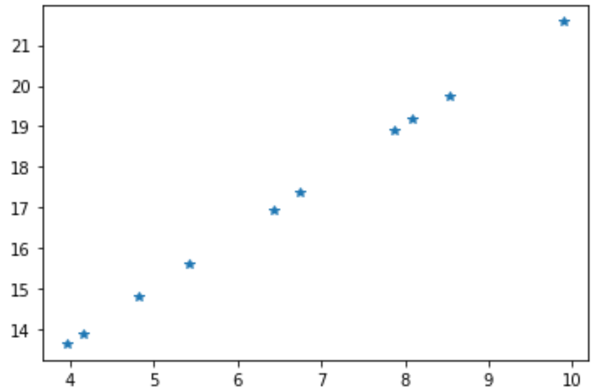
## 1. Synthetic linear

In [0]:
```
def get_linear(n_d=1, n_points=10, w=None, b=None, sigma=5):
  x = np.random.uniform(0, 10, size=(n_points, n_d))

  w = w or np.random.uniform(0.1, 10, n_d)
  b = b or np.random.uniform(-10, 10)
  y = np.dot(x, w) + b + np.random.normal(0, sigma, size=n_points)

  print('true w =', w, ';  b =', b)

  return x, y
```

In [4]:
```
x, y = get_linear(n_d=1, sigma=0)
plt.plot(x[:, 0], y, '*')
```

```
true w = [1.34032066] ;  b = 8.326857960042354
```

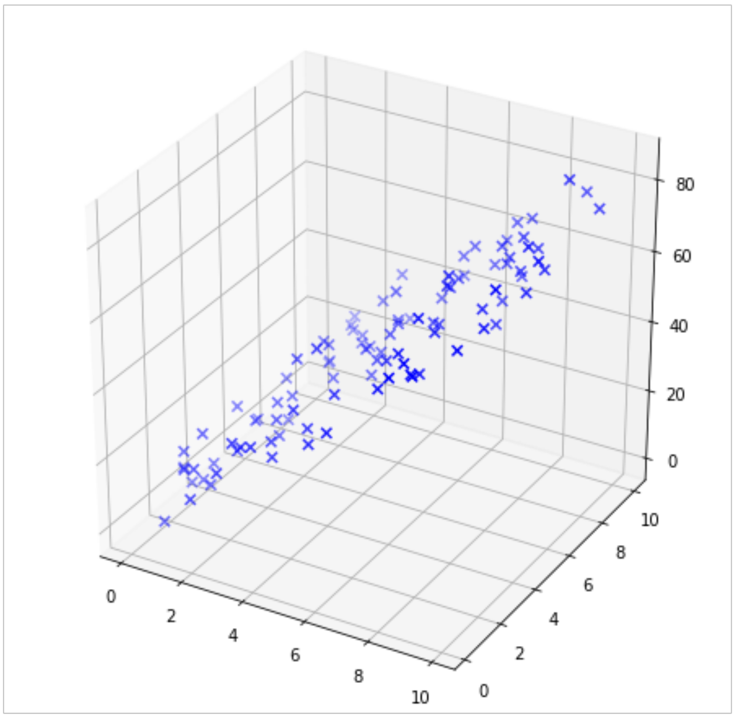
Out[4]: `[<matplotlib.lines.Line2D at 0x7f08a22aef28>]`



In [5]:
```
n_d = 2
x, y = get_linear(n_d=n_d, n_points=100)

fig = plt.figure(figsize=(8,8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(x[:,0], x[:,1], y, marker='x', color='b',s=40)
```

```
true w = [7.03409766 0.83697333] ;  b = 2.7928040906788194
```

Out[5]: `<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x7f08a1dab198>`




## 2. House prices

Subset of the the hous pricess kaggle dataset: https://www.kaggle.com/c/house-prices-advanced-regression-techniques (https://www.kaggle.com/c/house-prices-advanced-regression-techniques)

In [0]:
```
def house_prices_dataset(return_df=False, price_max=400000, area_max=400
00):
  path = 'data/train.csv'

  df = pd.read_csv(path, na_values="NaN", keep_default_na=False)

  useful_fields = ['LotArea',
                  'Utilities', 'OverallQual', 'OverallCond',
                  'YearBuilt', 'YearRemodAdd', 'ExterQual', 'ExterCond',
                  'HeatingQC', 'CentralAir', 'Electrical',
                  '1stFlrSF', '2ndFlrSF','GrLivArea',
                  'FullBath', 'HalfBath',
                  'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRms
AbvGrd',
                  'Functional','PoolArea',
                  'YrSold', 'MoSold'
                  ]
  target_field = 'SalePrice'

  cleanup_nums = {"Street":      {"Grvl": 0, "Pave": 1},
                  "LotFrontage": {"NA":0},
                  "Alley":       {"NA":0, "Grvl": 1, "Pave": 2},
                  "LotShape":    {"IR3":0, "IR2": 1, "IR1": 2, "Reg":3},
                  "Utilities":   {"ELO":0, "NoSeWa": 1, "NoSewr": 2, "Al
lPub": 3},
                  "LandSlope":   {"Sev":0, "Mod": 1, "Gtl": 3},
                  "ExterQual":   {"Po":0, "Fa": 1, "TA": 2, "Gd": 3, "E
x":4},
                  "ExterCond":   {"Po":0, "Fa": 1, "TA": 2, "Gd": 3, "E
x":4},
                  "BsmtQual":    {"NA":0, "Po":1, "Fa": 2, "TA": 3, "G
d": 4, "Ex":5},
                  "BsmtCond":    {"NA":0, "Po":1, "Fa": 2, "TA": 3, "G
d": 4, "Ex":5},
                  "BsmtExposure":{"NA":0, "No":1, "Mn": 2, "Av": 3, "G
d": 4},
                  "BsmtFinType1":{"NA":0, "Unf":1, "LwQ": 2, "Rec": 3, "
BLQ": 4, "ALQ":5, "GLQ":6},
                  "BsmtFinType2":{"NA":0, "Unf":1, "LwQ": 2, "Rec": 3, "
BLQ": 4, "ALQ":5, "GLQ":6},
                  "HeatingQC":   {"Po":0, "Fa": 1, "TA": 2, "Gd": 3, "E
x":4},
                  "CentralAir":  {"N":0, "Y": 1},
                  "Electrical":  {"NA":0, "Mix":1, "FuseP":2, "FuseF":
3, "FuseA": 4, "SBrkr": 5},
                  "KitchenQual": {"Po":0, "Fa": 1, "TA": 2, "Gd": 3, "E
x":4},
                  "Functional":  {"Sal":0, "Sev":1, "Maj2": 2, "Maj1":
3, "Mod": 4, "Min2":5, "Min1":6, 'Typ':7},
                  "FireplaceQu": {"NA":0, "Po":1, "Fa": 2, "TA": 3, "G
d": 4, "Ex":5},
                  "PoolQC":      {"NA":0, "Fa": 1, "TA": 2, "Gd": 3, "E
x":4},
                  "Fence":       {"NA":0, "MnWw": 1, "GdWo": 2, "MnPrv":
3, "GdPrv":4},
                  }

  df_X = df[useful_fields].copy()
  df_X.replace(cleanup_nums, inplace=True)  # convert continous categori
al variables to numerical
  df_Y = df[target_field].copy()

  x = df_X.to_numpy().astype(np.float32)
  y = df_Y.to_numpy().astype(np.float32)

  if price_max>0:
    idxs = y<price_max
    x = x[idxs]
```

In [7]:
```
x, y, df = house_prices_dataset(return_df=True)
print(x.shape, y.shape)
df.head()
```

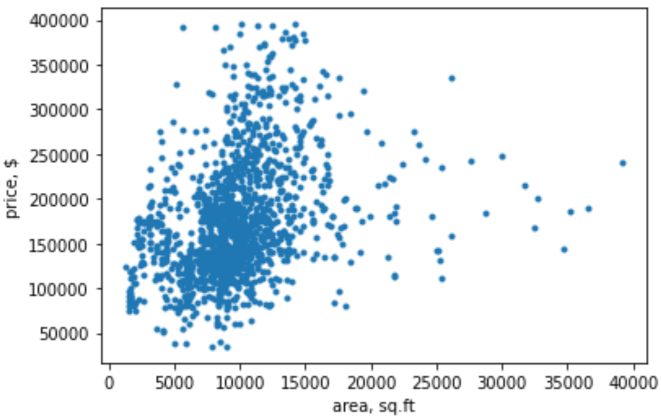
(1420, 24) (1420,)

Out[7]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Util |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 65 | 8450 | Pave | NA | Reg | Lvl | AllF |
| **1** | 2 | 20 | RL | 80 | 9600 | Pave | NA | Reg | Lvl | AllF |
| **2** | 3 | 60 | RL | 68 | 11250 | Pave | NA | IR1 | Lvl | AllF |
| **3** | 4 | 70 | RL | 60 | 9550 | Pave | NA | IR1 | Lvl | AllF |
| **4** | 5 | 60 | RL | 84 | 14260 | Pave | NA | IR1 | Lvl | AllF |

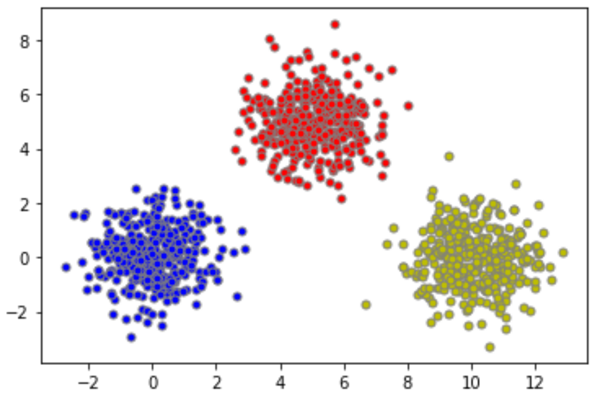
5 rows × 81 columns

In [8]:
```
plt.plot(x[:, 0], y, '.')
plt.xlabel('area, sq.ft')
plt.ylabel('price, $');
```




## 3. Blobs

In [9]:
```
x, y = make_blobs(n_samples=1000, centers=[[0,0], [5,5], [10, 0]])
colors = "bry"
for i, color in enumerate(colors):
    idx = y == i
    plt.scatter(x[idx, 0], x[idx, 1], c=color, edgecolor='gray', s=25)
```



## 4. Fashion MNIST

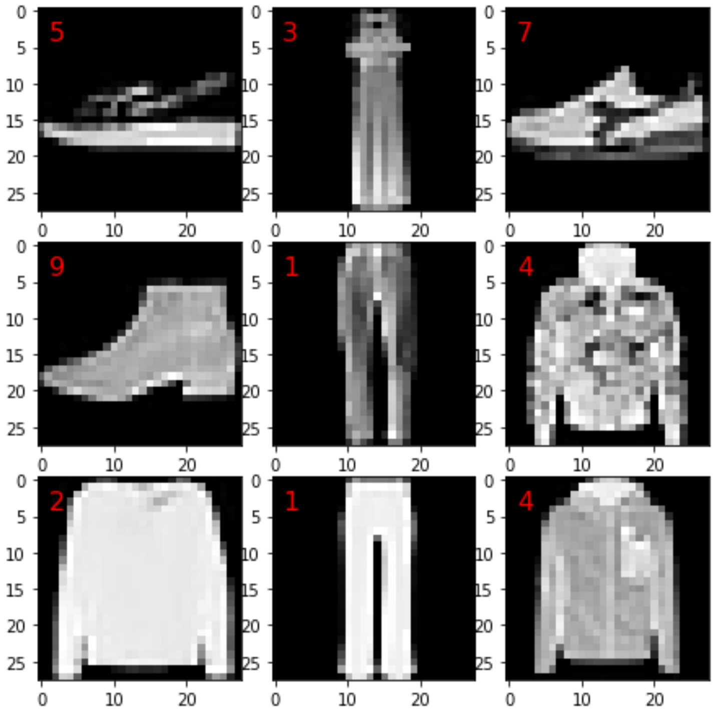
`Fashion-MNIST` is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. (from https://github.com/zalandoresearch/fashion-mnist (https://github.com/zalandoresearch/fashion-mnist))

In [10]:
```
fashion_mnist = tf.keras.datasets.fashion_mnist
(train_images, train_labels), (test_images, test_labels) = fashion_mnis
t.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-labels-idx1-ubyte.gz
32768/29515 [==================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-images-idx3-ubyte.gz
26427392/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-labels-idx1-ubyte.gz
8192/5148 [================================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-images-idx3-ubyte.gz
4423680/4422102 [==============================] - 0s 0us/step
```

Let's chech few samples:

In [11]:
```
n = 3
fig, ax = plt.subplots(n, n, figsize=(2*n, 2*n))
ax = [ax_xy for ax_y in ax for ax_xy in ax_y]
for axi, im_idx in zip(ax, np.random.choice(len(train_images), n**2)):
  im = train_images[im_idx]
  im_class = train_labels[im_idx]
  axi.imshow(im, cmap='gray')
  axi.text(1, 4, f'{im_class}', color='r', size=16)
plt.tight_layout(0,0,0)
```



Each training and test example is assigned to one of the following labels:

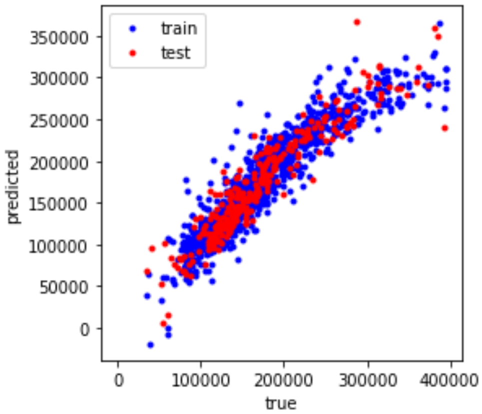
| Label | Description |
|---|---|
| 0 | T-shirt/top |
| 1 | Trouser |
| 2 | Pullover |
| 3 | Dress |
| 4 | Coat |
| 5 | Sandal |
| 6 | Shirt |
| 7 | Sneaker |
| 8 | Bag |
| 9 | Ankle boot |

# EXERCISE 1.

In [12]:
```
# Solution:
x, y = house_prices_dataset()

# 1. make train/test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)

# 2. fit the model
reg = linear_model.LinearRegression()
reg.fit(x_train, y_train)

# 3. evaluate MSE, MAD, and R2 on train and test datasets
#prediction:
y_p_train = reg.predict(x_train)
y_p_test = reg.predict(x_test)

# mse
print('train mse =', np.std(y_train - y_p_train))
print('test mse =', np.std(y_test - y_p_test))
# mse
print('train mae =', np.mean(np.abs(y_train - y_p_train)))
print('test mae =', np.mean(np.abs(y_test - y_p_test)))
# R2
print('train R2 =', reg.score(x_train, y_train))
print('test R2 =', reg.score(x_test, y_test))

# 4. plot y vs predicted y for test and train parts
plt.plot(y_train, y_p_train, 'b.', label='train')
plt.plot(y_test, y_p_test, 'r.', label='test')

plt.plot([0], [0], 'w.')  # dummy to have origin
plt.xlabel('true')
plt.ylabel('predicted')
plt.gca().set_aspect('equal')
plt.legend()
```

```
train mse = 24834.885
test mse = 24293.932
train mae = 18221.04
test mae = 17279.08
train R2 = 0.8534532342221349
test R2 = 0.8706671727120681
```

Out[12]: <matplotlib.legend.Legend at 0x7f089d87e278>




# EXERCISE 2.

In [0]:
```
fashion_mnist = tf.keras.datasets.fashion_mnist
(train_images, train_labels), (test_images, test_labels) = fashion_mnis
t.load_data()
```

We will reshape 2-d images to 1-d arrays for use in scikit-learn:

In [0]:
```
n_train = len(train_labels)
x_train = train_images.reshape((n_train, -1))
y_train = train_labels

n_test = len(test_labels)
x_test = test_images.reshape((n_test, -1))
y_test = test_labels
```

Now use a multinomial logistic regression classifier, and measure the accuracy:

In [15]:
```
#solution
# 1. Create classifier
multi_class = 'multinomial'
clf = linear_model.LogisticRegression(solver='sag', max_iter=20,
                                      multi_class=multi_class)

# 2. fit the model
t1 = timer()
clf.fit(x_train, y_train)
t2 = timer()
print ('training time: %.1fs'%(t2-t1))

# 3. evaluate accuracy on train and test datasets
print("training score : %.3f" % (clf.score(x_train, y_train)))
print("test score : %.3f" % (clf.score(x_test, y_test)))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_sag.py:330:
ConvergenceWarning: The max_iter was reached which means the coef_ did no
t converge
  "the coef_ did not converge", ConvergenceWarning)

training time: 40.6s
training score : 0.874
test score : 0.843
```