Лінійні моделі

In [1]:
```
import os
import sklearn
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
```

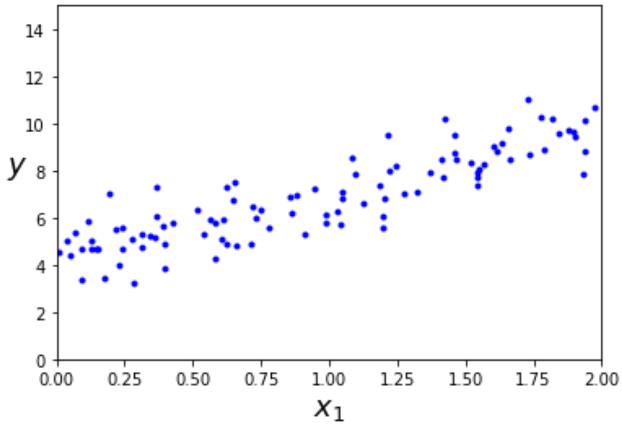
Лінійна регресія

Згенеруємо синтетичні дані для прикладу

In [2]:
```
np.random.seed(42)
```

In [3]:
```
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)
```

In [4]:
```
plt.plot(X, y, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.axis([0, 2, 0, 15])
plt.show()
```



In [5]:
```
X_b = np.c_[np.ones((100, 1)), X]  # add x0 = 1 to each instance
theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)
```

Знайдені коефіцієти

In [6]:
```
theta_best
```

Out[6]:
```
array([[4.21509616],
       [2.77011339]])
```

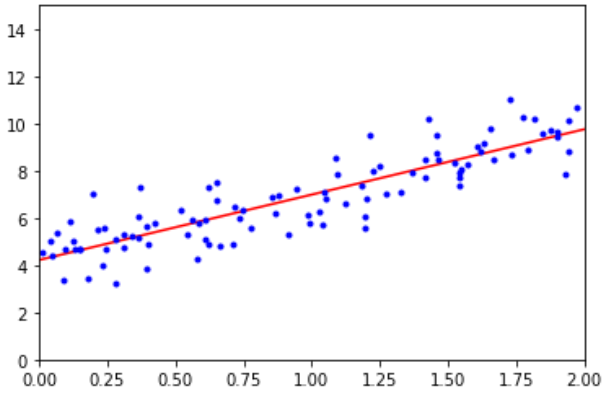
Як отримати значення функції регресії у новій точці?

In [7]:
```
X_new = np.array([[0], [2]])
X_new_b = np.c_[np.ones((2, 1)), X_new]  # add x0 = 1 to each instance
y_predict = X_new_b.dot(theta_best)
y_predict
```

Out[7]:
```
array([[4.21509616],
       [9.75532293]])
```

Судячи з графіку, виглядає логічно.

In [8]:
```
plt.plot(X_new, y_predict, "r-")
plt.plot(X, y, "b.")
plt.axis([0, 2, 0, 15])
plt.show()
```



Розвяжемо цю ж задачу за допомогою sklearn

In [9]:
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X, y)
lin_reg.intercept_, lin_reg.coef_
```

Out[9]:
```
(array([4.21509616]), array([[2.77011339]]))
```

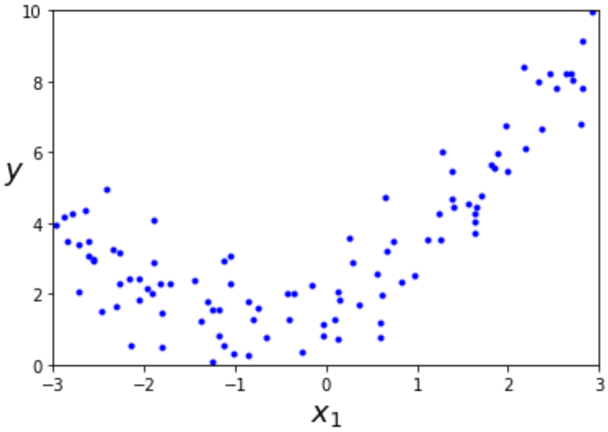
Поліноміальна регресія

In [10]:
```
import numpy as np
import numpy.random as rnd

np.random.seed(42)
```

Згенеруємо штучний датасет з відгуком y, що поліноміально залежить від ознак X.

In [11]:
```
m = 100
X = 6 * np.random.rand(m, 1) - 3
y = 0.5 * X**2 + X + 2 + np.random.randn(m, 1)
```

In [12]:
```
plt.plot(X, y, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.axis([-3, 3, 0, 10])
plt.show()
```



"Доповнимо" датасет поліноміальними ознаками

In [13]:
```
from sklearn.preprocessing import PolynomialFeatures
poly_features = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly_features.fit_transform(X)
print(X[0])
print(X_poly[0])
print(X[0]**2)
```

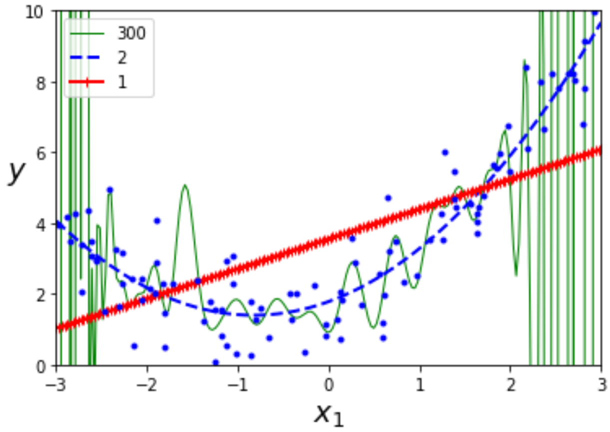
```
[-0.75275929]
[-0.75275929  0.56664654]
[0.56664654]
```

In [14]:
```
lin_reg = LinearRegression()
lin_reg.fit(X_poly, y)
lin_reg.intercept_, lin_reg.coef_
```

Out[14]:
```
(array([1.78134581]), array([[0.93366893, 0.56456263]]))
```

Давайте спробуємо різні степені поліноміальних ознак: 1, 2, 300

In [15]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

X_new = np.linspace(-3, 3, num=200).reshape(-1,1)

for style, width, degree in (("g-", 1, 300), ("b--", 2, 2), ("r-+", 2, 1)):
    polybig_features = PolynomialFeatures(degree=degree, include_bias=False)
    std_scaler = StandardScaler()
    lin_reg = LinearRegression()
    polynomial_regression = Pipeline([
            ("poly_features", polybig_features),
            ("std_scaler", std_scaler),
            ("lin_reg", lin_reg),
        ])
    polynomial_regression.fit(X, y)
    y_newbig = polynomial_regression.predict(X_new)
    plt.plot(X_new, y_newbig, style, label=str(degree), linewidth=width)

plt.plot(X, y, "b.", linewidth=3)
plt.legend(loc="upper left")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.axis([-3, 3, 0, 10])
plt.show()
```



Середньоквадратична помилка моделі

In [16]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

In [17]:
```
np.random.seed(42)
m = 100
X = 6 * np.random.rand(m, 1) - 3
y = 2 + X + 0.5 * X**2 + np.random.randn(m, 1)
```

In [18]:
```
X_train, X_val, y_train, y_val = train_test_split(X, y.ravel(), test_size=0.
5, random_state=10)
```

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

Out[19]:
```
(50, 1)
```

In [20]:
```
poly_scaler = Pipeline([
        ("poly_features", PolynomialFeatures(degree=5, include_bias=False)),
        ("std_scaler", StandardScaler())
    ])

X_train_poly_scaled = poly_scaler.fit_transform(X_train)
X_val_poly_scaled = poly_scaler.transform(X_val)
```

In [21]:
```
model = LinearRegression()
model.fit(X_train_poly_scaled, y_train)
```

Out[21]: LinearRegression()

In [22]:
```
y_val_predict = model.predict(X_val_poly_scaled)
val_error = mean_squared_error(y_val, y_val_predict)
```

In [23]:
```
print(val_error)
```

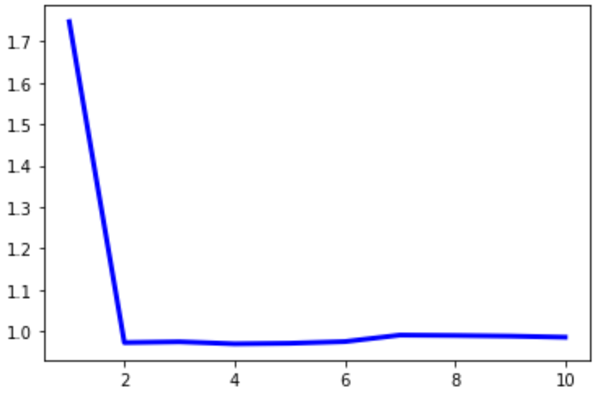
0.9418567491761436

In [24]:
```
def get_error(poly_degree, X_train, X_val, y_train, y_val):
    poly_scaler = Pipeline([
        ("poly_features", PolynomialFeatures(degree=poly_degree, include_bia
s=False)),
        ("std_scaler", StandardScaler())
    ])

    X_train_poly_scaled = poly_scaler.fit_transform(X_train)
    X_val_poly_scaled = poly_scaler.transform(X_val)

    model = LinearRegression()
    model.fit(X_train_poly_scaled, y_train)
    y_val_predict = model.predict(X_val_poly_scaled)

    val_error = mean_squared_error(y_val, y_val_predict)

    return val_error
```

In [25]:
```
val_errors = [get_error(poly_degree, X_train, X_val, y_train, y_val) for pol
y_degree in range(1,11)]
```

In [26]:
```
plt.plot(list(range(1,11)), np.sqrt(val_errors), "b-", linewidth=3, label="v
al")
```

Out[26]: [<matplotlib.lines.Line2D at 0x7f88eeeaab50>]



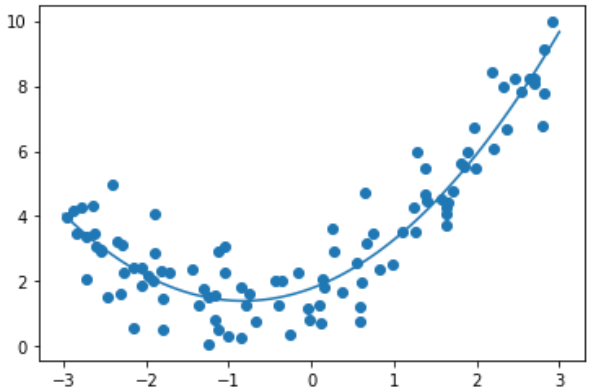
In [27]:
```
final_pipeline = poly_scaler = Pipeline([
        ("poly_features", PolynomialFeatures(degree=2, include_bias=False)),
        ("std_scaler", StandardScaler()),
        ("linear_model", LinearRegression())
    ])
```

In [28]:
```
final_pipeline.fit(X,y)
```

Out[28]:
```
Pipeline(steps=[('poly_features', PolynomialFeatures(include_bias=False)),
                ('std_scaler', StandardScaler()),
                ('linear_model', LinearRegression())])
```

In [29]:
```
X_test = np.linspace(-3, 3, 100)
plt.plot(X_test, final_pipeline.predict(X_test[:, np.newaxis]), label="Mode
l")
plt.scatter(X, y, label="True function")
```

Out[29]:
```
<matplotlib.collections.PathCollection at 0x7f88eee8fbd0>
```



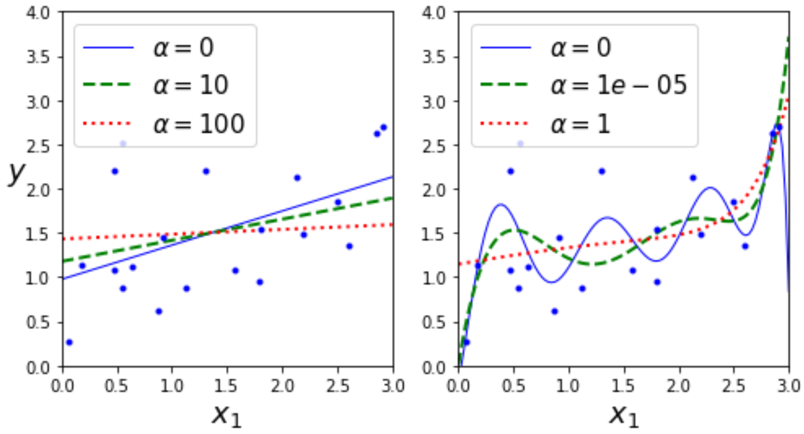
Регуляризація

In [30]:
```
np.random.seed(42)
m = 20
X = 3 * np.random.rand(m, 1)
y = 1 + 0.5 * X + np.random.randn(m, 1) / 1.5
X_new = np.linspace(0, 3, 100).reshape(100, 1)
```

In [31]:
```
from sklearn.linear_model import Ridge
ridge_reg = Ridge(alpha=1, random_state=42)
ridge_reg.fit(X, y)
ridge_reg.predict([[1.5]])
```

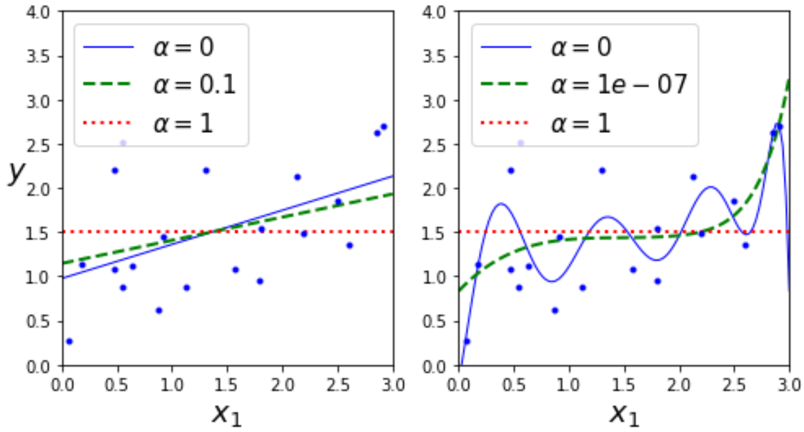
Out[31]:
```
array([[1.55071465]])
```

In [32]:
```
def plot_model(model_class, polynomial, alphas, degree = 10, **model_kargs):
    for alpha, style in zip(alphas, ("b-", "g--", "r:")):
        model = model_class(alpha, **model_kargs) if alpha > 0 else LinearRe
gression()
        if polynomial:
            model = Pipeline([
                    ("poly_features", PolynomialFeatures(degree=degree, incl
ude_bias=False)),
                    ("std_scaler", StandardScaler()),
                    ("regul_reg", model),
                ])
        model.fit(X, y)
        y_new_regul = model.predict(X_new)
        lw = 2 if alpha > 0 else 1
        plt.plot(X_new, y_new_regul, style, linewidth=lw, label=r"$\alpha =
{}$".format(alpha))
    plt.plot(X, y, "b.", linewidth=3)
    plt.legend(loc="upper left", fontsize=15)
    plt.xlabel("$x_1$", fontsize=18)
    plt.axis([0, 3, 0, 4])

plt.figure(figsize=(8,4))
plt.subplot(121)
plot_model(Ridge, polynomial=False, alphas=(0, 10, 100), random_state=42)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.subplot(122)
plot_model(Ridge, polynomial=True, alphas=(0, 10**-5, 1), random_state=42)

plt.show()
```



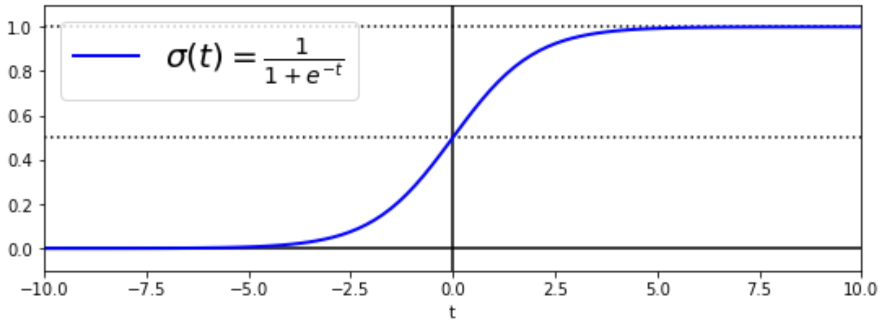
In [33]:
```
from sklearn.linear_model import Lasso

plt.figure(figsize=(8,4))
plt.subplot(121)
plot_model(Lasso, polynomial=False, alphas=(0, 0.1, 1), random_state=42)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.subplot(122)
plot_model(Lasso, polynomial=True, alphas=(0, 10**-7, 1), random_state=42)

plt.show()
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/sklearn/linea
r_model/_coordinate_descent.py:531: ConvergenceWarning: Objective did not con
verge. You might want to increase the number of iterations. Duality gap: 2.80
2867703827423, tolerance: 0.0009294783355207351
  positive)
```



Логістична регресія

In [34]:
```
t = np.linspace(-10, 10, 100)
sig = 1 / (1 + np.exp(-t))
plt.figure(figsize=(9, 3))
plt.plot([-10, 10], [0, 0], "k-")
plt.plot([-10, 10], [0.5, 0.5], "k:")
plt.plot([-10, 10], [1, 1], "k:")
plt.plot([0, 0], [-1.1, 1.1], "k-")
plt.plot(t, sig, "b-", linewidth=2, label=r"$\sigma(t) = \frac{1}{1 + e^{-
t}}$")
plt.xlabel("t")
plt.legend(loc="upper left", fontsize=20)
plt.axis([-10, 10, -0.1, 1.1])
plt.show()
```



In [35]:
```
from sklearn import datasets
iris = datasets.load_iris()
list(iris.keys())
```

Out[35]:
```
['data',
 'target',
 'frame',
 'target_names',
 'DESCR',
 'feature_names',
 'filename']
```

In [36]:
```
print(iris.DESCR)
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to
a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysi
s.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactio
ns
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

In [37]:
```
iris["data"].shape
```

Out[37]:
```
(150, 4)
```

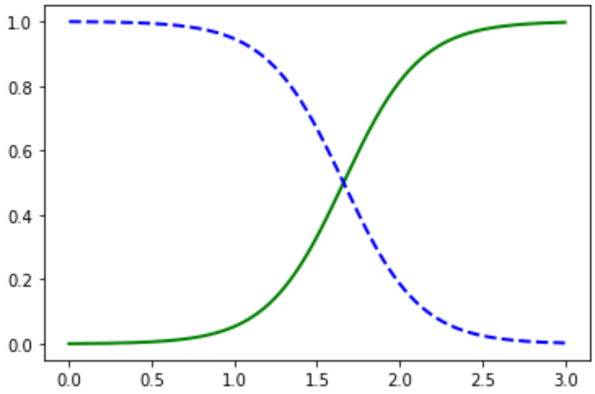
In [38]:
```
X = iris["data"][:, 3:]  # petal width
y = (iris["target"] == 2).astype(np.int)  # 1 if Iris virginica, else 0
```

In [39]:
```
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(random_state=42)
log_reg.fit(X, y)
```

Out[39]:
```
LogisticRegression(random_state=42)
```

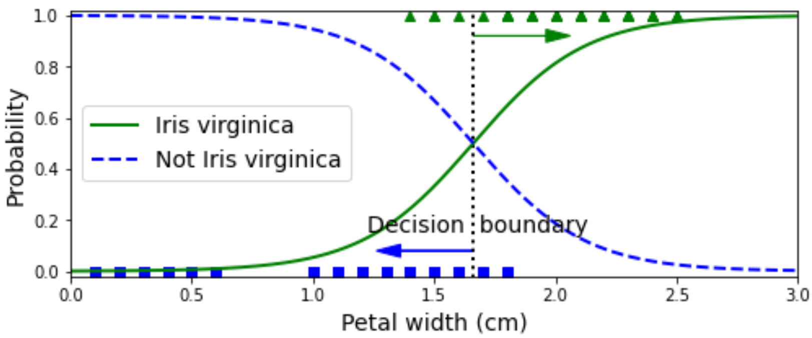
In [40]:
```
X_new = np.linspace(0, 3, 1000).reshape(-1, 1)
y_proba = log_reg.predict_proba(X_new)

plt.plot(X_new, y_proba[:, 1], "g-", linewidth=2, label="Iris virginica")
plt.plot(X_new, y_proba[:, 0], "b--", linewidth=2, label="Not Iris virginic
a")
```

Out[40]:
```
[<matplotlib.lines.Line2D at 0x7f88ee1286d0>]
```



In [41]:
```
X_new = np.linspace(0, 3, 1000).reshape(-1, 1)
y_proba = log_reg.predict_proba(X_new)
decision_boundary = X_new[y_proba[:, 1] >= 0.5][0]

plt.figure(figsize=(8, 3))
plt.plot(X[y==0], y[y==0], "bs")
plt.plot(X[y==1], y[y==1], "g^")
plt.plot([decision_boundary, decision_boundary], [-1, 2], "k:", linewidth=2)
plt.plot(X_new, y_proba[:, 1], "g-", linewidth=2, label="Iris virginica")
plt.plot(X_new, y_proba[:, 0], "b--", linewidth=2, label="Not Iris virginic
a")
plt.text(decision_boundary+0.02, 0.15, "Decision  boundary", fontsize=14, co
lor="k", ha="center")
plt.arrow(decision_boundary, 0.08, -0.3, 0, head_width=0.05, head_length=0.
1, fc='b', ec='b')
plt.arrow(decision_boundary, 0.92, 0.3, 0, head_width=0.05, head_length=0.1,
fc='g', ec='g')
plt.xlabel("Petal width (cm)", fontsize=14)
plt.ylabel("Probability", fontsize=14)
plt.legend(loc="center left", fontsize=14)
plt.axis([0, 3, -0.02, 1.02])
plt.show()
```

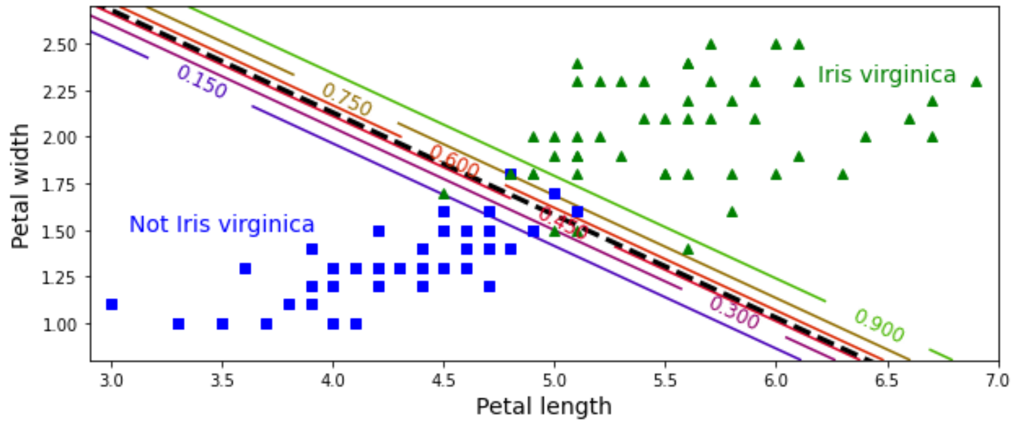
```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/matplotlib/pa
tches.py:1338: VisibleDeprecationWarning: Creating an ndarray from ragged nes
ted sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with d
ifferent lengths or shapes) is deprecated. If you meant to do this, you must
specify 'dtype=object' when creating the ndarray
  verts = np.dot(coords, M) + (x + dx, y + dy)
```



In [42]:
```
decision_boundary
```

Out[42]:
```
array([1.66066066])
```

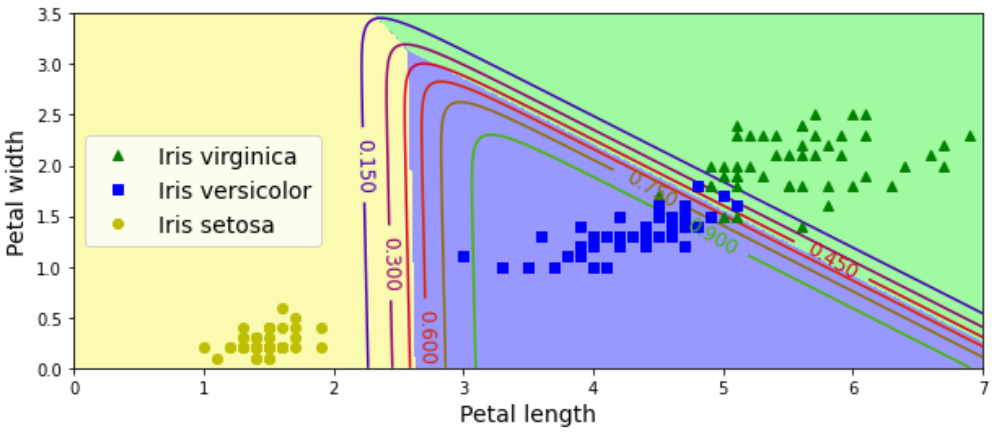
In [43]:
```
from sklearn.linear_model import LogisticRegression

X = iris["data"][:, (2, 3)]  # petal length, petal width
y = (iris["target"] == 2).astype(np.int)

log_reg = LogisticRegression(solver="lbfgs", C=10**10, random_state=42)
log_reg.fit(X, y)

x0, x1 = np.meshgrid(
        np.linspace(2.9, 7, 500).reshape(-1, 1),
        np.linspace(0.8, 2.7, 200).reshape(-1, 1),
    )
X_new = np.c_[x0.ravel(), x1.ravel()]

y_proba = log_reg.predict_proba(X_new)

plt.figure(figsize=(10, 4))
plt.plot(X[y==0, 0], X[y==0, 1], "bs")
plt.plot(X[y==1, 0], X[y==1, 1], "g^")

zz = y_proba[:, 1].reshape(x0.shape)
contour = plt.contour(x0, x1, zz, cmap=plt.cm.brg)


left_right = np.array([2.9, 7])
boundary = -(log_reg.coef_[0][0] * left_right + log_reg.intercept_[0]) / log
_reg.coef_[0][1]

plt.clabel(contour, inline=1, fontsize=12)
plt.plot(left_right, boundary, "k--", linewidth=3)
plt.text(3.5, 1.5, "Not Iris virginica", fontsize=14, color="b", ha="cente
r")
plt.text(6.5, 2.3, "Iris virginica", fontsize=14, color="g", ha="center")
plt.xlabel("Petal length", fontsize=14)
plt.ylabel("Petal width", fontsize=14)
plt.axis([2.9, 7, 0.8, 2.7])
plt.show()
```



In [44]:
```
X = iris["data"][:, (2, 3)]  # petal length, petal width
y = iris["target"]

softmax_reg = LogisticRegression(multi_class="multinomial",solver="lbfgs", C
=10, random_state=42)
softmax_reg.fit(X, y)
```

Out[44]:
```
LogisticRegression(C=10, multi_class='multinomial', random_state=42)
```

In [45]:
```
x0, x1 = np.meshgrid(
        np.linspace(0, 8, 500).reshape(-1, 1),
        np.linspace(0, 3.5, 200).reshape(-1, 1),
    )
X_new = np.c_[x0.ravel(), x1.ravel()]


y_proba = softmax_reg.predict_proba(X_new)
y_predict = softmax_reg.predict(X_new)

zz1 = y_proba[:, 1].reshape(x0.shape)
zz = y_predict.reshape(x0.shape)

plt.figure(figsize=(10, 4))
plt.plot(X[y==2, 0], X[y==2, 1], "g^", label="Iris virginica")
plt.plot(X[y==1, 0], X[y==1, 1], "bs", label="Iris versicolor")
plt.plot(X[y==0, 0], X[y==0, 1], "yo", label="Iris setosa")

from matplotlib.colors import ListedColormap
custom_cmap = ListedColormap(['#fafab0','#9898ff','#a0faa0'])

plt.contourf(x0, x1, zz, cmap=custom_cmap)
contour = plt.contour(x0, x1, zz1, cmap=plt.cm.brg)
plt.clabel(contour, inline=1, fontsize=12)
plt.xlabel("Petal length", fontsize=14)
plt.ylabel("Petal width", fontsize=14)
plt.legend(loc="center left", fontsize=14)
plt.axis([0, 7, 0, 3.5])
plt.show()
```



Нарешті, натренуємо модель на усіх ознаках.

In [46]:
```
X = iris["data"]
y = iris["target"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.15)
```

In [47]:
```
softmax_reg = LogisticRegression(multi_class="multinomial",solver="lbfgs", C
=10, random_state=42)
softmax_reg.fit(X_train, y_train)
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/sklearn/linea
r_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to converge (statu
s=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[47]:
```
LogisticRegression(C=10, multi_class='multinomial', random_state=42)
```

In [48]:
```
y_pred = softmax_reg.predict(X_test)
```

In [49]:
```
from sklearn.metrics import accuracy_score, confusion_matrix
```

In [50]:
```
accuracy_score(y_test, y_pred)
```

Out[50]:
```
1.0
```

In [51]:
```
confusion_matrix(y_test, y_pred)
```

Out[51]:
```
array([[9, 0, 0],
       [0, 8, 0],
       [0, 0, 6]])
```

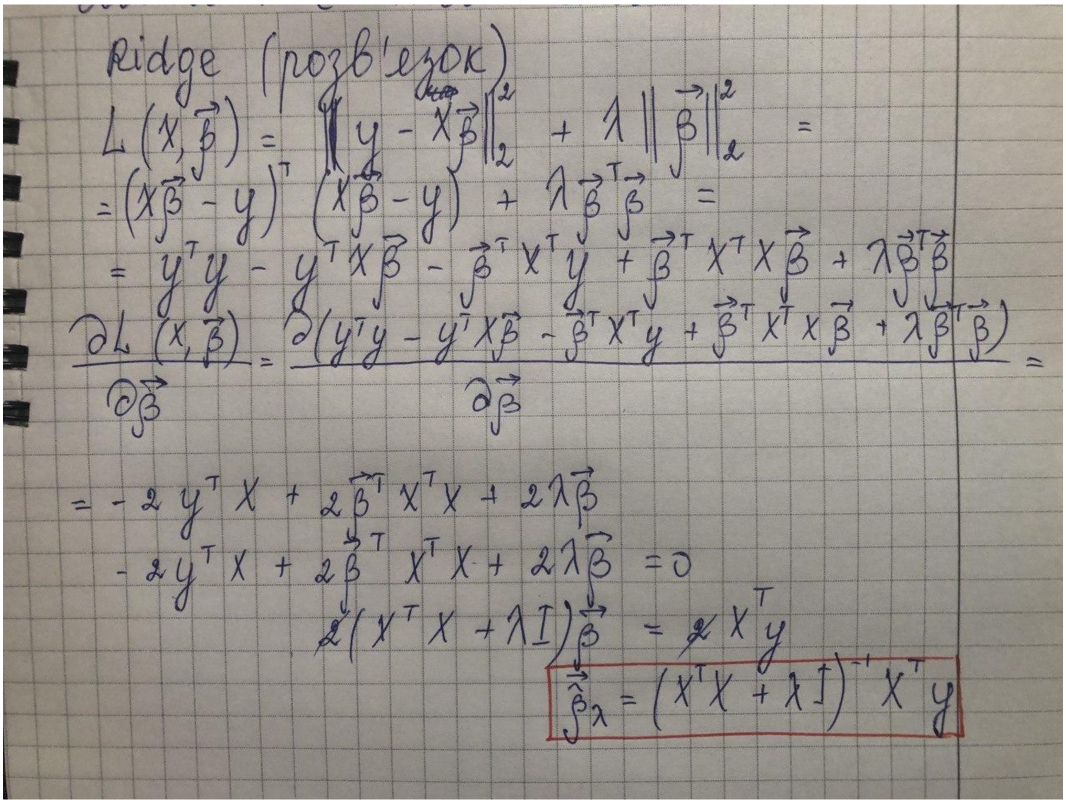
Завдання

In [52]:
```
import pandas as pd

from IPython.display import Image

from sklearn.linear_model import LinearRegression, Lasso, Ridge, LogisticReg
ression
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

Завдання 1. Знайдіть у явному вигляді розв'язок задачі лінійної регресії з квадратичною регуляризацією (Ridge). Сфотографуйте виведення та підв"яжіть до цього файлу (\<img src="image.png">)

In [53]:
```
PICTURE_PATH = "../images/"
Image(filename = PICTURE_PATH + "02-ridge.jpg", width=900, height=1600)
```

Out[53]:



Завдання 2. Натренуйте модель поліноміальної регресії зі степенями 1, 4, 15. Для степені 15 натренуйте модель з регуляризацією. Спробуйте різні параметри регуляризації. Прокоментуйте.

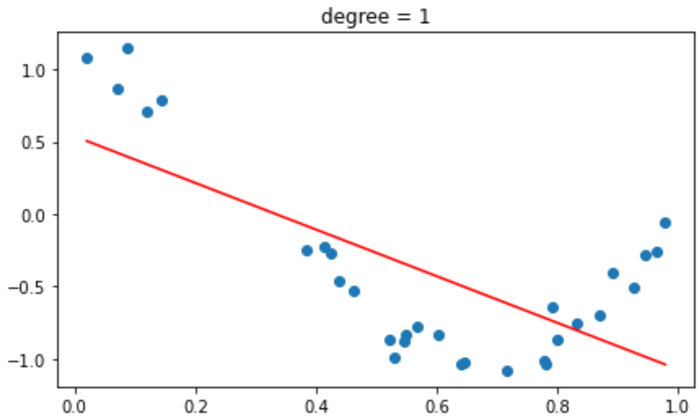
In [54]:
```
def true_fun(X):
    return np.cos(1.5 * np.pi * X)

np.random.seed(0)
n_samples = 30

X = np.sort(np.random.rand(n_samples))
y = true_fun(X) + np.random.randn(n_samples) * 0.1
```

In [55]:
```
X = np.reshape(X, (-1, 1)) # convert X to 2d array
```

In [56]:
```
results = []
```

In [57]:
```
linreg = LinearRegression()
linreg.fit(X, y)
b0, b1 = linreg.intercept_, linreg.coef_[0]
y_hat = linreg.predict(X)
results.append(['LR', 1, mean_squared_error(y, y_hat)])

plt.figure(figsize=(7,4))
plt.scatter(X[:,0], y)
plt.plot(X[:,0], y_hat, color='red')
plt.title('degree = 1')
```

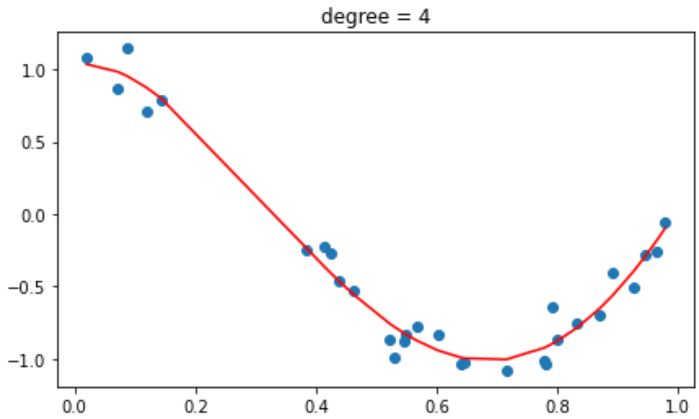
Out[57]:
```
Text(0.5, 1.0, 'degree = 1')
```



Does not look like linear relationship at all. Simple linear regression fails.

In [58]:
```
degree = 4
pf = PolynomialFeatures(degree, include_bias=False)
X_poly = pf.fit_transform(X)

linreg = LinearRegression()
linreg.fit(X_poly, y)
b0, b1 = linreg.intercept_, linreg.coef_[0]
y_hat = linreg.predict(X_poly)
results.append(('LR', degree, mean_squared_error(y, y_hat)))

plt.figure(figsize=(7,4))
plt.scatter(X[:,0], y)
plt.plot(X[:,0], y_hat, color='red')
plt.title(f'degree = {degree}')
```

Out[58]:
```
Text(0.5, 1.0, 'degree = 4')
```

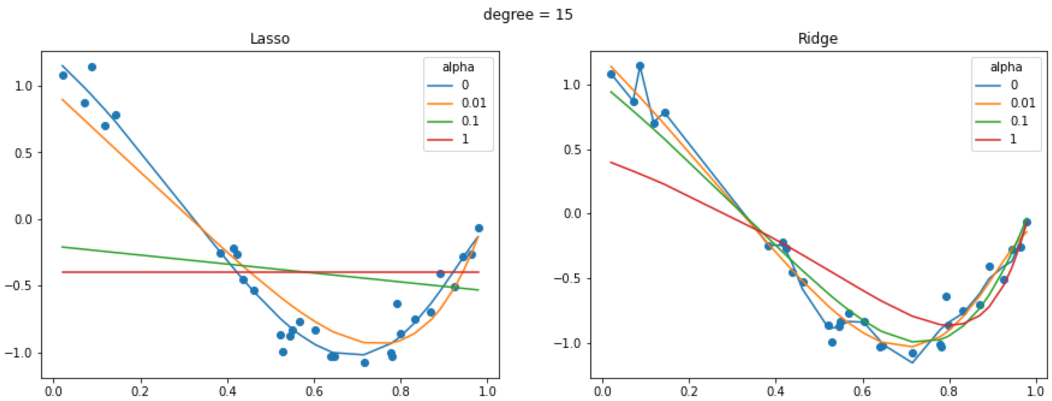


Looks pretty good. Line is pretty close to all points.

In [59]:
```
degree = 15
pf = PolynomialFeatures(degree, include_bias=False)
X_poly = pf.fit_transform(X)

fig, axes = plt.subplots(1,2, figsize=(15, 5))
axes[0].scatter(X[:,0], y)
axes[1].scatter(X[:,0], y)

for alpha in [0, 1e-2, 1e-1,  1]:
    linreg = Lasso(alpha=alpha)
    linreg.fit(X_poly, y)
    b0, b1 = linreg.intercept_, linreg.coef_[0]
    y_hat = linreg.predict(X_poly)
    results.append((f'Lasso({alpha})', degree, mean_squared_error(y, y_ha
t)))

    axes[0].plot(X[:,0], y_hat, label = alpha)
    axes[0].set_title('Lasso')
    axes[0].legend(title='alpha')

for alpha in [0, 1e-2, 1e-1,  1]:
    linreg = Ridge(alpha=alpha)
    linreg.fit(X_poly, y)
    b0, b1 = linreg.intercept_, linreg.coef_[0]
    y_hat = linreg.predict(X_poly)
    results.append((f'Ridge({alpha})', degree, mean_squared_error(y, y_ha
t)))

    axes[1].plot(X[:,0], y_hat, label = alpha)
    axes[1].set_title('Ridge')
    axes[1].legend(title='alpha')

fig.suptitle(f'degree = {degree}')
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/ipykernel_lau
ncher.py:11: UserWarning: With alpha=0, this algorithm does not converge wel
l. You are advised to use the LinearRegression estimator
  # This is added back by InteractiveShellApp.init_path()
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/sklearn/linea
r_model/_coordinate_descent.py:531: UserWarning: Coordinate descent with no r
egularization may lead to unexpected results and is discouraged.
  positive)
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/sklearn/linea
r_model/_coordinate_descent.py:531: ConvergenceWarning: Objective did not con
verge. You might want to increase the number of iterations. Duality gap: 0.17
612629534727617, tolerance: 0.0012875751792313249
  positive)
```

Out[59]:
```
Text(0.5, 0.98, 'degree = 15')
```



Lasso(0) and Ridge(0.01) are good at predicting values. Too much reguralization is bad for both models. Also Ridge(0) is overfitting - it's going to fail dramatically on new points.

In [60]:
```
pd.DataFrame(results, columns=['model', 'degree', 'mse']).sort_values('mse')
```

Out[60]:

	model	degree	mse
6	Ridge(0)	15	0.004986
1	LR	4	0.011565
2	Lasso(0)	15	0.011742
7	Ridge(0.01)	15	0.012628
8	Ridge(0.1)	15	0.024254
3	Lasso(0.01)	15	0.033041
9	Ridge(1)	15	0.116239
0	LR	1	0.225892
4	Lasso(0.1)	15	0.353285
5	Lasso(1)	15	0.429192

Ridge(0) with degree=15 has smaller MSE, but it's only because of overfitting, it doesn't look like this model describes data relationships and learns the noise. Linear regression with degree 4, Lasso(0) and Ridge(0.01) have almost the same score and all of them are quite good. LR (degree=1), Lasso(0.1) and Lasso(1) with degree=15 are underfitting.

Завдання 3. Натренуйте модель логістичної регресії на вибірці про класифікацію вина. Попередньо розбийте вибірку на тренувальну та тестову частини. Яка точність отриманої моделі? Матриця невідповідностей?

In [61]:
```
from sklearn.datasets import load_wine
data = load_wine()
```

In [62]:
```
X, y = data['data'], data['target']
cols = data['feature_names']
```

In [63]:
```
X = pd.DataFrame(X, columns = cols)
X.head()
```

Out[63]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenol
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	0.2
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	0.2
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	0.3
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	0.2
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	0.3

In [64]:
```
# train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7,
stratify=y, random_state = 42)

# standart scale data
scaler = StandardScaler()
scaler.fit(X_train)
X_train, X_test = scaler.transform(X_train), scaler.transform(X_test)
```

In [65]:
```
# default params
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy:', np.mean(y_test==y_pred))
confusion_matrix(y_test, y_pred)
```

```
Accuracy: 0.9814814814814815
```

Out[65]:
```
array([[18,  0,  0],
       [ 1, 20,  0],
       [ 0,  0, 15]])
```

There is only one point which was wrongly predicted - point from class 1 was predicted as class 0.

In [66]:
```
# optimize hyperparameters (just for fun, 98% score is already cool enough)
logreg = LogisticRegression(solver='saga',penalty='elasticnet', l1_ratio=0.0
1, C=0.1,  max_iter=10000)
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy:', np.mean(y_test==y_pred))
```

```
Accuracy: 1.0
```

In [67]:
```
confusion_matrix(y_test, y_pred)
```

Out[67]:
```
array([[18,  0,  0],
       [ 0, 21,  0],
       [ 0,  0, 15]])
```

Perfect score! On this test set at least.

In [ ]: