In [1]:
```
import os
import sklearn
import numpy as np



%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

Демонстраційна частина

Бінарна класифікація

In [2]:
```
from sklearn.svm import SVC
from sklearn import datasets

iris = datasets.load_iris()

## звузимо задачу до двох ознак, бінарної класифікації
X = iris["data"][:, (2, 3)]  # petal length, petal width
y = iris["target"]

setosa_or_versicolor = (y == 0) | (y == 1)
X = X[setosa_or_versicolor]
y = y[setosa_or_versicolor]

# SVM Classifier model
svm_clf = SVC(kernel="linear", C=float("inf")) # C=float("inf") відповідає нульовій толерантності до "порушників коридору"
svm_clf.fit(X, y)
```

Out[2]:
```
SVC(C=inf, kernel='linear')
```

Проілюструємо отриману модель

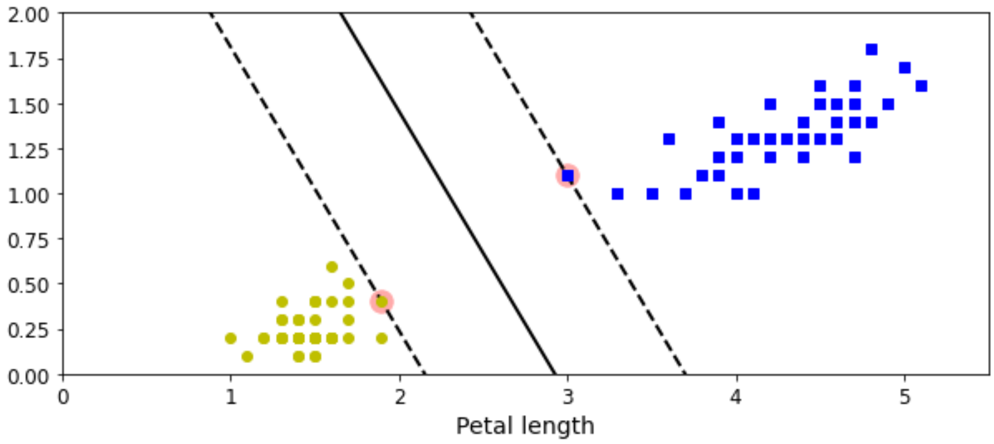
In [3]:
```
svm_clf.coef_[0]
```

Out[3]:
```
array([1.29411744, 0.82352928])
```

In [4]:
```
svm_clf.intercept_[0]
```

Out[4]:
```
-3.7882347112962464
```

In [5]:
```
x0 = np.linspace(0, 5.5, 200)

def plot_svc_decision_boundary(svm_clf, xmin, xmax):
    w = svm_clf.coef_[0]
    b = svm_clf.intercept_[0]

    # Розділова пряма виглядає як w0*x0 + w1*x1 + b = 0
    # => x1 = -w0/w1 * x0 - b/w1
    x0 = np.linspace(xmin, xmax, 200)
    decision_boundary = -w[0]/w[1] * x0 - b/w[1]

    margin = 1/w[1] # проекція на вертикальну вісь
    gutter_up = decision_boundary + margin
    gutter_down = decision_boundary - margin

    svs = svm_clf.support_vectors_
    plt.scatter(svs[:, 0], svs[:, 1], s=180, facecolors='#F
FAAAA')
    plt.plot(x0, decision_boundary, "k-", linewidth=2)
    plt.plot(x0, gutter_up, "k--", linewidth=2)
    plt.plot(x0, gutter_down, "k--", linewidth=2)

fig, axes = plt.subplots(ncols=1, figsize=(10,4), sharey=Tr
ue)

plot_svc_decision_boundary(svm_clf, 0, 5.5)
plt.plot(X[:, 0][y==1], X[:, 1][y==1], "bs")
plt.plot(X[:, 0][y==0], X[:, 1][y==0], "yo")
plt.xlabel("Petal length", fontsize=14)
plt.axis([0, 5.5, 0, 2])
plt.show()
```



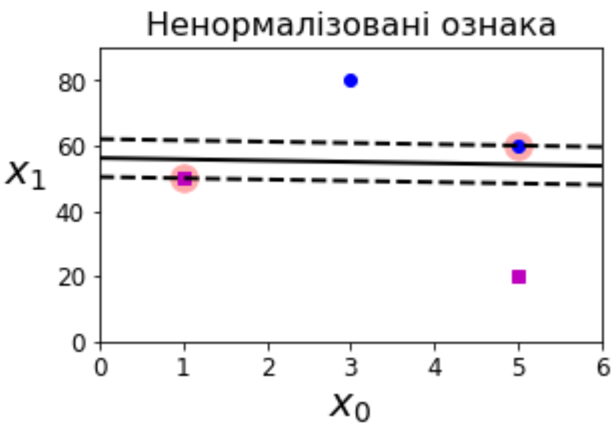
Чутливість до масштабування

In [6]:
```
# створимо штучний міні датасет
Xs = np.array([[1, 50], [5, 20], [3, 80], [5, 60]]).astype
(np.float64)
ys = np.array([0, 0, 1, 1])

# натренуємо модель
svm_clf = SVC(kernel="linear", C=100)
svm_clf.fit(Xs, ys)
```

Out[6]:
```
SVC(C=100, kernel='linear')
```

In [7]:
```
plt.figure(figsize=(4.5,2.7))
plt.plot(Xs[:, 0][ys==1], Xs[:, 1][ys==1], "bo")
plt.plot(Xs[:, 0][ys==0], Xs[:, 1][ys==0], "ms")

## скористаємося функцією, що ми ввели вище
plot_svc_decision_boundary(svm_clf, 0, 6)
plt.xlabel("$x_0$", fontsize=20)
plt.ylabel("$x_1$    ", fontsize=20, rotation=0)
plt.title("Ненормалізовані ознака", fontsize=16)
plt.axis([0, 6, 0, 90])
```

Out[7]:
```
(0.0, 6.0, 0.0, 90.0)
```



In [8]:
```
### Нормалізуємо ознаки
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

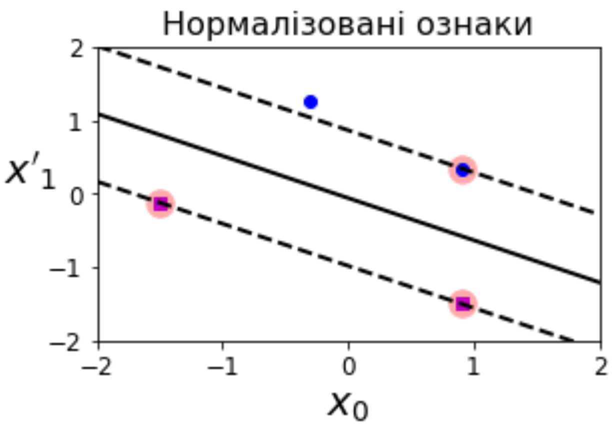
In [9]:
```
#help(StandardScaler)
```

In [10]:
```
X_scaled = scaler.fit_transform(Xs)
svm_clf.fit(X_scaled, ys)
```

Out[10]:
```
SVC(C=100, kernel='linear')
```

In [11]:
```
plt.figure(figsize=(4.5,2.7))
plt.plot(X_scaled[:, 0][ys==1], X_scaled[:, 1][ys==1], "b
o")
plt.plot(X_scaled[:, 0][ys==0], X_scaled[:, 1][ys==0], "m
s")
plot_svc_decision_boundary(svm_clf, -2, 2)
plt.xlabel("$x_0$", fontsize=20)
plt.ylabel("$x'_1$  ", fontsize=20, rotation=0)
plt.title("Нормалізовані ознаки", fontsize=16)
plt.axis([-2, 2, -2, 2])
```

Out[11]:
```
(-2.0, 2.0, -2.0, 2.0)
```



Чутливість до викидів (жорстка модель)

Додамо кілька викидів до датасету ірисів

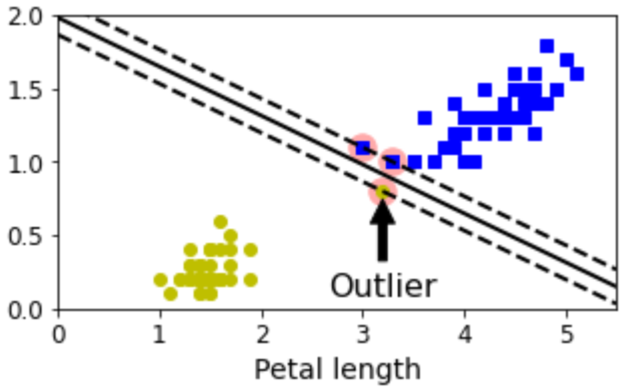
In [12]:
```
X_outliers = np.array([[3.4, 1.3], [3.2, 0.8]])
y_outliers = np.array([0, 0])
Xo1 = np.concatenate([X, X_outliers[:1]], axis=0)
yo1 = np.concatenate([y, y_outliers[:1]], axis=0)
Xo2 = np.concatenate([X, X_outliers[1:]], axis=0)
yo2 = np.concatenate([y, y_outliers[1:]], axis=0)
```

Натренуємо модель з низькою толерантністю до "порушників"

In [13]:
```
svm_clf2 = SVC(kernel="linear", C=10**9)
svm_clf2.fit(Xo2, yo2)
```

Out[13]:
```
SVC(C=1000000000, kernel='linear')
```

In [14]:
```
fig, axes = plt.subplots(ncols=1, figsize=(5,2.7), sharey=True)

plt.plot(Xo2[:, 0][yo2==1], Xo2[:, 1][yo2==1], "bs")
plt.plot(Xo2[:, 0][yo2==0], Xo2[:, 1][yo2==0], "yo")
plot_svc_decision_boundary(svm_clf2, 0, 5.5)
plt.xlabel("Petal length", fontsize=14)
plt.annotate("Outlier",
             xy=(X_outliers[1][0], X_outliers[1][1]),
             xytext=(3.2, 0.08),
             ha="center",
             arrowprops=dict(facecolor='black', shrink=0.1),
             fontsize=16,
            )
plt.axis([0, 5.5, 0, 2])

plt.show()
```

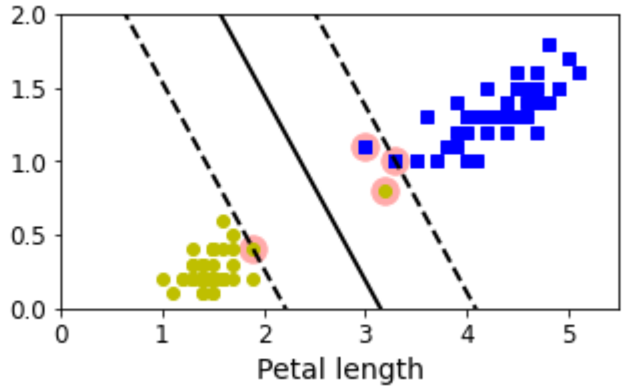


Зменшимо параметр C, що контролює нетолерантність до "порушників", до 1.

In [15]:
```
svm_clf3 = SVC(kernel="linear", C=1)
svm_clf3.fit(Xo2, yo2)
```

Out[15]: `SVC(C=1, kernel='linear')`

In [16]:
```
fig, axes = plt.subplots(ncols=1, figsize=(5,2.7), sharey=True)

plt.plot(Xo2[:, 0][yo2==1], Xo2[:, 1][yo2==1], "bs")
plt.plot(Xo2[:, 0][yo2==0], Xo2[:, 1][yo2==0], "yo")
plot_svc_decision_boundary(svm_clf3, 0, 5.5)
plt.xlabel("Petal length", fontsize=14)
plt.axis([0, 5.5, 0, 2])

plt.show()
```



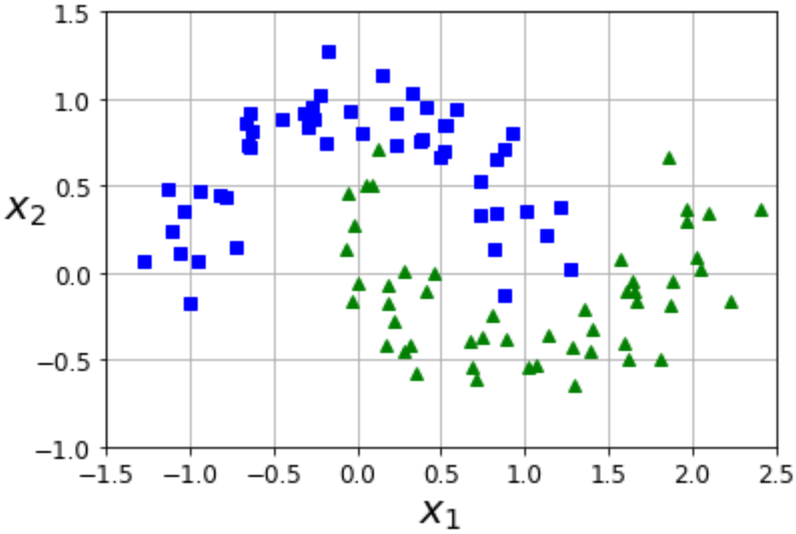
Нелінійна задача класифікації

Створемо штучний датасет

In [17]:
```
from sklearn.datasets import make_moons
X, y = make_moons(n_samples=100, noise=0.15, random_state=42)
```

In [18]:
```
def plot_dataset(X, y, axes):
    plt.plot(X[:, 0][y==0], X[:, 1][y==0], "bs")
    plt.plot(X[:, 0][y==1], X[:, 1][y==1], "g^")
    plt.axis(axes)
    plt.grid(True, which='both')
    plt.xlabel(r"$x_1$", fontsize=20)
    plt.ylabel(r"$x_2$", fontsize=20, rotation=0)
```

In [19]:
```
plot_dataset(X, y, [-1.5, 2.5, -1, 1.5])
plt.show()
```



Поліноміальне ядро

Ми можемо у явному вигляді відобразити ознаки у інший простір

In [20]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.svm import LinearSVC
```

In [21]:
```
polynomial_svm_clf = Pipeline([
        ("poly_features", PolynomialFeatures(degree=3)),
        ("scaler", StandardScaler()),
        ("svm_clf", LinearSVC(C=10, loss="hinge", random_st
ate=42))
    ])
```

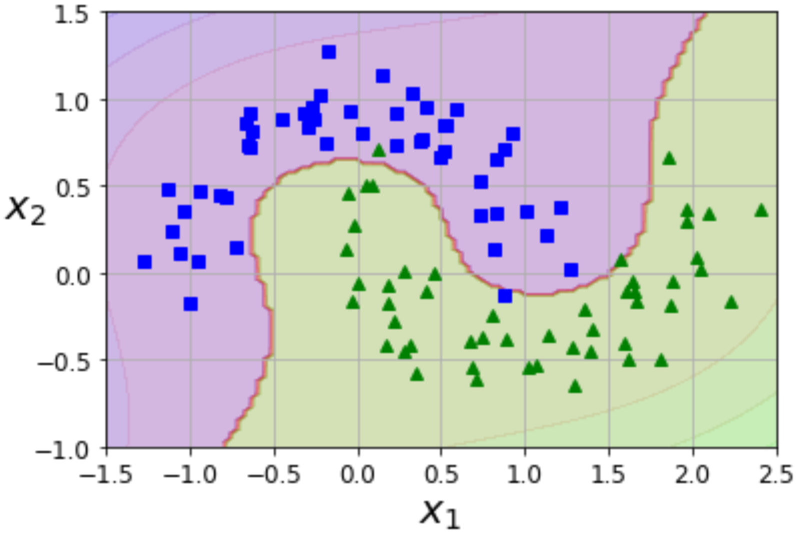
In [22]:
```
polynomial_svm_clf.fit(X, y)
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-pack
ages/sklearn/svm/_base.py:977: ConvergenceWarning: Liblinea
r failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

Out[22]:
```
Pipeline(steps=[('poly_features', PolynomialFeatures(degree
=3)),
                ('scaler', StandardScaler()),
                ('svm_clf', LinearSVC(C=10, loss='hinge', r
andom_state=42))])
```

In [23]:
```
def plot_predictions(clf, axes):
    x0s = np.linspace(axes[0], axes[1], 100)
    x1s = np.linspace(axes[2], axes[3], 100)
    x0, x1 = np.meshgrid(x0s, x1s)
    X = np.c_[x0.ravel(), x1.ravel()]
    y_pred = clf.predict(X).reshape(x0.shape)
    y_decision = clf.decision_function(X).reshape(x0.shape)
    plt.contourf(x0, x1, y_pred, cmap=plt.cm.brg, alpha=0.
2)
    plt.contourf(x0, x1, y_decision, cmap=plt.cm.brg, alpha
=0.1)
```

In [24]:
```
plot_predictions(polynomial_svm_clf, [-1.5, 2.5, -1, 1.5])
plot_dataset(X, y, [-1.5, 2.5, -1, 1.5])
plt.show()
```



Або, можемо використати поліноміальне ядро

In [25]:
```
from sklearn.svm import SVC

poly_kernel_svm_clf = Pipeline([
        ("scaler", StandardScaler()),
        ("svm_clf", SVC(kernel="poly", degree=3, coef0=1, C
=5))
    ])
poly_kernel_svm_clf.fit(X, y)
```

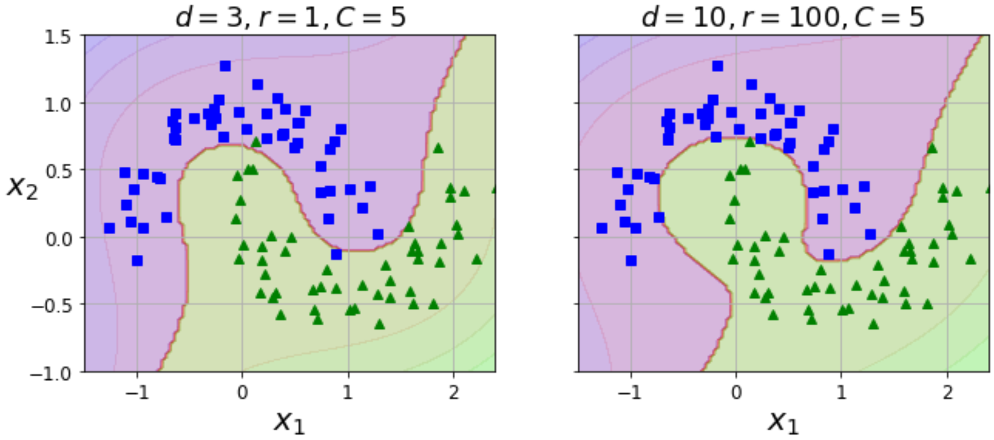
Out[25]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf', SVC(C=5, coef0=1, kernel='poly
'))])
```

In [26]:
```
## більше про поліноміальне ядро
# help(sklearn.metrics.pairwise.polynomial_kernel)
```

In [27]:
```
poly100_kernel_svm_clf = Pipeline([
        ("scaler", StandardScaler()),
        ("svm_clf", SVC(kernel="poly", degree=10, coef0=10
0, C=5))
    ])
poly100_kernel_svm_clf.fit(X, y)
```

Out[27]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf', SVC(C=5, coef0=100, degree=10,
kernel='poly'))])
```

In [28]:
```
fig, axes = plt.subplots(ncols=2, figsize=(10.5, 4), sharey
=True)

plt.sca(axes[0])
plot_predictions(poly_kernel_svm_clf, [-1.5, 2.45, -1, 1.
5])
plot_dataset(X, y, [-1.5, 2.4, -1, 1.5])
plt.title(r"$d=3, r=1, C=5$", fontsize=18)

plt.sca(axes[1])
plot_predictions(poly100_kernel_svm_clf, [-1.5, 2.45, -1,
1.5])
plot_dataset(X, y, [-1.5, 2.4, -1, 1.5])
plt.title(r"$d=10, r=100, C=5$", fontsize=18)
plt.ylabel("")

plt.show()
```



Більша степінь ядра --> більша складність моделі, що може призвести до перенавчання

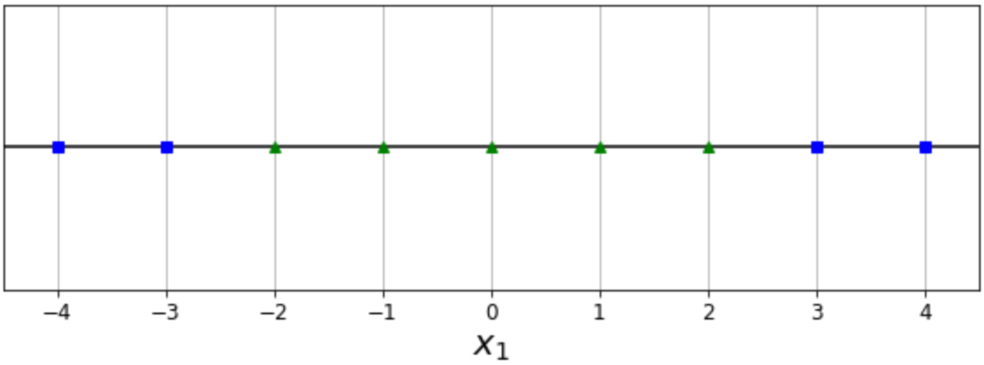
Гаусове ядро (радіальні базисні функції)

In [29]:
```
def gaussian_rbf(x, landmark, gamma):
    return np.exp(-gamma * np.linalg.norm(x - landmark, axi
s=1)**2)
```

In [30]:
```
X1D = np.linspace(-4, 4, 9).reshape(-1, 1)
y1D = np.array([0, 0, 1, 1, 1, 1, 1, 0, 0])
```

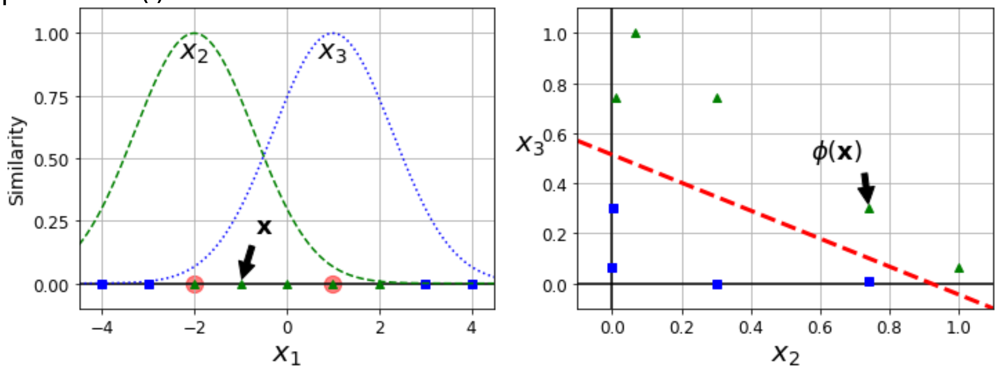
In [31]:
```
plt.figure(figsize=(10, 3))

plt.grid(True, which='both')
plt.axhline(y=0, color='k')
plt.plot(X1D[:, 0][y1D==0], np.zeros(4), "bs")
plt.plot(X1D[:, 0][y1D==1], np.zeros(5), "g^")
plt.gca().get_yaxis().set_ticks([])
plt.xlabel(r"$x_1$", fontsize=20)
plt.axis([-4.5, 4.5, -0.2, 0.2])
```

Out[31]:
```
(-4.5, 4.5, -0.2, 0.2)
```



In [32]:
```
gamma = 0.3

x1s = np.linspace(-4.5, 4.5, 200).reshape(-1, 1)
x2s = gaussian_rbf(x1s, -2, gamma)
x3s = gaussian_rbf(x1s, 1, gamma)

XK = np.c_[gaussian_rbf(X1D, -2, gamma), gaussian_rbf(X1D,
1, gamma)]
yk = np.array([0, 0, 1, 1, 1, 1, 1, 0, 0])

plt.figure(figsize=(10.5, 4))

plt.subplot(121)
plt.grid(True, which='both')
plt.axhline(y=0, color='k')
plt.scatter(x=[-2, 1], y=[0, 0], s=150, alpha=0.5, c="red")
plt.plot(X1D[:, 0][yk==0], np.zeros(4), "bs")
plt.plot(X1D[:, 0][yk==1], np.zeros(5), "g^")
plt.plot(x1s, x2s, "g--")
plt.plot(x1s, x3s, "b:")
plt.gca().get_yaxis().set_ticks([0, 0.25, 0.5, 0.75, 1])
plt.xlabel(r"$x_1$", fontsize=20)
plt.ylabel(r"Similarity", fontsize=14)
plt.annotate(r'$\mathbf{x}$',
             xy=(X1D[3, 0], 0),
             xytext=(-0.5, 0.20),
             ha="center",
             arrowprops=dict(facecolor='black', shrink=0.
1),
             fontsize=18,
            )
plt.text(-2, 0.9, "$x_2$", ha="center", fontsize=20)
plt.text(1, 0.9, "$x_3$", ha="center", fontsize=20)
plt.axis([-4.5, 4.5, -0.1, 1.1])

plt.subplot(122)
plt.grid(True, which='both')
plt.axhline(y=0, color='k')
plt.axvline(x=0, color='k')
plt.plot(XK[:, 0][yk==0], XK[:, 1][yk==0], "bs")
plt.plot(XK[:, 0][yk==1], XK[:, 1][yk==1], "g^")
plt.xlabel(r"$x_2$", fontsize=20)
plt.ylabel(r"$x_3$  ", fontsize=20, rotation=0)
plt.annotate(r'$\phi\left(\mathbf{x}\right)$',
             xy=(XK[3, 0], XK[3, 1]),
             xytext=(0.65, 0.50),
             ha="center",
             arrowprops=dict(facecolor='black', shrink=0.
1),
             fontsize=18,
            )
plt.plot([-0.1, 1.1], [0.57, -0.1], "r--", linewidth=3)
plt.axis([-0.1, 1.1, -0.1, 1.1])
```

```
plt.subplots_adjust(right=1)

plt.show()
```



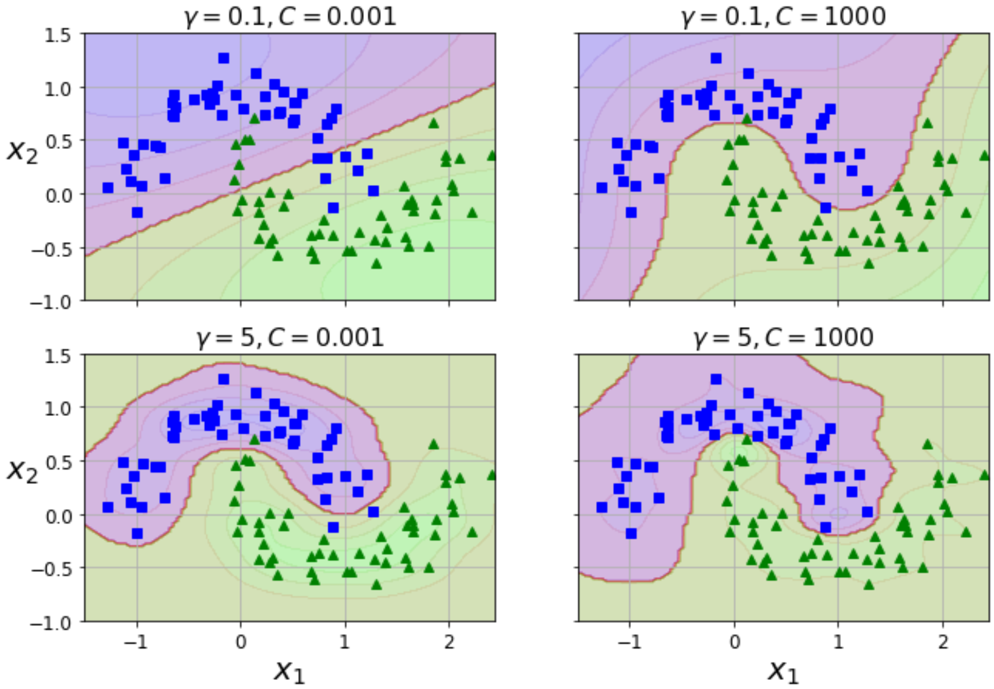
Повернемося до задачі з ірисами

In [33]:
```
rbf_kernel_svm_clf = Pipeline([
        ("scaler", StandardScaler()),
        ("svm_clf", SVC(kernel="rbf", gamma=5, C=0.001))
    ])
rbf_kernel_svm_clf.fit(X, y)
```

Out[33]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf', SVC(C=0.001, gamma=5))])
```

Використаємо різні значення параметрів gamma та C

In [34]:
```
from sklearn.svm import SVC

gamma1, gamma2 = 0.1, 5
C1, C2 = 0.001, 1000
hyperparams = (gamma1, C1), (gamma1, C2), (gamma2, C1), (ga
mma2, C2)

svm_clfs = []
for gamma, C in hyperparams:
    rbf_kernel_svm_clf = Pipeline([
            ("scaler", StandardScaler()),
            ("svm_clf", SVC(kernel="rbf", gamma=gamma, C=
C))
        ])
    rbf_kernel_svm_clf.fit(X, y)
    svm_clfs.append(rbf_kernel_svm_clf)

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10.5,
7), sharex=True, sharey=True)

for i, svm_clf in enumerate(svm_clfs):
    plt.sca(axes[i // 2, i % 2])
    plot_predictions(svm_clf, [-1.5, 2.45, -1, 1.5])
    plot_dataset(X, y, [-1.5, 2.45, -1, 1.5])
    gamma, C = hyperparams[i]
    plt.title(r"$\gamma = {}, C = {}$".format(gamma, C), fo
ntsize=16)
    if i in (0, 1):
        plt.xlabel("")
    if i in (1, 3):
        plt.ylabel("")

plt.show()
```



Вибір оптимальних параметрів

In [35]:
```
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

In [36]:
```
dataset = load_breast_cancer()
```

In [37]:
```
X, y = dataset['data'], dataset['target']
```

In [38]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, ra
ndom_state=42, stratify=y, test_size=0.3)
```

In [39]:
```
svm_clf = SVC(kernel="rbf", random_state=42)
svm_clf.fit(X_train, y_train)
```

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

In [40]:
```
y_pred = svm_clf.predict(X_test)
```

In [41]:
```
accuracy_score(y_test, y_pred)
```

Out[41]:
```
0.9064327485380117
```

Спробуємо знайти кращі гіперпараметри моделі

In [42]:
```
from sklearn.model_selection import  GridSearchCV
```

In [43]:
```
# Пошук параметрів
param_grid = {
    'gamma': [0.00001, 0.0001, 0.001, 0.01, 0.1],
    'C': [0.1,1,5,10, 20, 40, 80, 160, 320],
}
search = GridSearchCV(svm_clf, param_grid, n_jobs=-1)
search.fit(X_train, y_train)
print("Best parameter (CV score=%0.3f):" % search.best_scor
e_)
print(search.best_params_)
```

```
Best parameter (CV score=0.962):
{'C': 160, 'gamma': 1e-05}
```

In [44]:
```
svm_clf_best = SVC(kernel="rbf", **search.best_params_, random_state=42)
svm_clf_best.fit(X_train, y_train)
```

Out[44]:
```
SVC(C=160, gamma=1e-05, random_state=42)
```

In [45]:
```
y_pred = svm_clf_best.predict(X_test)
```

In [46]:
```
accuracy_score(y_test, y_pred)
```

Out[46]:
```
0.9298245614035088
```

Рандомізований пошук

In [47]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import reciprocal, uniform

param_distributions = {"gamma": reciprocal(0.00001, 0.1), "C": uniform(1, 200)}
rnd_search_cv = RandomizedSearchCV(svm_clf, param_distributions, n_iter=100, verbose=1, cv=3)
rnd_search_cv.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:    1.5s finished
```

Out[47]:
```
RandomizedSearchCV(cv=3, estimator=SVC(random_state=42), n_iter=100,
                   param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7fd72991d890>,
                                        'gamma': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7fd727842290>},
                   verbose=1)
```

In [48]:
```
print(rnd_search_cv.best_params_)
```

```
{'C': 116.82215030818507, 'gamma': 1.0020866574229947e-05}
```

In [49]:
```
svm_clf_best2 = SVC(kernel="rbf", **rnd_search_cv.best_params_, random_state=42)
svm_clf_best2.fit(X_train, y_train)
```

Out[49]:
```
SVC(C=116.82215030818507, gamma=1.0020866574229947e-05, random_state=42)
```

In [50]:
```
y_pred = svm_clf_best2.predict(X_test)
accuracy_score(y_test, y_pred)
```

Out[50]:
```
0.9298245614035088
```

Задача регресії

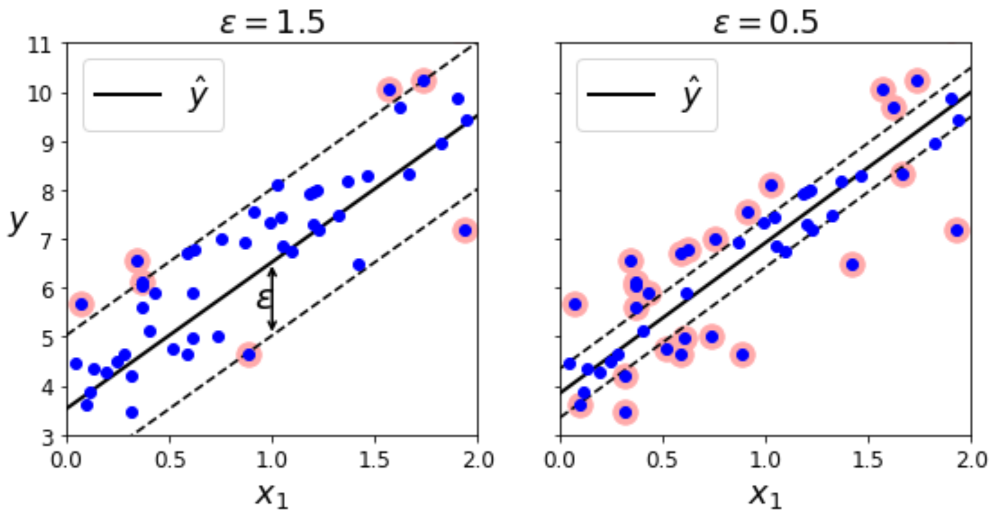
In [51]:
```
np.random.seed(42)
m = 50
X = 2 * np.random.rand(m, 1)
y = (4 + 3 * X + np.random.randn(m, 1)).ravel()
```

In [52]:
```
from sklearn.svm import LinearSVR

svm_reg = LinearSVR(epsilon=1.5, random_state=42)
svm_reg.fit(X, y)
```

Out[52]:
```
LinearSVR(epsilon=1.5, random_state=42)
```

In [53]:
```
svm_reg1 = LinearSVR(epsilon=1.5, random_state=42)
svm_reg2 = LinearSVR(epsilon=0.5, random_state=42)
svm_reg1.fit(X, y)
svm_reg2.fit(X, y)

def find_support_vectors(svm_reg, X, y):
    y_pred = svm_reg.predict(X)
    off_margin = (np.abs(y - y_pred) >= svm_reg.epsilon)
    return np.argwhere(off_margin)

svm_reg1.support_ = find_support_vectors(svm_reg1, X, y)
svm_reg2.support_ = find_support_vectors(svm_reg2, X, y)

eps_x1 = 1
eps_y_pred = svm_reg1.predict([[eps_x1]])
```

In [54]:
```
def plot_svm_regression(svm_reg, X, y, axes):
    x1s = np.linspace(axes[0], axes[1], 100).reshape(100, 1)
    y_pred = svm_reg.predict(x1s)
    plt.plot(x1s, y_pred, "k-", linewidth=2, label=r"$\hat{y}$")
    plt.plot(x1s, y_pred + svm_reg.epsilon, "k--")
    plt.plot(x1s, y_pred - svm_reg.epsilon, "k--")
    plt.scatter(X[svm_reg.support_], y[svm_reg.support_], s=180, facecolors='#FFAAAA')
    plt.plot(X, y, "bo")
    plt.xlabel(r"$x_1$", fontsize=18)
    plt.legend(loc="upper left", fontsize=18)
    plt.axis(axes)

fig, axes = plt.subplots(ncols=2, figsize=(9, 4), sharey=True)
plt.sca(axes[0])
plot_svm_regression(svm_reg1, X, y, [0, 2, 3, 11])
plt.title(r"$\epsilon = {}$".format(svm_reg1.epsilon), fontsize=18)
plt.ylabel(r"$y$", fontsize=18, rotation=0)
#plt.plot([eps_x1, eps_x1], [eps_y_pred, eps_y_pred - svm_reg1.epsilon], "k-", linewidth=2)
plt.annotate(
        '', xy=(eps_x1, eps_y_pred), xycoords='data',
        xytext=(eps_x1, eps_y_pred - svm_reg1.epsilon),
        textcoords='data', arrowprops={'arrowstyle': '<->', 'linewidth': 1.5}
    )
plt.text(0.91, 5.6, r"$\epsilon$", fontsize=20)
plt.sca(axes[1])
plot_svm_regression(svm_reg2, X, y, [0, 2, 3, 11])
plt.title(r"$\epsilon = {}$".format(svm_reg2.epsilon), fontsize=18)
plt.show()
```



In [55]:
```
np.random.seed(42)
m = 100
X = 2 * np.random.rand(m, 1) - 1
y = (0.2 + 0.1 * X + 0.5 * X**2 + np.random.randn(m, 1)/1
0).ravel()
```

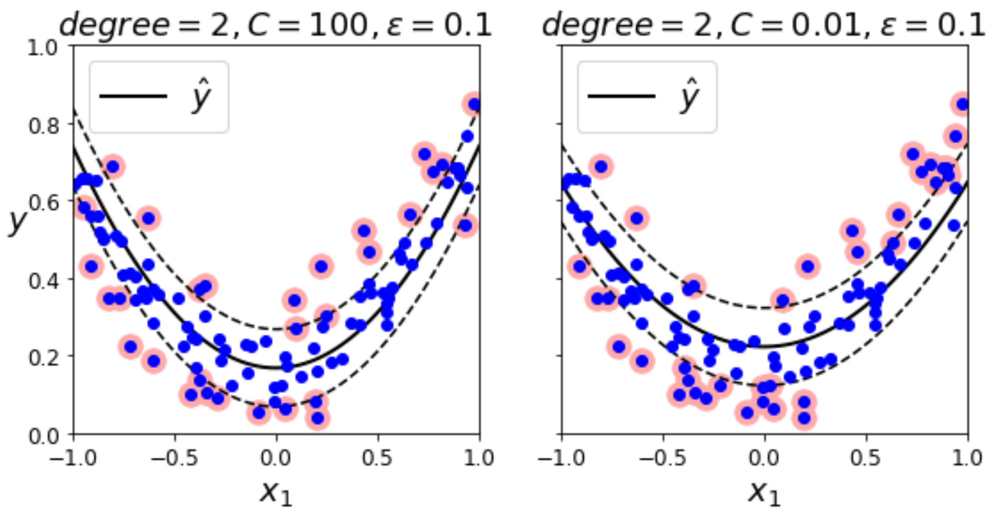
In [56]:
```
from sklearn.svm import SVR

svm_poly_reg = SVR(kernel="poly", degree=2, C=100, epsilon=
0.1, gamma="scale")
svm_poly_reg.fit(X, y)
```

Out[56]:
```
SVR(C=100, degree=2, kernel='poly')
```

In [57]:
```
from sklearn.svm import SVR

svm_poly_reg1 = SVR(kernel="poly", degree=2, C=100, epsilon
=0.1, gamma="scale")
svm_poly_reg2 = SVR(kernel="poly", degree=2, C=0.01, epsilo
n=0.1, gamma="scale")
svm_poly_reg1.fit(X, y)
svm_poly_reg2.fit(X, y)
```

Out[57]:
```
SVR(C=0.01, degree=2, kernel='poly')
```

In [58]:
```
fig, axes = plt.subplots(ncols=2, figsize=(9, 4), sharey=True)
plt.sca(axes[0])
plot_svm_regression(svm_poly_reg1, X, y, [-1, 1, 0, 1])
plt.title(r"$degree={}, C={}, \epsilon = {}$".format(svm_poly_reg1.degree, svm_poly_reg1.C, svm_poly_reg1.epsilon), fontsize=18)
plt.ylabel(r"$y$", fontsize=18, rotation=0)
plt.sca(axes[1])
plot_svm_regression(svm_poly_reg2, X, y, [-1, 1, 0, 1])
plt.title(r"$degree={}, C={}, \epsilon = {}$".format(svm_poly_reg2.degree, svm_poly_reg2.C, svm_poly_reg2.epsilon), fontsize=18)
plt.show()
```



Завдання

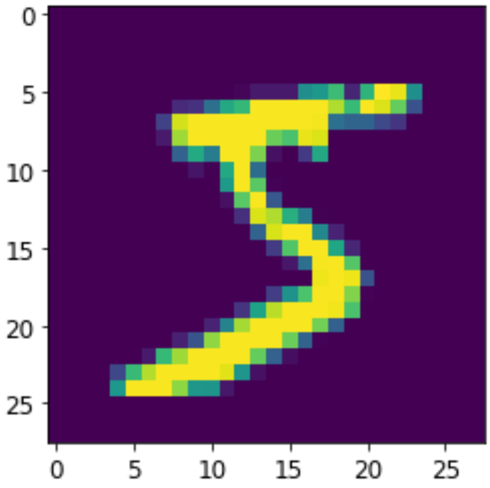
In [59]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import (
    GridSearchCV, RandomizedSearchCV, train_test_split)
```

Завдання 1. Завантажте датасет рукописних цифр MNIST як вказано нижче. Натренуйте SVM з лінійним ядром. Яка отримана точність? Натренуйте також модель логістичної регресії.

In [60]:
```
from sklearn.datasets import fetch_openml
mnist = fetch_openml('mnist_784', version=1, cache=True)

X = mnist["data"]
y = mnist["target"].astype(np.uint8)

X_train = X[:60000]
y_train = y[:60000]
X_test = X[60000:]
y_test = y[60000:]
```

In [61]:
```
plt.imshow(X_train[0].reshape(28,28))
print("y =", y_train[0])
```

```
y = 5
```



In [62]:
```
%%time
svm = SVC(kernel='linear', verbose=True, random_state=42, c
ache_size=400, max_iter=1000)
svm.fit(X_train, y_train)
```

```
[LibSVM]CPU times: user 4min 12s, sys: 767 ms, total: 4min
12s
Wall time: 4min 12s

/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-pack
ages/sklearn/svm/_base.py:249: ConvergenceWarning: Solver t
erminated early (max_iter=1000).  Consider pre-processing y
our data with StandardScaler or MinMaxScaler.
  % self.max_iter, ConvergenceWarning)
```

Out[62]:
```
SVC(cache_size=400, kernel='linear', max_iter=1000, random_
state=42,
    verbose=True)
```

In [63]:
```
yhat = svm.predict(X_test)
```

In [64]:
```
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.8004
```

In [65]:
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-pack
ages/sklearn/linear_model/_logistic.py:764: ConvergenceWarn
ing: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the d
ata as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.h
tml
Please also refer to the documentation for alternative solv
er options:
    https://scikit-learn.org/stable/modules/linear_model.ht
ml#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[65]:
```
LogisticRegression()
```

In [66]:
```
yhat = logreg.predict(X_test)
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.9255
```

Завдання 2. Нормалізуйте ознаки і знов натренуйте модель з лінійним ядром. Як змінилася точність?

In [67]:
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(kernel='linear', verbose=True, random_state
=42, cache_size=400, max_iter=1000))])

pipe.fit(X_train, y_train)
```

```
[LibSVM]

/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-pack
ages/sklearn/svm/_base.py:249: ConvergenceWarning: Solver t
erminated early (max_iter=1000).  Consider pre-processing y
our data with StandardScaler or MinMaxScaler.
  % self.max_iter, ConvergenceWarning)
```

Out[67]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svc',
                 SVC(cache_size=400, kernel='linear', max_i
ter=1000,
                     random_state=42, verbose=True))])
```

In [68]:
```
yhat = pipe.predict(X_test)
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.807
```

Accuracy is higher, but not significantly.

Завдання 3. Натренуйте модель з гаусовим ядром. Як змінилася точність?

In [69]:
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(kernel='rbf', verbose=True, random_state=4
2, cache_size=400, max_iter=1000))])

pipe.fit(X_train, y_train)
```

```
[LibSVM]

/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-pack
ages/sklearn/svm/_base.py:249: ConvergenceWarning: Solver t
erminated early (max_iter=1000).  Consider pre-processing y
our data with StandardScaler or MinMaxScaler.
  % self.max_iter, ConvergenceWarning)
```

Out[69]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svc',
                 SVC(cache_size=400, max_iter=1000, random_
state=42,
                     verbose=True))])
```

In [70]:
```
yhat = pipe.predict(X_test)
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.9664
```

Accuracy of SVM with rbf kernel is much higher comperetively to linear one.

Завдання 4. Оберіть найкращі параметри шляхом повного перебору (GridSearch) та рандомізованого пошуку (RandomSearchCV). Використайте лише частину тренувальної вибірки (у ролі валідаційної). Натренуйте модель на усій тренувальній вибірці. Як змінилася точність?

In [71]:
```
std_scaler =StandardScaler()
std_scaler.fit(X_train)
```

Out[71]:
```
StandardScaler()
```

In [80]:
```
samples = 10000
grid_params = {
    'C':[0,1,5,10],
    'gamma': [
        scale_gamma*0.1, scale_gamma, scale_gamma*10,
        auto_gamma*0.1, auto_gamma, auto_gamma*10,],
#     'kernel': ('poly', 'rbf'),
#     'degree': [3,5]
}

gs = GridSearchCV(
    estimator=SVC(),
    n_jobs=-1,
    cv=3,
    scoring='accuracy',
    verbose=True,
    param_grid=grid_params
)

%time gs.fit(std_scaler.transform(X_train[:samples]), y_tra
in[:samples])
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fit
s

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 co
ncurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  4.0m
in
[Parallel(n_jobs=-1)]: Done  72 out of  72 | elapsed: 13.6m
in finished

CPU times: user 26.5 s, sys: 157 ms, total: 26.7 s
Wall time: 14min 3s
```

Out[80]:
```
GridSearchCV(cv=3, estimator=SVC(), n_jobs=-1,
             param_grid={'C': [0, 1, 5, 10],
                         'gamma': [2.06632285641914e-08, 2.
0663228564191396e-07,
                                   2.0663228564191398e-06,
                                   0.00012755102040816325,
                                   0.0012755102040816326,
                                   0.012755102040816325]},
             scoring='accuracy', verbose=True)
```

In [74]:
```
scale_gamma = 1 / (X_train.shape[1] * X_train.var())
auto_gamma = 1 / X_train.shape[1]

scale_gamma, auto_gamma
```

Out[74]:
```
(2.0663228564191396e-07, 0.0012755102040816326)
```

In [81]:
```
gs.best_score_
```

Out[81]:
```
0.9400997688251129
```

In [82]:
```
gs.best_params_
```

Out[82]:
```
{'C': 5, 'gamma': 0.0012755102040816326}
```

In [83]:
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(**gs.best_params_))])

%time pipe.fit(X_train, y_train)
```

```
CPU times: user 8min 23s, sys: 152 ms, total: 8min 23s
Wall time: 8min 23s
```

Out[83]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svc', SVC(C=5, gamma=0.001275510204081632
6))])
```

In [84]:
```
yhat = pipe.predict(X_test)
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.9729
```

In [90]:
```
samples = 10000
grid_params = {
    'C':[0,1,5,10],
    'gamma': [
        scale_gamma*0.1, scale_gamma, scale_gamma*10,
        auto_gamma*0.1, auto_gamma, auto_gamma*10,],
    'kernel': ('poly', 'rbf'),
    'degree': [3,5]
}
rs = RandomizedSearchCV(
    estimator=SVC(),
    n_iter = 20,
    n_jobs=-1,
    cv=3,
    scoring='accuracy',
    verbose=True,
    param_distributions=grid_params,
    random_state=42,

)

%time rs.fit(std_scaler.transform(X_train[:samples]), y_tra
in[:samples])
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fit
s

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 co
ncurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  4.1m
in
[Parallel(n_jobs=-1)]: Done  60 out of  60 | elapsed: 10.0m
in finished

CPU times: user 26.7 s, sys: 129 ms, total: 26.9 s
Wall time: 10min 29s
```

Out[90]:
```
RandomizedSearchCV(cv=3, estimator=SVC(), n_iter=20, n_jobs
=-1,
                   param_distributions={'C': [0, 1, 5, 10],
'degree': [3, 5],
                                        'gamma': [2.0663228
5641914e-08,
                                                  2.0663228
564191396e-07,
                                                  2.0663228
564191398e-06,
                                                  0.0001275
5102040816325,
                                                  0.0012755
102040816326,
                                                  0.0127551
02040816325],
                                        'kernel': ('poly',
'rbf')},
                   random_state=42, scoring='accuracy', ver
bose=True)
```

In [91]:
```
rs.best_score_
```

Out[91]:
```
0.9400997688251129
```

In [92]:
```
rs.best_params_
```

Out[92]:
```
{'kernel': 'rbf', 'gamma': 0.0012755102040816326, 'degree':
5, 'C': 5}
```

In [93]:
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(**rs.best_params_))])

%time pipe.fit(X_train, y_train)
```

```
CPU times: user 8min 25s, sys: 139 ms, total: 8min 25s
Wall time: 8min 25s
```

Out[93]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svc', SVC(C=5, degree=5, gamma=0.00127551
02040816326))])
```

In [94]:
```
yhat = pipe.predict(X_test)
print('Accuracy', np.mean(yhat==y_test))
```

```
Accuracy 0.9729
```

GridSearchCV and RandomizedSearchCV give us same parameteres. It shows us best accuracy obtained, especially if it is trained on full train set.

In [ ]:
```

```