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 толера
нтності 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]:

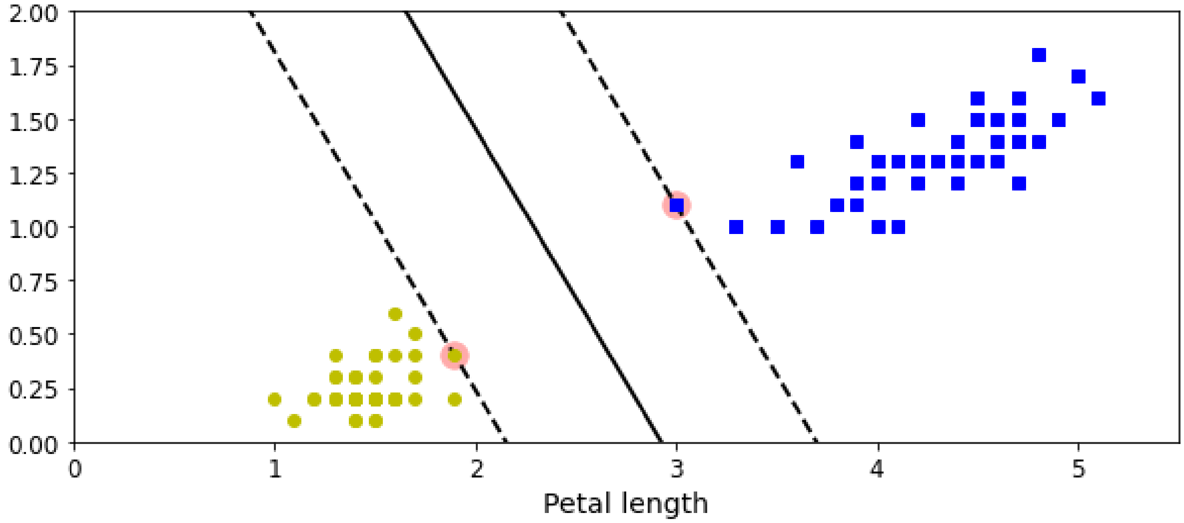
```
svm_clf.intercept_[0]
```

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='#FFAAAA')
    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=True)

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]:

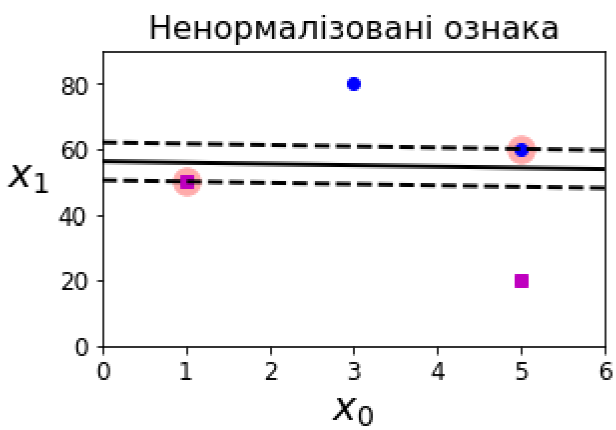
```
SVC(C=100, kernel='linear')
```

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]:

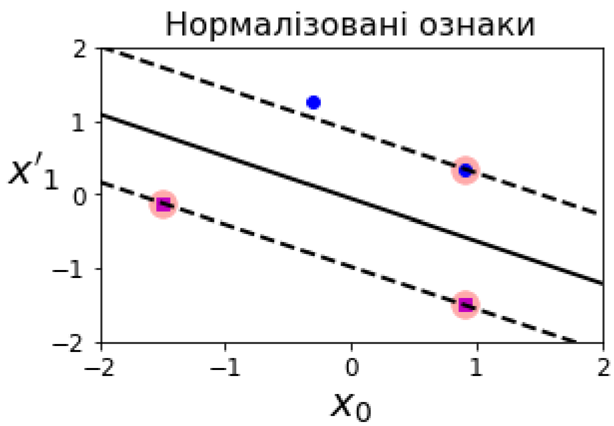
```
SVC(C=100, kernel='linear')
```

In [11]:

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

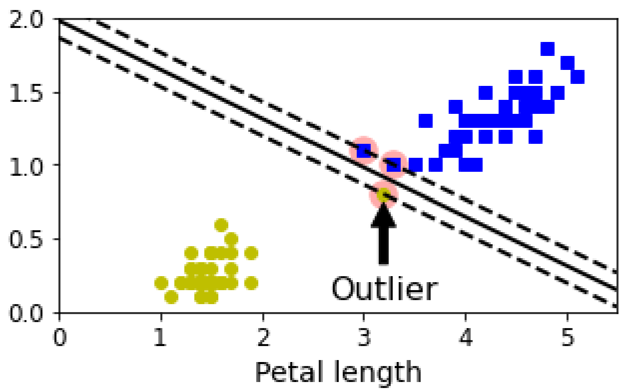
```
svm_clf2 = SVC(kernel="linear", C=10**9)
svm_clf2.fit(Xo2, yo2)
```

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]:

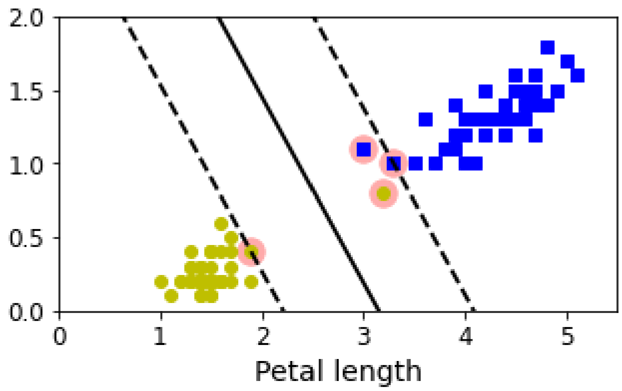
```
svm_clf3 = SVC(kernel="linear", C=1)
svm_clf3.fit(Xo2, yo2)
```

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]:

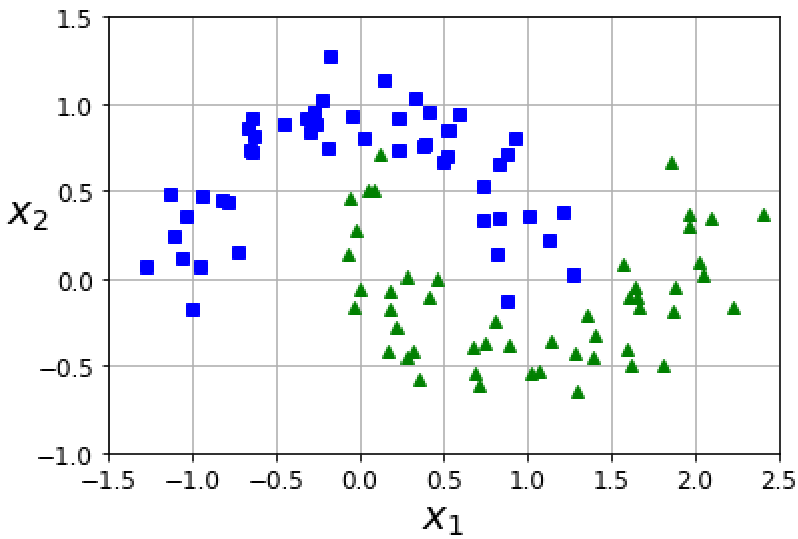
```
from sklearn.datasets import make_moons
X, y = make_moons(n_samples=100, noise=0.15, random_state=42)
```

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_state=42))
    ])
```

In [22]:

```
polynomial_svm_clf.fit(X, y)
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:976: Con
vergenceWarning: Liblinear failed to converge, increase the number of iterati
ons.
  warnings.warn("Liblinear failed to converge, increase "
```

Out[22]:

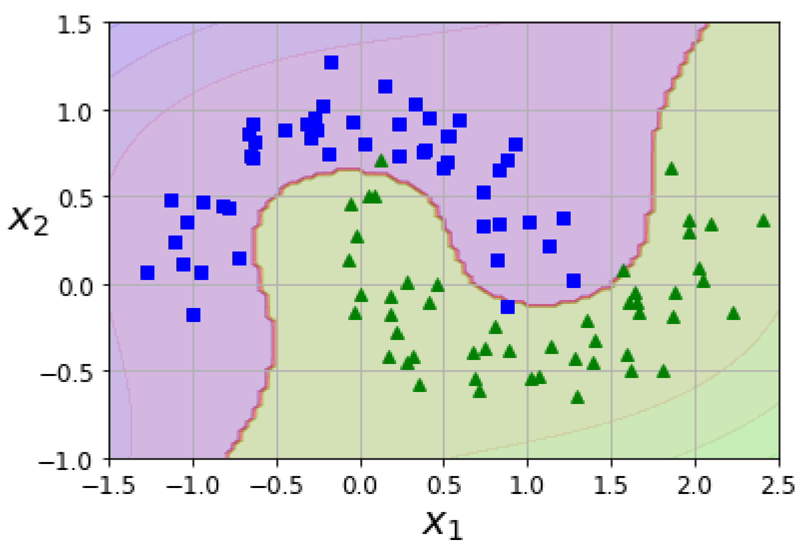
```
Pipeline(steps=[('poly_features', PolynomialFeatures(degree=3)),
                ('scaler', StandardScaler()),
                ('svm_clf', LinearSVC(C=10, loss='hinge', random_state=42))])
```

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]:

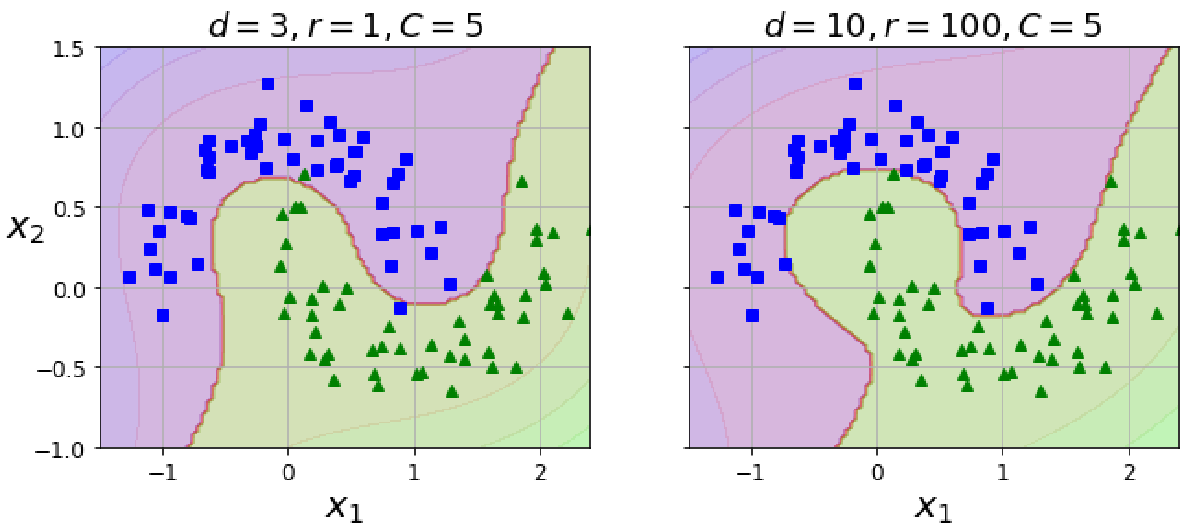
```
poly100_kernel_svm_clf = Pipeline([
        ("scaler", StandardScaler()),
        ("svm_clf", SVC(kernel="poly", degree=10, coef0=100, C=5))
    ])
poly100_kernel_svm_clf.fit(X, y)
```

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, axis=1)**2)
```

In [30]:

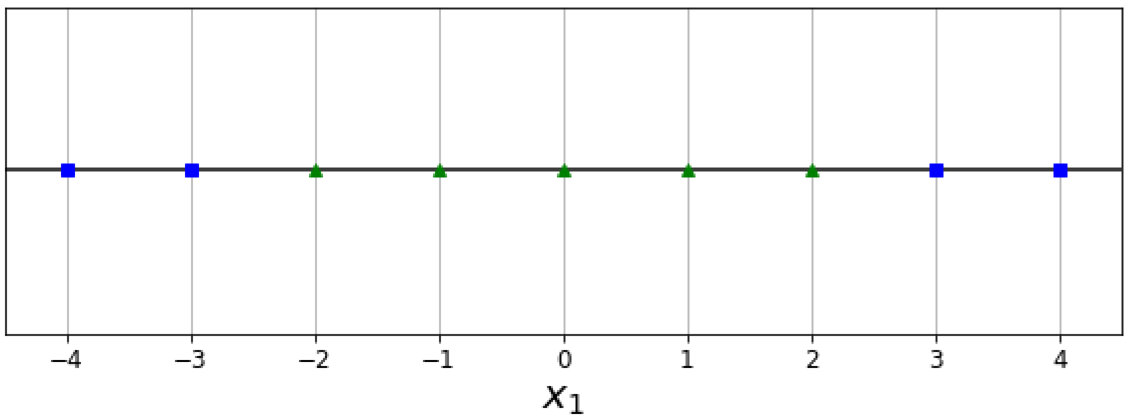
```
X1D = np.linspace(-4, 4, 9).reshape(-1, 1)
y1D = np.array([0, 0, 1, 1, 1, 1, 1, 0, 0])
```

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])
```

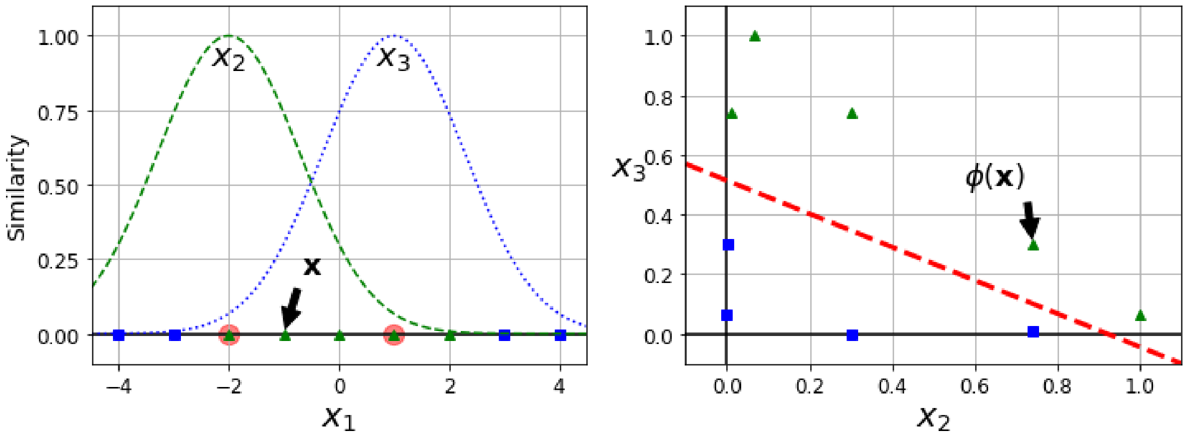
Out[31]:

```
(-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)
```

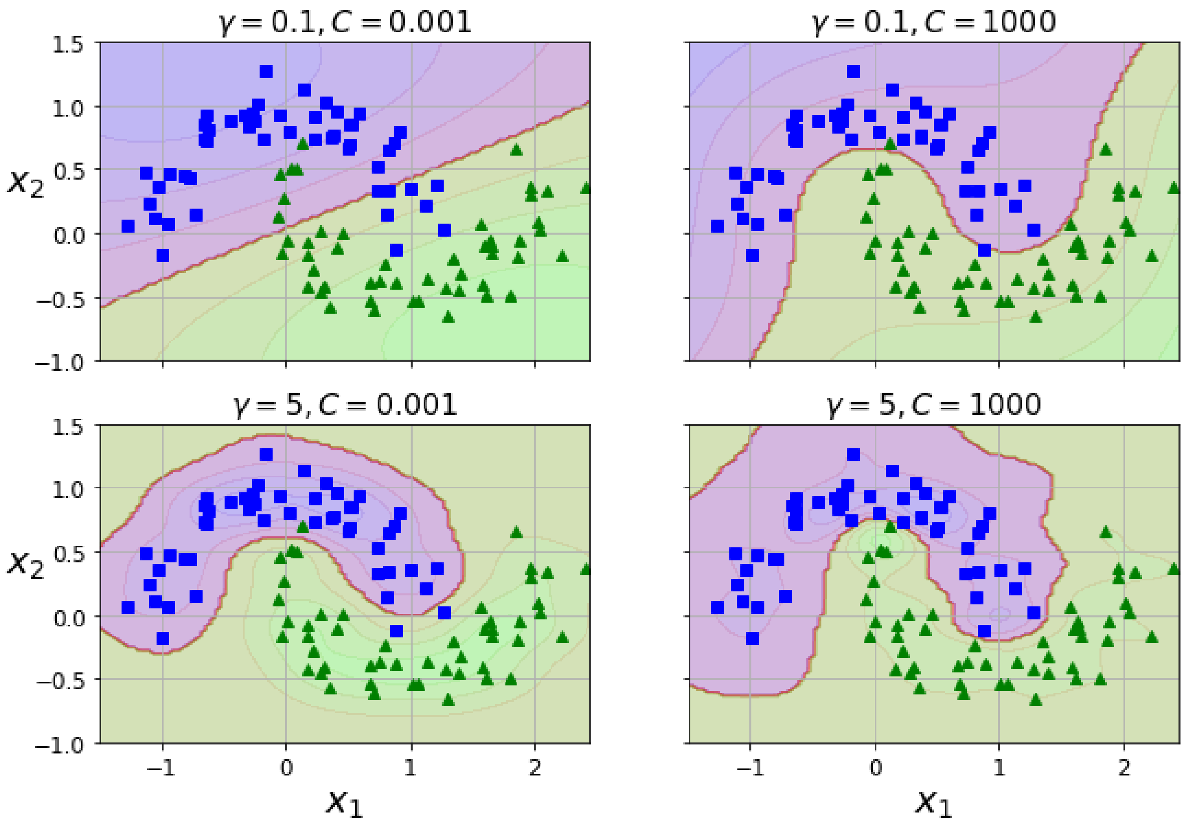
Out[33]:

```
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), (gamma2, 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), fontsize=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, random_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_score_)
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 worke
rs.
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:    2.1s finished
```

Out[47]:

```
RandomizedSearchCV(cv=3, estimator=SVC(random_state=42), n_iter=100,
                   param_distributions={'C': <scipy.stats._distn_infrastructu
re.rv_frozen object at 0x000001A10FF1F100>,
                                        'gamma': <scipy.stats._distn_infrastr
ucture.rv_frozen object at 0x000001A10FAE4C10>},
                   verbose=1)
```

In [48]:

```
print(rnd_search_cv.best_params_)
```

```
{'C': 60.64919216978571, 'gamma': 1.1096091721659939e-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=60.64919216978571, gamma=1.1096091721659939e-05, random_state=42)
```

In [50]:

```
y_pred = svm_clf_best2.predict(X_test)
accuracy_score(y_test, y_pred)
```

Out[50]:

```
0.935672514619883
```

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]:

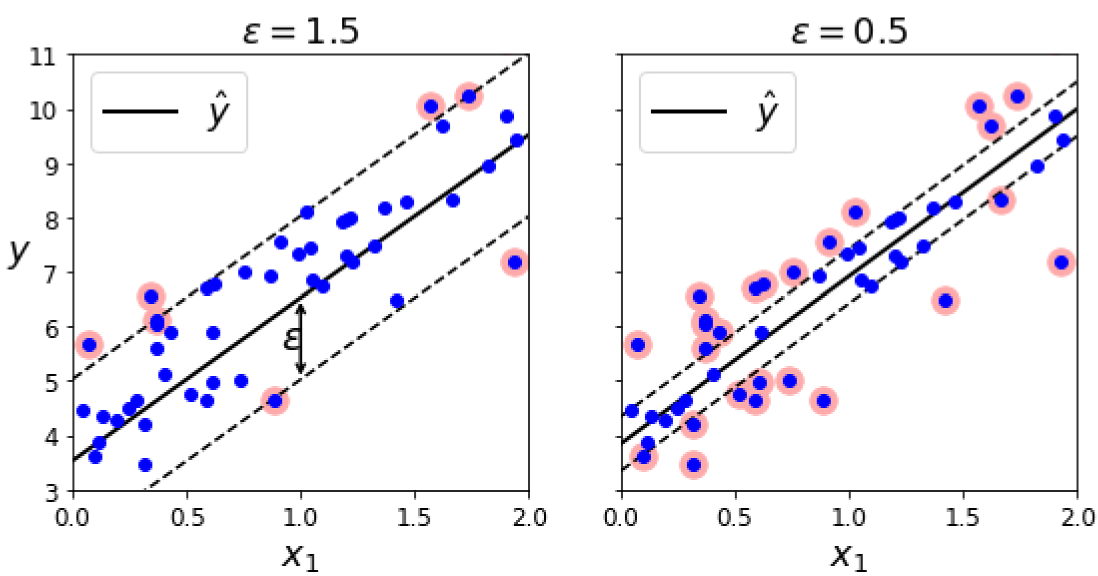
```
LinearSVR(epsilon=1.5, random_state=42)
```

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)/10).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]:

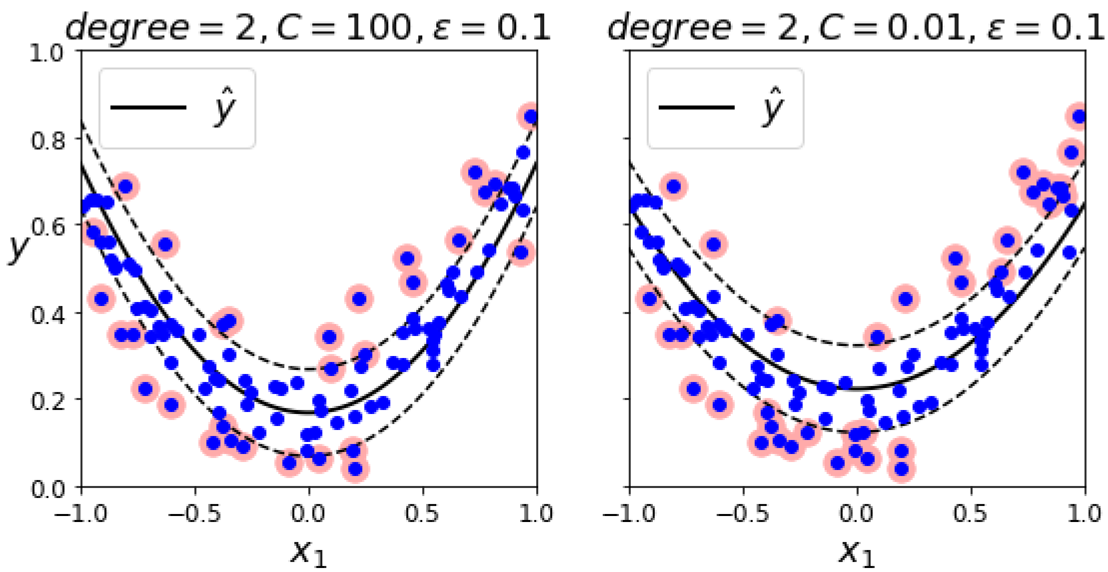
```
from sklearn.svm import SVR

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, epsilon=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

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

In [59]:

```
np.random.seed(42)#for reproducibility

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:]
```

For the sake of somewhat adequate fit time we'll reduce num_iters to 500-1000

In [60]:

```
%%time
from sklearn.svm import LinearSVC
clf = LinearSVC()
%time clf.fit(X_train,y_train)

y_train_pred = clf.predict(X_train)
y_pred = clf.predict(X_test)
print(f"LinearSVC:\ntraining set accuracy:{accuracy_score(y_train,y_train_pred):.4f}\ntest set accuracy:{accuracy_score(y_test,y_pred):.4f}")
```

```
Wall time: 2min 23s
LinearSVC:
training set accuracy:0.8349
test set accuracy:0.8236
Wall time: 2min 23s

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:976: Con
vergenceWarning: Liblinear failed to converge, increase the number of iterati
ons.
  warnings.warn("Liblinear failed to converge, increase "
```

In [61]:

```
%%time
clf = SVC(kernel='linear',max_iter=500)
%time clf.fit(X_train,y_train)
y_train_pred = clf.predict(X_train)
y_pred = clf.predict(X_test)
print(f"SVC(linear kernel):\ntraining set accuracy:{accuracy_score(y_train,y_train_pred):.
4f}\ntest set accuracy:{accuracy_score(y_test,y_pred):.4f}")
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=500).  Consider pre-proces
sing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'
```

```
Wall time: 4min 23s
SVC(linear kernel):
training set accuracy:0.8218
test set accuracy:0.8124
Wall time: 18min 5s
```

In [62]:

```
%%time
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
%time clf.fit(X_train,y_train)
y_train_pred = clf.predict(X_train)
y_pred = clf.predict(X_test)
print(f"LogReg:\ntraining set accuracy:{accuracy_score(y_train,y_train_pred):.4f}\ntest se
t accuracy:{accuracy_score(y_test,y_pred):.4f}")
```

```
Wall time: 18.2 s
LogReg:
training set accuracy:0.9339
test set accuracy:0.9255
Wall time: 18.4 s
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\linear_model\_logisti
c.py:762: ConvergenceWarning: lbfgs failed to converge (status=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
  n_iter_i = _check_optimize_result(
```

I like LogReg training time

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

We'll normalize using StandardScaler

In [63]:

```
%%time
for clf in [LinearSVC(), SVC(kernel='linear',max_iter=500),LogisticRegression()]:
    pipeline = Pipeline([('Scaler', StandardScaler()),('Classifier',clf)])
    %time pipeline.fit(X_train,y_train)
    print('Pipeline fitted; started predicting\n')
    y_train_pred = pipeline.predict(X_train)
    y_pred = pipeline.predict(X_test)

    print(f"Classifier: {clf}\ntraining set accuracy:{accuracy_score(y_train,y_train_pred)
:.4f}\ntest set accuracy:{accuracy_score(y_test,y_pred):.4f}\n\n")
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:976: Con
vergenceWarning: Liblinear failed to converge, increase the number of iterati
ons.
  warnings.warn("Liblinear failed to converge, increase "

Wall time: 8min 39s
Pipeline fitted; started predicting

Classifier: LinearSVC()
training set accuracy:0.9224
test set accuracy:0.9114



C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=500).  Consider pre-proces
sing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 4min 23s
Pipeline fitted; started predicting

Classifier: SVC(kernel='linear', max_iter=500)
training set accuracy:0.7916
test set accuracy:0.7819



C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\linear_model\_logisti
c.py:762: ConvergenceWarning: lbfgs failed to converge (status=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
  n_iter_i = _check_optimize_result(

Wall time: 18 s
Pipeline fitted; started predicting

Classifier: LogisticRegression()
training set accuracy:0.9435
test set accuracy:0.9246


Wall time: 26min 31s
```

As may be seen, under the influence of StandardScaler accuracy of linearSVC has improved from 0.8 to 0.9, accuracy of SVC with linear kernel has somewhat dropped (0.82-0.79) and accuracy of LogReg has remained stable

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

In [64]:

```
%%time
for s in [None,StandardScaler()]:
    pipeline = Pipeline([
        ('scaler',s),
        ('classifier',SVC(kernel='rbf',max_iter=500))])
    %time pipeline.fit(X_train,y_train)
    y_train_pred = pipeline.predict(X_train)
    y_pred = pipeline.predict(X_test)

    print(f"\nClassifier: Gaussian SVC\nScaler:{s}\ntraining set accuracy:{accuracy_score(
y_train,y_train_pred):.4f}\ntest set accuracy:{accuracy_score(y_test,y_pred):.4f}")
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=500).  Consider pre-proces
sing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 6min 44s

Classifier: Gaussian SVC
Scaler:None
training set accuracy:0.9898
test set accuracy:0.9797

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=500).  Consider pre-proces
sing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 8min 45s

Classifier: Gaussian SVC
Scaler:StandardScaler()
training set accuracy:0.9836
test set accuracy:0.9631
Wall time: 45min 6s
```

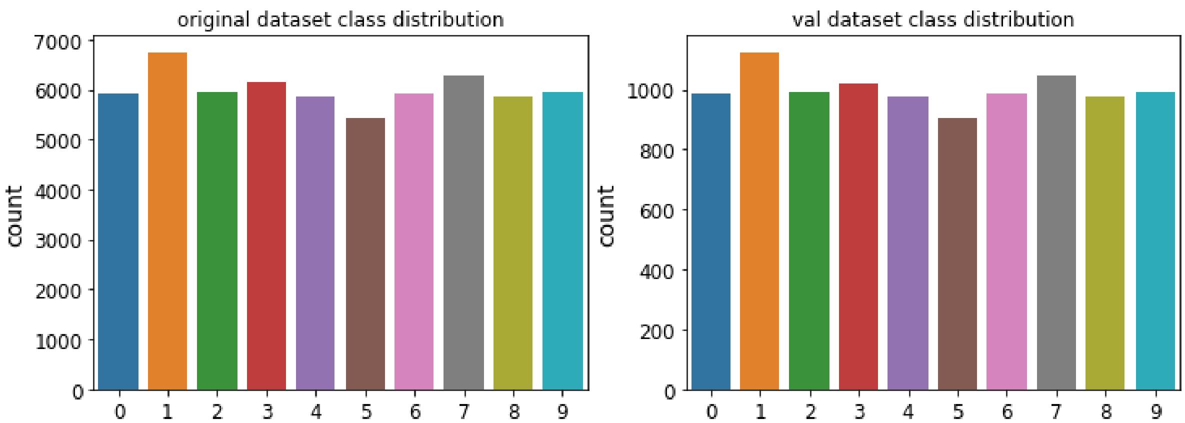
Gaussian SVC has higher accuracy. Interestingly, usage of StandardScaler decreases the accuracy

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?

We'll use 10k samples; balance of classes will be preserved via StratifiedShuffleSplit

In [65]:

```
import seaborn as sns

from sklearn.model_selection import StratifiedShuffleSplit
sss = StratifiedShuffleSplit(test_size=10000)

for _, val_ind in sss.split(X_train,y_train):
    X_val = X_train[val_ind]
    y_val = y_train[val_ind]

fig, ax = plt.subplots(1,2,figsize=(12,4))

sns.countplot(x=y_train,ax=ax[0]).set_title('original dataset class distribution')
sns.countplot(x=y_val,ax=ax[1]).set_title('val dataset class distribution');
```



In [66]:

```
%%time
scale = (1/(X[0].shape[0]*X_train.var()))#calculate adequate gamma according to the docs

gamma_vals = np.geomspace(scale*10**(-3),scale*10**2,num=6)
possible_gammas = np.sort(np.concatenate((gamma_vals,2*gamma_vals)))

grid_search_params = {
    'gamma': possible_gammas,#generate scale close to a default correct value
    'C': [0.1, 1,5,7.5, 10, 15, 20, 30, 50, 150]
}

clf = SVC(kernel='rbf',max_iter=1000)
grid_search = GridSearchCV(clf,grid_search_params,n_jobs=-1,verbose=3,cv=2)
%time grid_search.fit(X_val,y_val)


clf = grid_search.best_estimator_
print(f"grid_search best params: {grid_search.best_params_}\nclf params:\n{clf.get_params
()}")
for s in [None,StandardScaler()]:
    pipeline = Pipeline([
        ('scaler',s),
        ('classifier',clf)])
    %time pipeline.fit(X_train,y_train)
    print('Clf fitted')
    y_train_pred = pipeline.predict(X_train)
    print('Calculated predictions on training set')
    y_pred = pipeline.predict(X_test)

    print(f"\nClassifier: Gaussian SVC @params:(C={clf.C}, gamma={clf.gamma})\nScaler:{s}
\ntraining set accuracy:{accuracy_score(y_train,y_train_pred):.4f}\ntest set accuracy:{acc
uracy_score(y_test,y_pred):.4f}")
```

```
Fitting 2 folds for each of 120 candidates, totalling 240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:  9.1min
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed: 35.0min
[Parallel(n_jobs=-1)]: Done 240 out of 240 | elapsed: 62.0min finished
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 1h 2min 50s
grid_search best params: {'C': 5, 'gamma': 4.1326457128382766e-07}
clf params:
{'C': 5, 'break_ties': False, 'cache_size': 200, 'class_weight': None, 'coef
0': 0.0, 'decision_function_shape': 'ovr', 'degree': 3, 'gamma': 4.1326457128
382766e-07, 'kernel': 'rbf', 'max_iter': 1000, 'probability': False, 'random_
state': None, 'shrinking': True, 'tol': 0.001, 'verbose': False}

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 9min 54s
Clf fitted
Calculated predictions on training set

Classifier: Gaussian SVC @params:(C=5, gamma=4.1326457128382766e-07)
Scaler:None
training set accuracy:1.0000
test set accuracy:0.9857

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 20min 55s
Clf fitted
Calculated predictions on training set

Classifier: Gaussian SVC @params:(C=5, gamma=4.1326457128382766e-07)
Scaler:StandardScaler()
training set accuracy:0.4669
test set accuracy:0.4649
Wall time: 2h 28min 47s
```

Interestingly, some of grid-search selected gammas drop accuracy of standardized rbf SVC to 0.45. With fewer options of gamma there are no similar accuracy drops.

For default gamma and same C, accuracy is totally fine, but still 1% smaller than for non-normalized data

In [67]:

```
%%time
pipeline = Pipeline([
    ('scaler',StandardScaler()),
    ('classifier',SVC(max_iter=1000,gamma='scale',C=5))])
%time pipeline.fit(X_train,y_train)
print('Clf fitted')
y_train_pred = pipeline.predict(X_train)
print('Calculated predictions on training set')
y_pred = pipeline.predict(X_test)
print(f"Grid Search Gaussian SVC: C=5,gamma='scale'\nScaler: StandardScaler()\ntraining set accuracy:{accuracy_score(y_train,y_train_pred):.4f}\ntest set accuracy:{accuracy_score(y_test,y_pred):.4f}\n\n")
```

```
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: ConvergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-processing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 9min 45s
Clf fitted
Calculated predictions on training set
Grid Search Gaussian SVC: C=5,gamma='scale'
Scaler: StandardScaler()
training set accuracy:0.9976
test set accuracy:0.9719


Wall time: 25min 23s
```

Random Search

In [68]:

```
%%time
random_search_params = {'C':np.logspace(0,2,num=20),'gamma':possible_gammas}
random_search = RandomizedSearchCV(SVC(max_iter=1000),param_distributions=random_search_pa
rams,n_iter=100,cv=3,n_jobs=-1,verbose=3)

%time random_search.fit(X_val,y_val)

print(f'Best params:{random_search.best_estimator_}')
clf = random_search.best_estimator_

for s in [None,StandardScaler()]:
    pipeline = Pipeline([
        ('scaler',s),
        ('classifier',clf)])
    %time pipeline.fit(X_train,y_train)
    print('Clf fitted')
    y_train_pred = pipeline.predict(X_train)
    print('Calculated predictions on training set')
    y_pred = pipeline.predict(X_test)
    print(f"\nClassifier: Random Search Gaussian SVC\nScaler: {s}\ntraining set accuracy:{
accuracy_score(y_train,y_train_pred):.4f}\ntest set accuracy:{accuracy_score(y_test,y_pred
):.4f}")
```

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

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed: 10.4min
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed: 34.5min
[Parallel(n_jobs=-1)]: Done 280 tasks      | elapsed: 84.2min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 89.4min finished
C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 1h 30min 7s
Best params:SVC(C=1.6237767391887217, gamma=4.1326457128382766e-07, max_iter=
1000)

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 8min 58s
Clf fitted
Calculated predictions on training set

Classifier: Random Search Gaussian SVC
Scaler: None
training set accuracy:0.9988
test set accuracy:0.9853

C:\Users\eddie\kma_course_env\lib\site-packages\sklearn\svm\_base.py:246: Con
vergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-proce
ssing your data with StandardScaler or MinMaxScaler.
  warnings.warn('Solver terminated early (max_iter=%i).'

Wall time: 19min 48s
Clf fitted
Calculated predictions on training set

Classifier: Random Search Gaussian SVC
Scaler: StandardScaler()
training set accuracy:0.3839
test set accuracy:0.3872
Wall time: 2h 48min 57s
```

Under RandomSearch accuracy on normalized data drops even more. Interestingly, with C=5,C=1.62 and the same gamma accuracy is almost identical.

Overall, fine-tuned SVC can reach test-set accuracy of 0.99.

In [ ]: