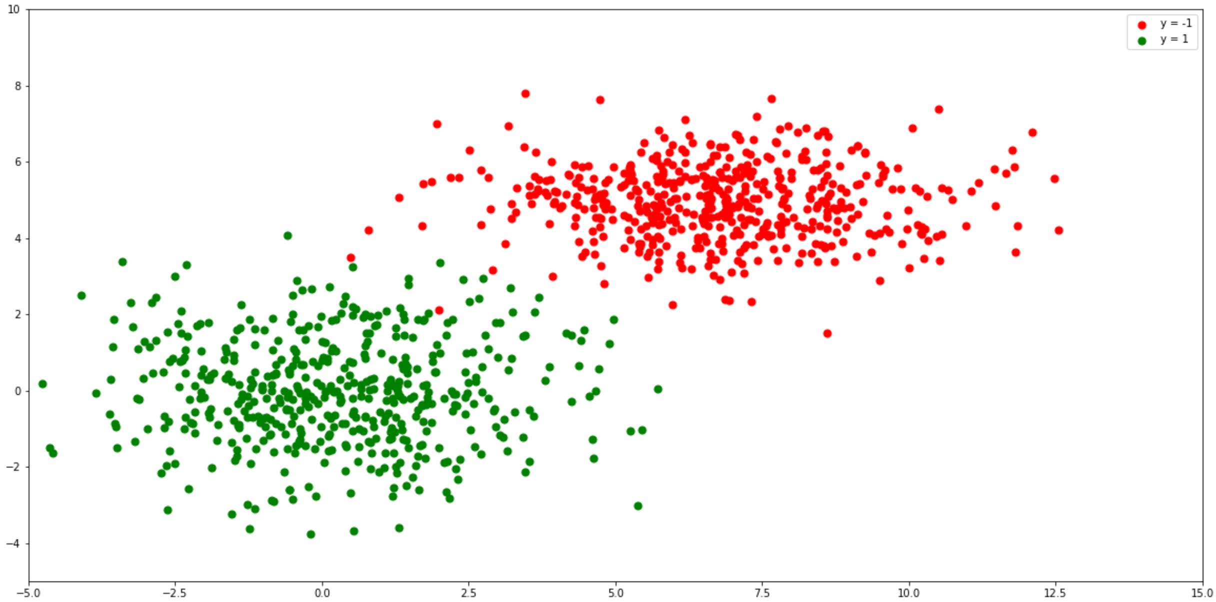
Семинар 5

Исследуем зависимость положения разделяющей гиперплоскости в методе опорных векторов в зависимости от значения гиперпараметра C.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

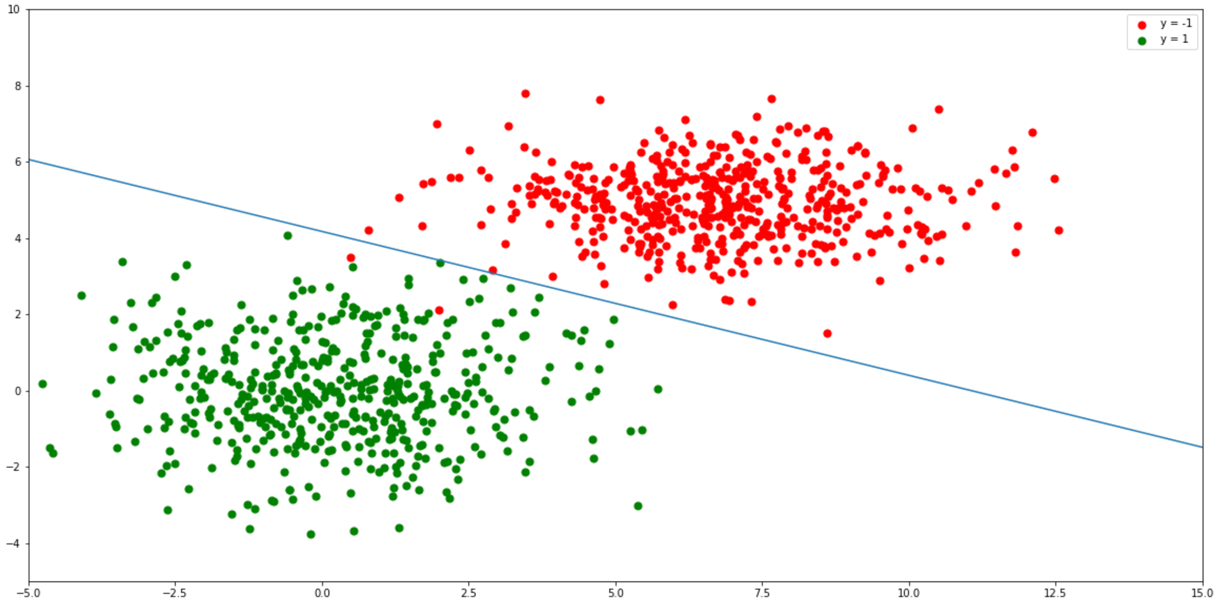
In [2]:
```
class_size = 500

plt.figure(figsize=(20, 10))
mean0 = [7, 5]
cov0 = [[4, 0], [0, 1]]  # diagonal covariance
mean1 = [0, 0]
cov1 = [[4, 0], [0, 2]]
data0 = np.random.multivariate_normal(mean0, cov0, class_size)
data1 = np.random.multivariate_normal(mean1, cov1, class_size)
data = np.vstack((data0, data1))
y = np.hstack((-np.ones(class_size), np.ones(class_size)))

plt.scatter(data0[:, 0], data0[:, 1], c='red', s=50)
plt.scatter(data1[:, 0], data1[:, 1], c='green', s=50)
plt.legend(['y = -1', 'y = 1'])
axes = plt.gca()
axes.set_xlim([-5, 15])
axes.set_ylim([-5, 10])
plt.show()
```



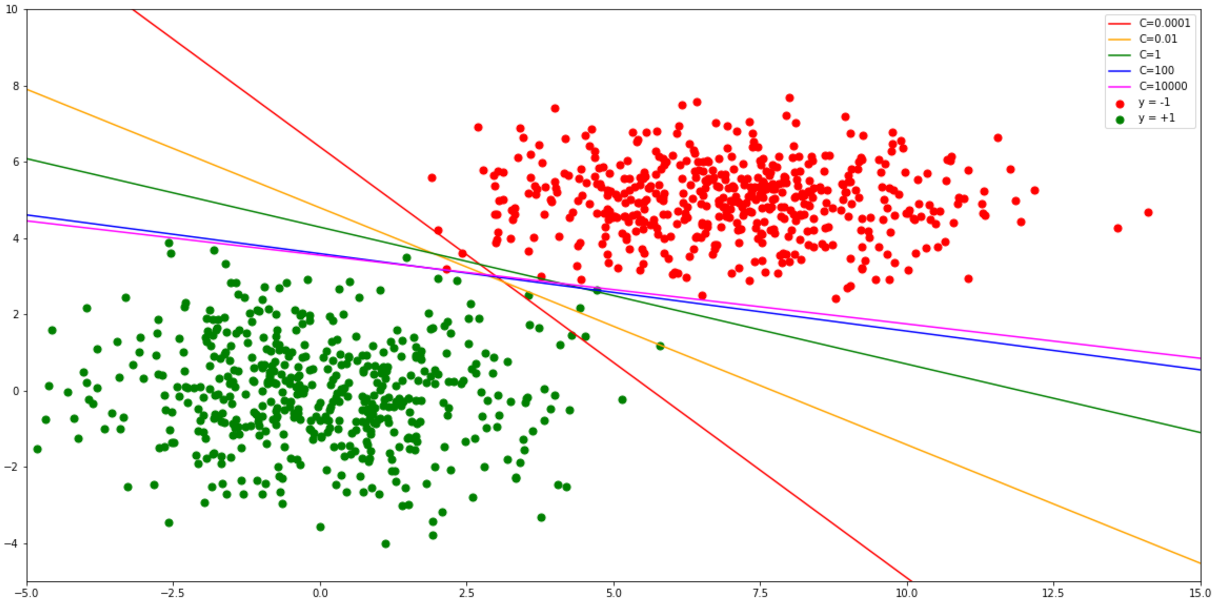
In [3]:
```
from sklearn.svm import SVC

SVM_classifier = SVC(C=0.01, kernel='linear') # changing C here
SVM_classifier.fit(data, y)
```

Out[3]:
```
SVC(C=0.01, kernel='linear')
```

In [4]:
```python
from sklearn.svm import SVC

SVM_classifier = SVC(C=100, kernel='linear') # changing C here
SVM_classifier.fit(data, y)

w_1 = SVM_classifier.coef_[0][0]
w_2 = SVM_classifier.coef_[0][1]
w_0 = SVM_classifier.intercept_[0]


plt.figure(figsize=(20,10))
plt.scatter(data0[:, 0], data0[:, 1], c='red', s=50)
plt.scatter(data1[:, 0], data1[:, 1], c='green', s=50)
plt.legend(['y = -1', 'y = 1'])
x_arr = np.linspace(-10, 15, 3000)
plt.plot(x_arr, -(w_0 + w_1 * x_arr) / w_2)
axes = plt.gca()
axes.set_xlim([-5,15])
axes.set_ylim([-5,10])
plt.show()
```



In [5]:
```python
plt.figure(figsize=(20,10))
plt.scatter(data0[:, 0], data0[:, 1], c='red', s=50, label='y = -1')
plt.scatter(data1[:, 0], data1[:, 1], c='green', s=50, label='y = +1')
#plt.legend(['y = -1', 'y = 1'])
x_arr = np.linspace(-10, 15, 3000)
colors = ['red', 'orange', 'green', 'blue', 'magenta']

for i, C in enumerate([0.0001, 0.01, 1, 100, 10000]):
    SVM_classifier = SVC(C=C, kernel='linear')
    SVM_classifier.fit(data, y)
    w_1 = SVM_classifier.coef_[0][0]
    w_2 = SVM_classifier.coef_[0][1]
    w_0 = SVM_classifier.intercept_[0]
    plt.plot(x_arr, -(w_0 + w_1 * x_arr) / w_2, color=colors[i], label='C='+str(C))

axes = plt.gca()
axes.set_xlim([-5,15])
axes.set_ylim([-5,10])
plt.legend(loc=0)
plt.show()
```



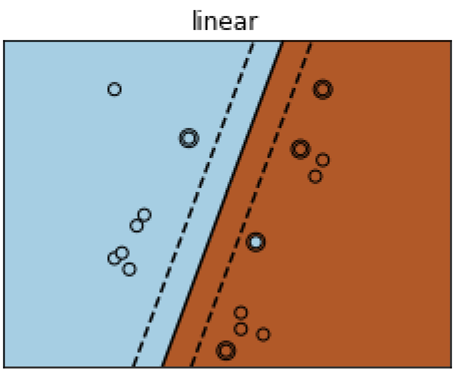
Гиперпараметр C отвечает за то, что является более приоритетным для классификатора, — "подгонка" под обучающую выборку или максимизация ширины разделяющей полосы.

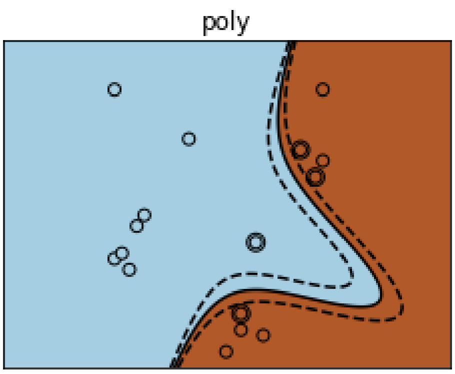
- При больших значениях C классификатор сильно настраивается на обучение, тем самым сужая разделяющую полосу.
- При маленьких значениях C классификатор расширяет разделяющую полосу, при этом допуская ошибки на некоторых объектах обучающей выборки.

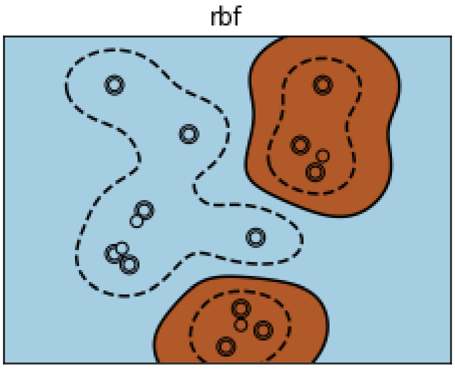
In [7]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm


# Our dataset and targets
X = np.c_[(.4, -.7),
          (-1.5, -1),
          (-1.4, -.9),
          (-1.3, -1.2),
          (-1.1, -.2),
          (-1.2, -.4),
          (-.5, 1.2),
          (-1.5, 2.1),
          (1, 1),
          # --
          (1.3, .8),
          (1.2, .5),
          (.2, -2),
          (.5, -2.4),
          (.2, -2.3),
          (0, -2.7),
          (1.3, 2.1)].T
Y = [0] * 8 + [1] * 8

# figure number
fignum = 1

# fit the model
for kernel in ('linear', 'poly', 'rbf'):
    clf = svm.SVC(kernel=kernel, gamma=2)
    clf.fit(X, Y)

    # plot the line, the points, and the nearest vectors to the plane
```

```
    plt.figure(fignum, figsize=(4, 3))
    plt.clf()

    plt.scatter(clf.support_vectors_[:, 0], clf.support_vectors_[:, 1], s=80,
                facecolors='none', zorder=10, edgecolors='k')
    plt.scatter(X[:, 0], X[:, 1], c=Y, zorder=10, cmap=plt.cm.Paired,
                edgecolors='k')

    plt.axis('tight')
    x_min = -3
    x_max = 3
    y_min = -3
    y_max = 3

    XX, YY = np.mgrid[x_min:x_max:200j, y_min:y_max:200j]
    Z = clf.decision_function(np.c_[XX.ravel(), YY.ravel()])

    # Put the result into a color plot
    Z = Z.reshape(XX.shape)
    plt.figure(fignum, figsize=(4, 3))
    plt.pcolormesh(XX, YY, Z > 0, cmap=plt.cm.Paired)
    plt.contour(XX, YY, Z, colors=['k', 'k', 'k'], linestyles=['--', '-', '--'],
                levels=[-.5, 0, .5])

    plt.xlim(x_min, x_max)
    plt.ylim(y_min, y_max)

    plt.xticks(())
    plt.yticks(())
    plt.title(kernel)
    fignum = fignum + 1
plt.show()
```







In [6]:

```
import numpy as np
np.random.seed(0)

import matplotlib.pyplot as plt

from sklearn import datasets
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.calibration import calibration_curve

X, y = datasets.make_classification(n_samples=100000, n_features=20,
                                    n_informative=2, n_redundant=2)

train_samples = 100  # Samples used for training the models

X_train = X[:train_samples]
X_test = X[train_samples:]
y_train = y[:train_samples]
y_test = y[train_samples:]

# Create classifiers
lr = LogisticRegression()
gnb = GaussianNB()
svc = LinearSVC(C=1.0)
rfc = RandomForestClassifier()


# #############################################################################
# Plot calibration plots

plt.figure(figsize=(10, 10))
ax1 = plt.subplot2grid((3, 1), (0, 0), rowspan=2)
ax2 = plt.subplot2grid((3, 1), (2, 0))

ax1.plot([0, 1], [0, 1], "k:", label="Perfectly calibrated")
for clf, name in [(lr, 'Logistic'),
                  (gnb, 'Naive Bayes'),
                  (svc, 'Support Vector Classification'),
                  (rfc, 'Random Forest')]:
    clf.fit(X_train, y_train)
    if hasattr(clf, "predict_proba"):
        prob_pos = clf.predict_proba(X_test)[:, 1]
    else:  # use decision function
        prob_pos = clf.decision_function(X_test)
        prob_pos = \
            (prob_pos - prob_pos.min()) / (prob_pos.max() - prob_pos.min())
    fraction_of_positives, mean_predicted_value = \
        calibration_curve(y_test, prob_pos, n_bins=10)
```

```
    ax1.plot(mean_predicted_value, fraction_of_positives, "s-",
             label="%s" % (name, ))

    ax2.hist(prob_pos, range=(0, 1), bins=10, label=name,
             histtype="step", lw=2)

ax1.set_ylabel("Fraction of positives")
ax1.set_ylim([-0.05, 1.05])
ax1.legend(loc="lower right")
ax1.set_title('Calibration plots  (reliability curve)')

ax2.set_xlabel("Mean predicted value")
ax2.set_ylabel("Count")
ax2.legend(loc="upper center", ncol=2)

plt.tight_layout()
plt.show()
```