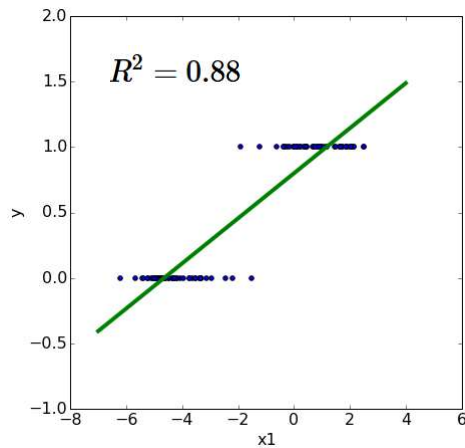
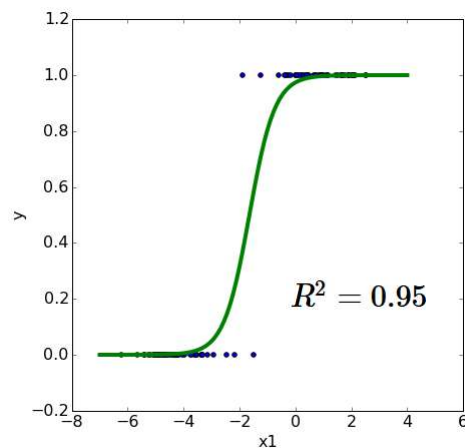


logistic regression for classification



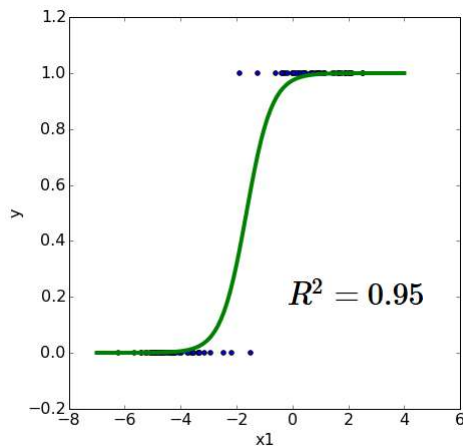
We need to make
assumptions *linear relationship*
 about the
model *linear model*
 that generated the data.

logistic regression for classification



We need to make
assumptions *linearly separable*
 about the
model *logistic model*
 that generated the data.

logistic regression: logistic model



$$f(x, \theta) = g(\theta_0 + \theta_1 x_1)$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

logistic regression: cost function

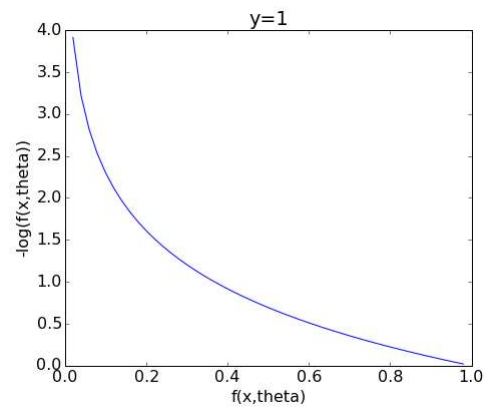
$$J(\theta) = -\left[\frac{1}{n} \sum_{i=1}^n y^{(i)} \log(f(x^{(i)}, \theta)) + (1 - y^{(i)}) \log(1 - f(x^{(i)}, \theta))\right]$$

We know that $y^{(i)}$ is either 0 or 1. If $y^{(i)} = 1$ then the cost function $J(\theta)$ is incremented by $-\log(f(x^{(i)}, \theta))$.

Similarly, if $y^{(i)} = 0$ then the cost function $J(\theta)$ is incremented by $-\log(1 - f(x^{(i)}, \theta))$.

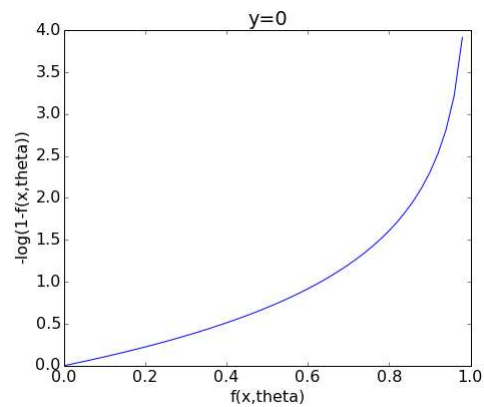
logistic regression: cost function

We know that $y^{(i)}$ is either 0 or 1. If $y^{(i)} = 1$ then the cost function $J(\theta)$ is incremented by $-\log(f(x^{(i)}, \theta))$.



logistic regression: cost function

Similarly, if $y^{(i)} = 0$ then the cost function $J(\theta)$ is incremented by $-\log(1 - f(x^{(i)}, \theta))$.



logistic regression

Fit a logistic model

$$f(x, \theta) = g(\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_m x_m) = g(\theta' x)$$

to the data set such that the cost function

$$J(\theta) = -\left[\frac{1}{n} \sum_{i=1}^n y^{(i)} \log(f(x^{(i)}, \theta)) + (1 - y^{(i)}) \log(1 - f(x^{(i)}, \theta))\right]$$

is minimal using gradient descent

$$\theta_j := \theta_j - \alpha \frac{1}{n} \sum_{i=1}^n (f(x^{(i)}, \theta) - y^{(i)}) x_j^{(i)}$$

```
import sklearn.datasets as ds
from sklearn.preprocessing import StandardScaler

dataset2D = pd.read_csv("dataset2D.csv")

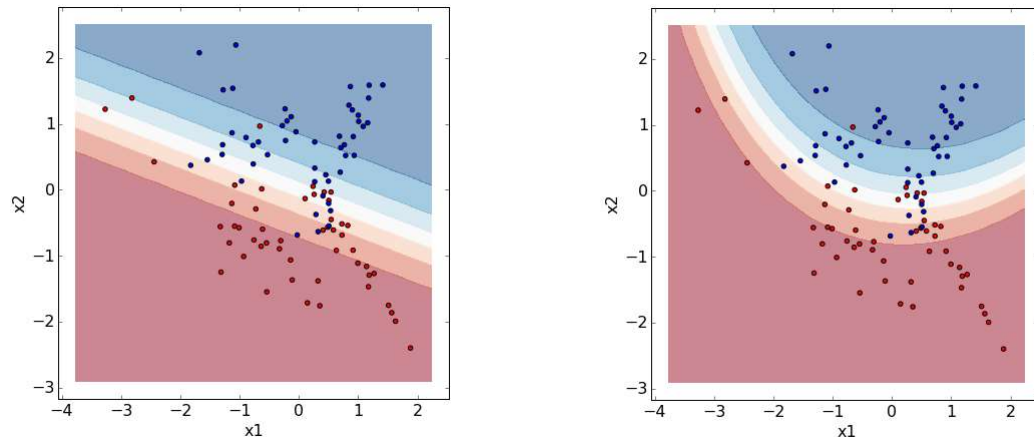
X = dataset2D.copy()
y = X.pop('y')

model = LogisticRegression(C=100000)
model.fit(X,y)
score = model.score(X, y)

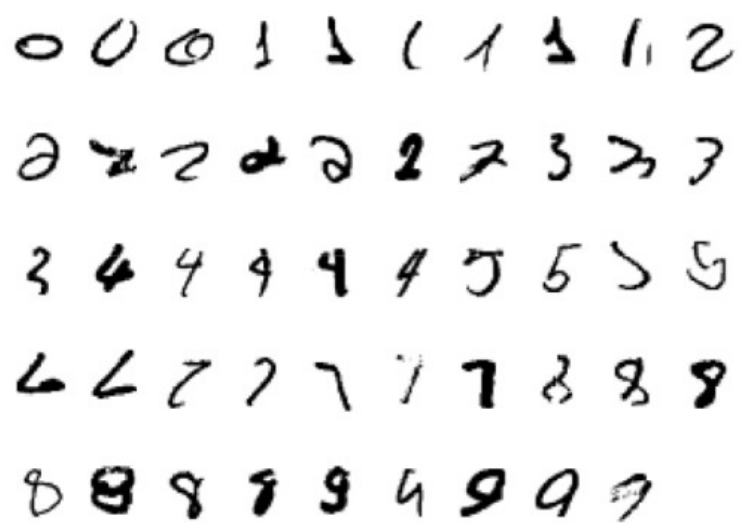
plt.title("accuracy = %.2f" % score)
compomics_import.plot_decision_boundary(model,X,y)
plt.show()
```

```
predictions = model.predict_proba(X)
print predictions[:10]
```

non-linear logistic regression



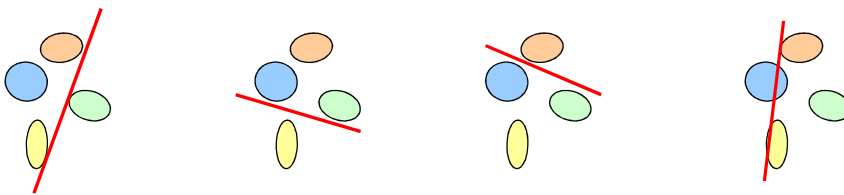
multiclass classification



one against all

One-against-all $\rightarrow k$ by k

+1	-1	-1	-1
-1	+1	-1	-1
-1	-1	+1	-1
-1	-1	-1	+1



one against one

All-pairs $\rightarrow k$ by $\binom{k}{2}$

+1	+1	+1	0	0	0
-1	0	0	+1	+1	0
0	-1	0	-1	0	+1
0	0	-1	0	-1	-1

