

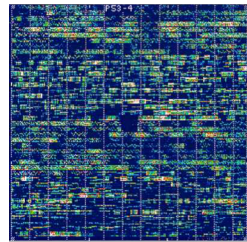
# *Classification*

**Methods Course: Gene Expression Data Analysis**

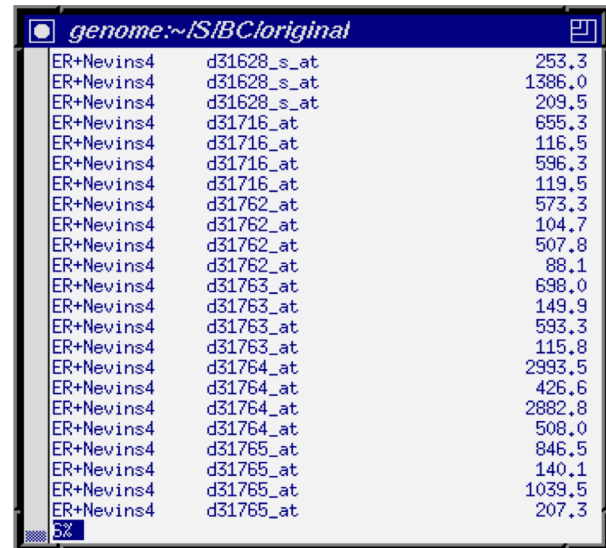
**-Day Five –**

*Rainer Spang*

# Ms. Smith



DNA Chip of Ms. Smith



Gene ID	Expression Value
ER+Nevins4 d31628_s_at	253.3
ER+Nevins4 d31628_s_at	1386.0
ER+Nevins4 d31628_s_at	209.5
ER+Nevins4 d31716_at	655.3
ER+Nevins4 d31716_at	116.5
ER+Nevins4 d31716_at	596.3
ER+Nevins4 d31716_at	119.5
ER+Nevins4 d31762_at	573.3
ER+Nevins4 d31762_at	104.7
ER+Nevins4 d31762_at	507.8
ER+Nevins4 d31762_at	88.1
ER+Nevins4 d31763_at	698.0
ER+Nevins4 d31763_at	149.9
ER+Nevins4 d31763_at	593.3
ER+Nevins4 d31763_at	115.8
ER+Nevins4 d31764_at	2993.5
ER+Nevins4 d31764_at	426.6
ER+Nevins4 d31764_at	2882.8
ER+Nevins4 d31764_at	508.0
ER+Nevins4 d31765_at	846.5
ER+Nevins4 d31765_at	140.1
ER+Nevins4 d31765_at	1039.5
ER+Nevins4 d31765_at	207.3

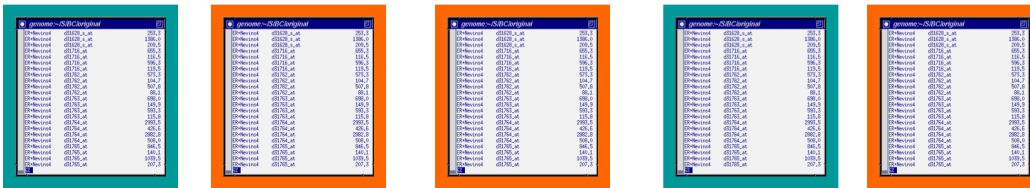
Expression profile of Ms. Smith



Ms. Smith



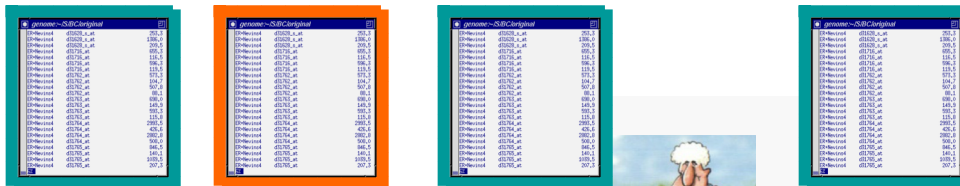
# Training sets and test sets



Five terminal windows, each displaying a list of training data samples. The windows are titled 'grosswrt~Z8BCarOriginal'. Each window shows a list of 20 rows of data, with columns for 'grosswrt' and 'Z8BCarOriginal'. The data is identical in all five windows.

grosswrt	Z8BCarOriginal
250.1	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0

Use the training samples ...



Four terminal windows, each displaying a list of training data samples. The windows are titled 'grosswrt~Z8BCarOriginal'. Each window shows a list of 20 rows of data, with columns for 'grosswrt' and 'Z8BCarOriginal'. The data is identical in all four windows.

grosswrt	Z8BCarOriginal
250.1	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0
1500.0	1500.0

... to learn how to predict test samples



Ms. Smith

**Biomarker**

# *Prediction with 1 gene (biomarker)*

Color coded expression levels of trainings samples

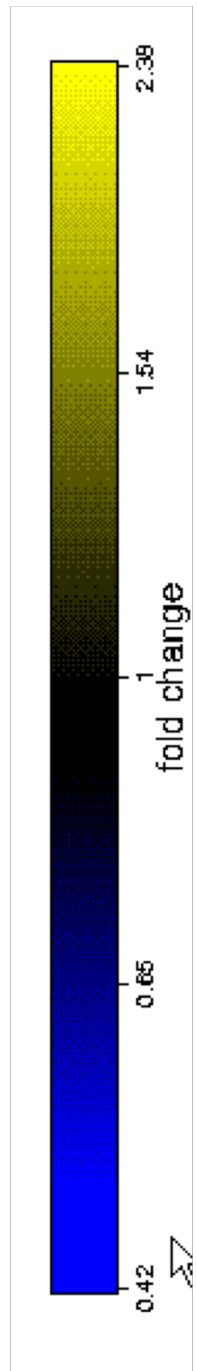


Ms. Smith  → type A

Ms. Smith  → type B

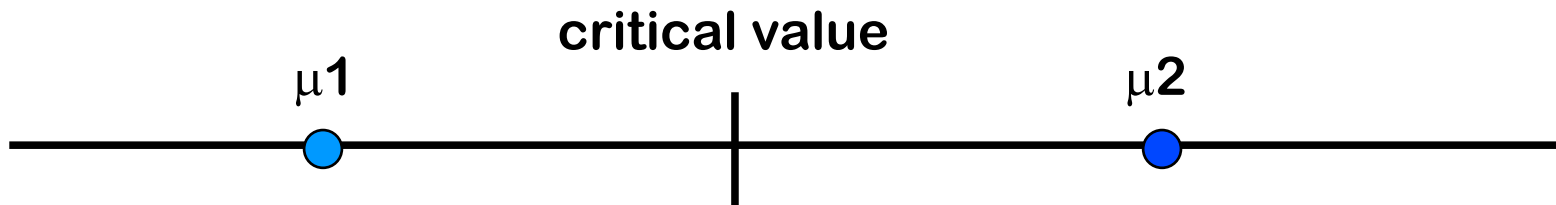
Ms. Smith  → borderline

Which color shade is a good decision boundary?



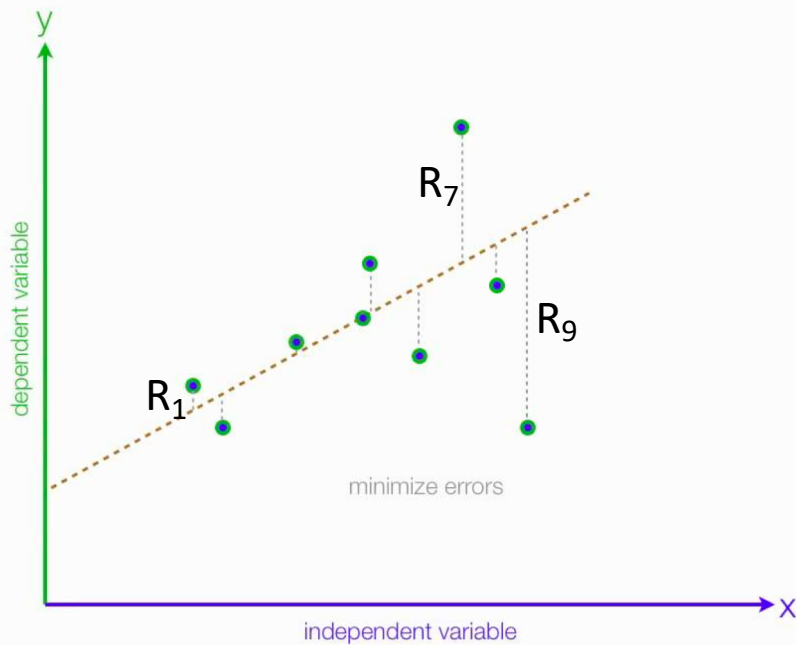
# *Solution 1: Model the classes (Discriminant Analysis)*

$$x_0 = \frac{\hat{\mu}_1 + \hat{\mu}_2}{2}$$



**Find the mean in each class and choose the middle as critical value**

# Linear Regression

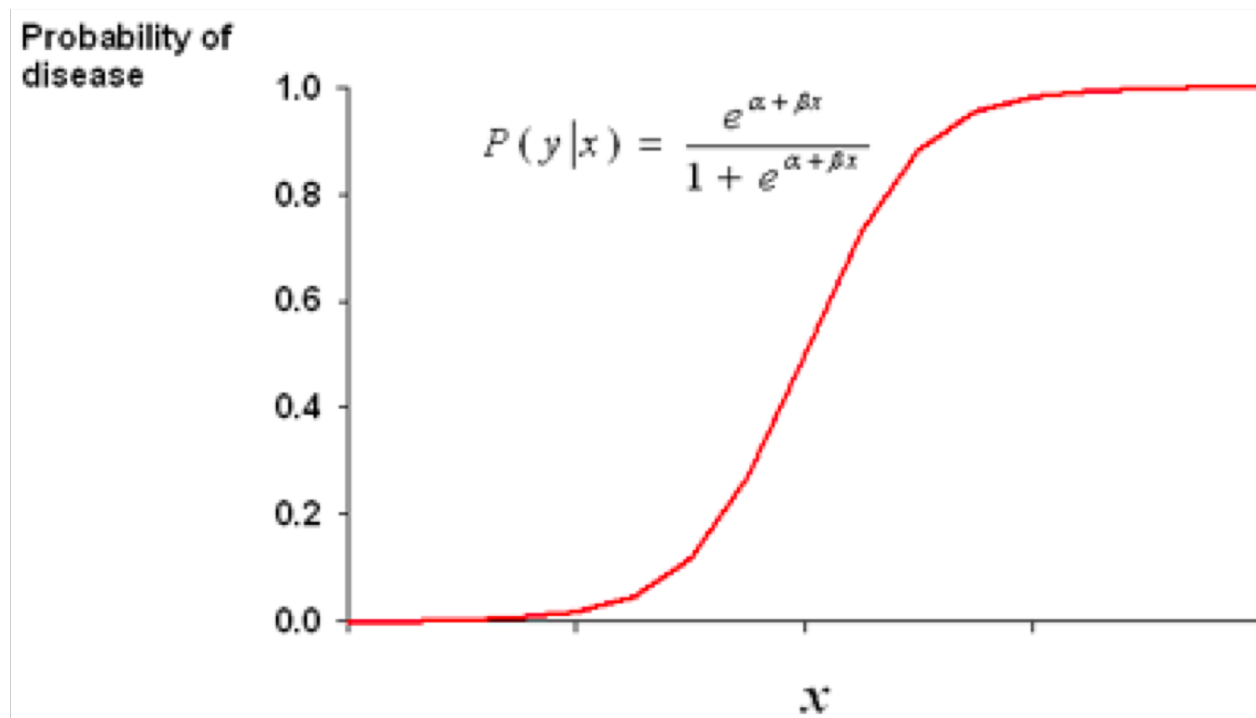


$$y = a + \beta x$$

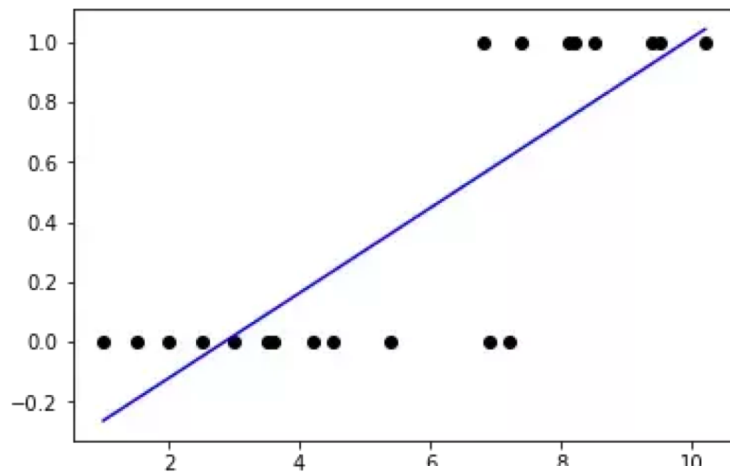
Find  $\beta_0, \beta_1$  such that the sum of squared residuals  $R_1^2 + \dots + R_n^2$  is minimal



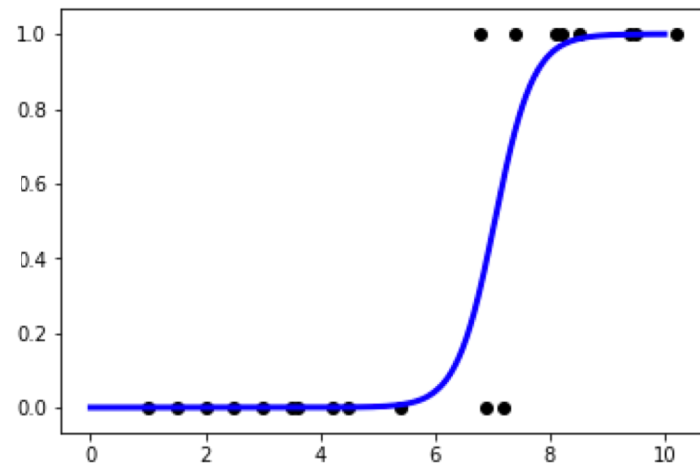
# *The Logit Function*



# *Solution2: Logistic Regression*

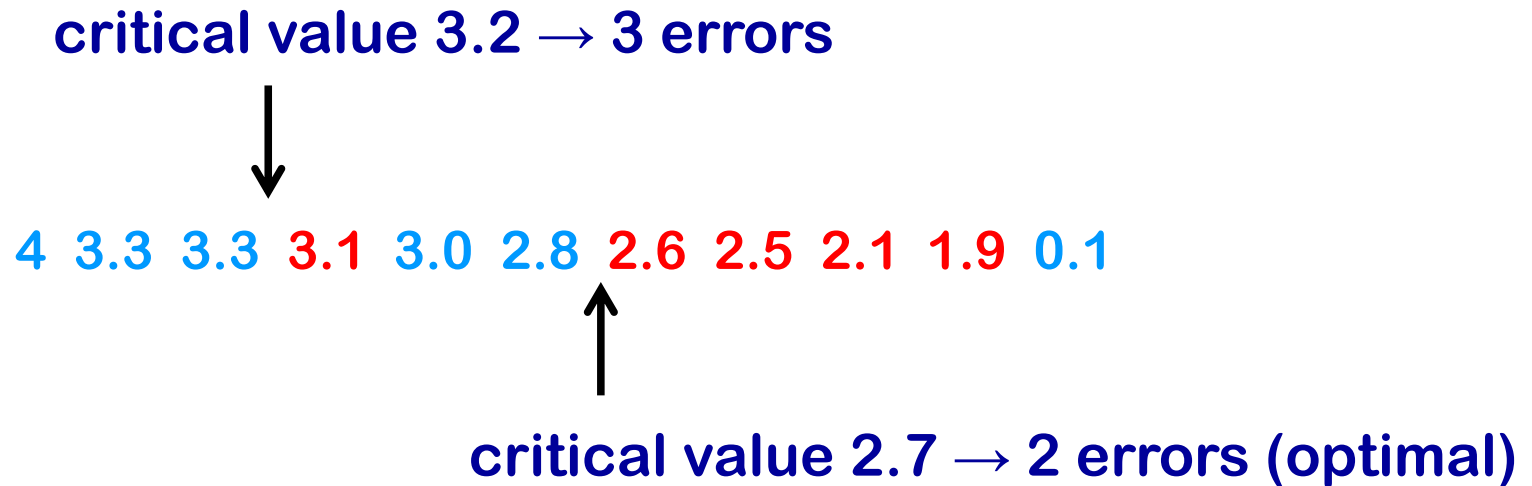


Linear regression on  
binary data



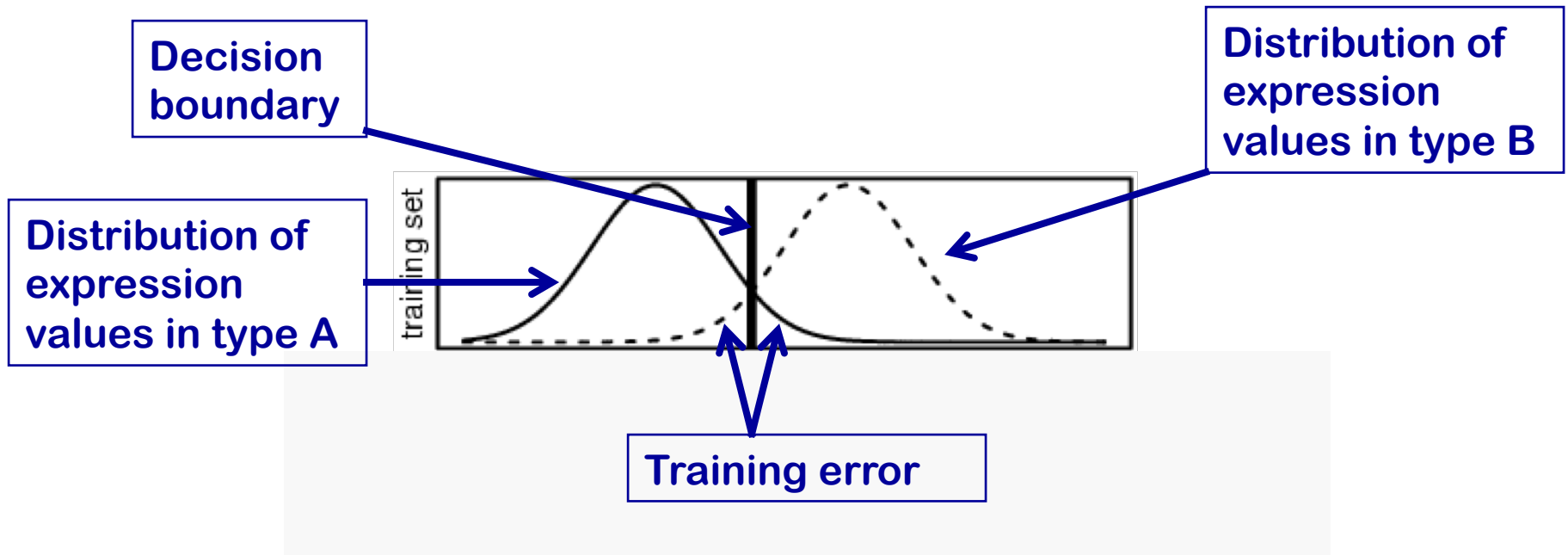
Logistic regression

## *Solution3: Go straight for the boundary (Statistical Learning)*

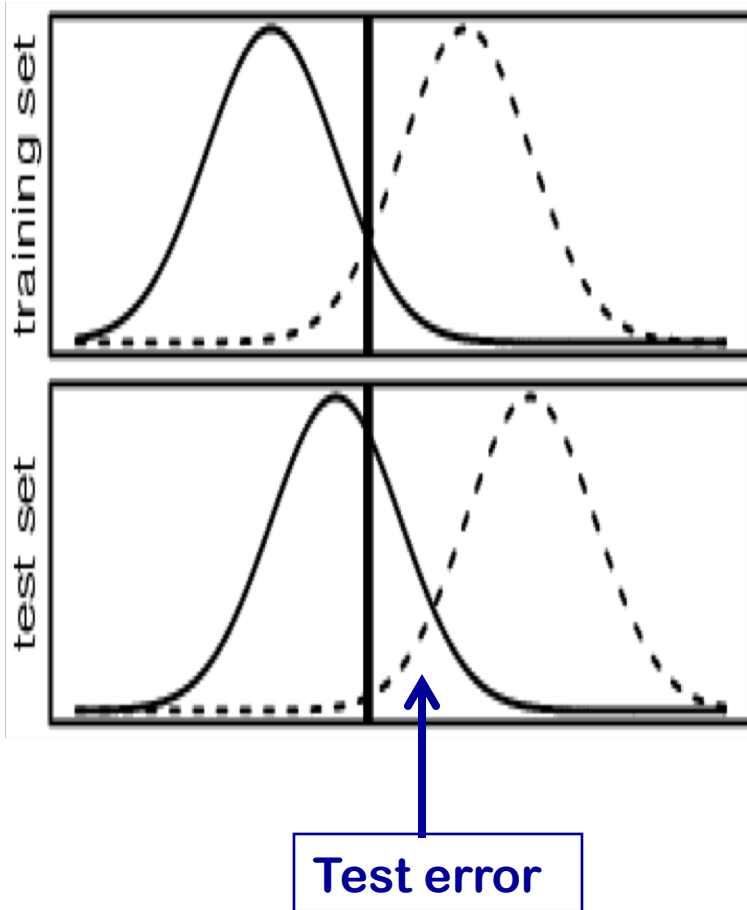


*The number of misclassifications can be easily optimized on the training data*

# *Minimize the training error*



# Overfitting



The decision boundary was chosen to minimize the training error

The two distributions of expression values for type A and B will be similar but not identical in a set of new cases

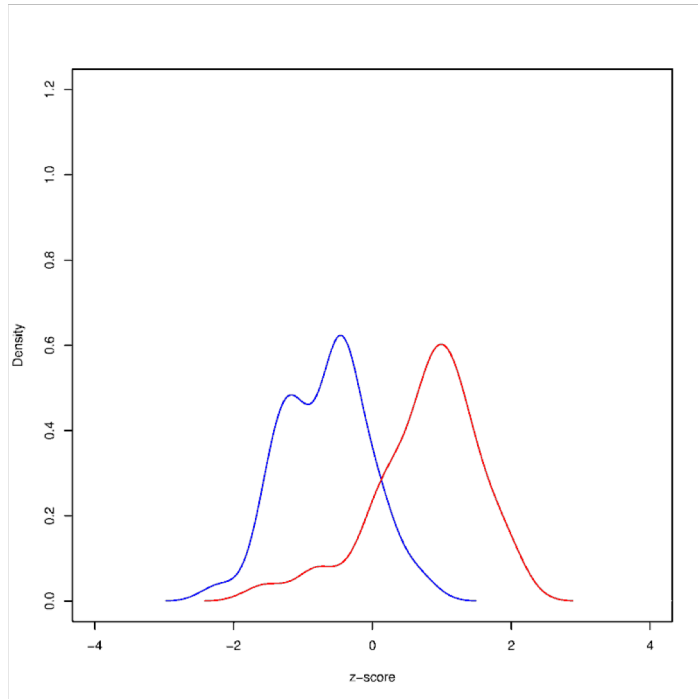
We can not adjust the decision boundary because we do not know the class of the new samples

Test errors are in average bigger then training errors

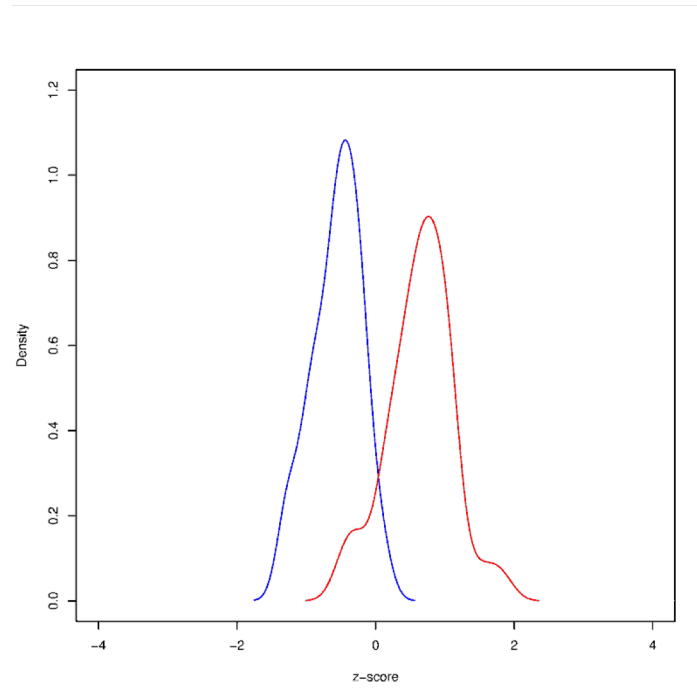
This phenomenon is called *overfitting*

# Signatures

# *Accumulating information across genes*



**The top gene**



**The average of  
the top 10 genes**

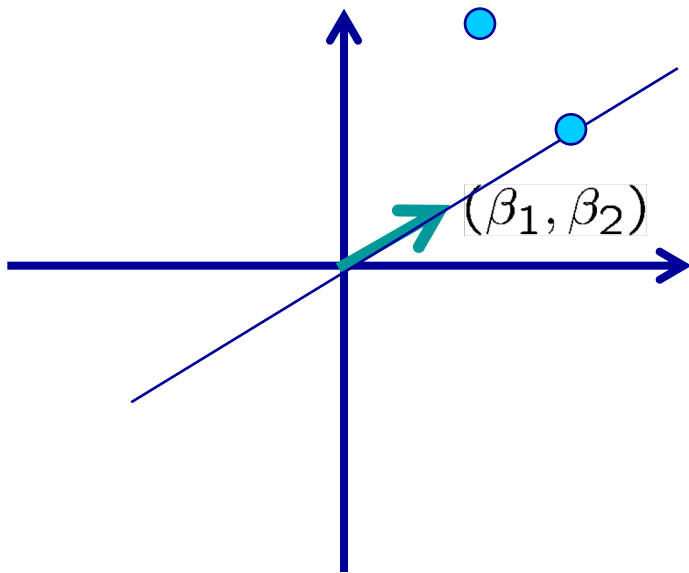
# *Using a weighted average*

$$\beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n$$

*With “good weights” you get an improved separation*

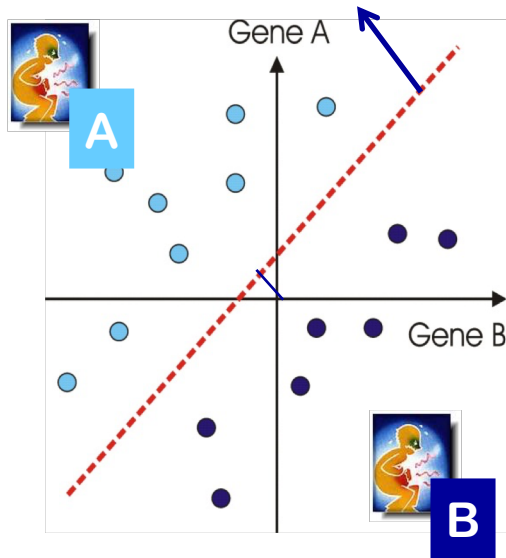


# *The geometry of weighted averages*

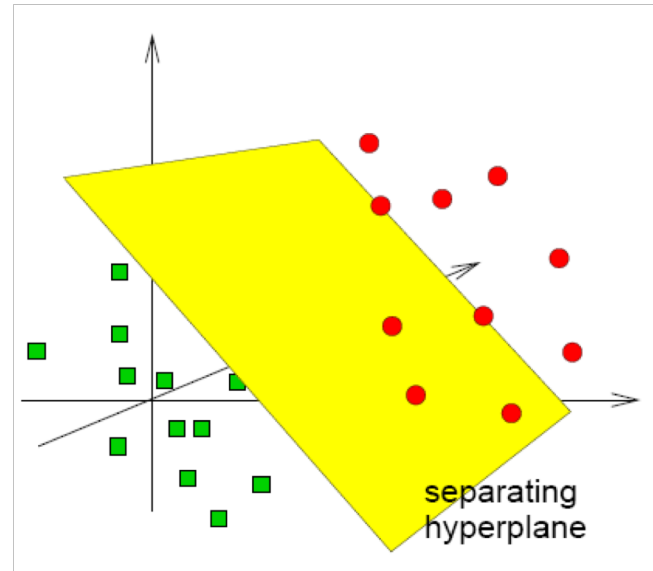


Calculating a weighted average is identical to projecting (orthogonally) the expression profiles onto the line defined by the weights vector

# *Separating Hyperplanes*



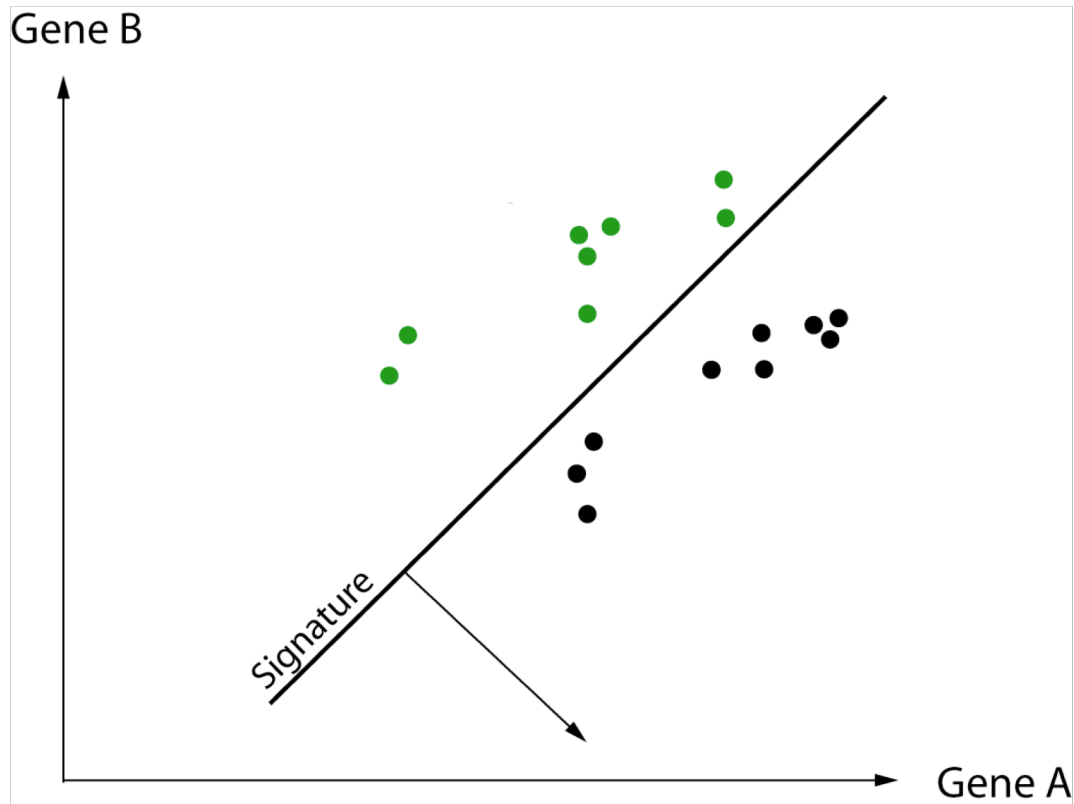
2 genes



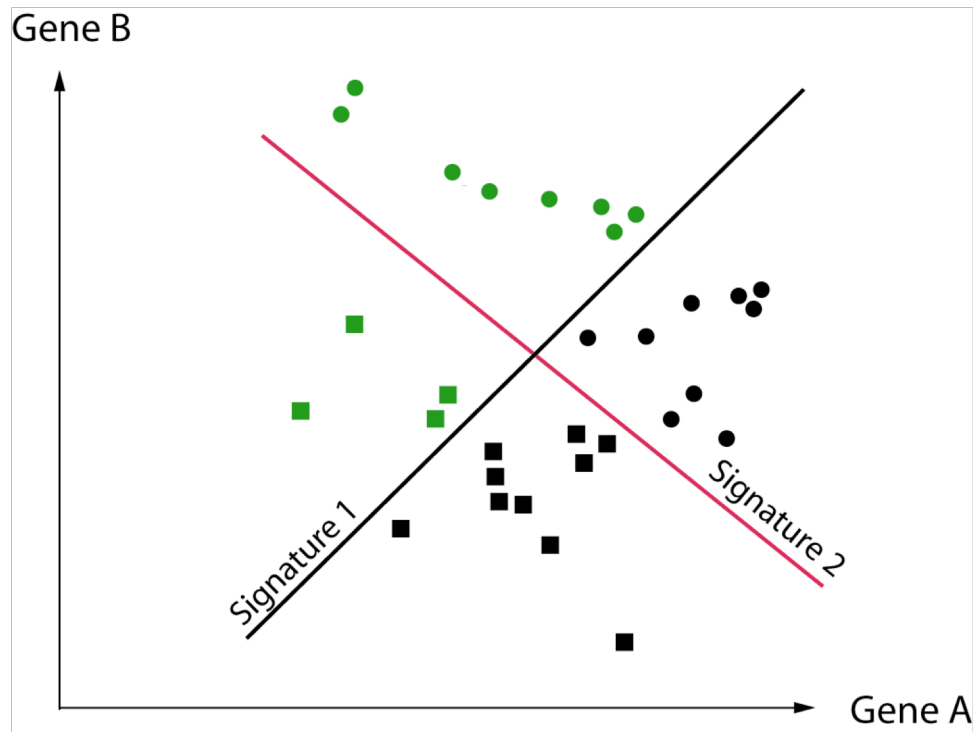
3 genes

Together with an offset the weight vector defines an orthogonal hyperplane that cuts the data in two groups

*There are valid signatures without any differently expressed gene*



# *A list of genes does not define a signature yet*



# Learning Methods

*With only one gene the number of misclassifications can be easily optimized on the training data*

critical value 3.2 → 3 errors



4 3.3 3.3 3.1 3.0 2.8 2.6 2.5 2.1 1.9 0.1

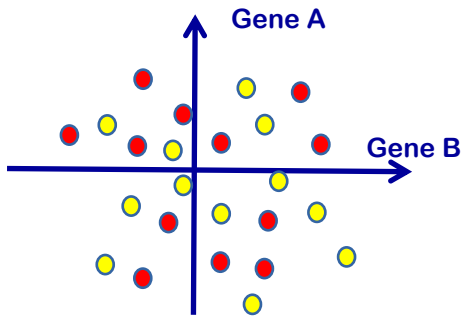


critical value 2.7 → 2 errors (optimal)

*Idea: Optimize the weights such that training error becomes minimal*

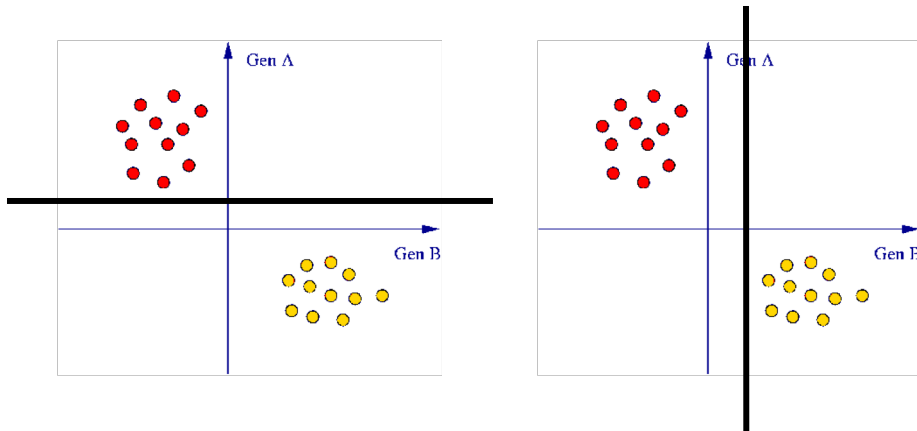
$$\beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n$$

*In high dimensions only one of these problems exists*



*Problem 1:*

No separating line



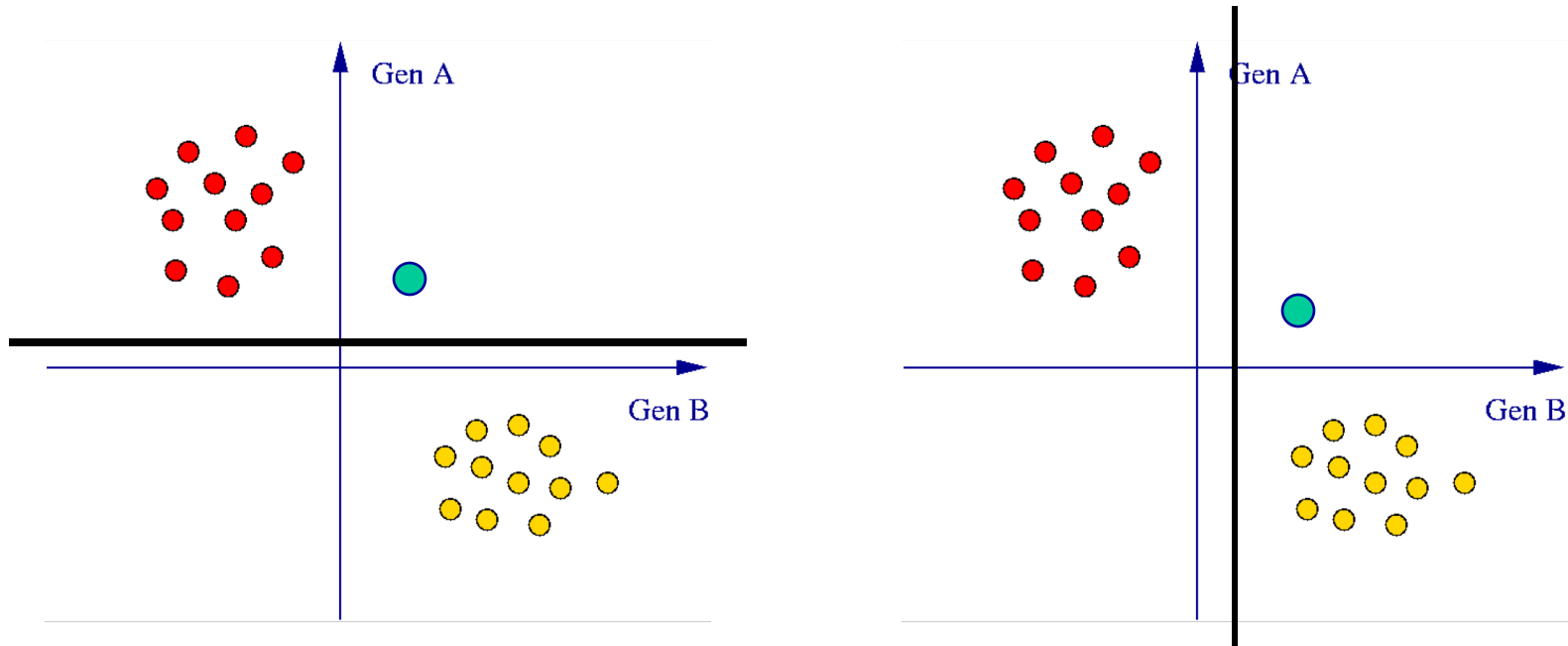
*Problem 2:*

Many separating lines

*Why is this a problem?*



# *What about Ms. Smith ?*



*This problem is also related to overfitting*

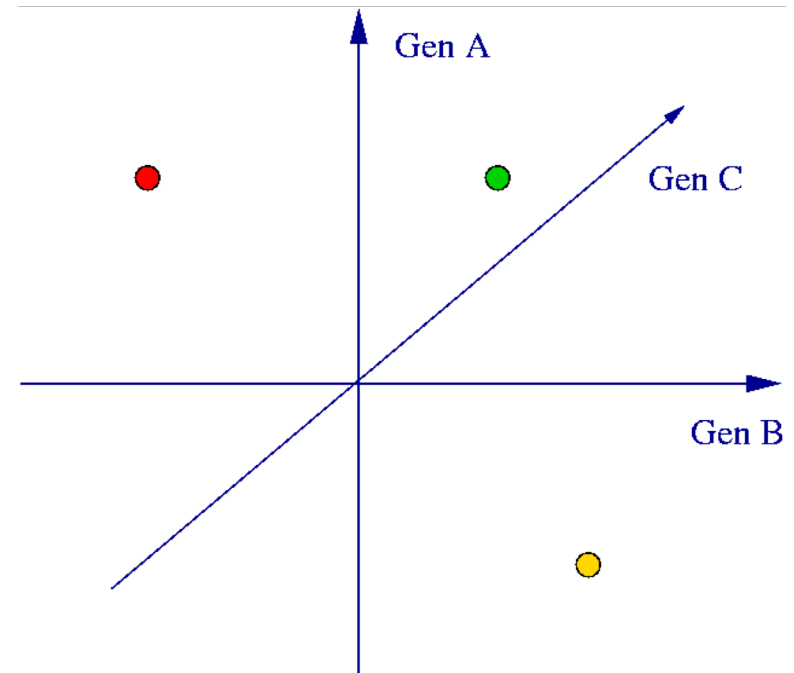
# *Prediction with 30,000 genes*

With the microarray we have more genes than patients

Think about this in three dimensions

There are three genes, two patients with known diagnosis (red and yellow) and Ms. Smith (green)

There is always one plane separating red and yellow with Ms. Smith on the yellow side and a second separating plane with Ms. Smith on the red side

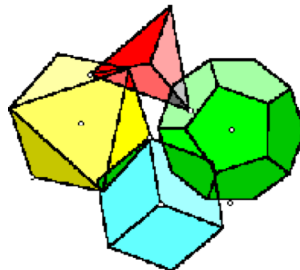
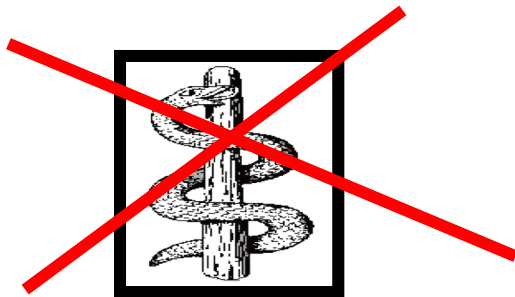


**OK! If all points fall onto one line it does not always work. However, for measured values this is very unlikely and never happens in praxis.**

# *The overfitting disaster*

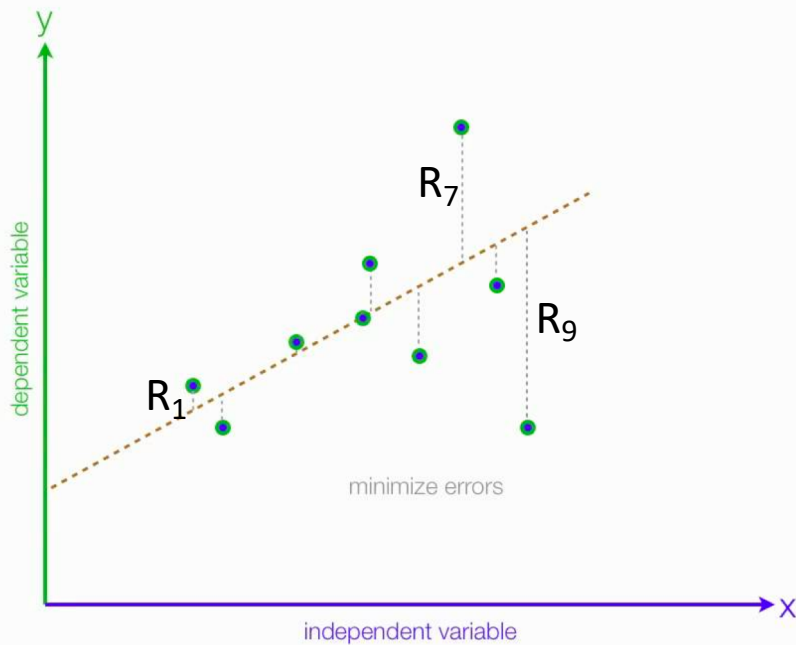
From the data alone we can not decide which genes are important for the diagnosis, nor can we give a reliable diagnosis for a new patient

This has little to do medicine. It is a geometrical problem.



# Regression and the LASSO

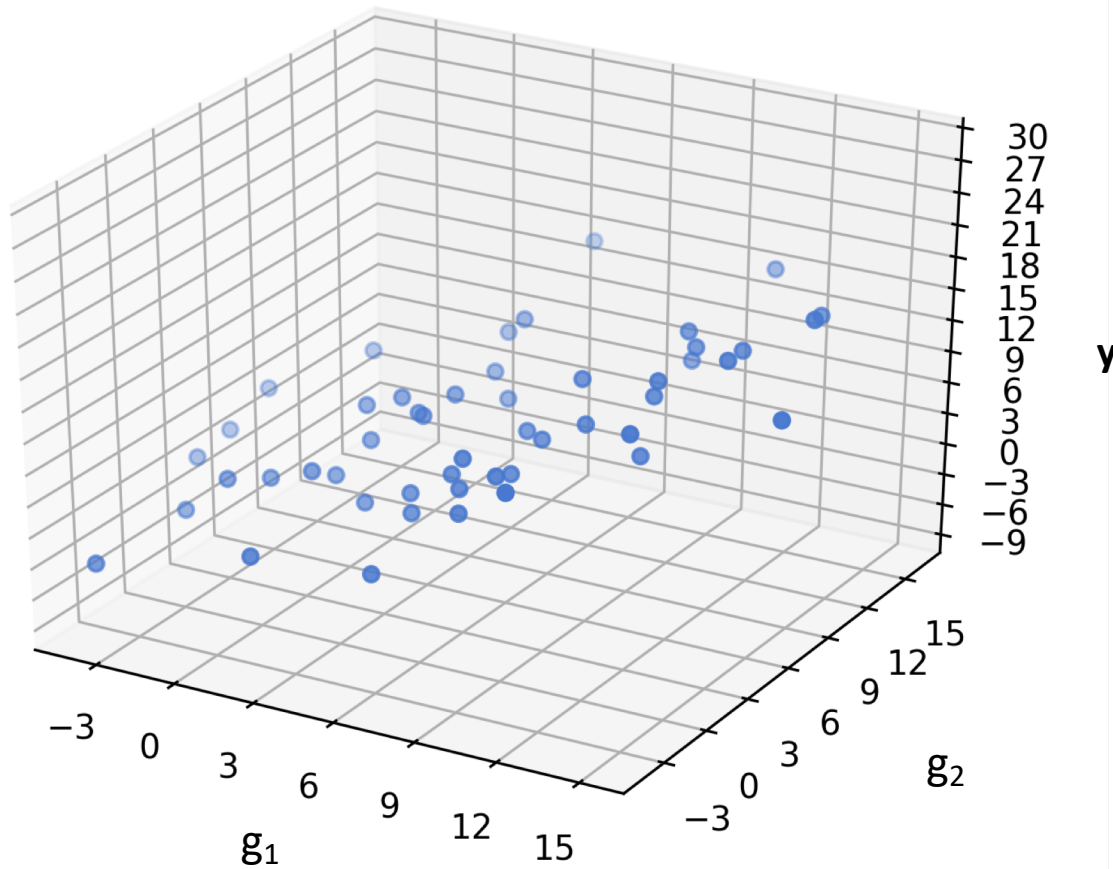
*We want to predict  $y$  from  $x$*



$$y = \beta_0 + \beta_1 x$$

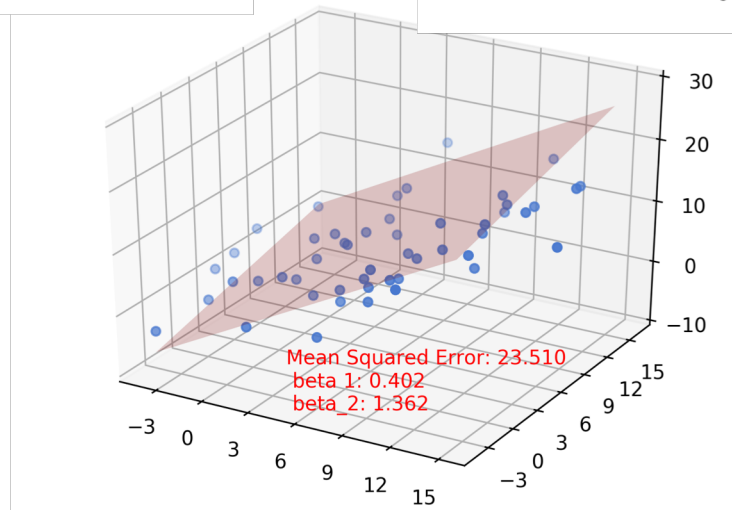
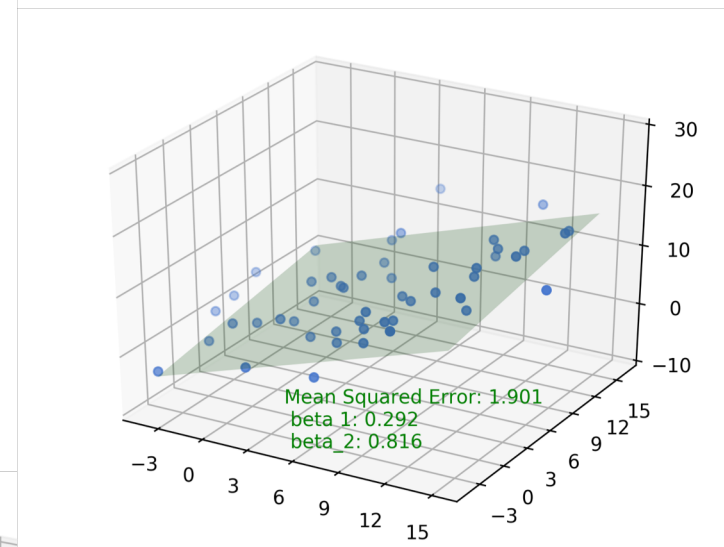
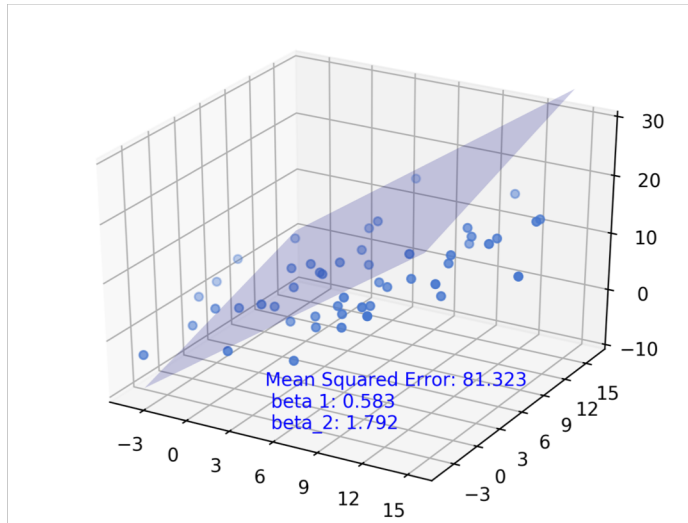
Find  $\beta_0, \beta_1$  such that the sum of squared residuals  $R_1^2 + \dots + R_n^2$  is minimal

*We want to predict  $y$  from  $g_1$  and  $g_2$*



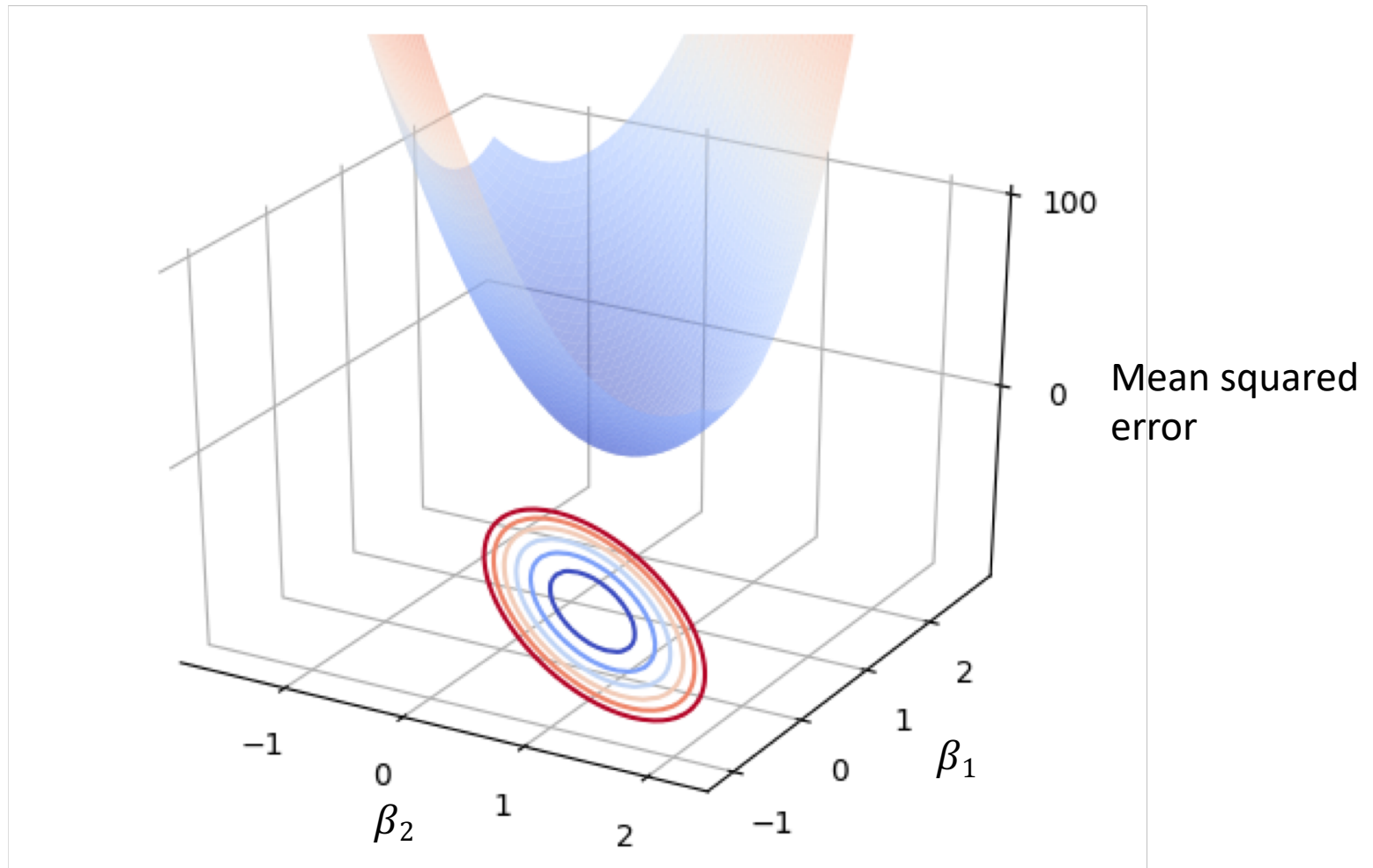
$$y = \beta_1 g_1 + \beta_2 g_2$$

# *Different parameters give different squared residuals*



$$y = \beta_1 g_1 + \beta_2 g_2$$

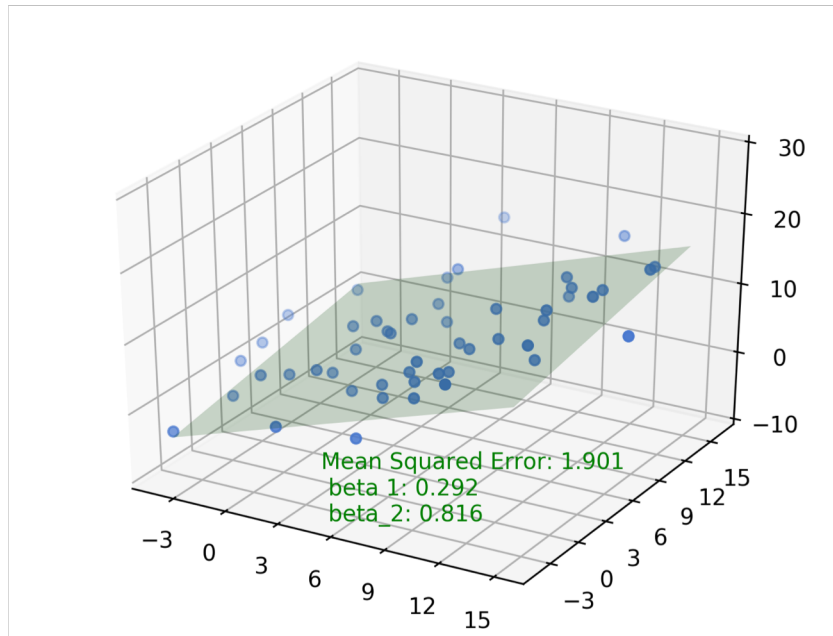
# Ordinary least square regression



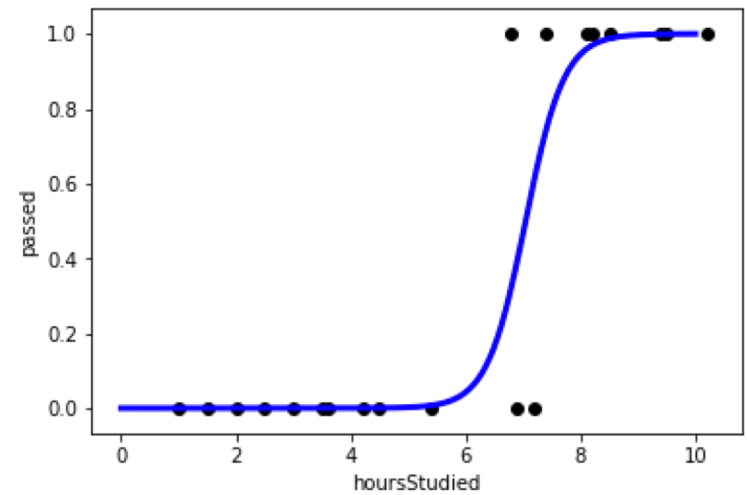
$$y = \beta_1 g_1 + \beta_2 g_2$$



# *From a fitting plane to a diagnosis*

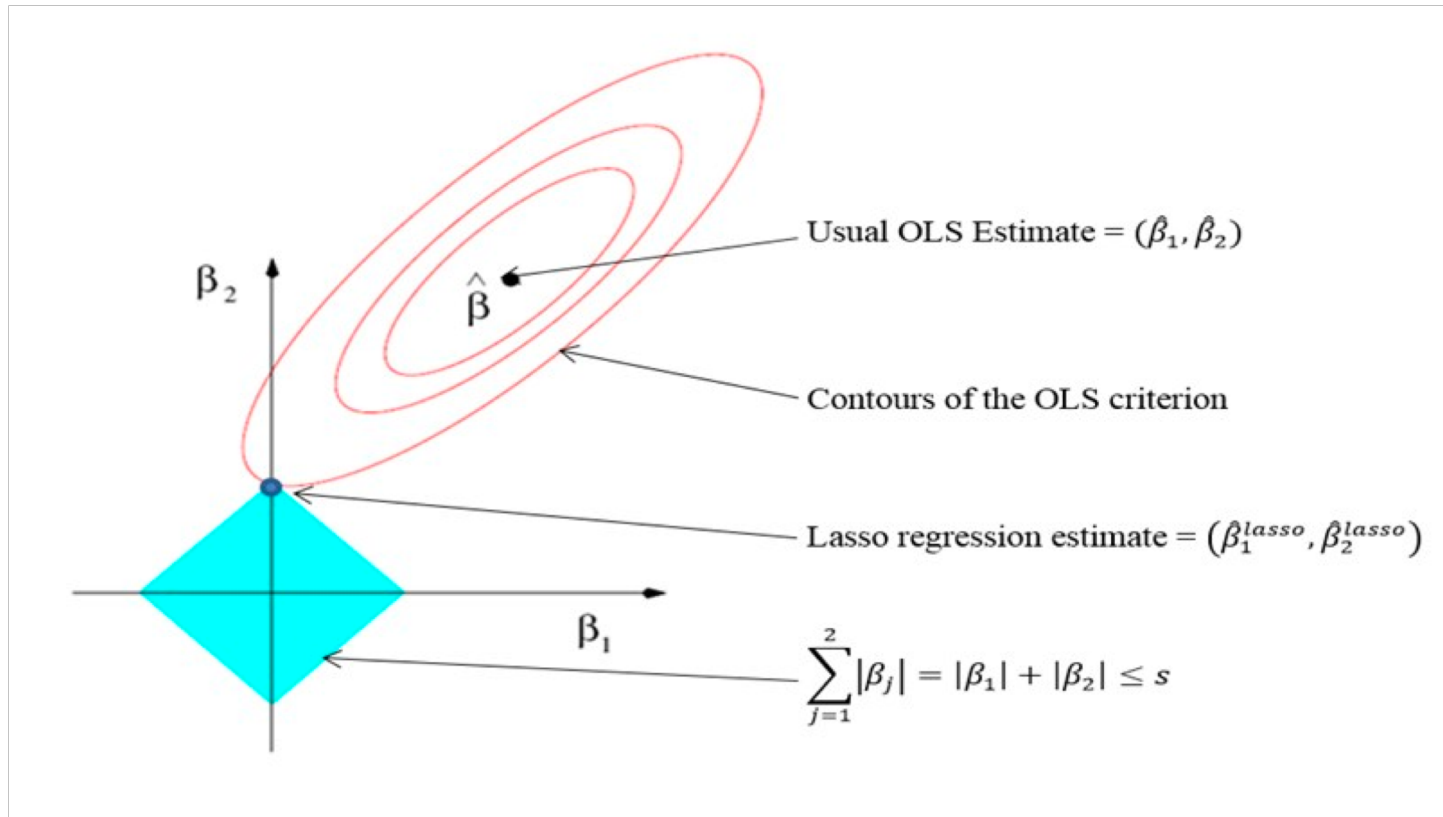


Regression with many features



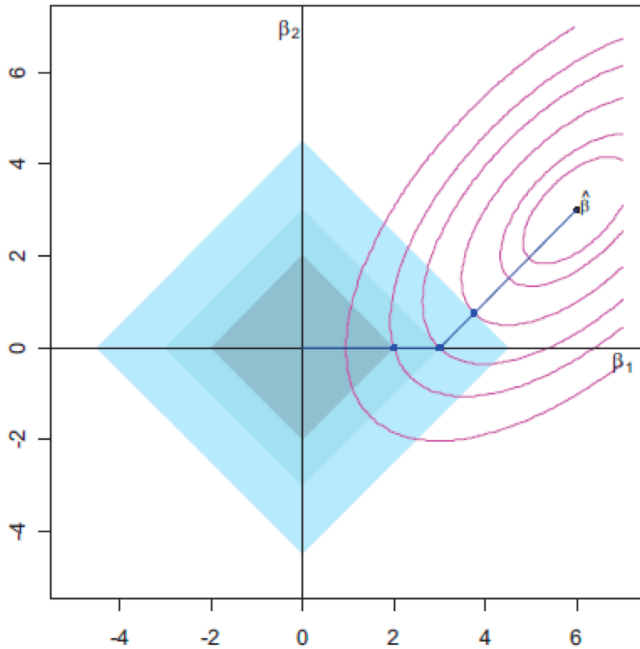
Logistic regression with many features

*If we minimize the squared error only in a diamond shaped area, we get sparse models*



$$(\hat{\alpha}, \hat{\beta}) = \arg \min \left\{ \sum_{i=1}^N \left( y_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 \right\} \quad \text{subject to } \sum_j |\beta_j| \leq t.$$

*By making the diamond smaller (shrinkage), we can reduce the number of genes in the model*



$$(\hat{\alpha}, \hat{\beta}) = \arg \min \left\{ \sum_{i=1}^N \left( y_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 \right\} \quad \text{subject to } \sum_j |\beta_j| \leq t.$$

# *How much shrinkage is good ?*

Train	Train	Select	Train	Train
-------	-------	--------	-------	-------

Train	Train	Train	Select	Train
-------	-------	-------	--------	-------

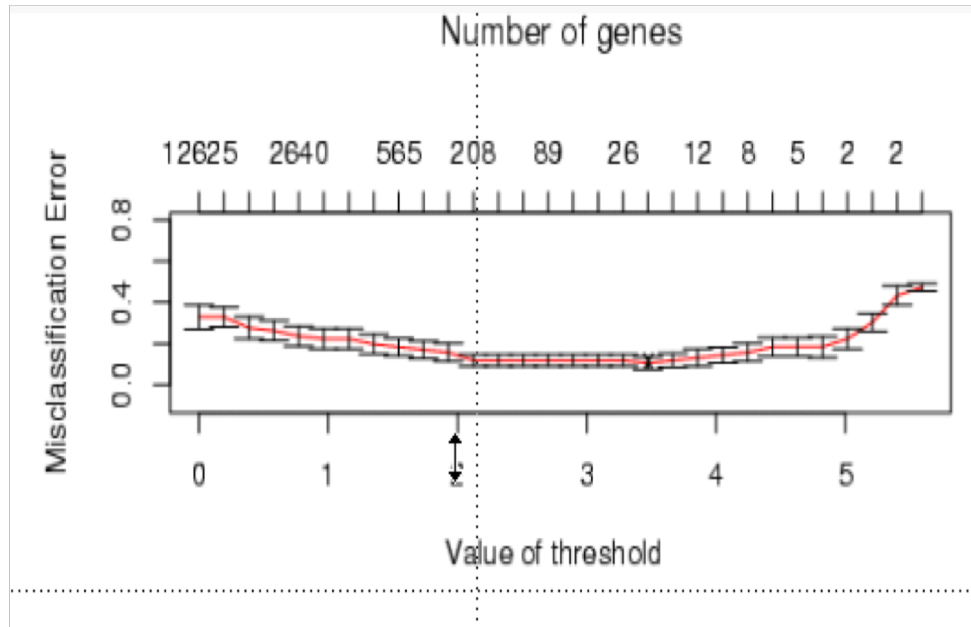
*cross  
validation*

Compute the CV-Performance for several values of  $\Delta$

Pick the  $\Delta$  that gives you the smallest number of CV-Misclassifications

PAM does this routinely

# *Model Selection Output of PAM*



**Small  $t$** , many genes poor performance due to **overfitting**

**High  $t$** , few genes, poor performance due to lack of information – **underfitting** –

The optimal  $t$  is somewhere in the middle

# Validation

# *How to distinguish a meaningful signature from a meaningless signature?*

The meaningless signature might be separating

- *small training error* –

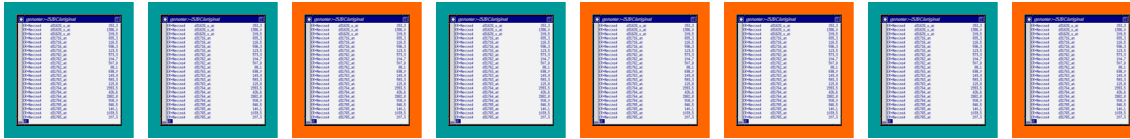
... but it will not be predictive

- *large error in applications* –

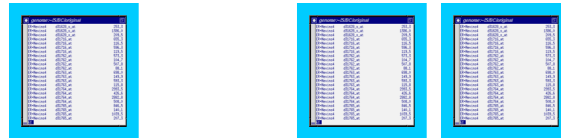
The goal is not a separating signature but a predictive signature:

**Good performance in clinical practice !!!**

# Test Sets



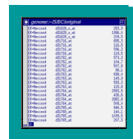
Split data into ...



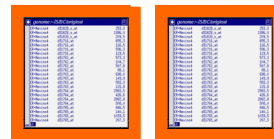
test ...



... and training data



ok



ok mistake



# *Cross Validation*



**You can not evaluate a fitted classification model (= signature) using cross validation**

**Cross validation only evaluates the algorithm with which the signature was build**

**Gene selection must be repeated for every relearning step in the cross validation **In the loop gene selection****

# *External Validation and Documentation*

Documenting a signature is conceptually different from giving a list of genes, although is is what most publications give you

In order to validate a signature on external data or apply it in practice:

- All **model parameters** need to be specified

**The scale** of the normalized data to which the model refers needs to be specified

# *Establishing a signature*



Split Data into  
Training and  
Test Data

Test data only:  
Internal validation  
Full quantitative  
specification

External  
Validations

Training data only:  
Machine Learning  
- select genes  
- find the optimal number of genes  
- learn model parameters

## ***DOs AND DONTs :***

1. Decide on your diagnosis model (PAM,SVM,etc...) and don't change your mind later on
2. Split your profiles randomly into a training set and a test set
3. Put the data in the test set away ... far away
4. Train your model only using the data in the training set  
(select genes, define centroids, calculate normal vectors for large margin separators, ...)

**don't even think of touching the test data at this time**

5. Apply the model to the test data ...

**don't even think of changing the model at this time**

6. Do steps 1-5 only once and accept the result ...

**don't even think of optimizing this procedure**

*Questions*

