

## Development of Predictive Models and Feature Selection Using LASSO and Elastic Net

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25 Sep 2012

## Introduction

- Feature selection is an important scientific requirement of genomic studies when  $p$  is large than no. of samples ( $N \ll p$ )
- In most cases predictors are correlated
- Usually no. of predictors that relevant or informative are very few
- It is difficult to identify informative features when noisy predictors are present.

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## LASSO and Elastic Net ( $l_1$ and $l_2$ penalty)

### Lasso and Elastic Net

Linear regression methods for prediction and variable selection when the number of predictors exceeds the number of sample units ( $p \gg N$ ).

### Lasso: ( $l_1$ penalty)

the largest number of predictors is equal to number of samples

$$\beta^{lasso} = \arg \min_{\beta} \left( \sum_{i=1}^n (y_i - \mathbf{x}_i^T \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \right)$$

$\lambda$  is chosen such that the mean squared prediction error is minimum

### Elastic net: Lasso $\Leftarrow$ Elastic net $\Rightarrow$ Ridge regression

Number of predictors with non zero weights (coefficients) depend on the penalty

$$\beta^{ENet} = \arg \min_{\beta} \left( \|y - X\beta\|^2 + \lambda \left( \alpha \sum_{i=1}^p |\beta_i| + \frac{1}{2} (1 - \alpha) \sum_{i=1}^p \beta_i^2 \right) \right)$$

Elastic Net penalty is a mixture of the  $l_1$  (lasso) and  $l_2$  (ridge) penalties.  $\alpha$  is the mixing parameter.

## Assessment of prediction error

- 3-fold cross validations
- leave one out cross validations [LOOCV]

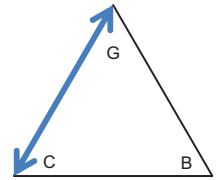
## Predictive Fingerprints

Predictive model for gene expression using Finger Prints [FP] information (GC)

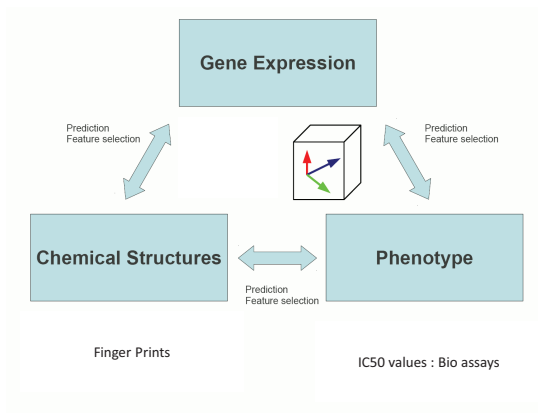
- Information:
1. Gene module (Y)
  2. FPs matrix (X)

- Output:
1. List of predictive features (FPS).
  2. Predictive model

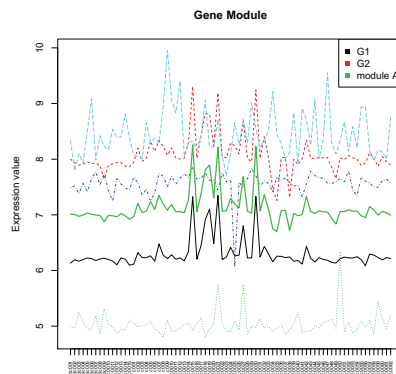
Methods:  
**LASSO and Elastic Net**



## QSTAR Project



## Prediction of Gene Module using Fingerprints



Focused on a Gene Module A which is formed by average expressions of the two correlated genes.

### Data Structure

- Response: Expression levels of Gene Module A: mean gene expressions of the two correlated genes on 62 compounds
- Predictors: Unique fingerprint features 268 out of 16698 finger prints: each fingerprint feature is a binary vector indicating whether it is present or absent in the 62 compounds.

### The Model

$$Y_i = \beta_0 + \sum_{j=1}^P \beta_j FP_{ij} + \epsilon_i$$

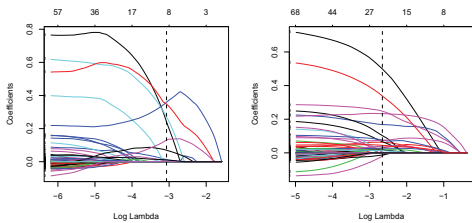
$$FP_{ij} = \begin{cases} 1 & \text{if presents in the compound} \\ 0 & \text{Otherwise} \end{cases}$$

### Leave One Out cross validations for LASSO

assess the model in terms of prediction error:

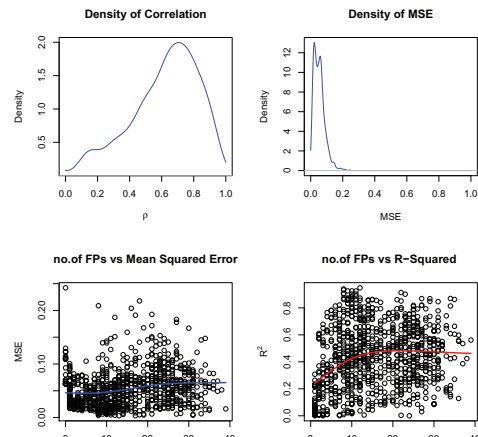
- the estimated  $R^2$  value is 57.024%
- correlation between  $Y$  and  $\hat{Y}_{-j}$  is 0.755.
- the estimated  $MSE$  is about 0.078

### LASSO and Elastic Net

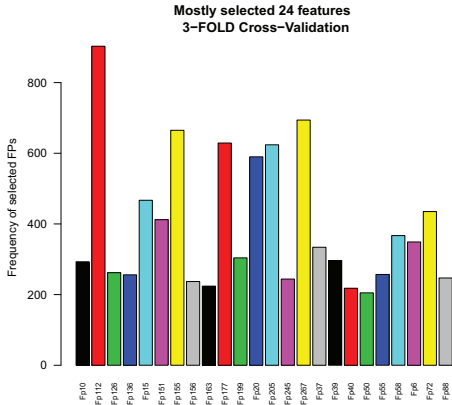


10 finger prints selected with LASSO (left panel) while Elastic net (right panel) with mixing parameter,  $\alpha = 0.3$ , selects 21 finger prints. LASSO results is subset of the Elastic Net results.

### 3-Fold Cross Validations for LASSO

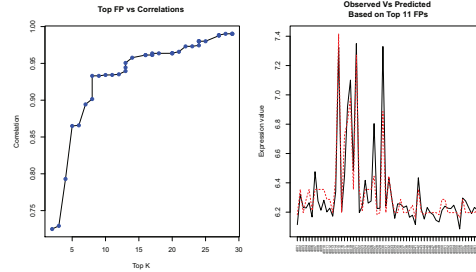


### Mostly selected 24 features



### Relaxed LASSO on top 11 finger prints

Refit the LASSO model while considering the top 11 finger prints:



correlation between observed and predicted values is 0.914

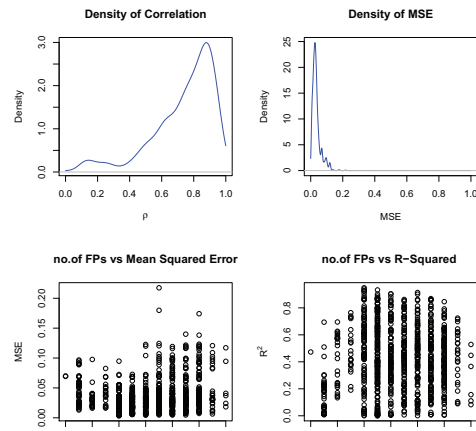
### Relaxed LASSO

Idea:

- 1 use the lasso to select the set of non-zero predictors
- 2 apply the lasso again, but using only the selected predictors from the first step

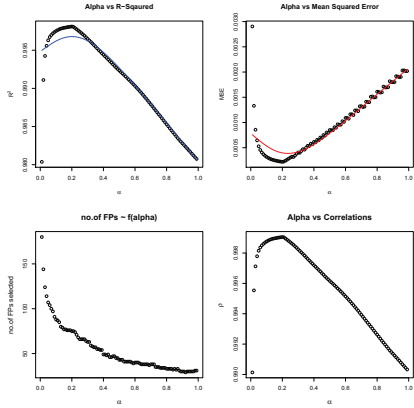
Pros: the variables in the second step have less competition from noise variables, cross-validation will tend to pick a smaller value for  $\lambda$ , and hence their coefficients will be shrunken less than those in the initial estimate.

### 3-fold cross validations for Relaxed LASSO



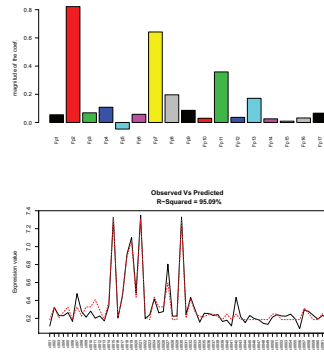
### Elastic Net over fine grid of $\alpha$

optimum  $\alpha$  which give rise minimum MSE and maximum  $R^2$  is 0.2.



### Results based on 3-fold CV ( $\alpha=0.2$ )

panel 1 shows mostly selected 17 (at least 50% of the time) finger prints.



lower panel indicates the prediction based on refitting the Elastic net with top FPs

### Results based on Elastic net, LOOCV

$\alpha = 0.2$

- ➊ 75 finger prints are selected based on elastic net with  $\alpha = 0.2$
- ➋  $R^2$  value is 99.81%

LOOCV at  $\alpha = 0.2$

- ➊ MSE for LOOCV is 0.0156
- ➋  $R^2$  value is 57.024%

### Summary of Results

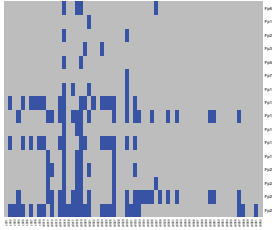
No. of finger prints selected at different methods

	LASSO	Elastic Net ( $\alpha=0.2$ )	CV.LASSO	Relaxed LASSO	CV.Elastic Net ( $\alpha=0.2$ )
LASSO	30	27	29	2	14
Elastic Net ( $\alpha=0.2$ )		75	33	6	16
CV LASSO			42	3	16
Relaxed LASSO				12	1
CV Elastic Net ( $\alpha=0.2$ )					17

*presence and absence of finger prints*

if fingerprint is present ■

if fingerprint is NOT present ■



Thank you for your attention!  
Dank u voor uw aandacht!

*Winding up*

- different methods lead to different finger print signatures
- there are overlapping fingerprints
- core fingerprint list: fingerprints common in 3-fold cross validated LASSO and 3-fold cross validated Elastic net ( $\alpha = 0.2$ )
- the Gene module A can be predicted using these finger print features and correlation between predicted and observed values are around 0.95
- need to check whether these finger prints represent interesting chemical compounds