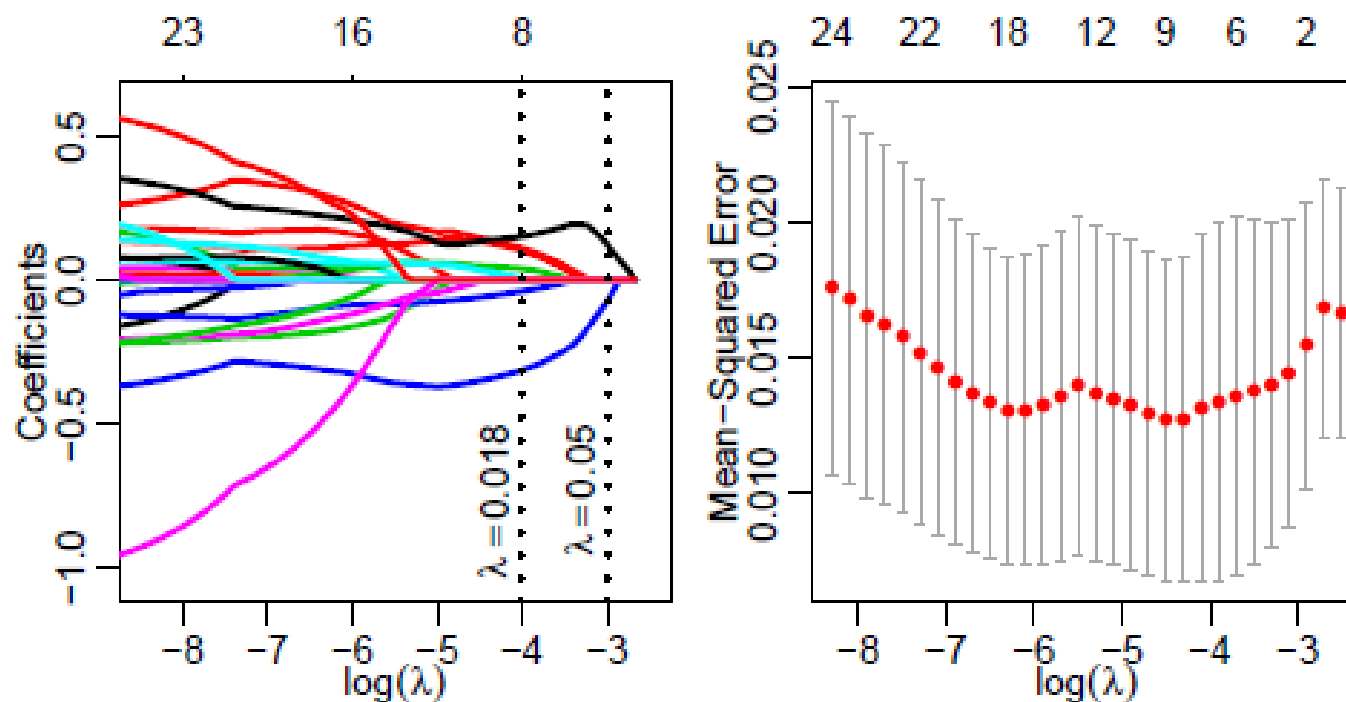


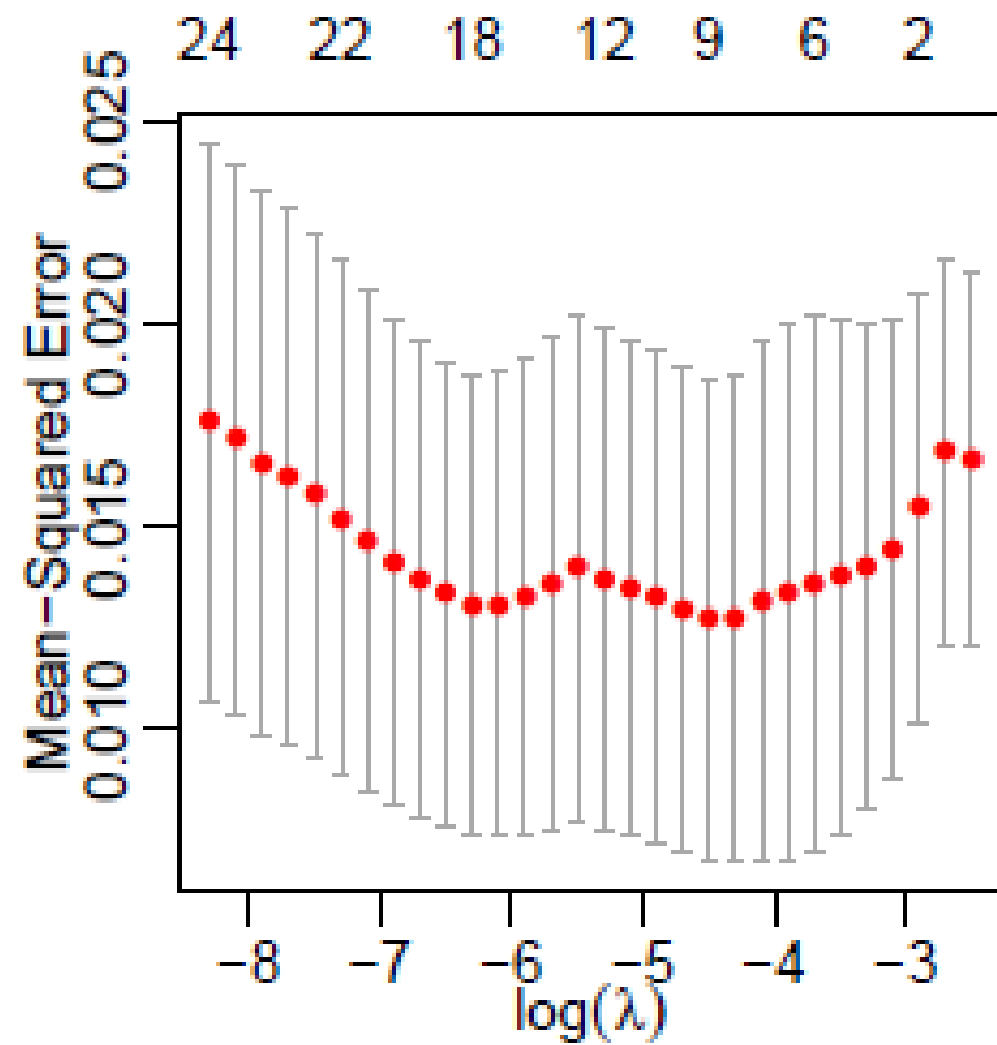
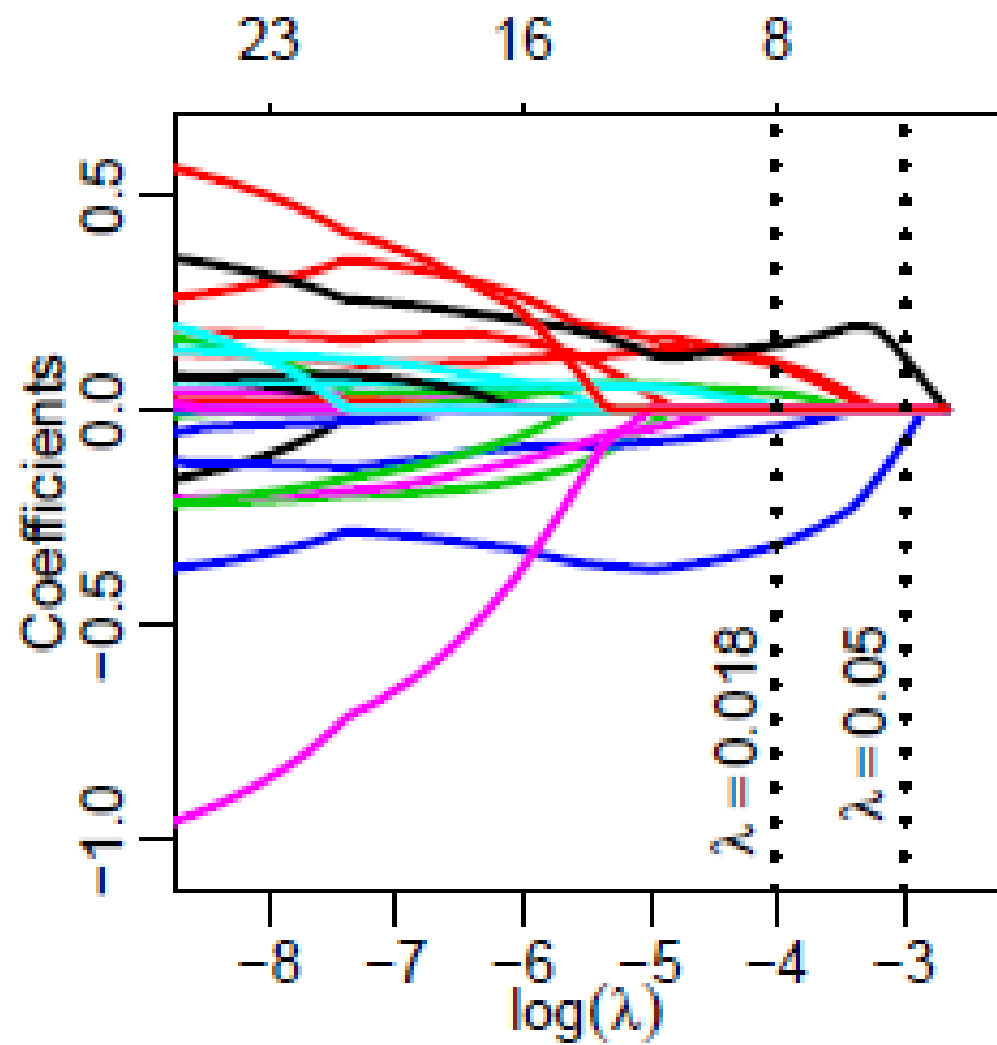
Exercise 19

Presenters: Oriane Kopp and Myroslava Volosko

Questioners: Anja Probst and Jazmin Valeriano

We again consider the pyrimidine data set presented in the lecture. It contains 74 activity measurements of the enzyme DHFR in a bacterium in the presence of different pyrimidines characterized by 26 physico-chemical properties. Those properties are quantified by the variables X1 to X26; the activity of DHFR is the response variable Y. The following figure shows the regularization path (left) and the result of a leave-one-out cross validation (right):



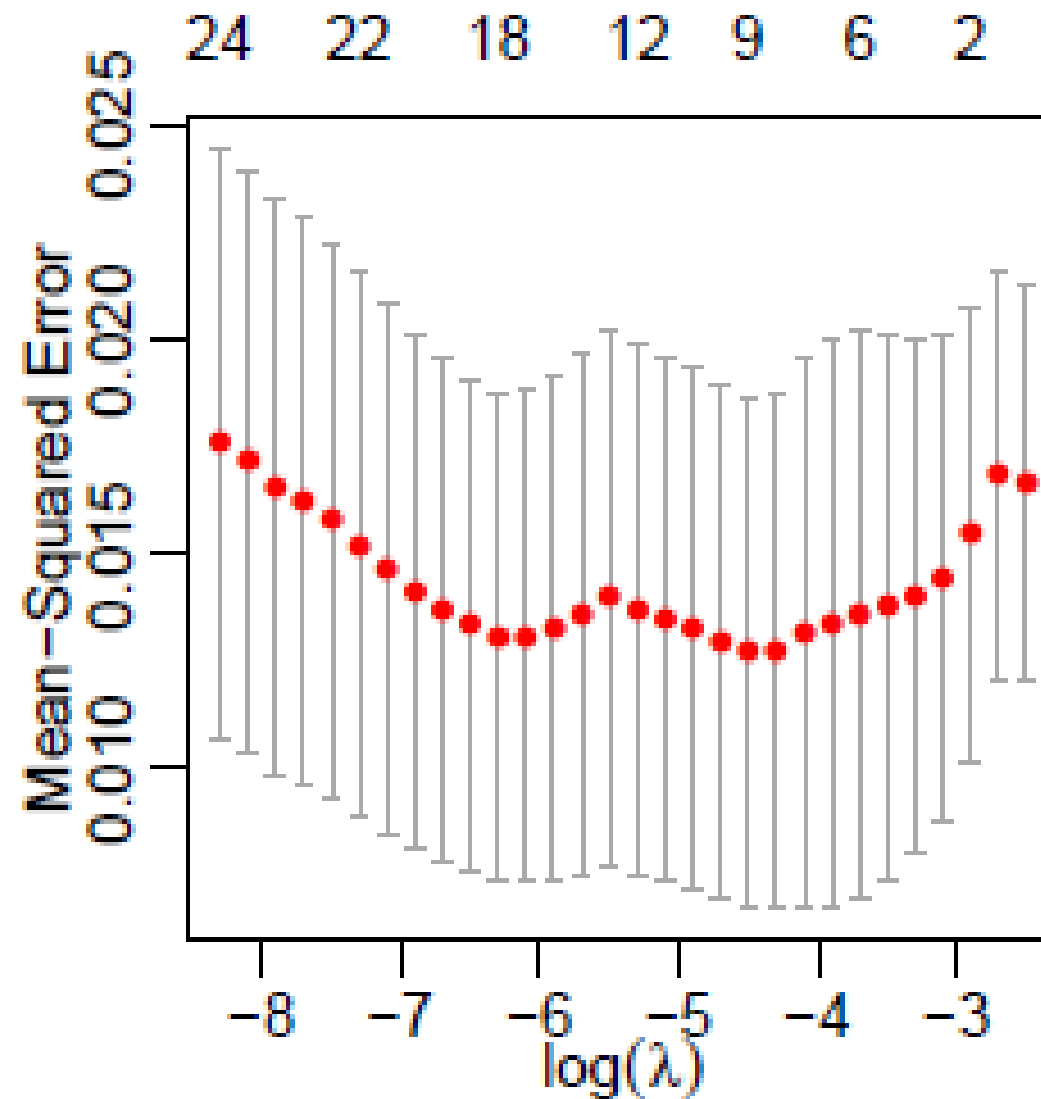


LASSO 🧐

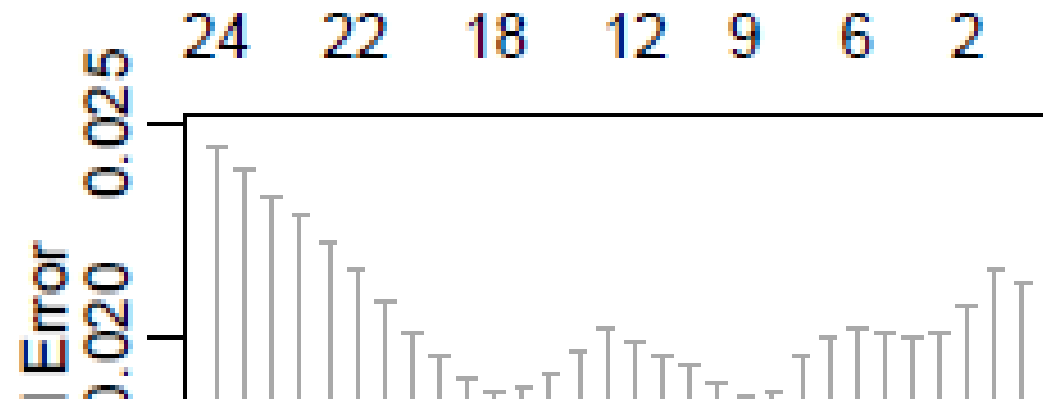
- Least Absolute Shrinkage and Selection Operator
- Find vector of coefficients β that minimizes the penalized residual sum of squares

$$\text{RSS} + \lambda \sum_{j=1}^p |\beta_j| = \|Y - \mathbf{X}\beta\|^2 + \lambda \sum_{j=1}^p |\beta_j|$$

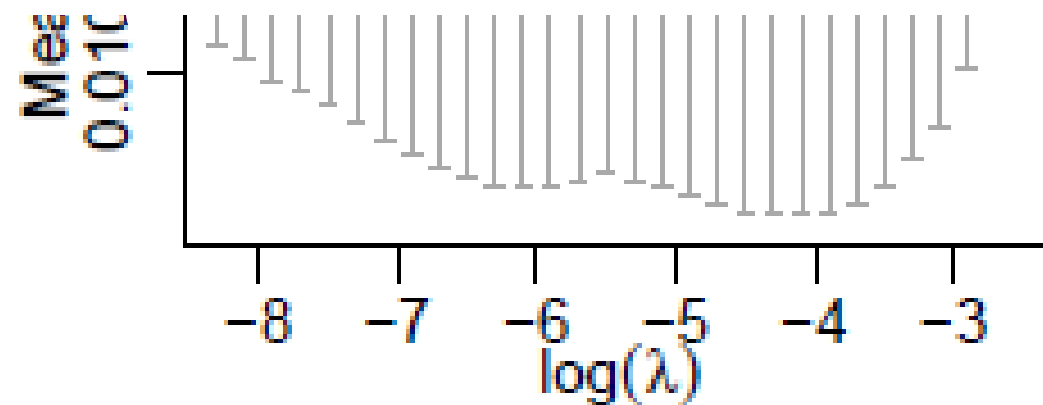
a) What is the optimal range for the regularization parameter ?



a) What is the optimal range for the regularization parameter ?



“Best” model is the one with minimum CV-value

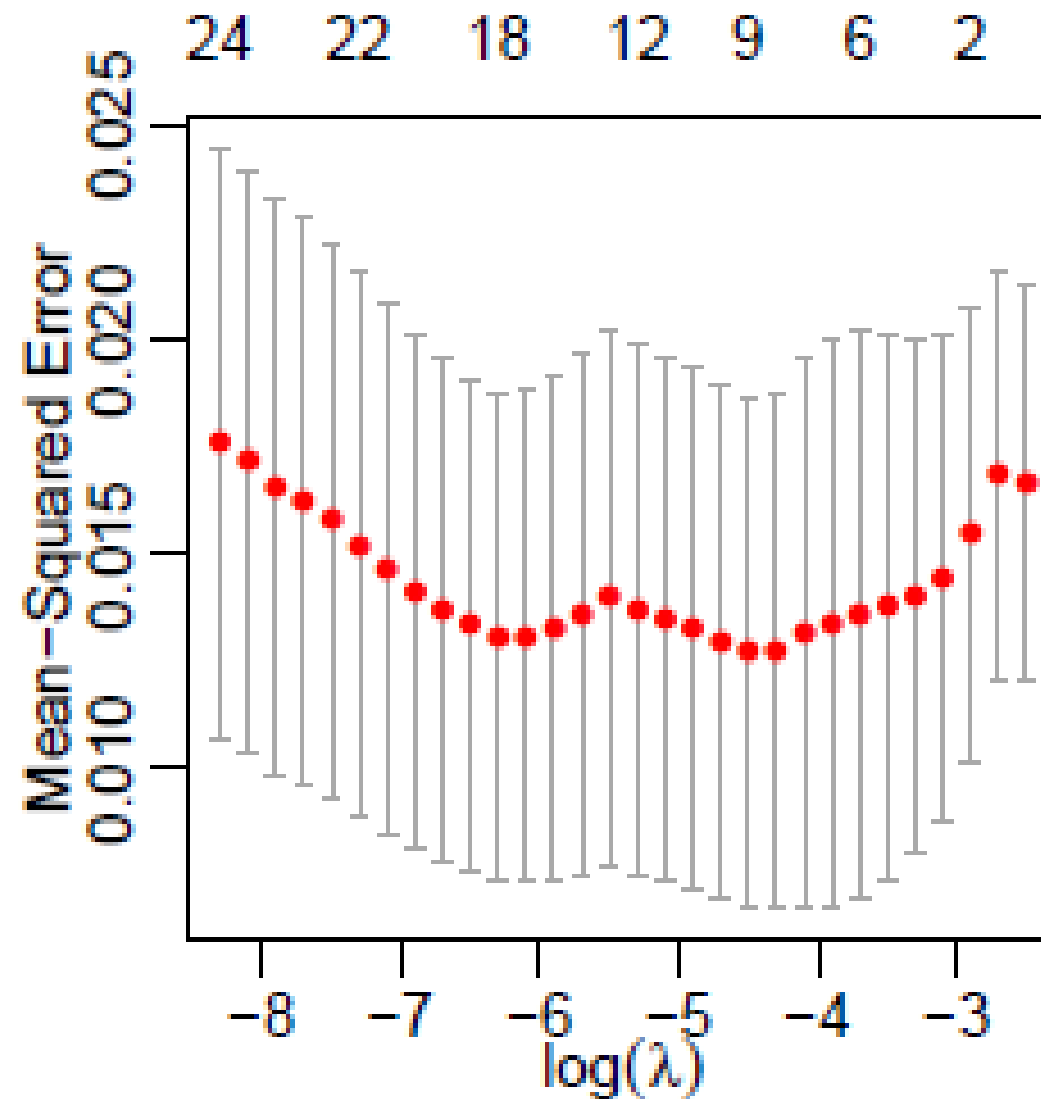


What is CV-value?

- (Leave-one-out) Cross-validation value
- Remove one data point of the dataset and fit the model on the remaining data points → test the model on the data point you put aside → repeat

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2$$

a) What is the optimal range for the regularization parameter ?



a) What is the optimal range for the regularization parameter ?

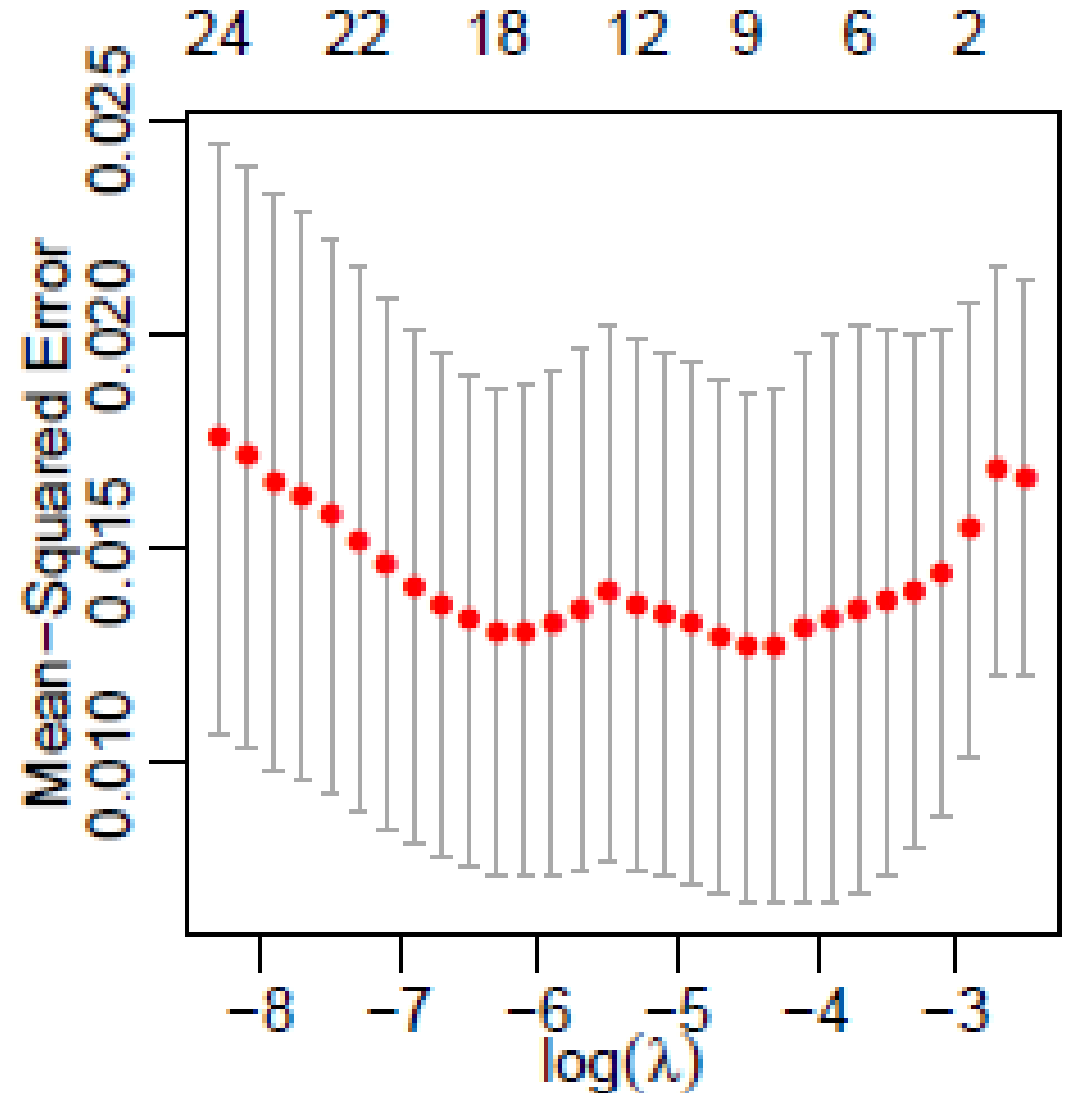
$[-5, -3] \rightarrow$ lambda should be positive

$[0.0001, 0.001] \rightarrow$ in log $[-9, -7]$

$[0.005, 0.05] \rightarrow$ in log $[-5.2, -3]$

$[0.1, 1] \rightarrow$ in log $[-2, 0]$

$[3, 5] \rightarrow$ in log $[1, 1.6]$



a) What is the optimal range for the regularization parameter ?

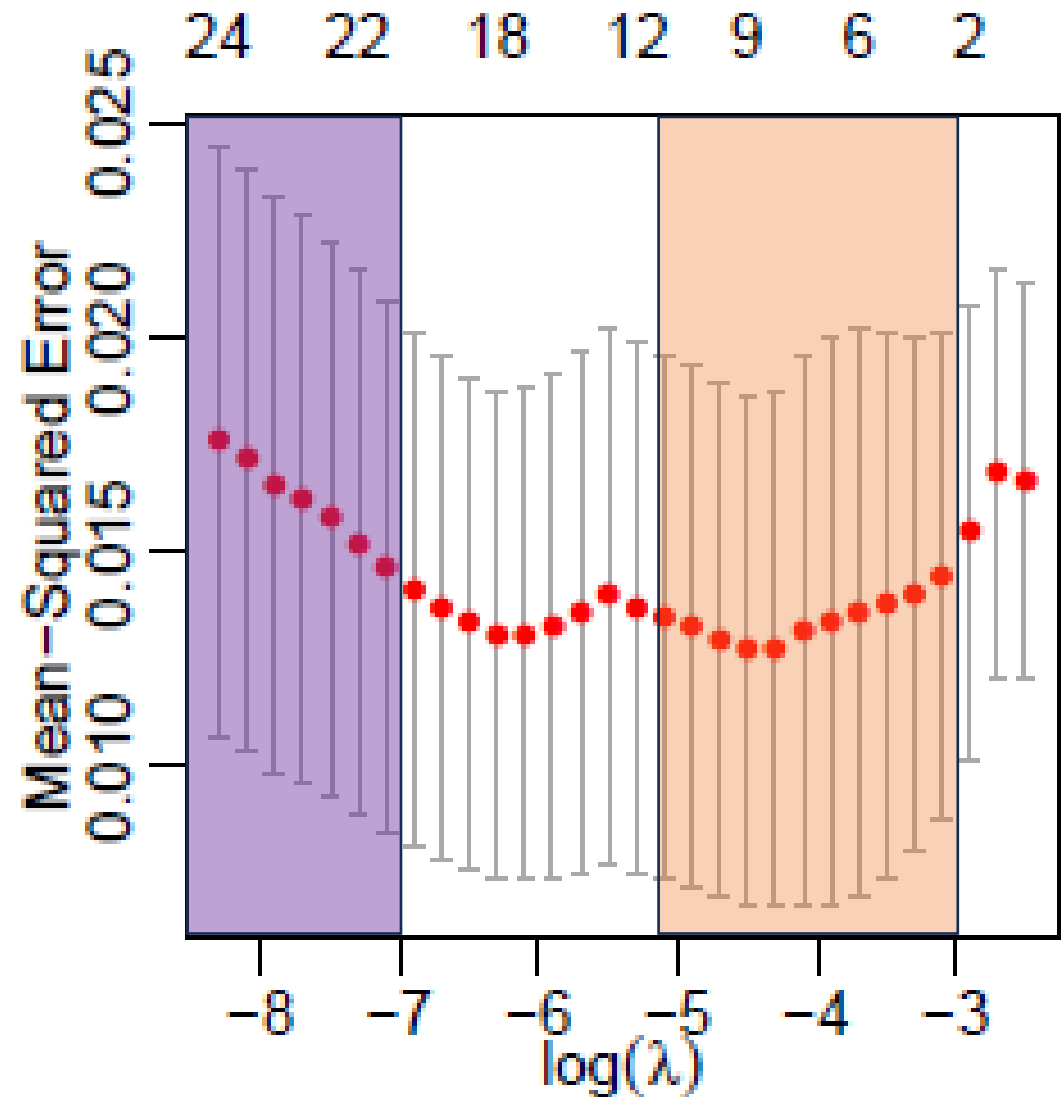
~~$[-5, -3] \rightarrow$ lambda should be positive~~

$[0.0001, 0.001] \rightarrow$ in log $[-9, -7]$

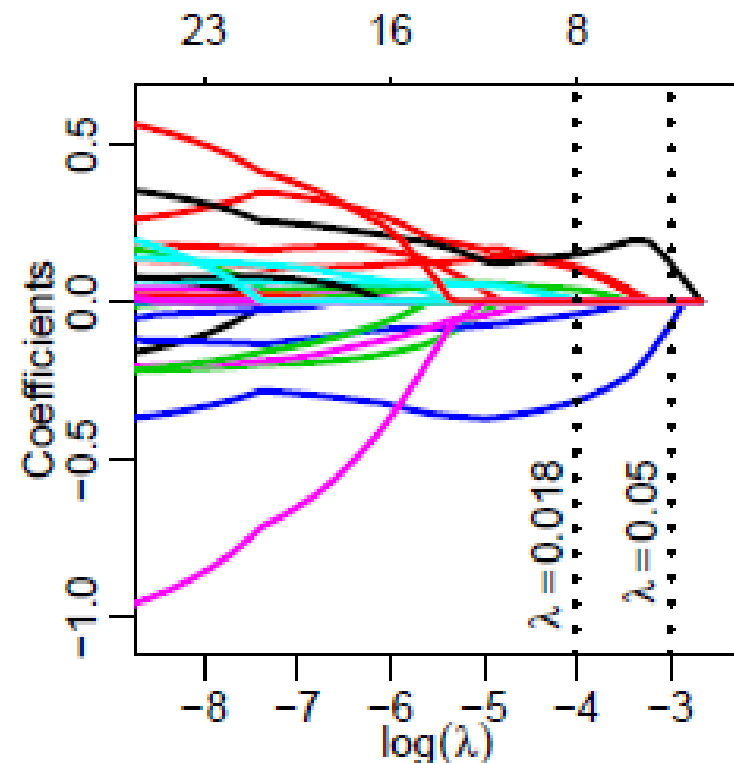
$[0.005, 0.05] \rightarrow$ in log $[-5.2, -3]$

~~$[0.1, 1] \rightarrow$ in log $[-2, 0]$~~

~~$[3, 5] \rightarrow$ in log $[1, 1.6]$~~



b) When choosing $\lambda = 0.018$ (left dotted line in left plot), we get the following coefficients (rounded):



27 x 1 sparse Matrix of class "dgCMatrix"

```

1
(Intercept) 0.600
x1          .
x2          .
x3          .
x4         -0.040
x5          .
x6          .
x7          .
x8          0.103
x9          0.001
x10         .
x11         .
x12         .

```

```

x13 .
x14 .
x15 0.039
x16 .
x17 0.008
x18 .
x19 .
x20 0.112
x21 .
x22 -0.316
x23 .
x24 .
x25 0.150
x26 .

```

b) How many variables are selected in this model? Write down the corresponding model equation.

```
27 x 1 sparse Matrix of class "dgCMatrix"
```

```
      1  
(Intercept) 0.600  
x1           .  
x2           .  
x3           .  
x4          -0.040  
x5           .  
x6           .  
x7           .  
x8           0.103  
x9           0.001  
x10          .  
x11          .  
x12          .
```

```
x13          .  
x14          .  
x15          0.039  
x16          .  
x17          0.008  
x18          .  
x19          .  
x20          0.112  
x21          .  
x22         -0.316  
x23          .  
x24          .  
x25          0.150  
x26          .
```

b) How many variables are selected in this model? Write down the corresponding model equation.

```
27 x 1 sparse Matrix of class "dgCMatrix"
      1
(Intercept) 0.600
x1           .
x2           .
x3           .
x4          -0.040
x5           .
x6           .
x7           .
x8           0.103
x9           0.001
x10          .
x11          .
x12          .
x13          .
x14          .
x15          0.039
x16          .
x17          0.008
x18          .
x19          .
x20          0.112
x21          .
x22         -0.316
x23          .
x24          .
x25          0.150
x26          .
```

Only keep the variables that have nonzero coefficients

b) How many variables are selected in this model? Write down the corresponding model equation.

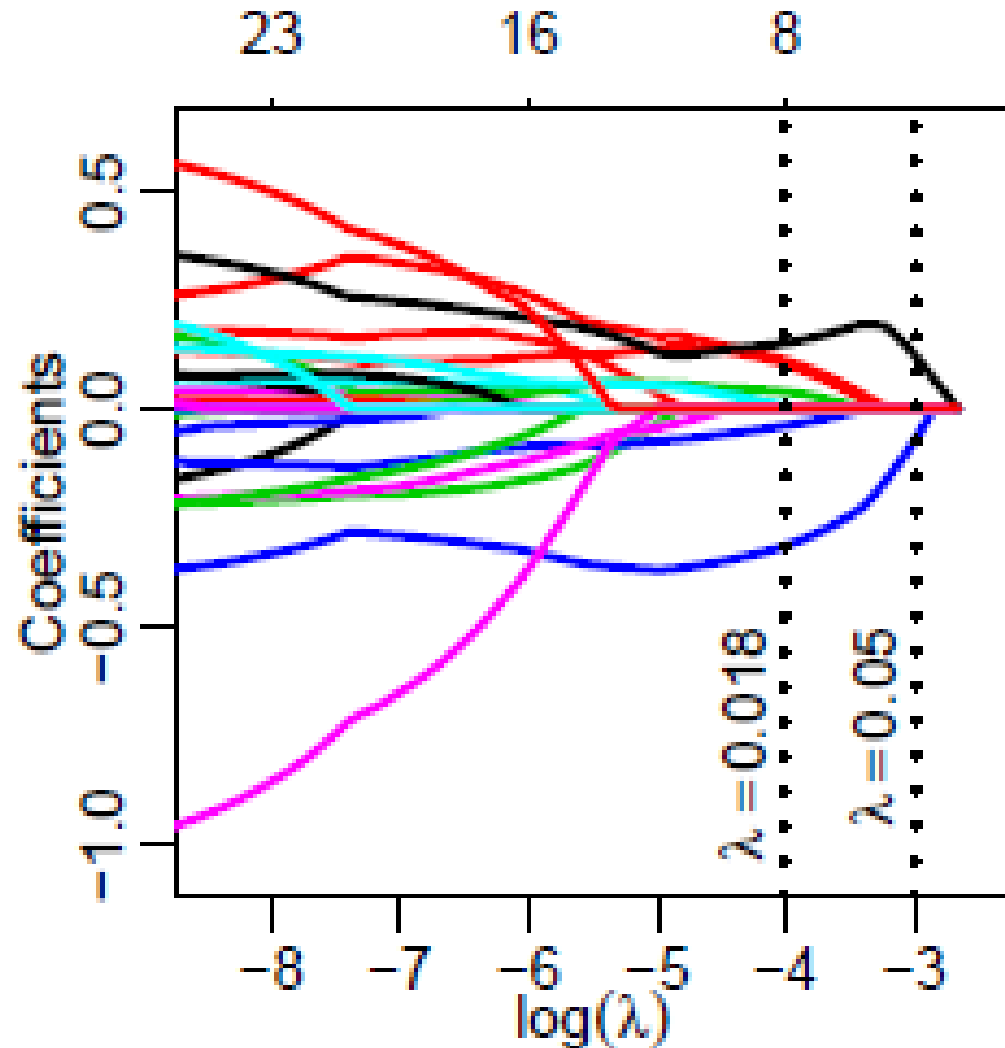
```

27 x 1 sparse Matrix of class "dgCMatrix"
      1
(Intercept) 0.600
x1          .
x2          .
x3          .
x4        -0.040
x5          .
x6          .
x7          .
x8         0.103
x9         0.001
x10         .
x11         .
x12         .
x13         .
x14         .
x15         0.039
x16         .
x17         0.008
x18         .
x19         .
x20         0.112
x21         .
x22        -0.316
x23         .
x24         .
x25         0.150
x26         .

```

$$Y = 0.600 - 0.040x_4 + 0.103x_8 + 0.001x_9 + 0.039x_{15} + 0.008x_{17} + 0.112x_{20} - 0.316x_{22} + 0.150x_{25} + E, \quad E \sim N(0, \sigma^2)$$

c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



27 x 1 sparse Matrix of class "dgCMatrix"

```

      1
(Intercept) 0.600
x1          .
x2          .
x3          .
x4        -0.040
x5          .
x6          .
x7          .
x8         0.103
x9         0.001
x10         .
x11         .
x12         .

```

```

x13 .
x14 .
x15 0.039
x16 .
x17 0.008
x18 .
x19 .
x20 0.112
x21 .
x22 -0.316
x23 .
x24 .
x25 0.150
x26 .

```

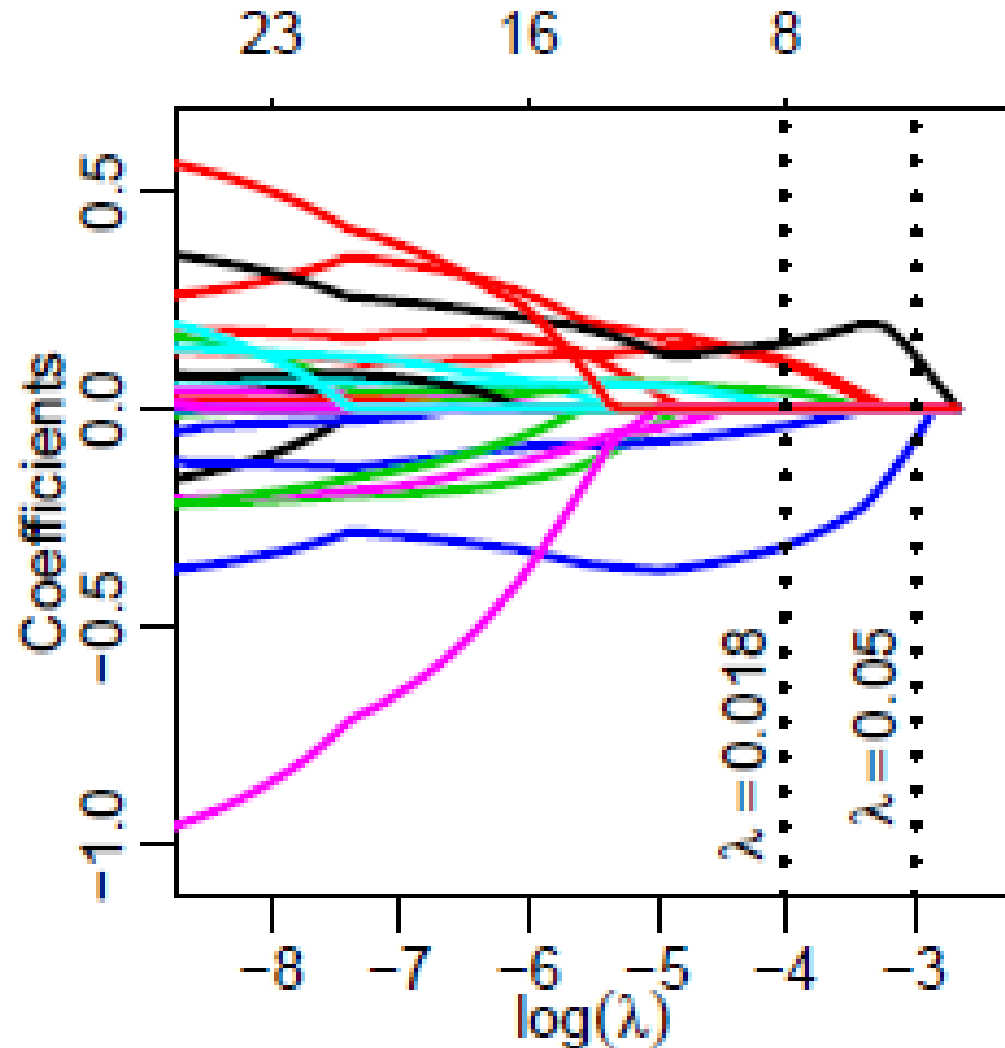
What do we know?

- Values with coefficient 0 with a bigger lambda won't suddenly reappear with a smaller lambda, so we know from b) that only x4, x8, x9, x15, x17, x20, x22 or x25 can still be in the model
- X4, X8, X22
- X4, X20
- **X14**, X22, X25
- X15, X17, X22
- X22, X25

What do we know?

- Values with coefficient 0 with a bigger lambda won't suddenly reappear with a smaller lambda, so we know from b) that only x4, x8, x9, x15, x17, x20, x22 or x25 can still be in the model
- X4, X8, X22
- X4, X20
- ~~X14, X22, X25~~
- X15, X17, X22
- X22, X25

c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



27 x 1 sparse Matrix of class "dgCMatrix"

```

      1
(Intercept) 0.600
x1          .
x2          .
x3          .
x4        -0.040
x5          .
x6          .
x7          .
x8         0.103
x9         0.001
x10         .
x11         .
x12         .

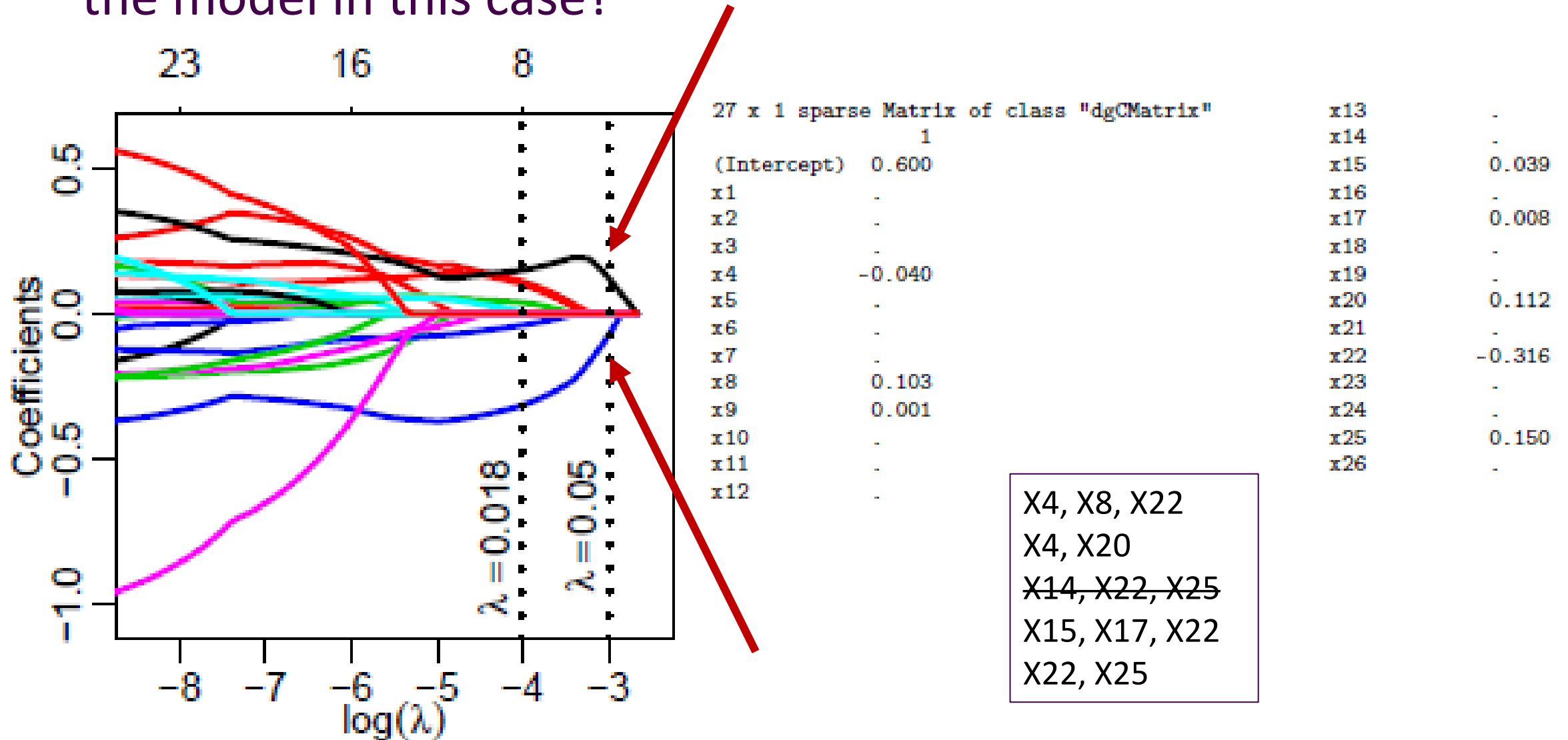
```

```

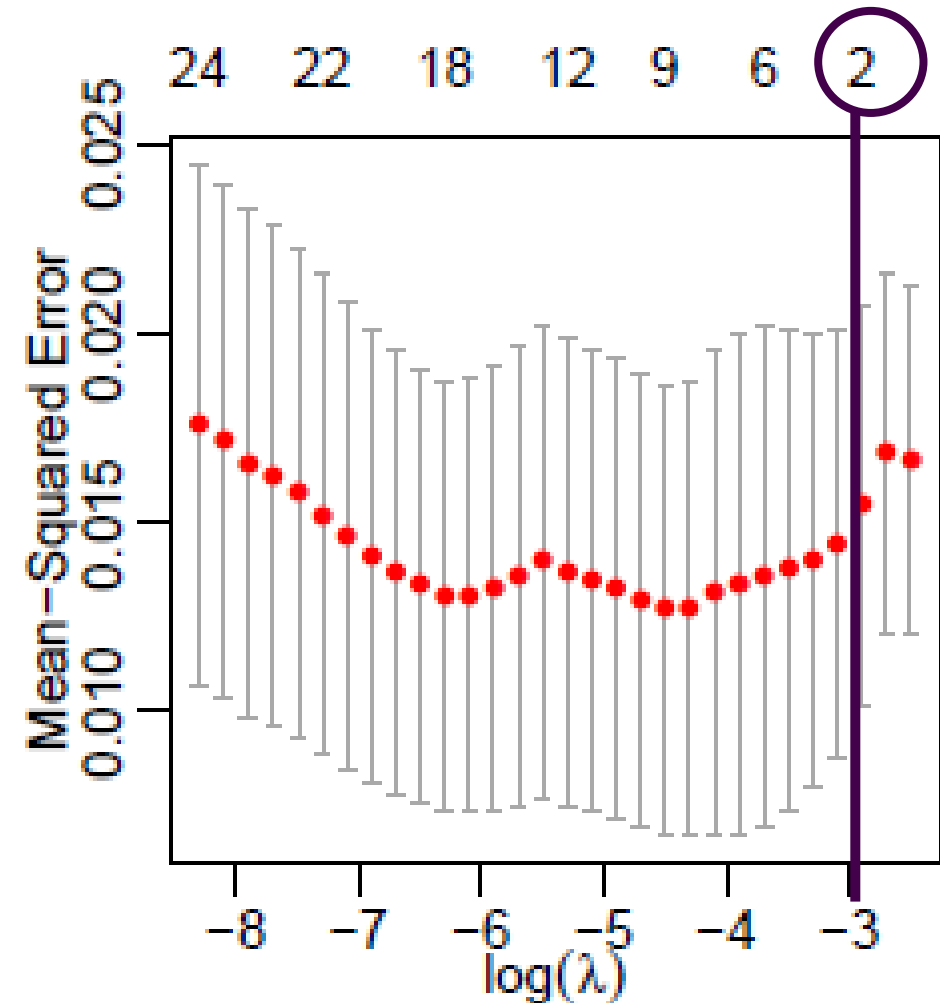
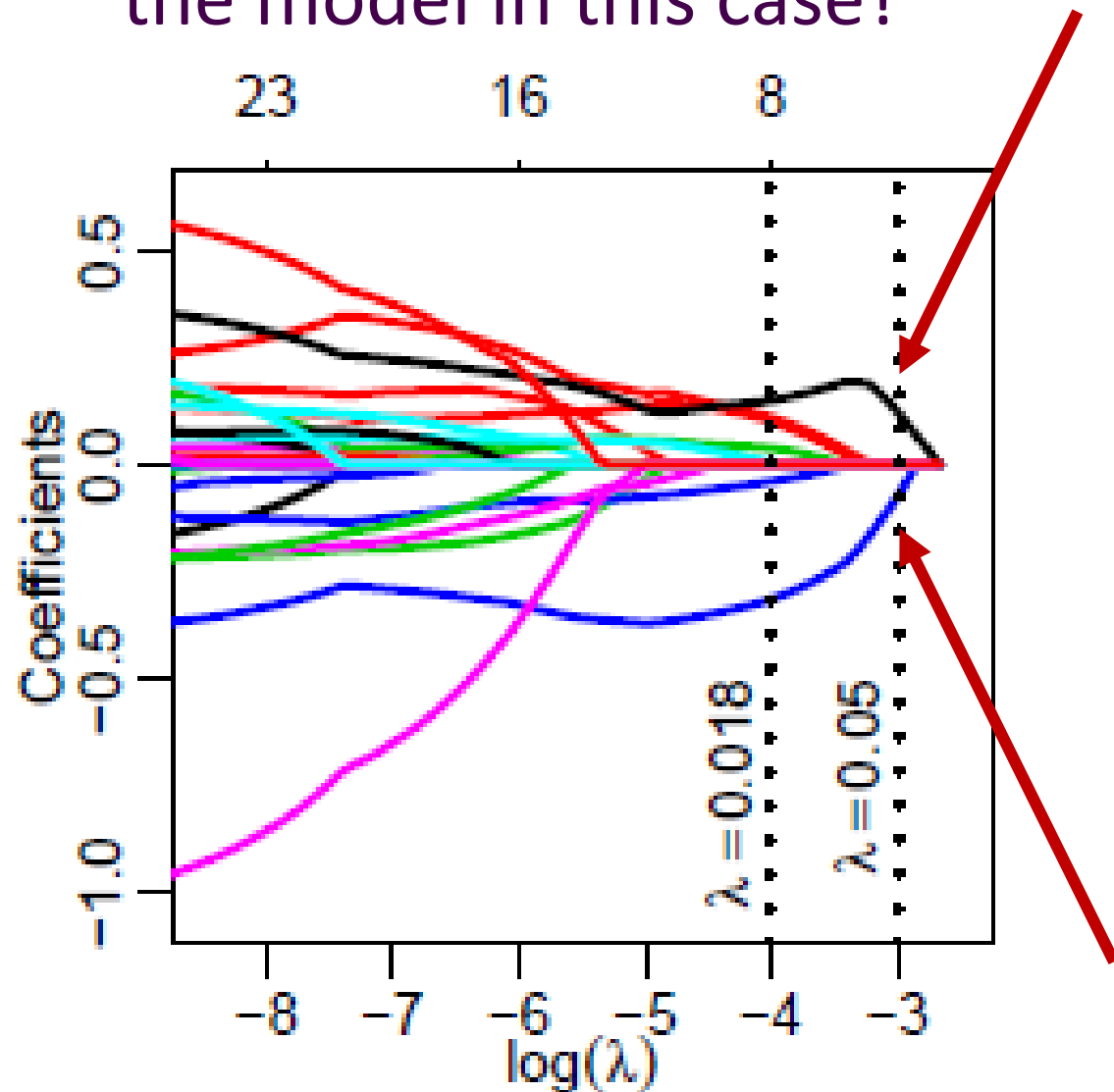
x13 .
x14 .
x15 0.039
x16 .
x17 0.008
x18 .
x19 .
x20 0.112
x21 .
x22 -0.316
x23 .
x24 .
x25 0.150
x26 .

```

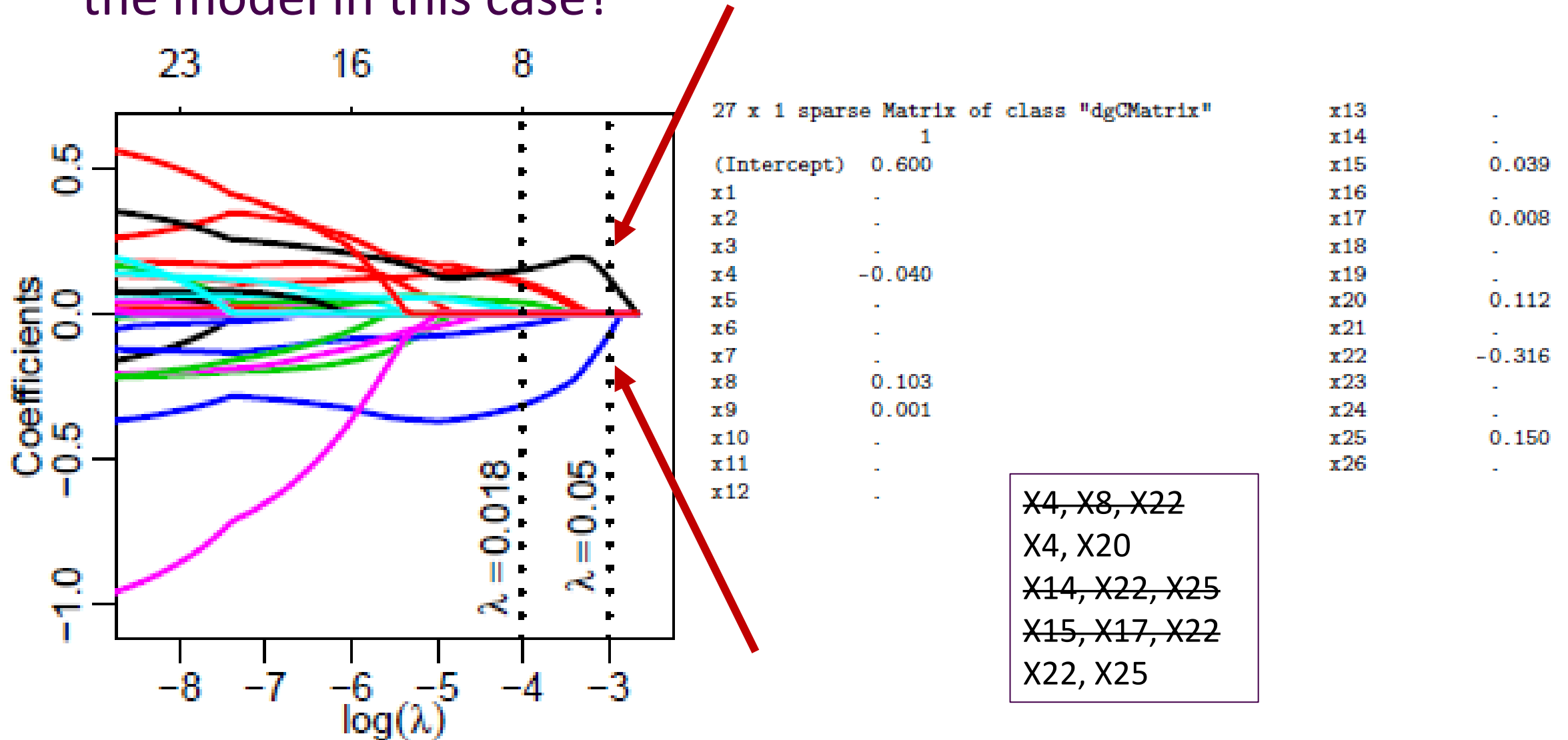
c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



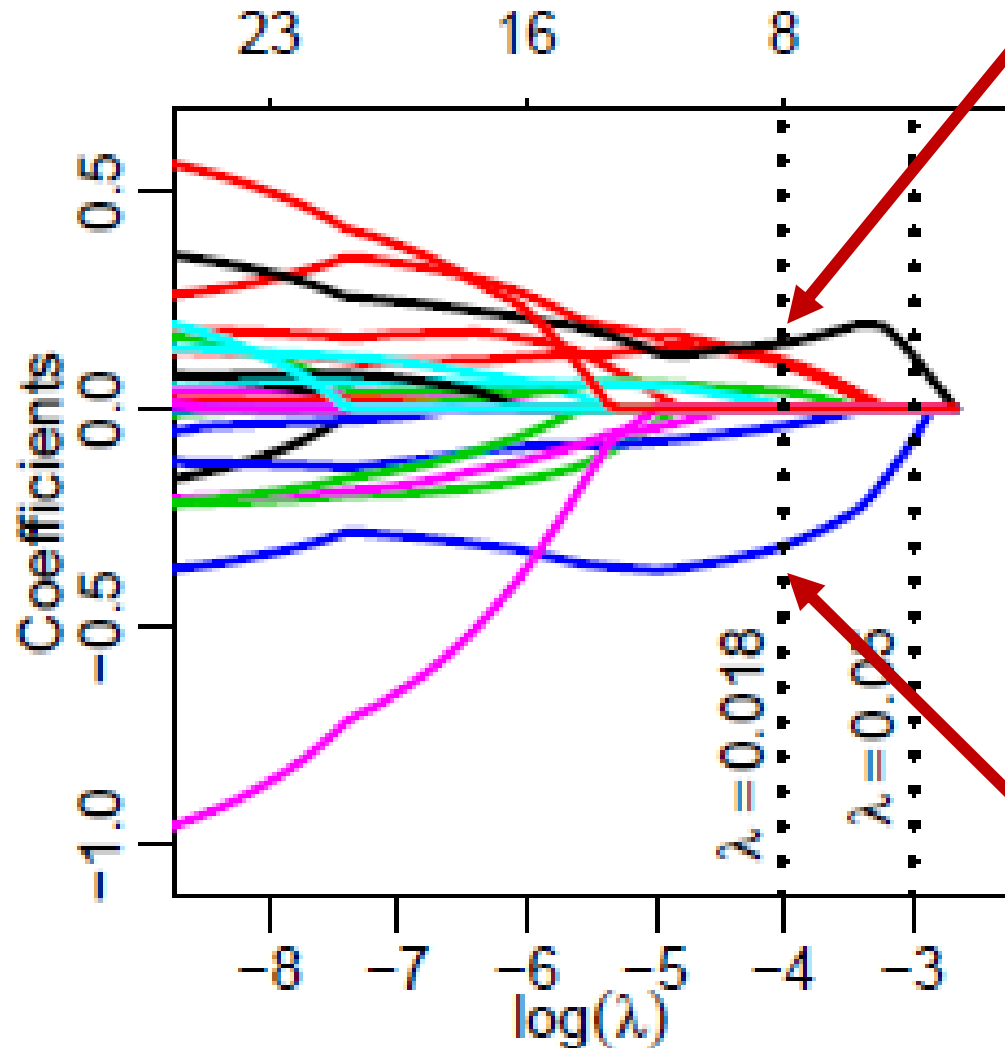
c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



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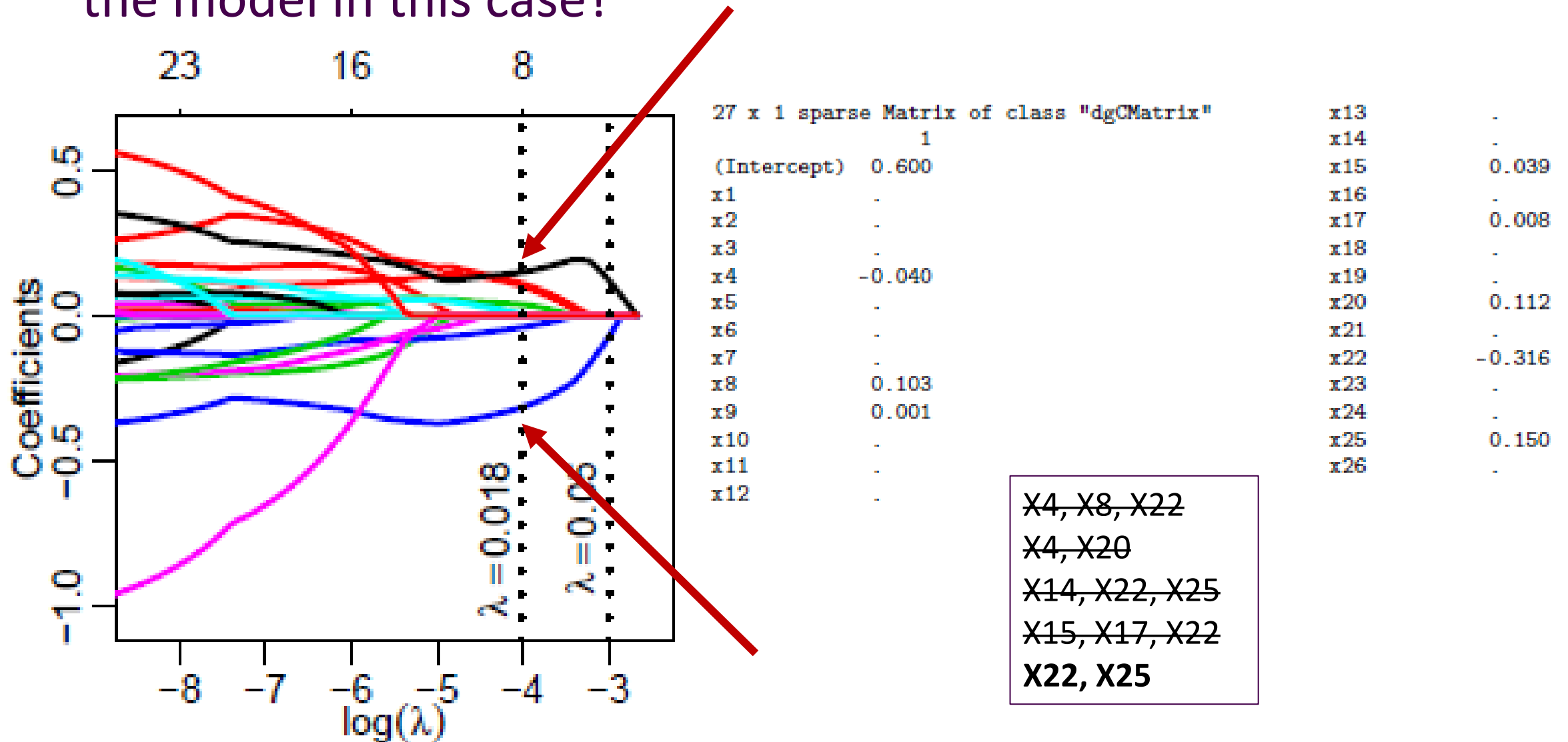
27 x 1 sparse Matrix of class "dgCMatrix"

```
(Intercept)  1
              0.600
x1            .
x2            .
x3            .
x4           -0.040
x5            .
x6            .
x7            .
x8            0.103
x9            0.001
x10           .
x11           .
x12           .
```

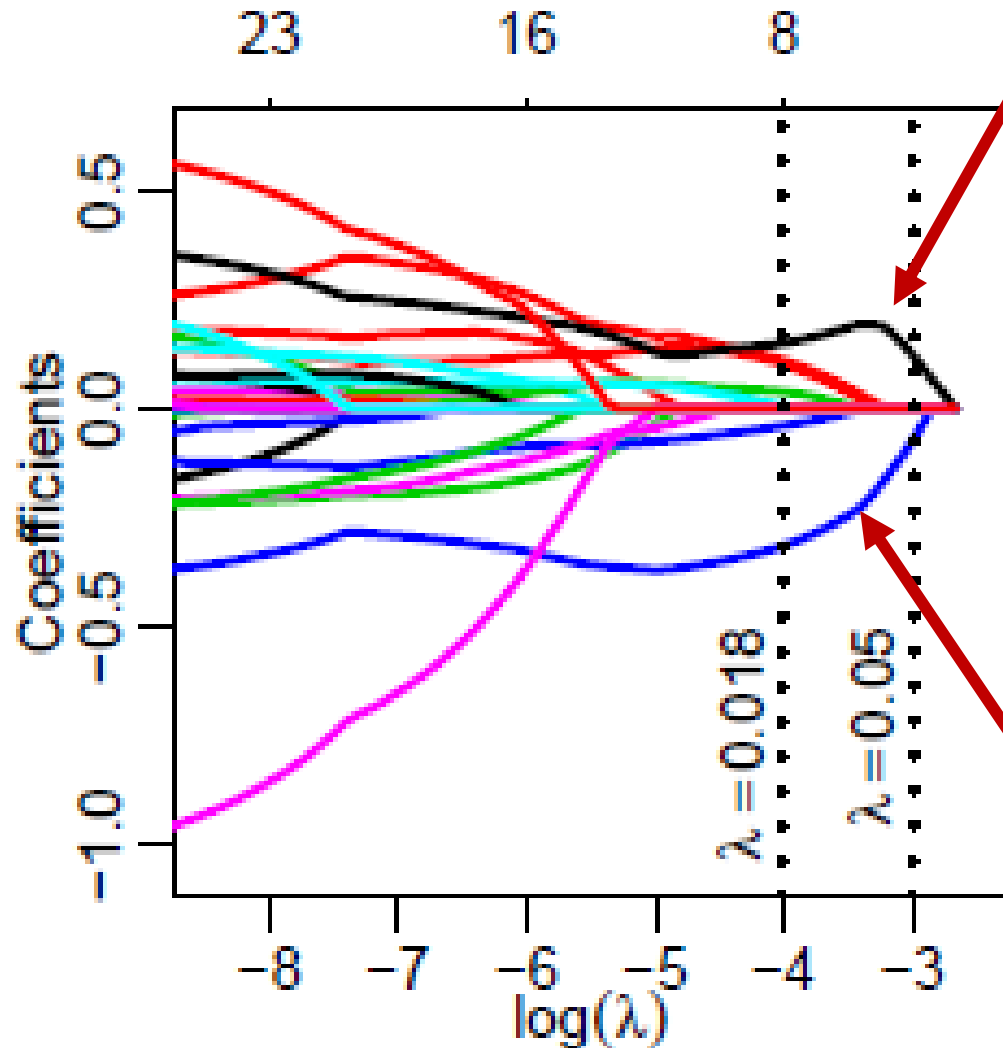
```
x13            .
x14            .
x15            0.039
x16            .
x17            0.008
x18            .
x19            .
x20            0.112
x21            .
x22           -0.316
x23            .
x24            .
x25            0.150
x26            .
```

Only the variables with the biggest and smallest coefficient in model from b) remains

c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



c) Assume now that we choose $\lambda = 0.05$ (right dotted line in left plot). Which variables remain in the model in this case?



27 x 1 sparse Matrix of class "dgCMatrix"

	1
(Intercept)	0.600
x1	.
x2	.
x3	.
x4	-0.040
x5	.
x6	.
x7	.
x8	0.103
x9	0.001
x10	.
x11	.
x12	.

x13	.
x14	.
x15	0.039
x16	.
x17	0.008
x18	.
x19	.
x20	0.112
x21	.
x22	-0.316
x23	.
x24	.
x25	0.150
x26	.

$$Y = \beta_0 + \beta_1 x_{25} + \beta_2 x_{22} + E, \quad E \sim N(0, \sigma^2)$$

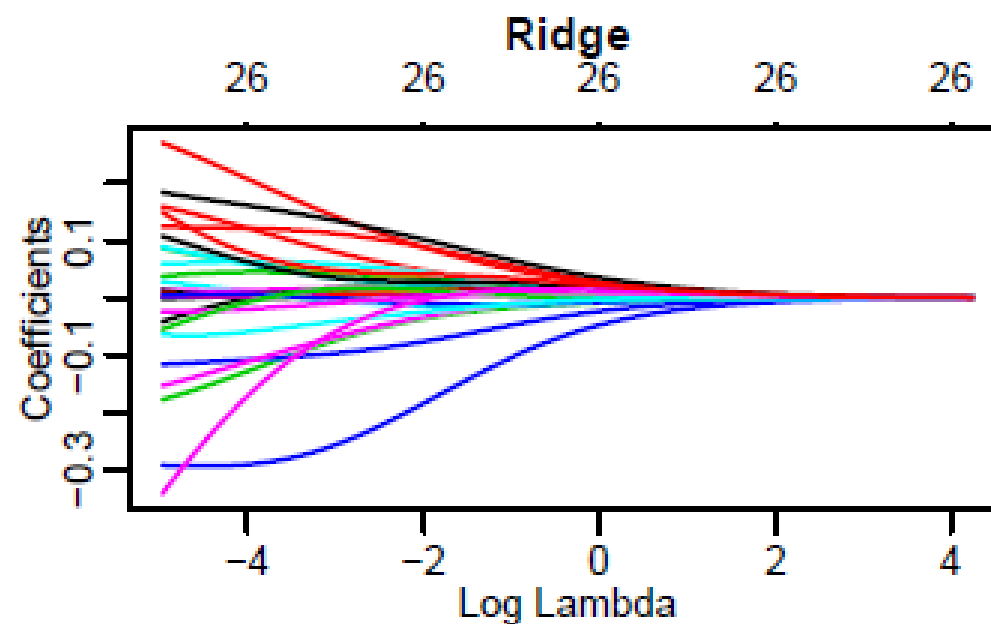
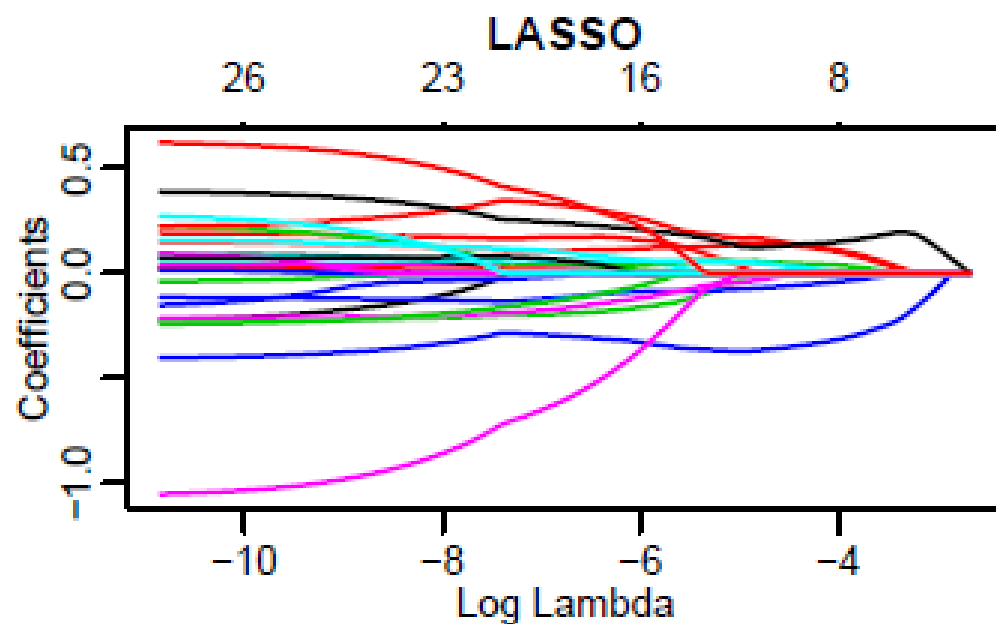
Conclusion 🤖

- In this exercise, the point is not to find the correct model but to “play” with LASSO
- LASSO is great for viewing the dynamic of the coefficients of the variable
- Hard to tell the exact values for regularization parameter and path just by looking....

Questions? 😊



From the lecture (slide 161)



K-fold vs Leave-one-out cross validation

K-fold

- Split the dataset in k subsets
- Remove one subset and fit the model on the remaining subsets
- Test the model on the set you put aside
- Repeat for each subset

Leave-one-out

- Remove one data point (from response vector and model matrix)
- Fit the model on the remaining data points
- Test the model on the data point you removed
- Repeat for each data point

K-fold vs Leave-one-out cross validation

K-fold

- Split the dataset in k subsets
- Remove one subset and fit the model on the remaining subsets
- Test the model on the set you put aside
- Repeat for each subset

→ Better for big datasets

Leave-one-out

- Remove one data point (from response vector and model matrix)
- Fit the model on the remaining data points
- Test the model on the data point you removed
- Repeat for each data point

Why does the AIC approach not work for ridge and LASSO regression?

- Ridge regression does not perform variable selection.
- LASSO is nowadays often used for high-dimensional data ($n = p$, or even $p > n$): e.g., with genetic data. AIC only works for $n \gg p$

→ That's why we use cross-validation