

Regularisation

Eltecon Data Science Course by Emarsys

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November 18, 2020

Homework

- Presenters:
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 - Emerson, Ian - Ralbovszki Judit

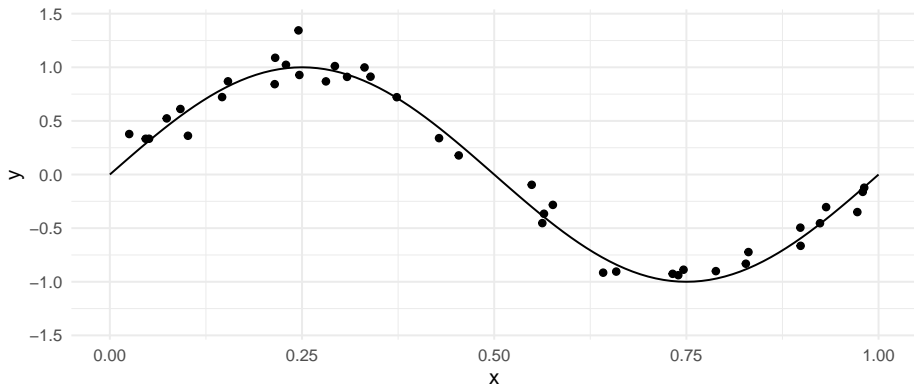
Goal of the lesson

- introduce the concept of **regularisation**
- define and try out **ridge** and **LASSO** regression
- conduct model selection on a real world example

Section 1

Regularisation

Recap



Recap

	train RMSE	test RMSE	CV RMSE
k_0	0.71	0.54	0.68
k_1	0.45	0.51	0.45
k_5	0.11	0.08	0.11
k_30	0.09	1.49	0.34

Quiz

- 1 The test error is always larger than the train error.
- 2 The overfitting error tends to increase with model complexity.
- 3 The smaller the overfitting error the better the fitted model.
- 4 If the fitted model parameters vary a lot across different samples of the same data one should check for overfitting.

Share your results in Socrative!

What is Regularisation

Idea: Use a different estimator to estimate the linear regression model. Add a **penalty term** to the error function to discourage the coefficients from reaching large values.

$$E(w) = E_D(w) + \lambda E_W(w)$$

where $E_D(w)$ is the **data-dependent error**, $E_W(w)$ **regularisation term** and λ is the **regularisation parameter** that controls the relative importance of these two terms.

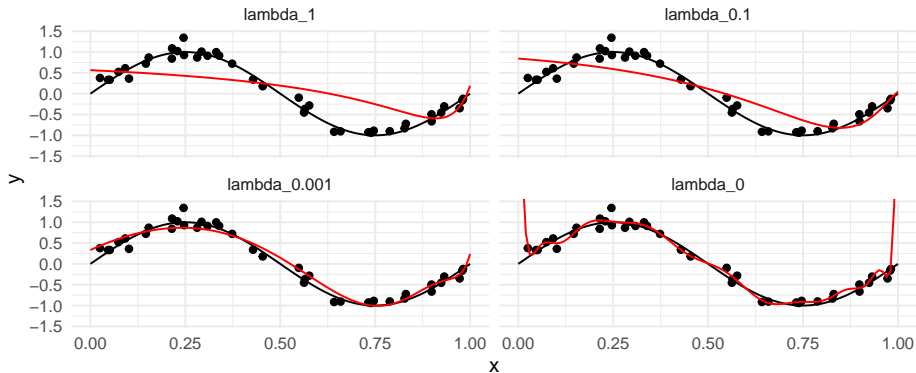
The Ridge

Minimise the following loss function:

$$L(w) = \sum_i^N (w^T x_i - y_i)^2 + \lambda \sum_j^k (w_j)^2$$

Luckily, it has a **closed form solution**.

The Ridge



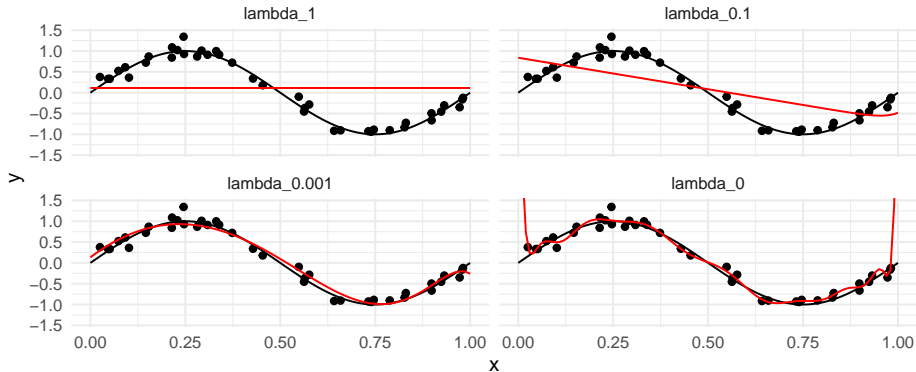
The LASSO

Minimise the following loss function:

$$L(w) = \sum_i^N (w^T x_i - y_i)^2 + \lambda \sum_j^k |w_j|$$

Unfortunately, it has **no closed form solution**. One has to use a clever algorithm to find the solution (shooting algorithm).

The LASSO

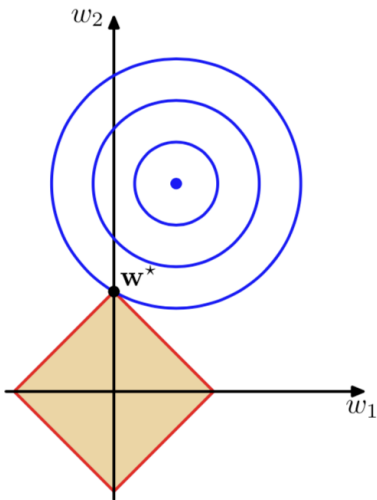
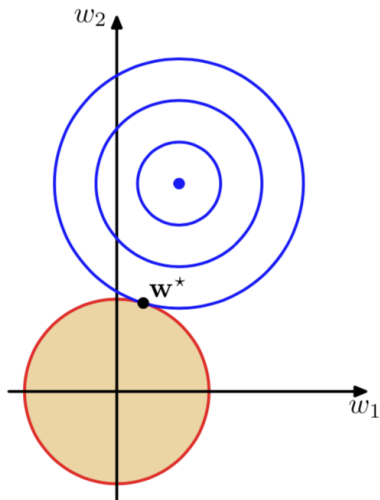


The Bias-Variance trade-off

$$MSE(\hat{w}) = E[(\hat{w} - w)^2] = \underbrace{E[(\hat{w} - w)]^2}_{\text{bias}} + \underbrace{E[(\hat{w} - E\hat{w})^2]}_{\text{variance}}$$

- OLS is unbiased estimator
- ridge and LASSO are **biased but have a smaller variance** than least squares
- by optimally choosing λ it is possible to obtain an estimator with smaller MSE

Ridge vs. Lasso



SMS Spam Prediction

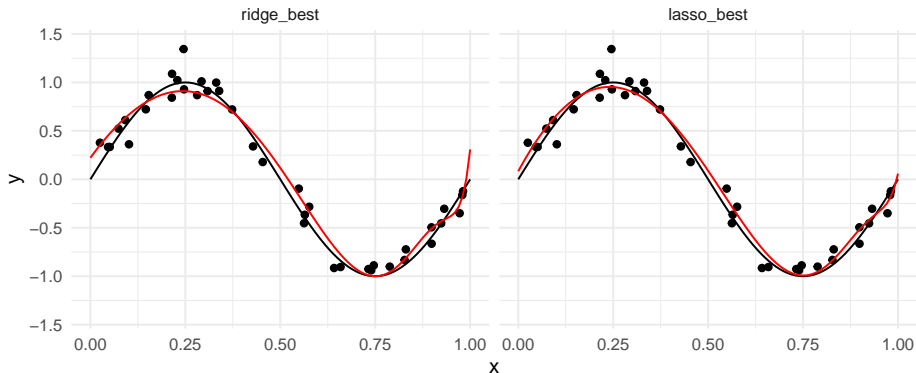
Let's see how it works in practice! `spam_pred_reg.R`

Practice Time

- Task: Implement the same model with Lasso penalty! Use the function documentation!
- Share your results in Socrative!
- You have 10 minutes.

How to choose lambda?

Cross-validate!



How to choose lambda?

	train MSE	test MSE	CV MSE
k_0	0.51	0.30	0.46
k_1	0.20	0.26	0.20
k_5	0.01	0.01	0.01
k_30	0.01	2.23	0.11
ridge_best	0.02	0.02	0.02
lasso_best	0.01	0.01	0.02

SMS Spam Prediction

Let's see how it works in practice! `spam_pred_reg.R`

Practice Time

- Task: Find the optimal lambda value with Lasso penalty!
- Share your results in Socrative!
- You have 10 minutes.

Ridge vs. Lasso

- both are useful when k is large relative to N
- ridge is useful when regressors are highly collinear
- LASSO when true regression parameter vector is sparse and regressors are not highly collinear
- one can use LASSO as variable selection method

Regularisation

Advantages:

- allows to train complex models on limited size data
- computationally cheap (not always true)

Disadvantages:

- not clear how to choose λ

Section 2

Model Selection Example

Online News Popularity

- Articles published from January 7 2013 to January 7 2015 on Mashable:
<http://archive.ics.uci.edu/ml/datasets/Online+News+Popularity>
- **Target:** number of shares in social networks
- **Predictors:** different summary measures of article content (e.g.: links, images, videos, keywords)

Homework

- Implement cross-validation to find the optimal lambda parameter for the ridge regression on the Spam prediction example.
- Use any library/function for cross-validation except the one used in the class (you might check the caret package or use your own implementation)
- Choose at least 2 potential lambda values and report their cross-validated accuracy.
- Presenters:
 - Bat-Erdene, Boldmaa - Kashirin, Andrey
 - Im Seongwon - Kim Yeonggyeong
 - Szőnyi Máté - Tran, Dung

Resources

- Bishop, Christopher: Pattern Recognition and Machine Learning
- Gareth J., Witten D., Hastie T. and Tibshirani R.: An Introduction to Statistical Learning