Report Template
FYS-STK3155 - Project X

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Regression methods are some of the most fundamental methods for machine learning. However, the classical methods such as Ordinary Least Squares (OLS) are often subject to overfitting and poor generalization. The Runge function illustrates this, where interpolation using higher degrees of polynomial does not improve the fit. To tackle these problems, we analyze the regularized regression techniques Ridge and Lasso, in addition to resampling methods such as Bootstrap and cross-validation.

In this project, OLS, Ridge and Lasso regression were first implemented followed by gradient decent methods such as momentum, ADAgrad, RMSprop and ADAM. Using these methods the model performance was evaluated and analyzed for different polynomial degrees. To measure the model, mean squared error (MSE) and the coefficient of determination.

The main result showed that . . .

The implications of these results are . . .

I. OPPGAVE 2

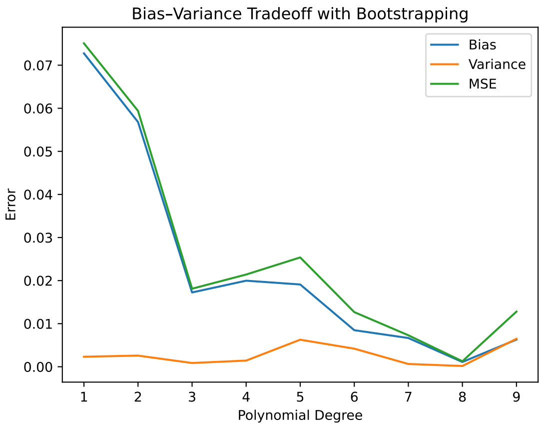

Figure 1: Plot showing the Bias-Variance-Tradeoff

As shown in Figure 1 the bias decreases with higher polynomial degrees.

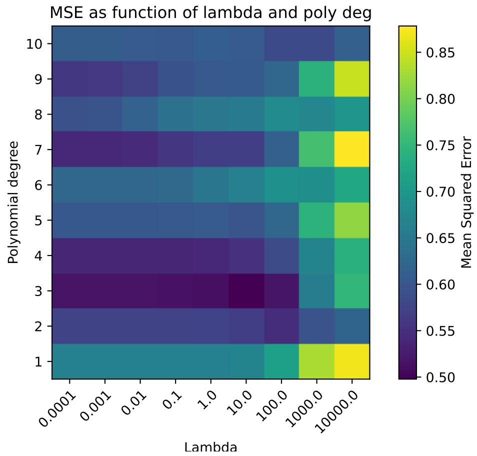

Figure 2: Heatmap showing MSE of Ridge regression for different polynomial degrees and lambda values.

From Figure 2, it is possible to see...

II. INTRODUCTION

Regression methods are among the fundamental building blocks for machine learning. Their simplicity and systematic approach make the methods widely used for modeling relationships between variables. However, the simplest techniques such as linear regression, face multiple challenges such as overfitting and poor performance when applied to complex or limited datasets [1]. Thus, regularized versions such as Ridge and Lasso regression, in addition to resampling techniques such as Bootstrap and cross-validation are used to address these issues. By using these methods, it is also possible to get an insight into the tradeoffs between bias and variance [2].

In this project, the focus is on the Runge function, which is a function that shows the Runge Phenomena. Carl David Tolme Runge showed that polynomial interpolation of this function using increasing degrees does not improve the fit, but instead the error often increases [3]. By fitting polynomials of different degrees using OLS, Ridge and Lasso regression, the performance of the model will be evaluated for the different complexities. Moreover, gradient decent methods, including momentum, ADAgrad, RMSprop and ADAM, will be implemented as iterative alternatives to the closed-form solutions. Finally, resampling techniques such as Bootstrap and cross-validation will be explored to understand the bias-variance tradeoff.

This report is divided into four sections and organized as follows. Section II: Methods describes the theoretical backgorund and implementation details of the used models. Section III: Results and Discussion presents, analyzes and discusses the obtained results for different methods, polynomial degrees, data sizes and parameters. Section IV: Conclusion concludes our main findings and summarizes their implications.

III. OPPGAVE5

a) MSE is often used to evaluate the performance of a machine learning model [2]

b) [4]

IV. METHODS

A. Method 1/X

B. Implementation

C. Use of AI tools

During the implementation of the code Artificial intelligence such as ChatGPT were used for error correction and debugging. In particular, AI were used for help in clarification of error messages. The immediate feedback accelerated the debugging phase which potentially saved a lot of time spent on finding and correcting minor issues in the code

V. RESULTS AND DISCUSSION

VI. CONCLUSION

[1] S. Kumar and V. Bhatnagar, Journal of Intelligent Systems and Computing (2022), URL `https://en.wikipedia.org/wiki/Regression_analysis`.

[2] T. Hastie, R.Tibshirani, and J.Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition. Springer Series in Statistics* (Springer, New York, 2009), URL `https://link.springer.com/book/10.1007%2F978-0-387-84858-7`.

[3] Wikipedia contributors, *Runge's phenomenon* (2025), [Online; accessed 25-September-2025], URL `https://en.wikipedia.org/wiki/Runge%27s_phenomenon`.

[4] P. et al., Journal of Machine Learning Research pp. 2825–2830 (2011), URL `https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html`.