Lecture 13
Model Selection and Hyperparameter Tuning

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DATASCI 112

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1. Recap
2. Model Selection and Hyperparameter Tuning
3. Grid Search

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How do we choose between all the options (scaler, k, etc.)?

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The distinction isn't important. We always use cross-validation and pick the model / hyperparameter with the smallest test error.

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for features in [["win", "summer"],
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  print(features, -scores.mean())
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What is the best value of k?

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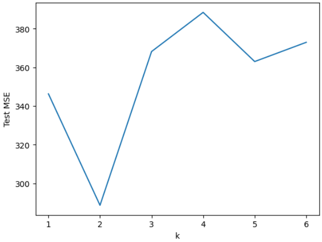

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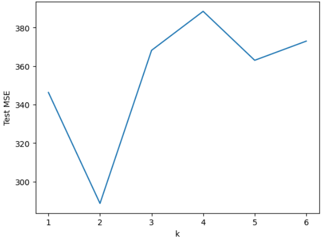
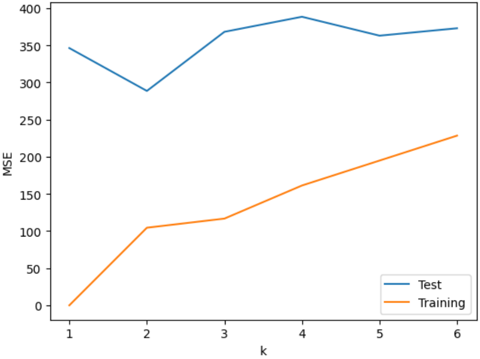


The best value of k is 2.

Training vs. Test Error

Here are the training and test MSEs on the same graph.



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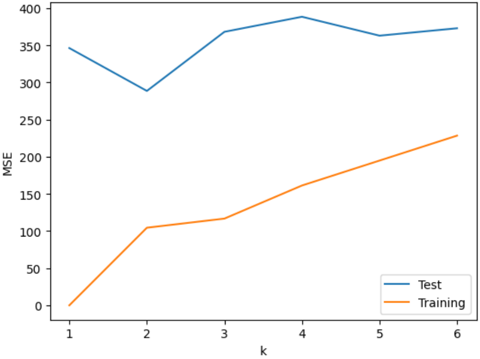

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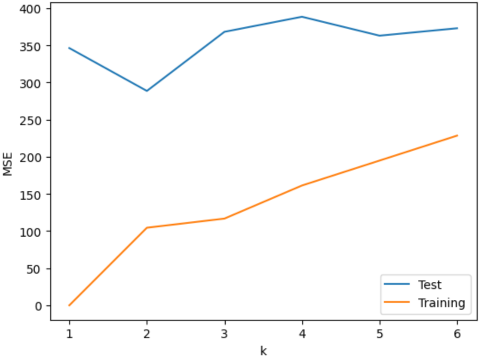

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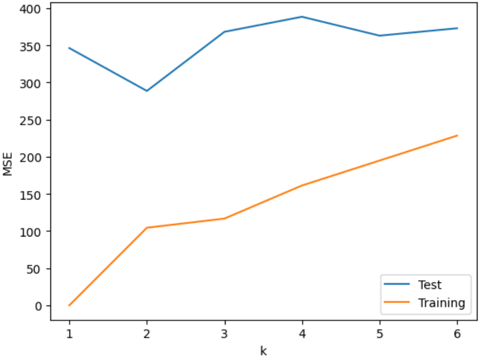

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If we optimize for training MSE, then we will pick $k = 1$, but this has worse test MSE.

In other words, the $k = 1$ model has **overfit** to the training data.

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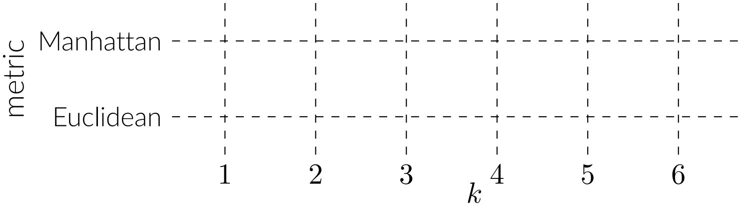

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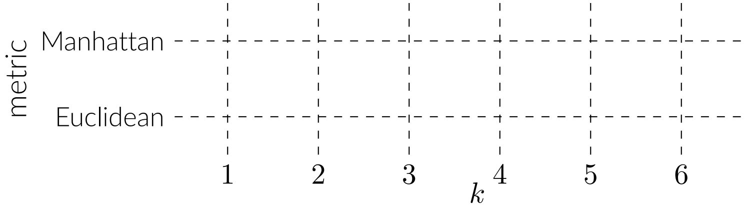

Scikit-Learn's `GridSearchCV` automates the creation of a grid with all combinations.

Grid Search in Scikit-Learn

Let's try out `GridSearchCV` in a Colab.

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And that's not even considering models besides k-nearest neighbors!

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  - start with guesses for all parameters,
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You will have the chance to practice this on Lab 4, which is a kaggle competition to build the best machine learning model. There will be prizes for the winners!