Bais-Variance Trade Off Overfitting Vs. Underfitting

Polynomial Regression – Bias Variation Trade - off

- We have seen that a higher order polynomial model performs significantly better than a standard linear regression model.
- But how can we choose the optimal degree for the polynomial?
- What trade-offs are we to consider as we increase model complexity?

Polynomial Regression – Bias Variation Trade - off

- In general, increasing model complexity in search for better performance leads to a **Bias-Variance trade-off**.
- We want to have a model that can generalize well to new unseen data, but can also account for variance and patterns in the known data.

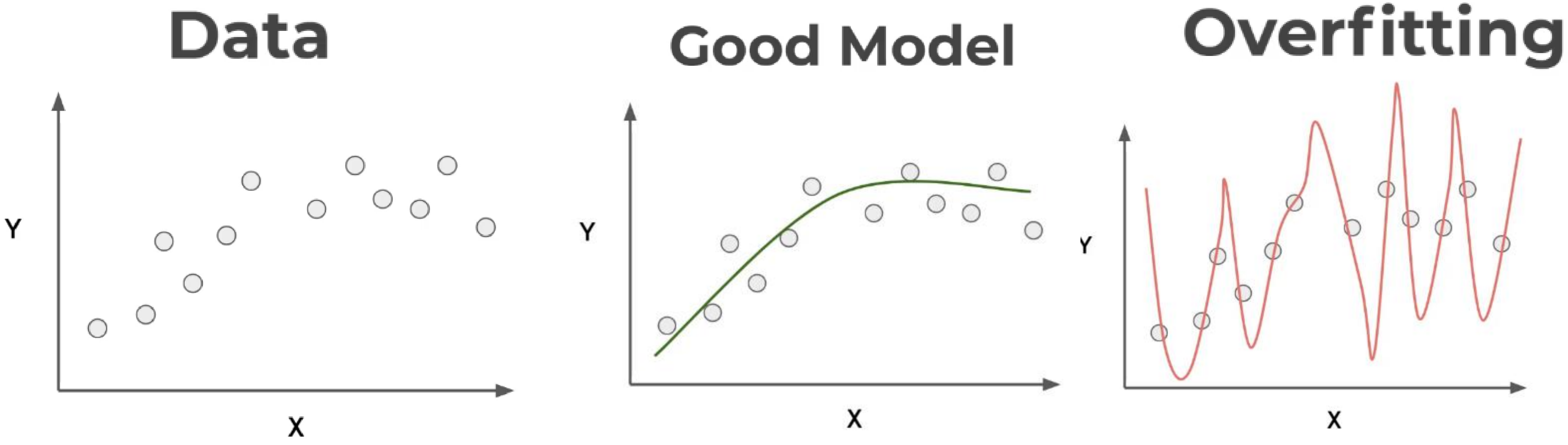
Polynomial Regression – Bias Variation Trade - off

- Extreme bias or extreme variance both lead to bad models.
- We can visualize this effect by considering a model that underfits (high bias) or a model that overfits (high variance).
- Let's start with a model that overfits to a dataset...

Polynomial Regression – Bias Variation Trade - off

- **Overfitting**
  - The model fits too much to the noise from the data.
  - This often results in **low error on training sets but high error on test/validation sets.**

Polynomial Regression – Bias Variation Trade - off



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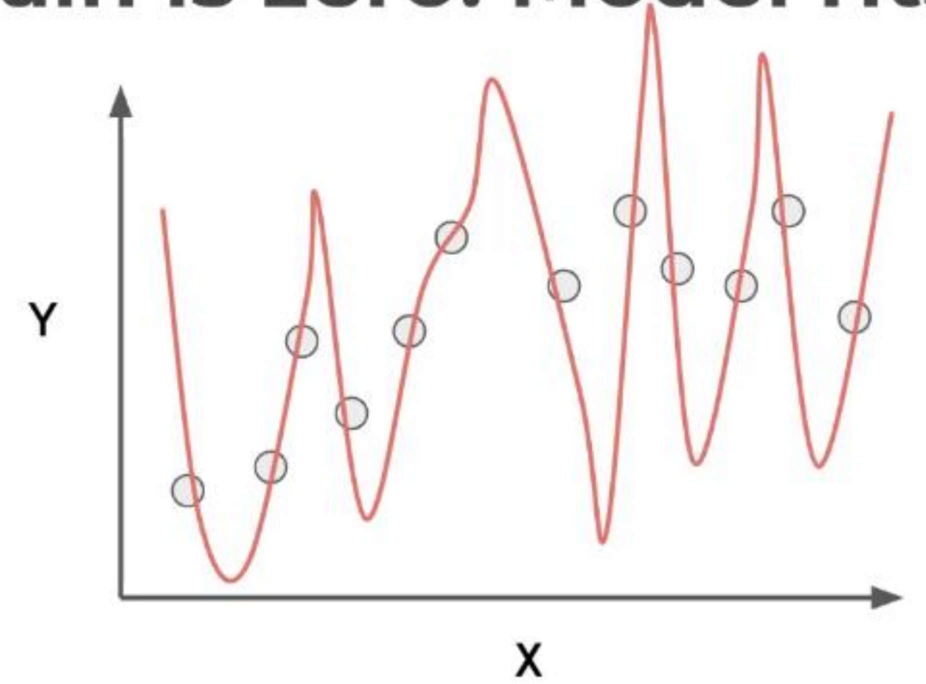
- **Error on train is zero! Model fits perfectly!**



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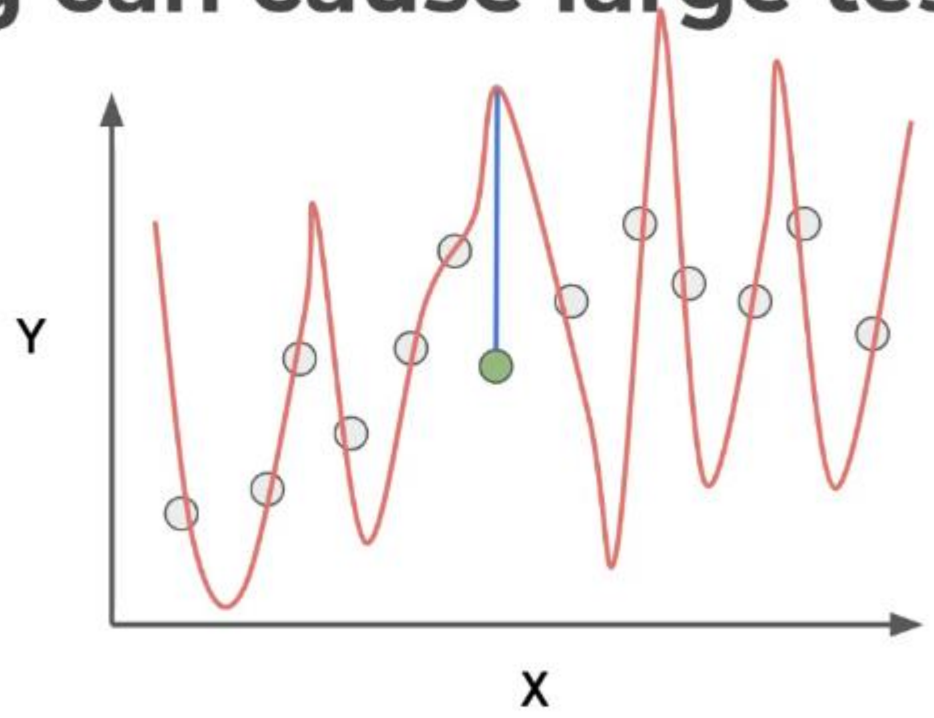
- **Overfitting can cause large test errors!**



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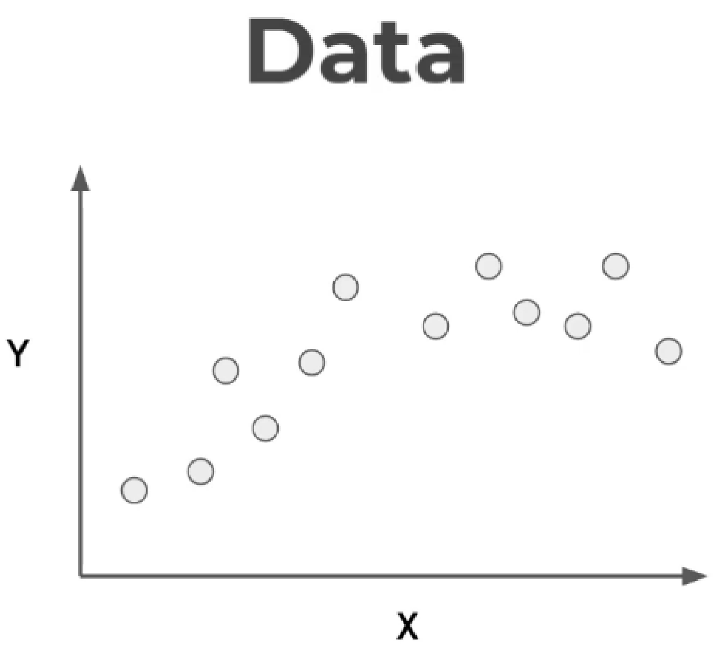
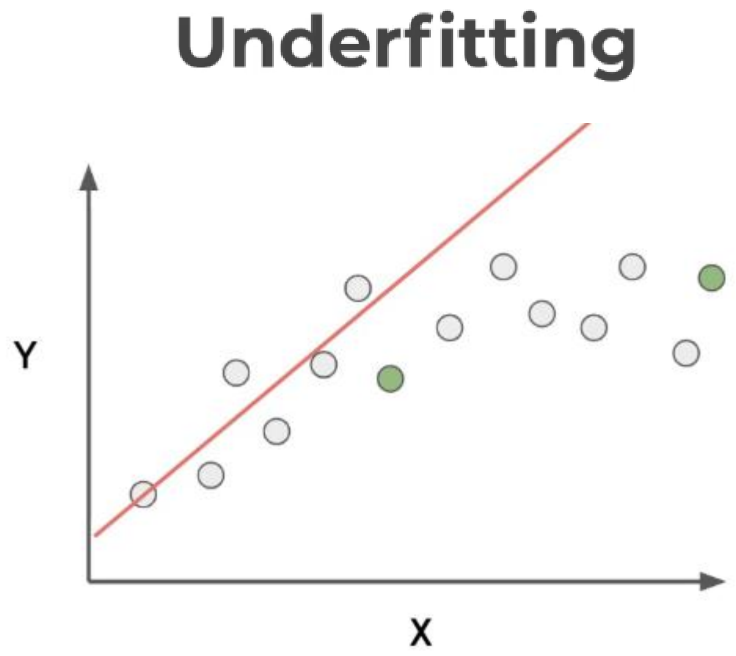
- **Overfitting**
  - Model is fitting too much to noise and variance in the training data.
  - Model will perform very well on training data, but have poor performance on new unseen data.

Polynomial Regression – Bias Variation Trade - off

- **Underfitting**
  - Model does not capture the underlying trend of the data and does not fit the data well enough.
  - Low variance but high bias.
  - Underfitting is often a result of an excessively simple model.

Polynomial Regression – Bias Variation Trade - off





Polynomial Regression – Bias Variation Trade - off

- **Underfitting**
  - Model has high bias and is generalizing too much.
  - Underfitting can lead to poor performance in both training and testing data sets.

Polynomial Regression – Bias Variation Trade - off

- **Overfitting versus Underfitting**
  - Overfitting can be harder to detect, since good performance on training data could lead to a model that appears to be performing well.

Polynomial Regression – Bias Variation Trade - off

- This data was easy to visualize, but how can we see underfitting and overfitting when dealing with multi dimensional data sets?
- First let's imagine we trained a model and then measured its error versus model complexity (e.g. higher order polynomials).

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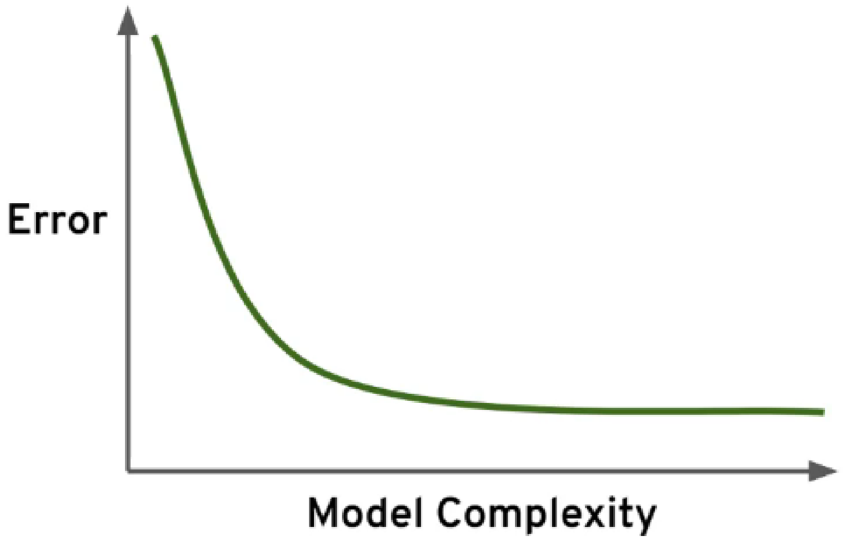
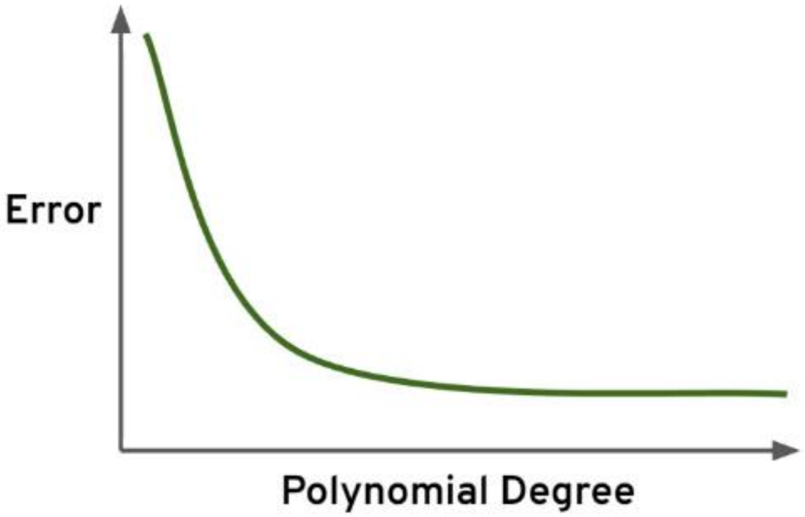
- Good Model





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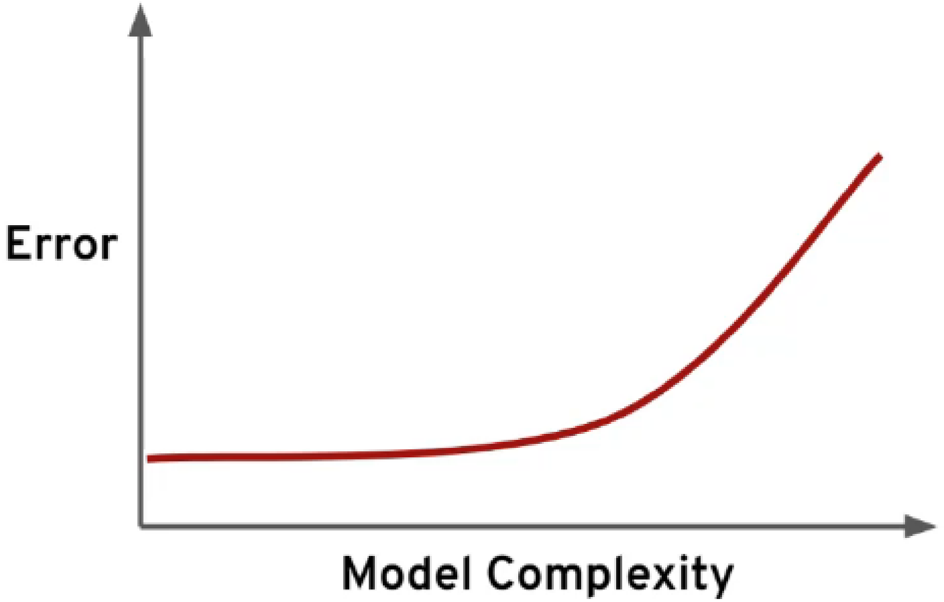
- Bad Model



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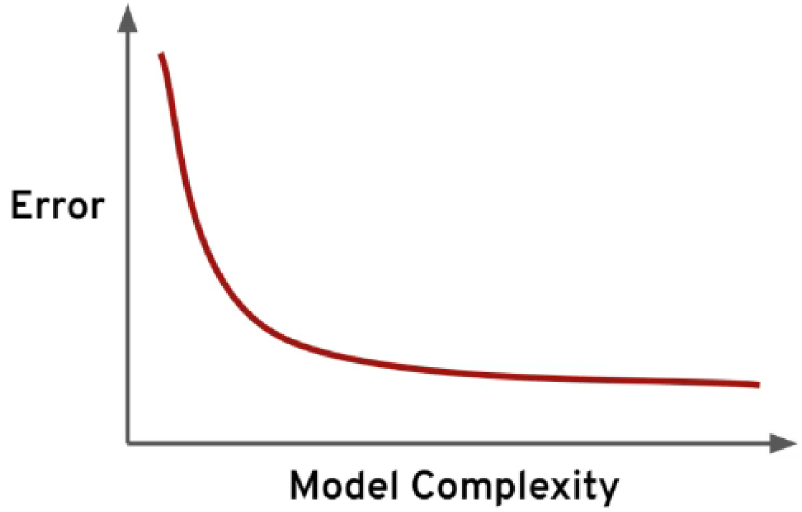
- When thinking about **overfitting** and **underfitting** we want to keep in mind the relationship of model performance on the training set versus the test/validation set.

Polynomial Regression – Bias Variation Trade - off

- Let's imagine we split our data into a **training set** and a **test set**
- We first see performance on the **training set**



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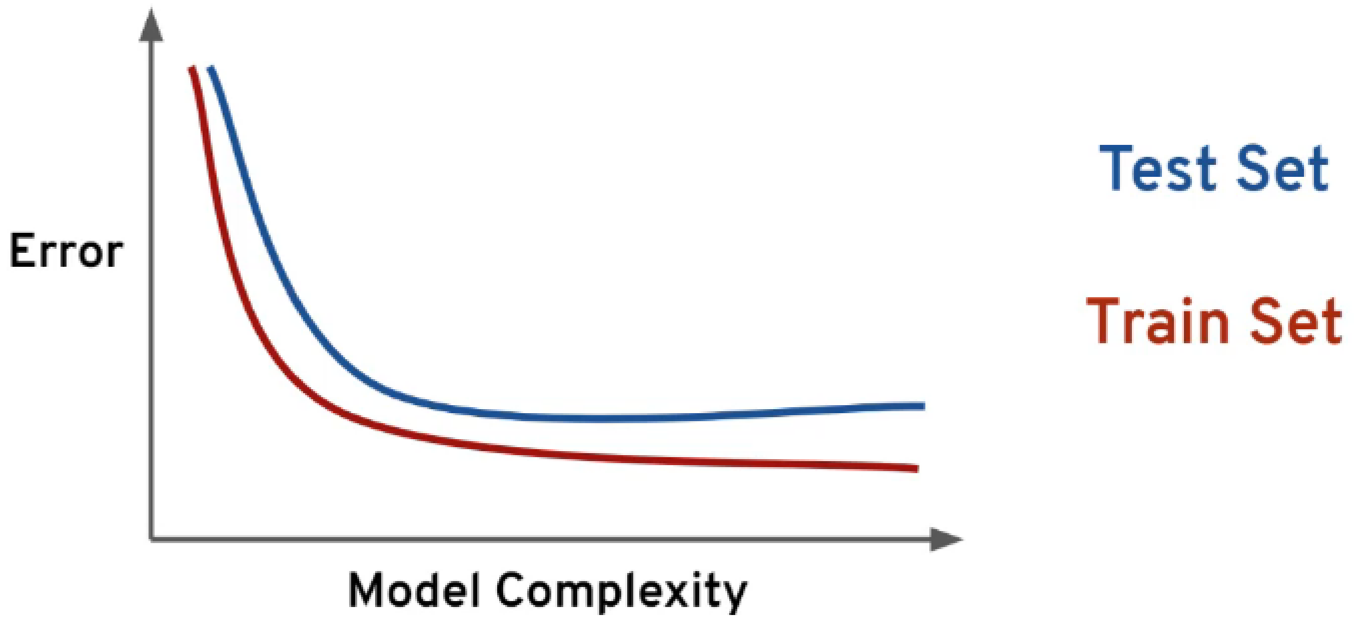
- We first see performance on the **training set**
- Next we check performance on the **test set**



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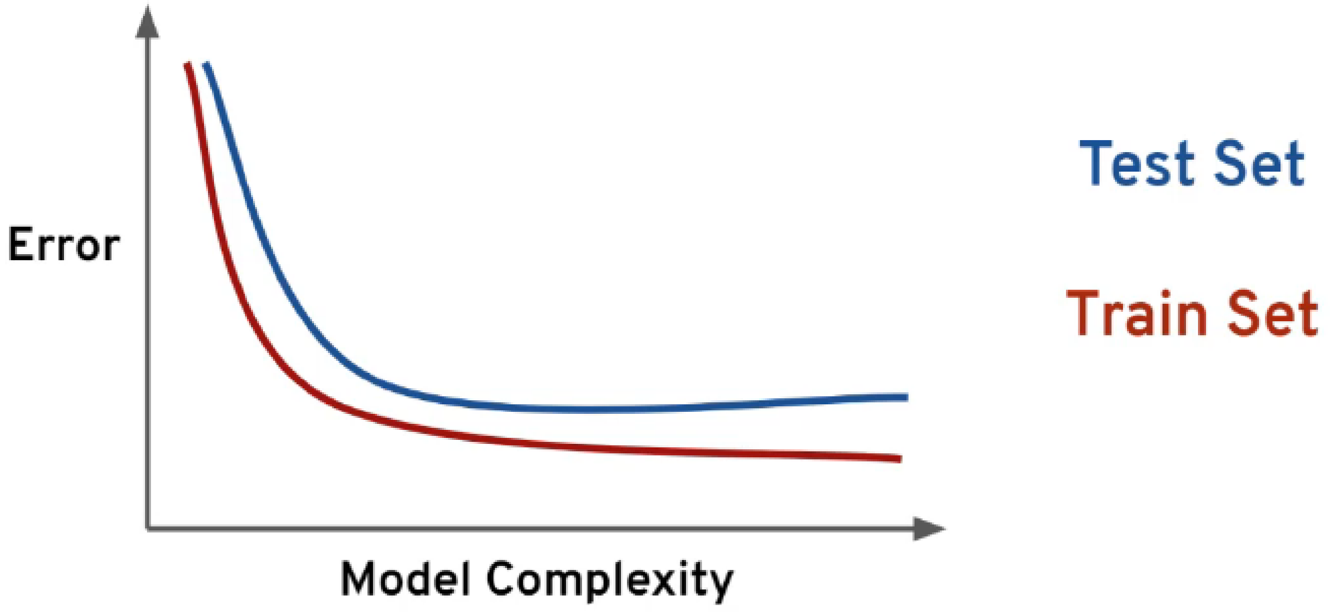
- Ideally the model would perform well on both, with similar behavior.



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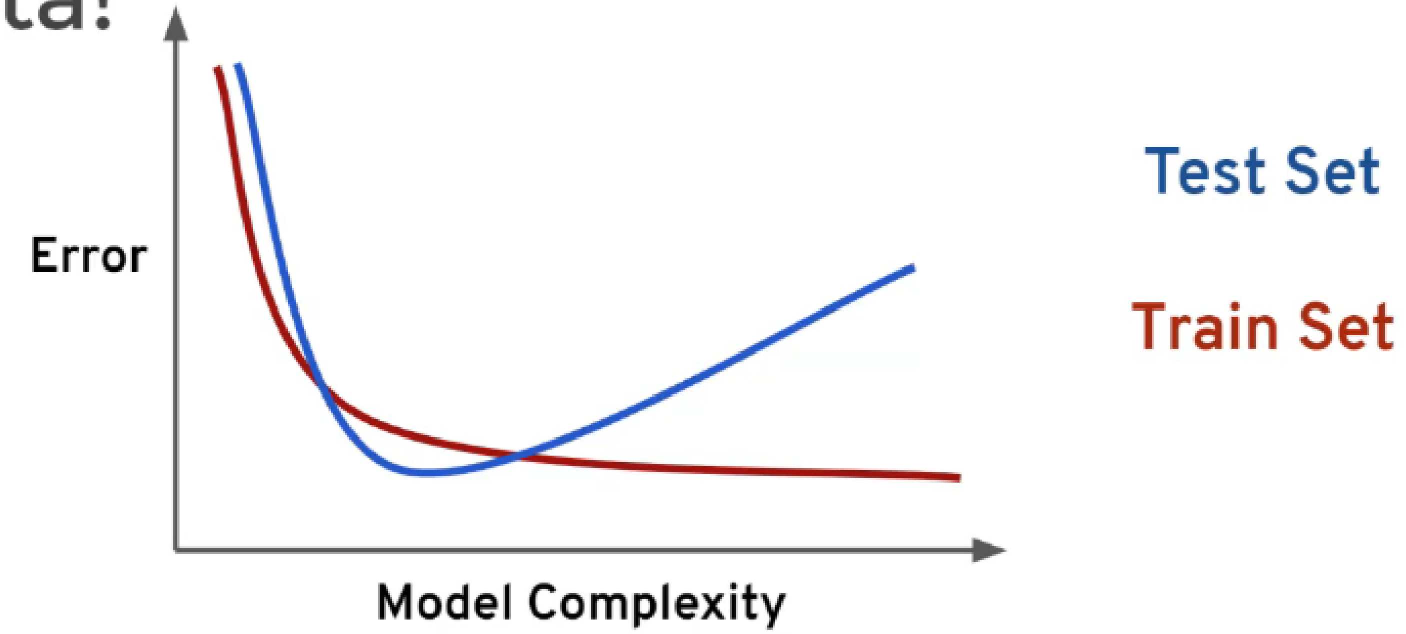
- But what happens if we overfit on the training data? That means we would perform poorly on new test data!



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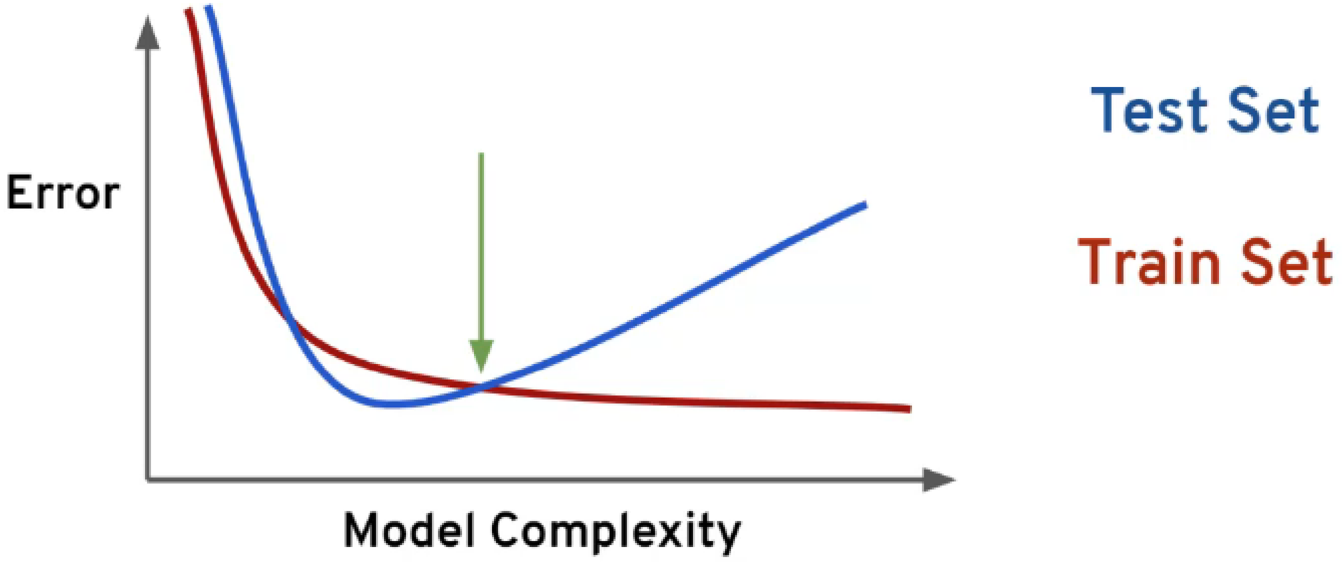
- This is a good indication too much complexity, you should look for the point to determine appropriate values!



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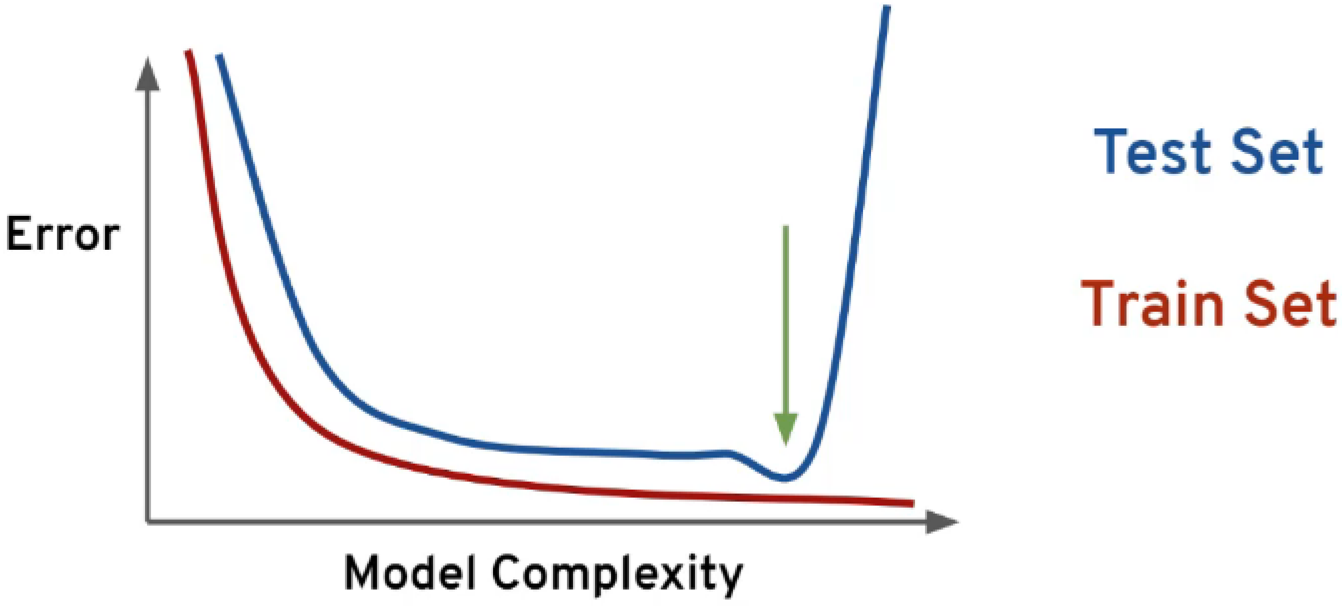
- For certain algorithms this test error jump can be sudden instead of gradual.



Polynomial Regression – Bias Variation Trade - off

- This means when deciding optimal model complexity **and** wanting to fairly evaluate our model's performance, we can consider both the train error and test error to select an ideal complexity.

Polynomial Regression – Bias Variation Trade - off

- In the case of Polynomial Regression, complexity directly relates to degree of the polynomial, but many machine learning algorithms have their own hyperparameters that can increase complexity.

Polynomial Regression – Bias Variation Trade - off

- Let’s explore this further in