The limits of OLS, prediction as evaluation, and cross validation

Advanced Quantitative Methods 2019

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Null-Hypothesis Significance Testing (again)

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- Gives a measure of how likely it is that the results we observe are due to random chance $\rightarrow$
- Allows us to draw inference about the population from a sample with some certainty

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- Testing many relationships will inevitably result in significant results
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- Relationships may be seen due to overfitting or influential observations

P-hacking

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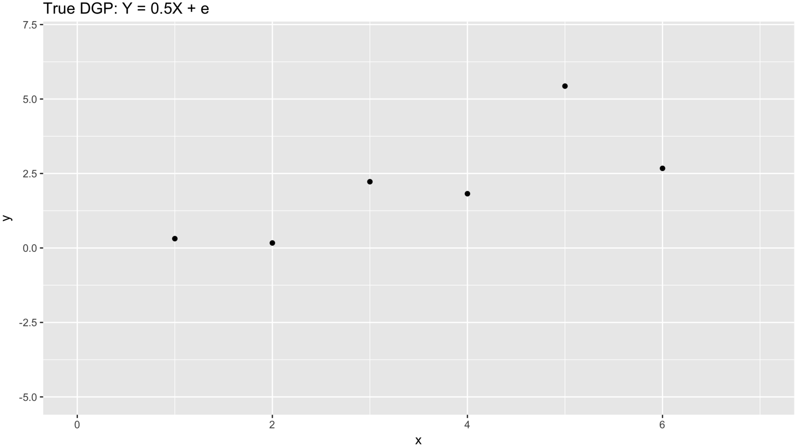
- Difficult to avoid
- Often associated with overfitting

An instructive example of overfitting



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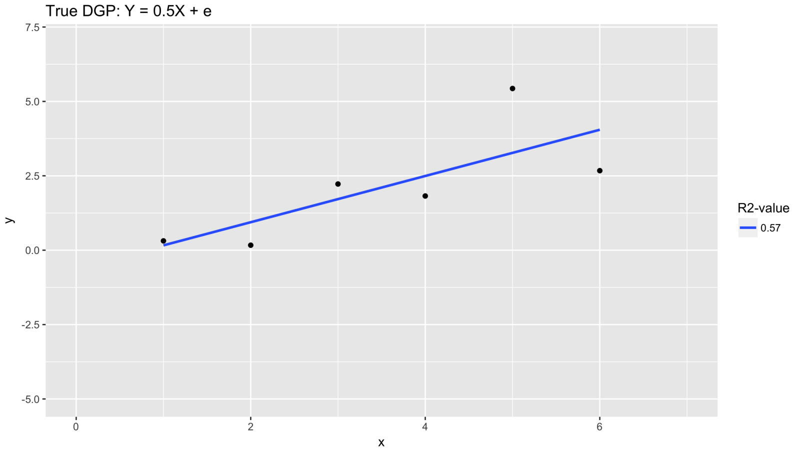

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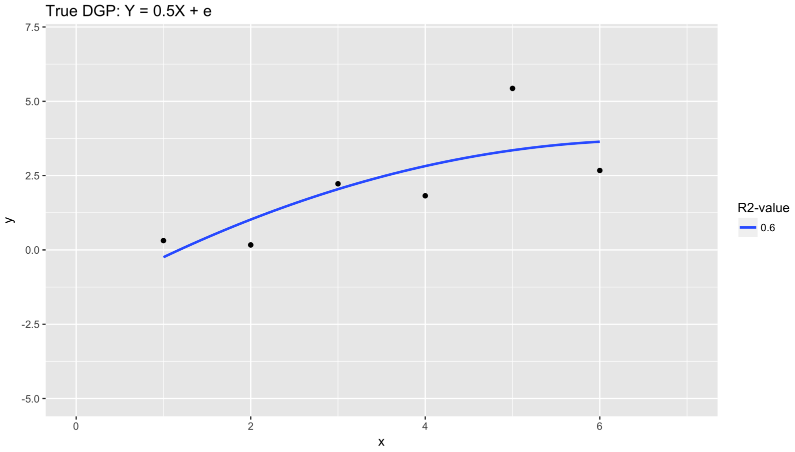

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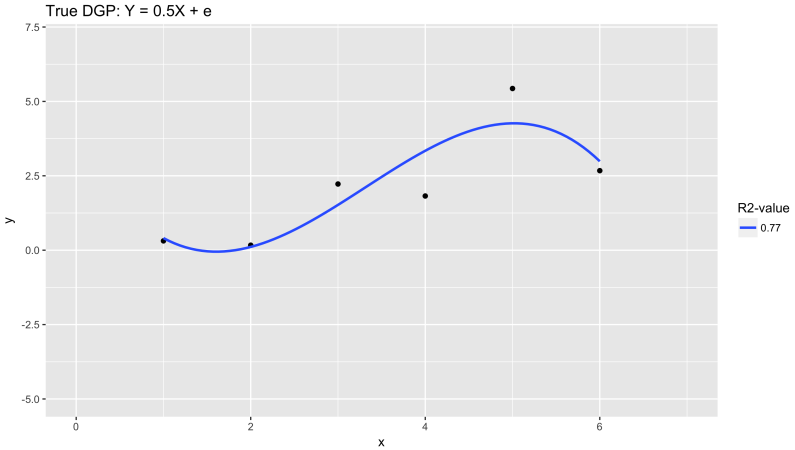

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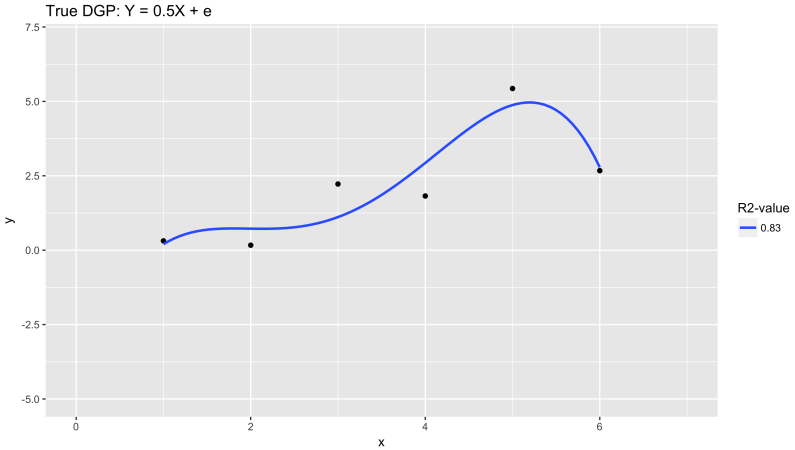

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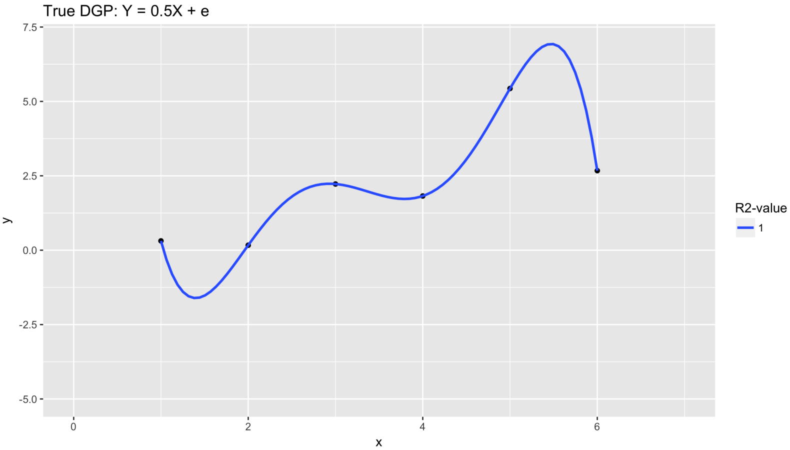

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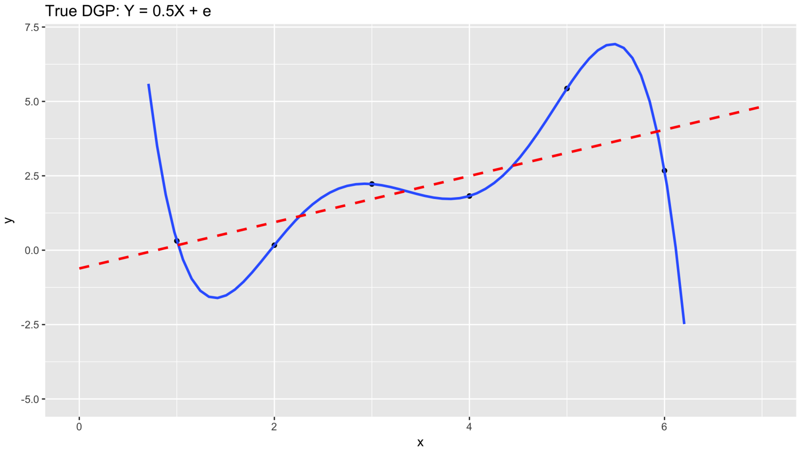

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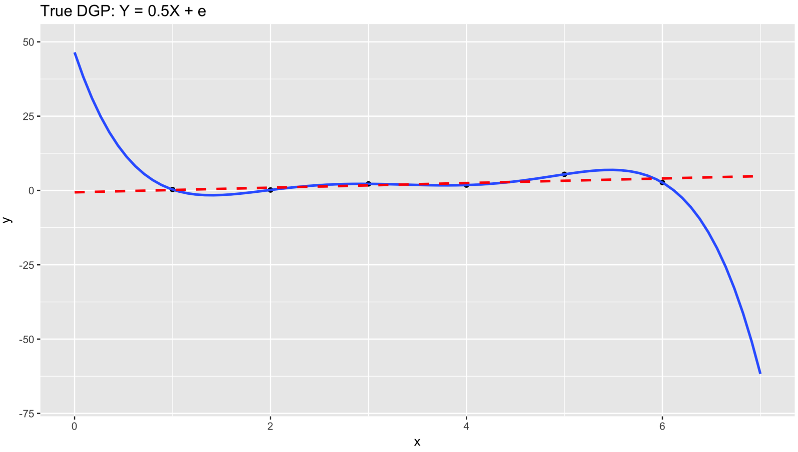

Enter: Predictive Methods

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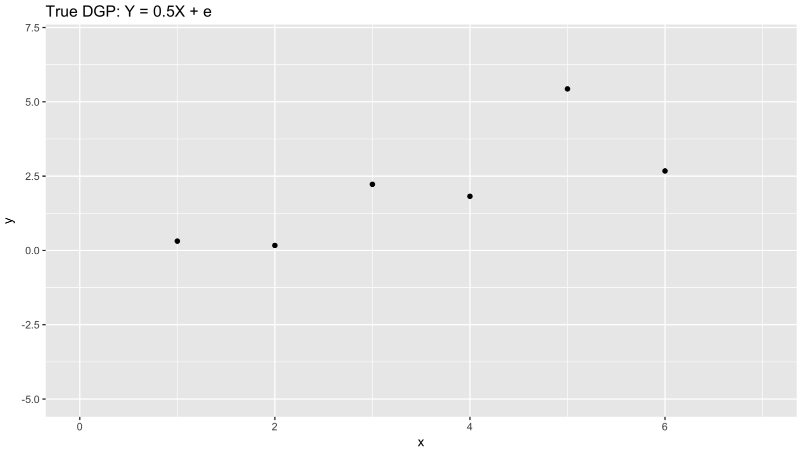
Is predictive modeling not sensitive to overfitting?


True DGP: Y = 0.5X + e
7.5
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2
4
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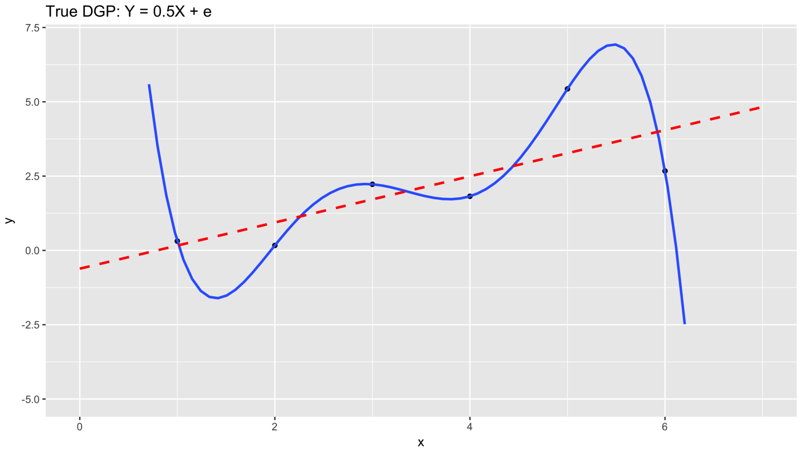
x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- The best 'test' data is data completely set aside by the researcher

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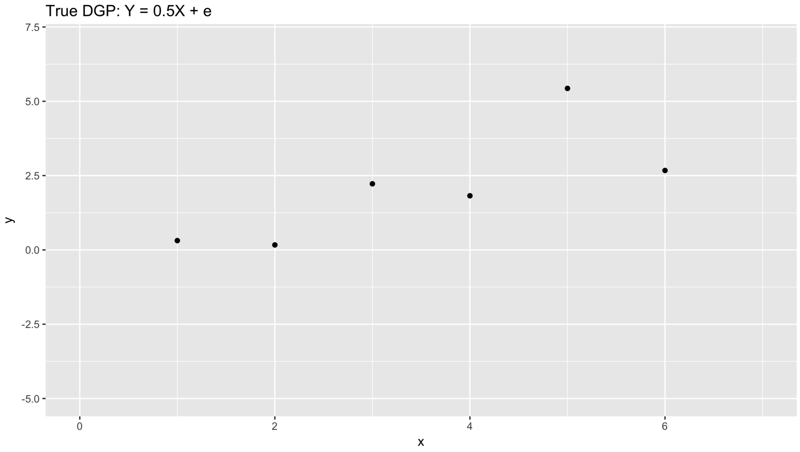
  8. Repeat 1-7 an appropriate number of times
  9. Calculate the mean (or some other quantity of interest) for the evaluation criteria across all simulations

Cross-Validation in practice



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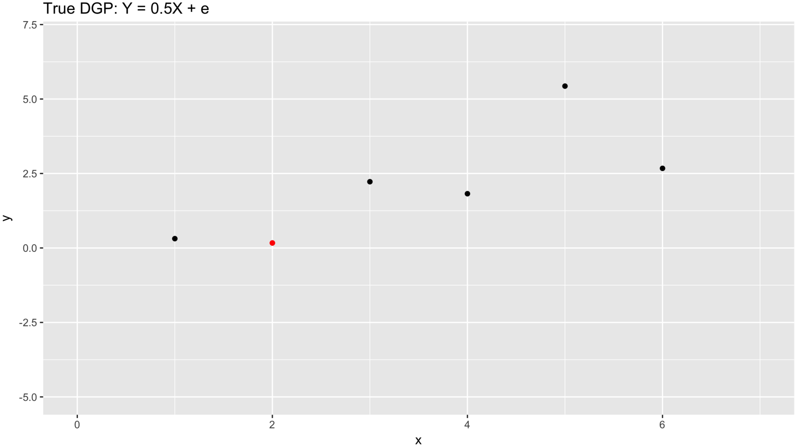

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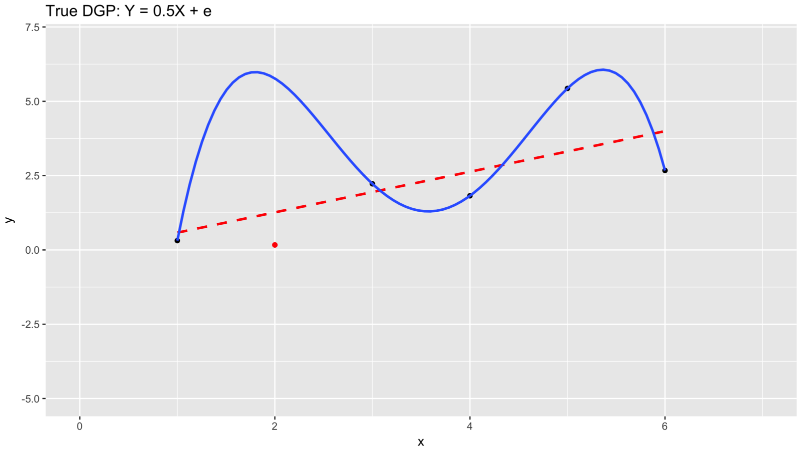

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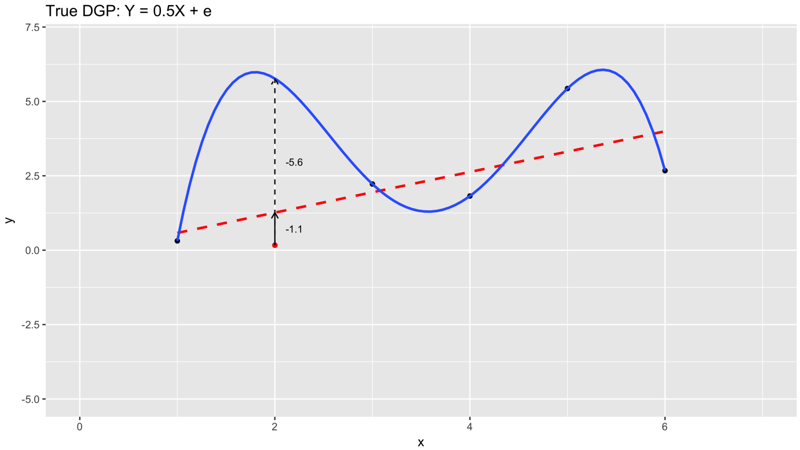

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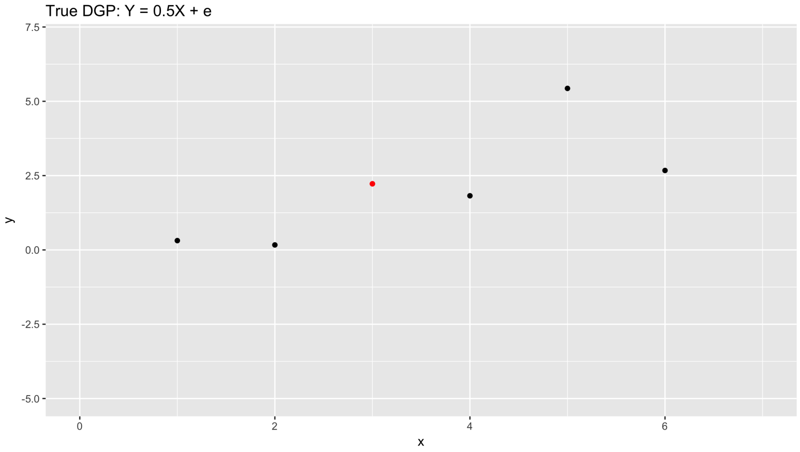

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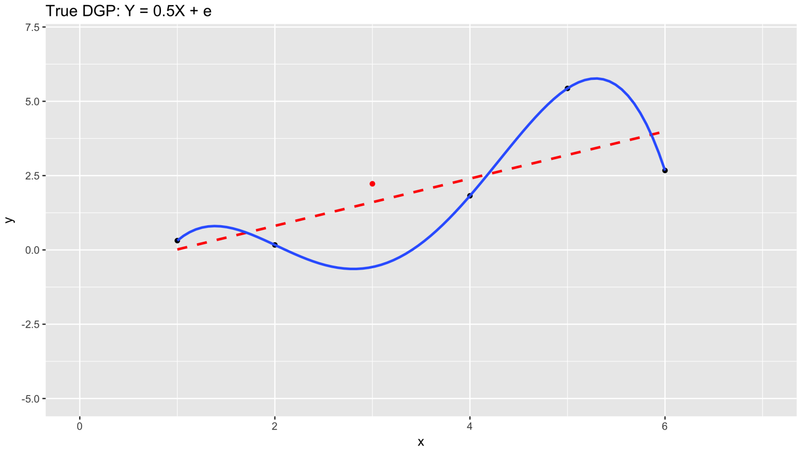

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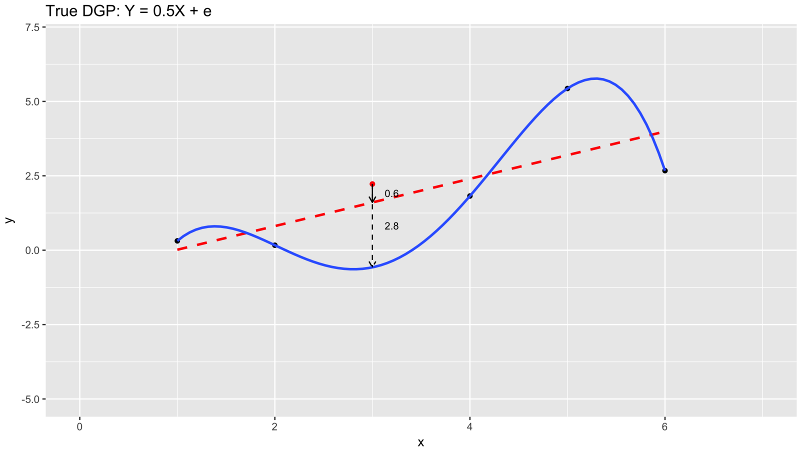

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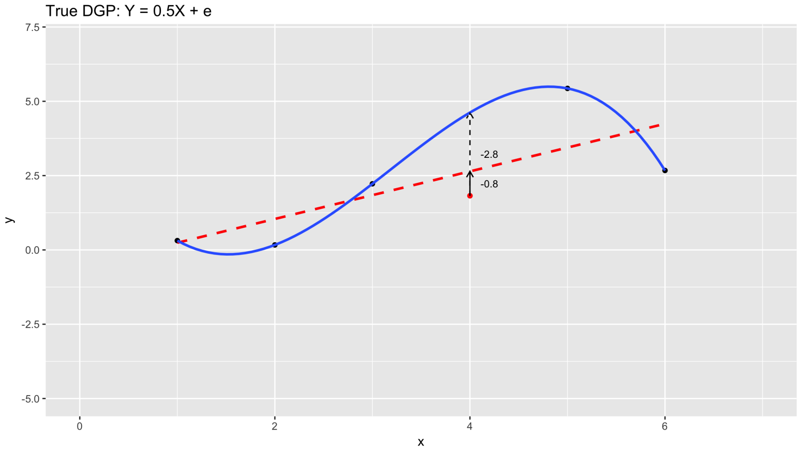

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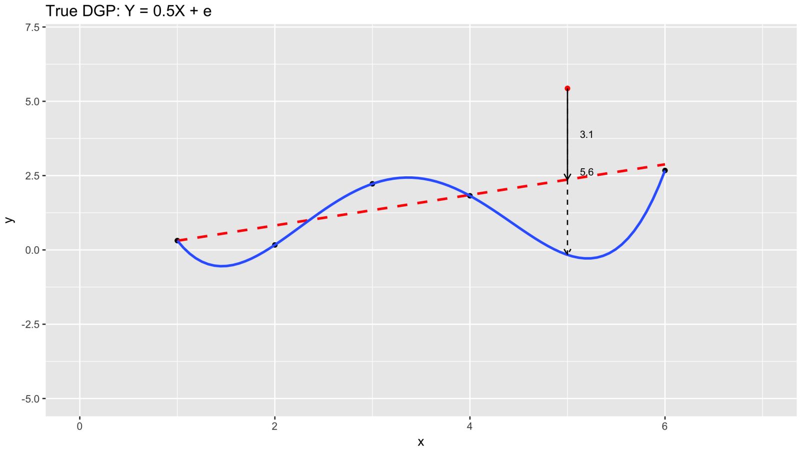

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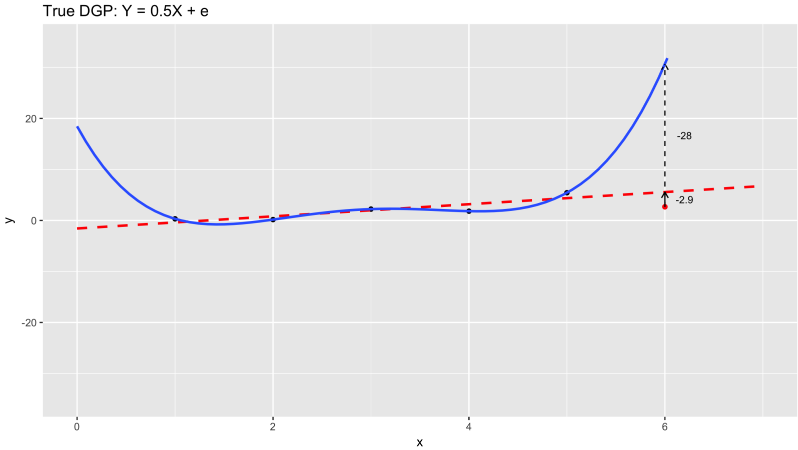

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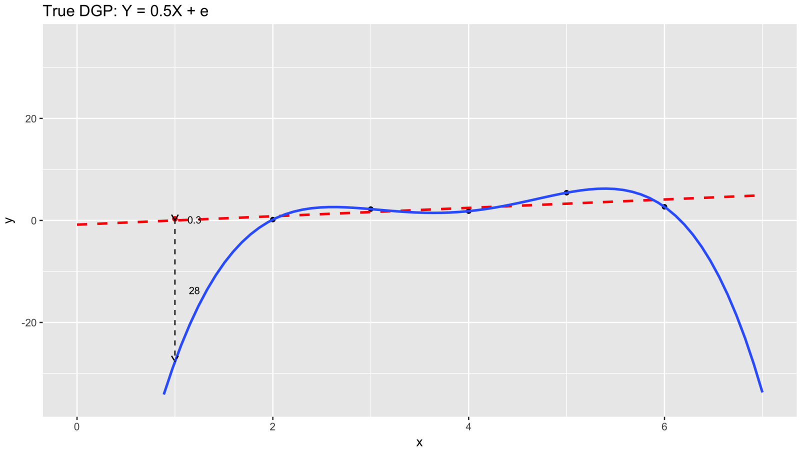

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- Correct fit CV RMSE≈ 1.8
- Overfit CV MAPE≈ 12.1
- Overfit CV RMSE≈ 16.6

Cross-Validation in practice

- Correct fit CV MAPE without extremes ≈ 1.4
- Correct fit CV RMSE without extremes ≈ 1.7
- Overfit CV MAPE without extremes ≈ 4.2
- Overfit CV RMSE without extremes ≈ 4.4

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- Allows for more nuanced analysis of variables than NHST
- Can easily be combined with NHST studies

Application: Ward et al 2010

- Uses predictive methodology to evaluate Fearon & Laitin 2003 and Collier & Hoeffler 2004

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- Shows the dangers of not thinking about prediction

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	Fearon & Laitin model	
Threshold	*Correctly predicted*	*False positives*
0.5	0/107	0
0.3	1/107	3
0.1	15/107	66

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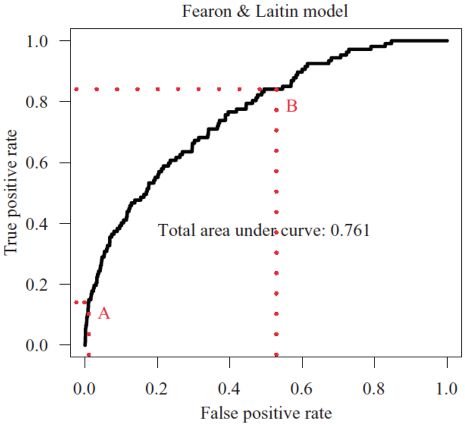

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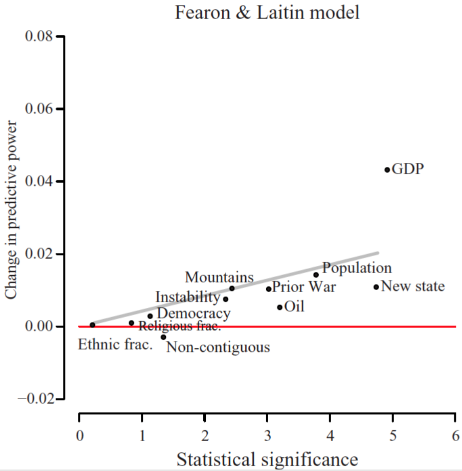

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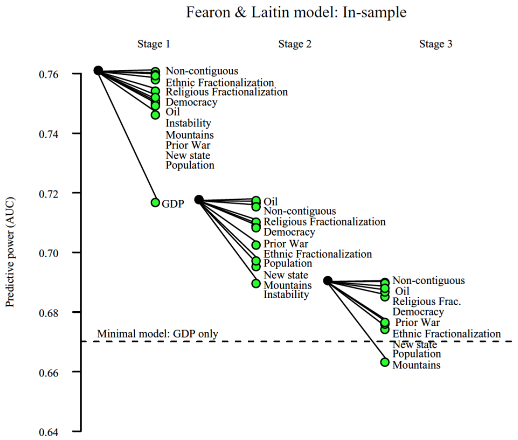

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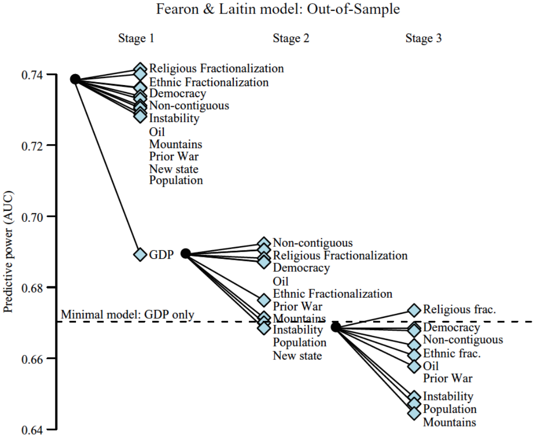

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- (k-fold) Cross Validation is a useful tool for implementing out of sample forecasts in a study