Regression Fit

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- 6. More . . .

R^2

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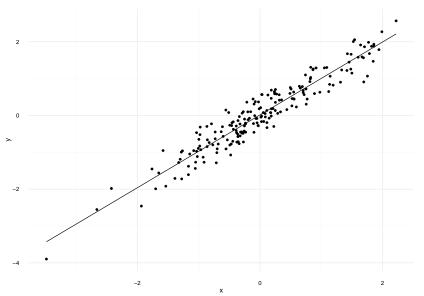
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 $ightharpoonup R^2 \in [0,1]$ where 1 is all points are on a line/plane

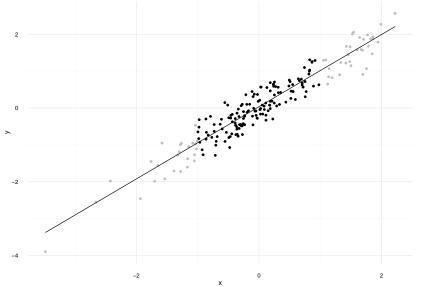
R-squared is dependent on scale of X



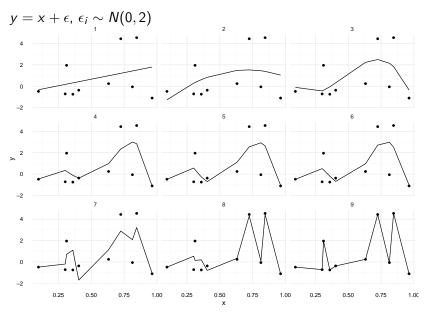
$$\hat{\sigma}^2 = 0.3, R^2 = 0.91$$

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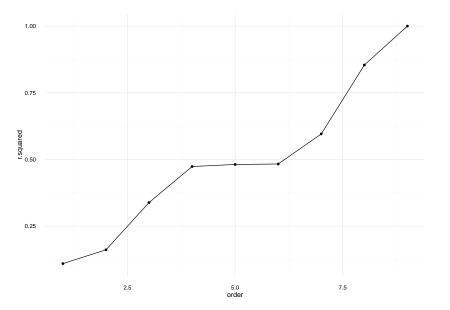
Same data, regression on subset



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- 3. Cannot compare different datasets (including transformed Y)
- 4. Not variance "explained" in causal sense

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- \triangleright Often suggested as alternative to R^2

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- ▶ Doesn't fix any important problem with R². Pointless for comparing models

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- 3. To interpret $\hat{\sigma}$ need to compare to scale (variance) of \mathbf{y} , but then almost the same as R^2 .

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- ▶ Inherits most of the same problems as R^2
- Assumes that linear model is correct, not whether it is a good model

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- 2. Focus on results/average of many models not the "best" model

Next time

Comparing predictive performance of models using cross-validation

References

► Gary King "How Not to Lie With Statistics: Avoiding Common Mistakes in Quantitative Political Science."

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- ▶ Cosmo Shalizi, F-Tests, R2 ad, and Other Distractions.
- R-squared: useful or evil?