# S&DS 361/661: Data Analysis

## Iterative fitting


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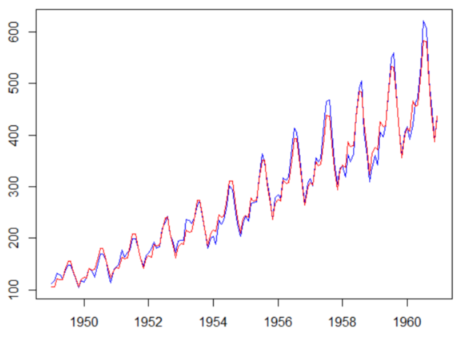

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- iterative fitting

# Iterative fitting steps

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- $log(\cdot)$ (or a shifted version such as $log(1 + \cdot)$ if there are values at or near zero)
- square-root

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For each explanatory variable, draw a scatterplot with the response variable. Identify the most predictive explanatory variable (if any), and devise a function of that variable (e.g. least-squares line, least-squares quadratic, ...) to predict the response.

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- Select the "simplest" function whose residuals show no (predictive) pattern. If you'd like you can place your residuals in a null-lineup; if they stand out, that indicates that there's likely a real pattern remaining. (But with experience, you'll get a better feel for whether or not there's a meaningful pattern. Then you might only draw a null line-up in tough cases or in order to convince a reader of your analysis.)

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- You might even use "iterative fitting" to find a good function for a single variable by finding one relationship at a time (recall the AirPassengers data).
- If it's not clear which variable is most predictive, you might compare the R-squared values of their (not necessarily linear) fits.

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- If recalculating the parameters is inconvenient, you can instead use the sum of the individual regression functions as your overall regression function.
- Repeat this process again with the new residuals and the remaining explanatory variables, and stop when none of the remaining explanatory variables have a (predictive) relationship with the residuals.

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- If you already have a lot of terms, you might have a lot of potential interactions to check. (With $k$ terms, there are $k$ choose 2 interaction terms.) In that case, you might not want to bother with this step.