Andrew Gard - equitable.equations@gmail.com

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We build a model using the sample data with the goal of applying it to new data from the population to make predictions about response variables of interest.

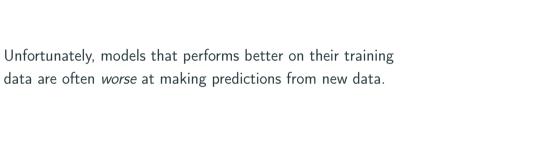
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For instance, linear regression picks out the line that minimizes the squared residuals (RSE) in the set while logistic regression minimizes residual deviance. A classification models might be optimized to identify as high a proportion of the sample correctly as possible.



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Unfortunately, models that performs better on their training data are often *worse* at making predictions from new data. **Overfitting** refers to when a model goes too far out of its way to accommodate the peculiarities of the set used to build it, integrating random noise as if it were meaningful information.

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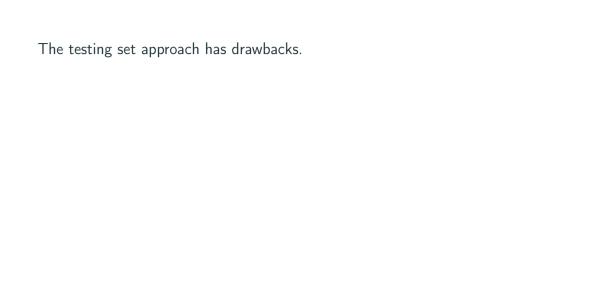
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The idea is simple: the sample data is split into two sets, a **training set** used to fit the model and a **testing set** used to evaluate the model.



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On the other hand, the approach is easy to understand, and to code. It's also very computationally effective.