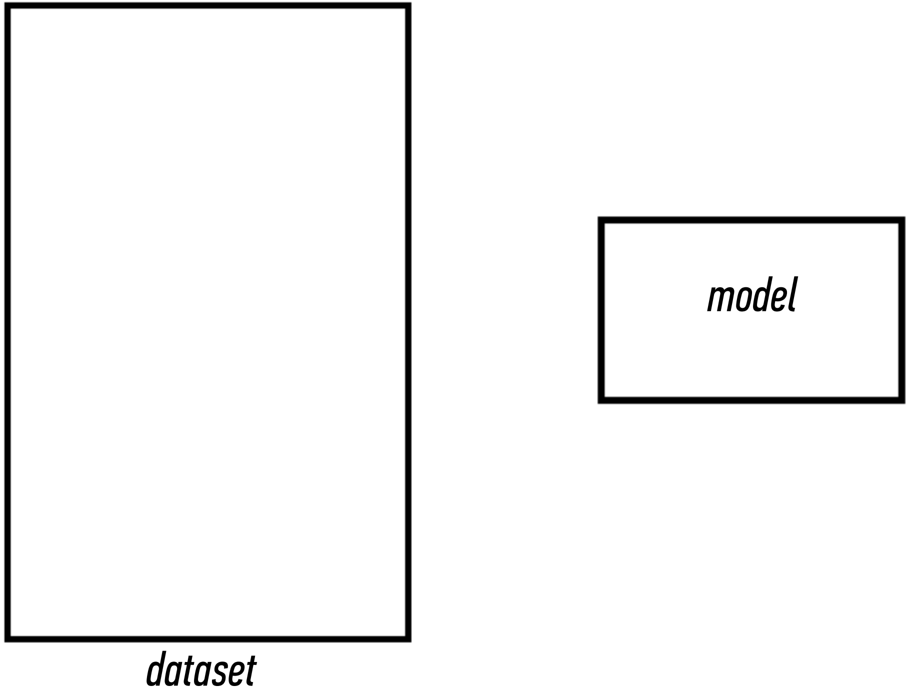
GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

CROSS-VALIDATION

Q: What steps does a classification problem require?



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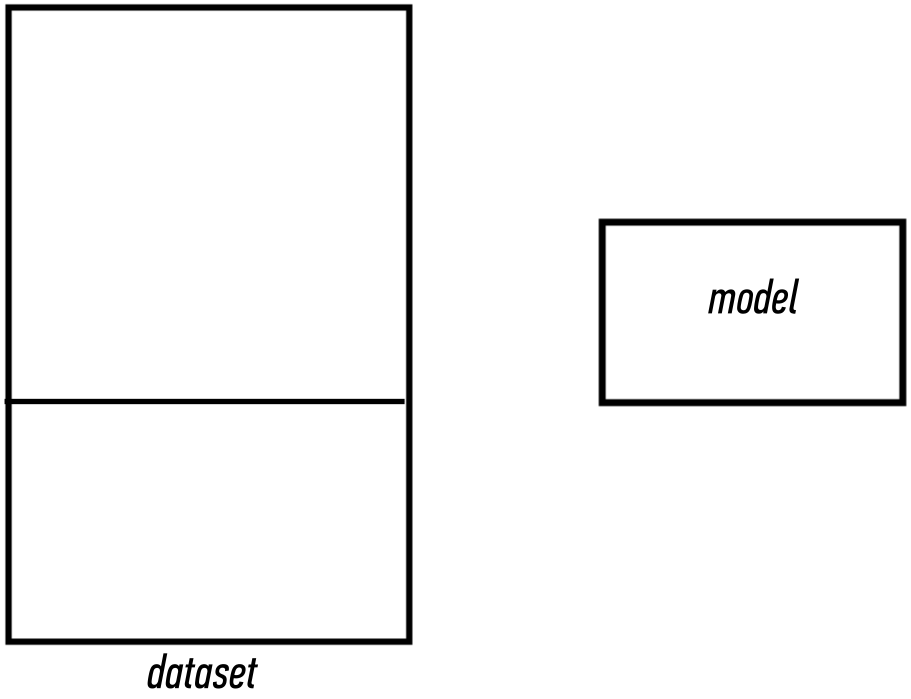
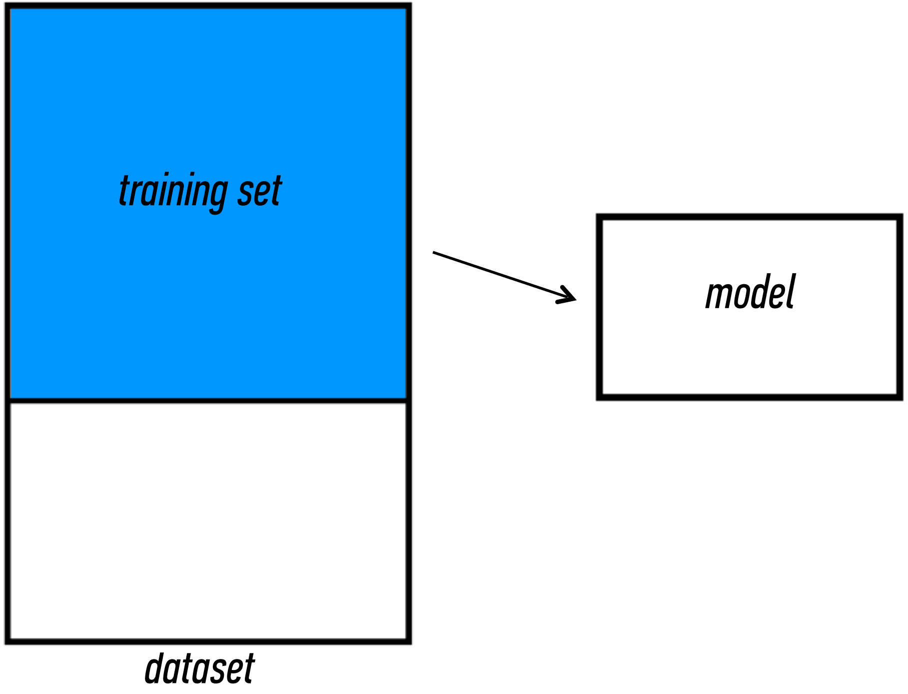


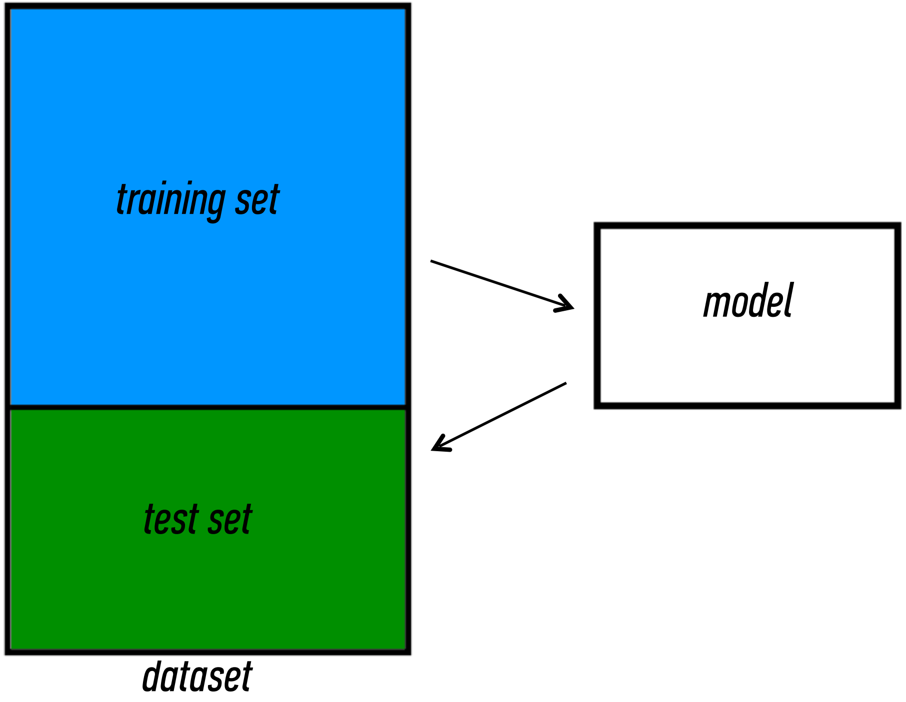
Q: What steps does a classification problem require?

1) split dataset
2) train model



Q: What steps does a classification problem require?

1) split dataset
2) train model
3) test model



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1) split dataset
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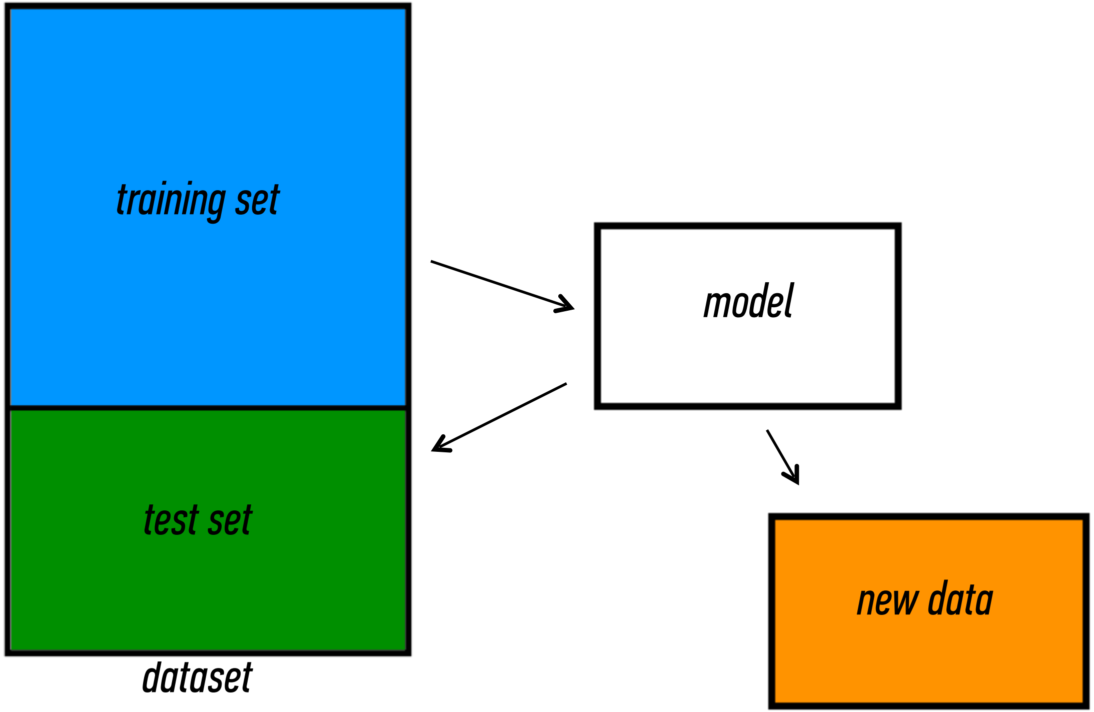

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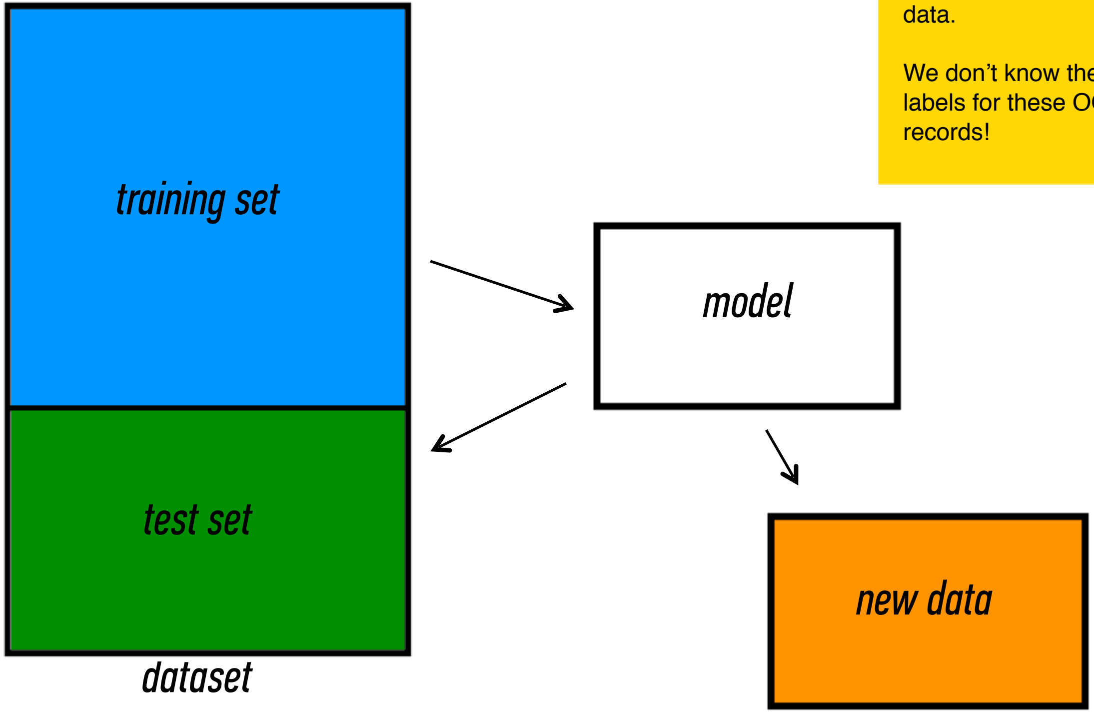


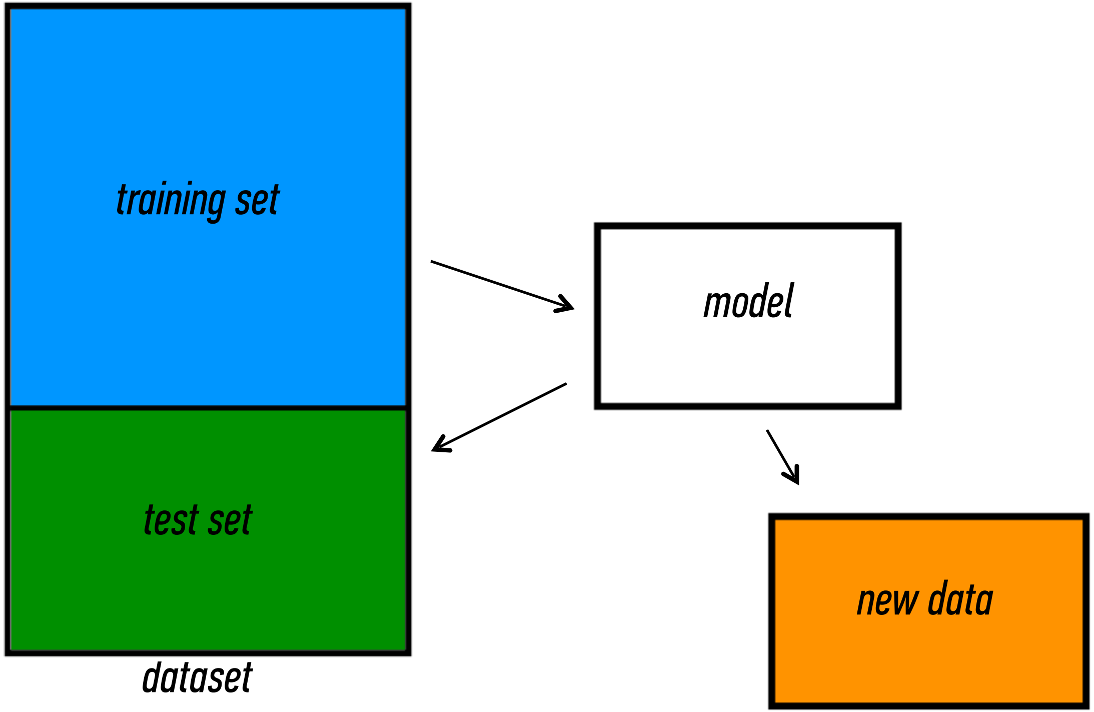
NOTE

This new data is called *out of sample* data.

We don't know the labels for these OOS records!

III. BUILDING EFFECTIVE CLASSIFIERS

Q: What types of prediction error will we run into?



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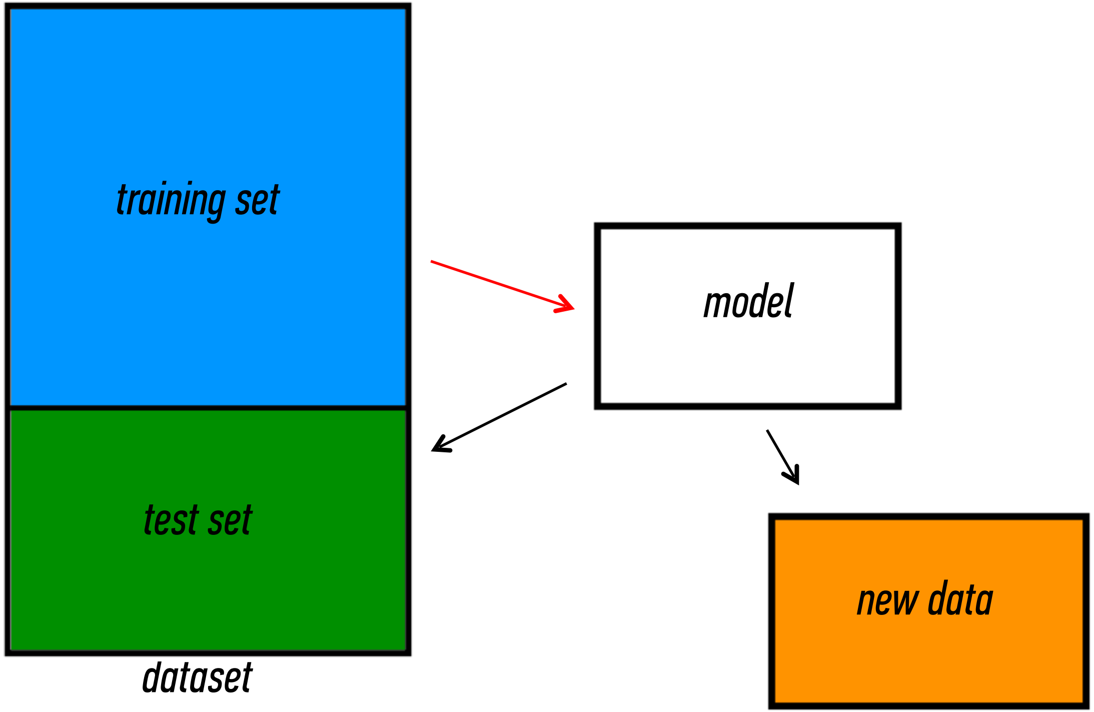

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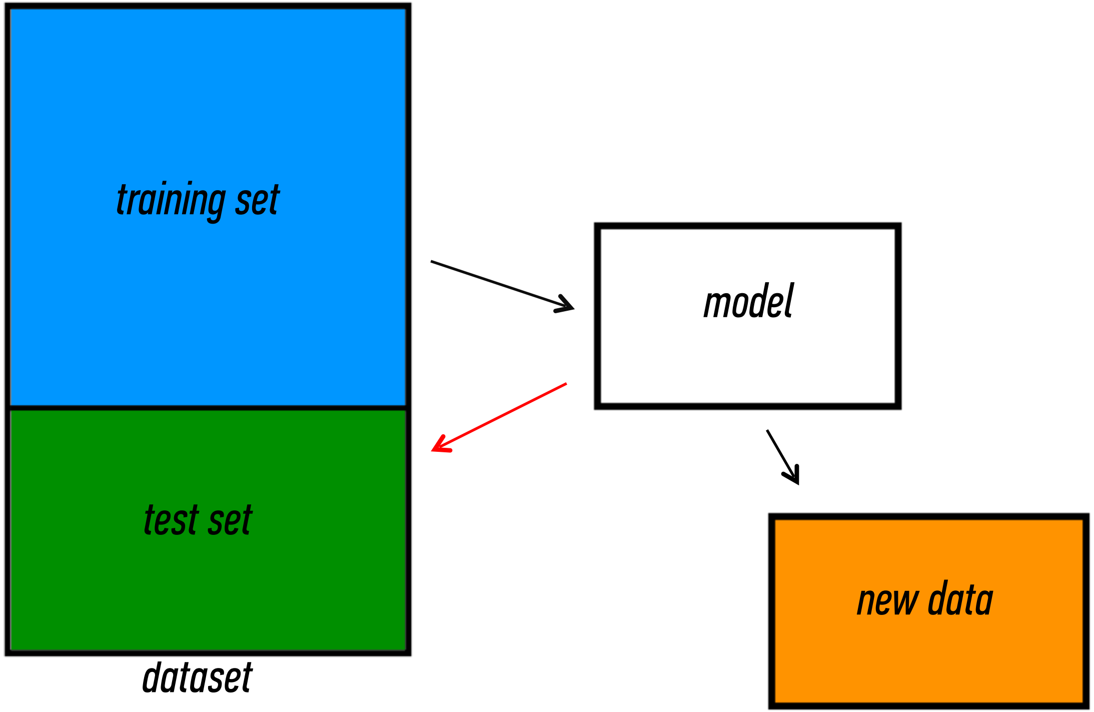

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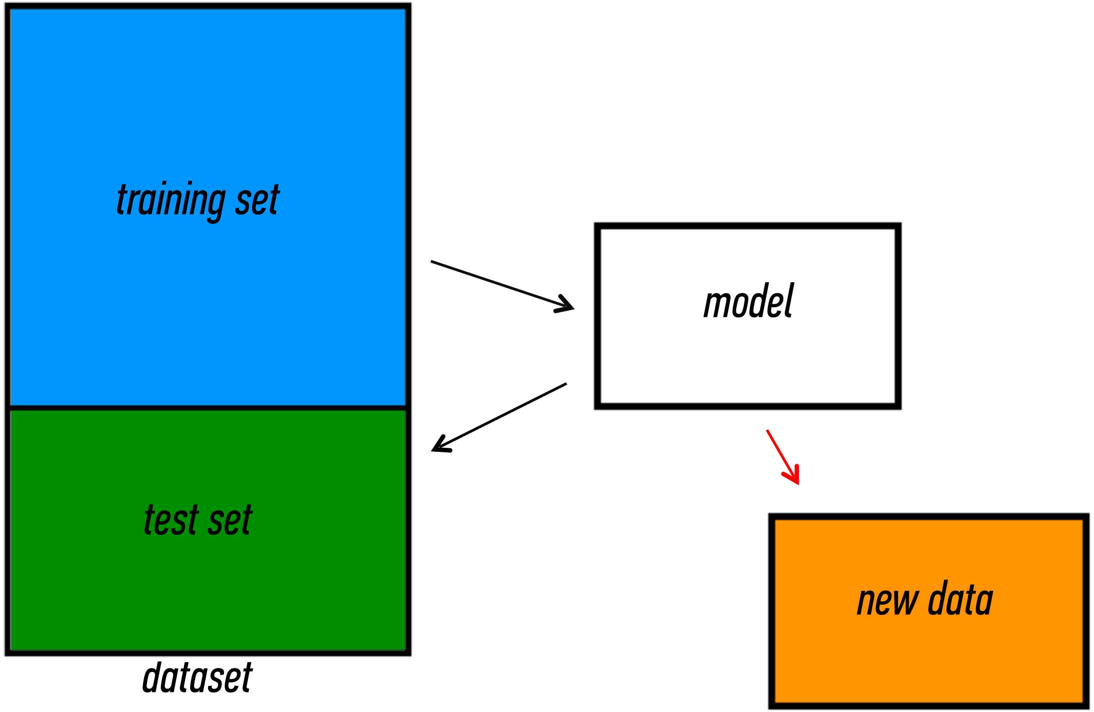

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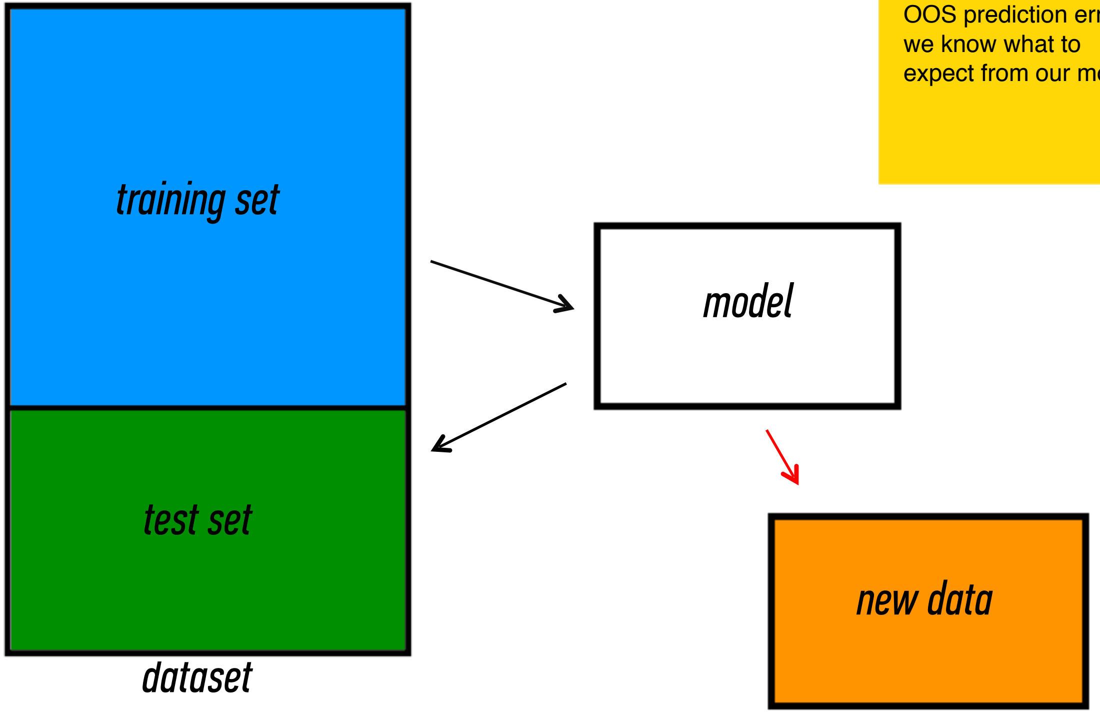

NOTE

We want to estimate OOS prediction error so we know what to expect from our model.

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NOTE

This phenomenon is called *overfitting*.

OVERFITTING

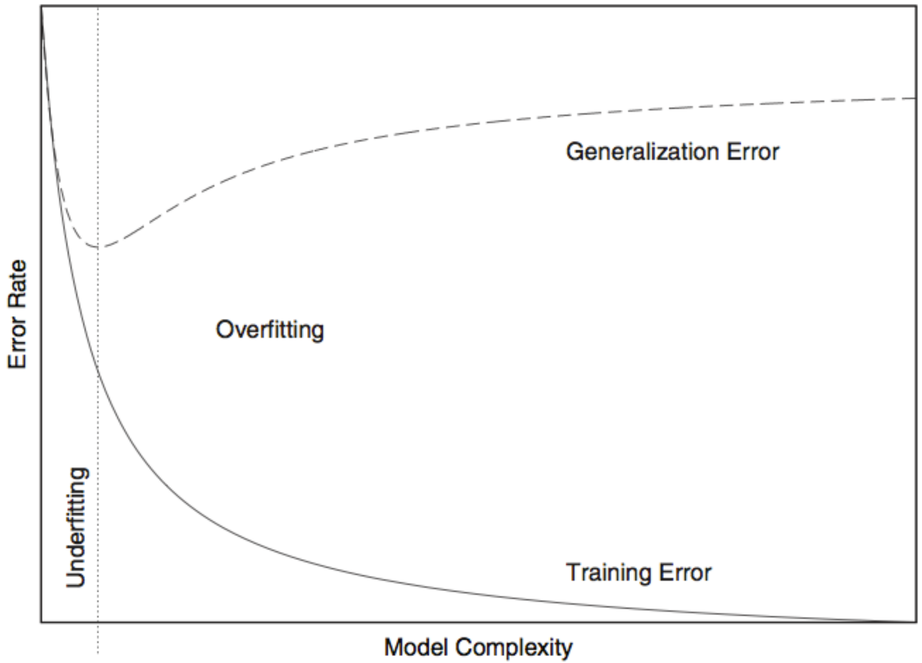
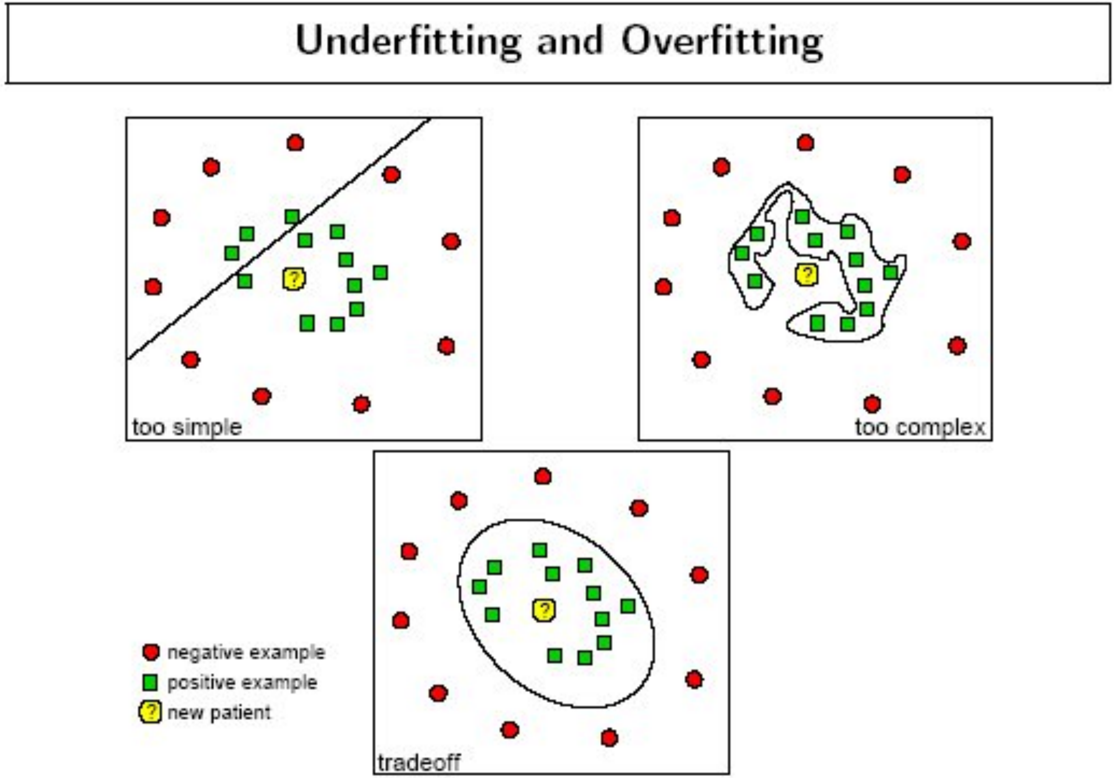


FIGURE 18-1. Overfitting: as a model becomes more complex, it becomes increasingly able to represent the training data. However, such a model is overfitted and will not generalize well to data that was not used during training.

source: Data Analysis with Open Source Tools, by Philipp K. Janert. O'Reilly Media, 2011.

OVERFITTING - EXAMPLE



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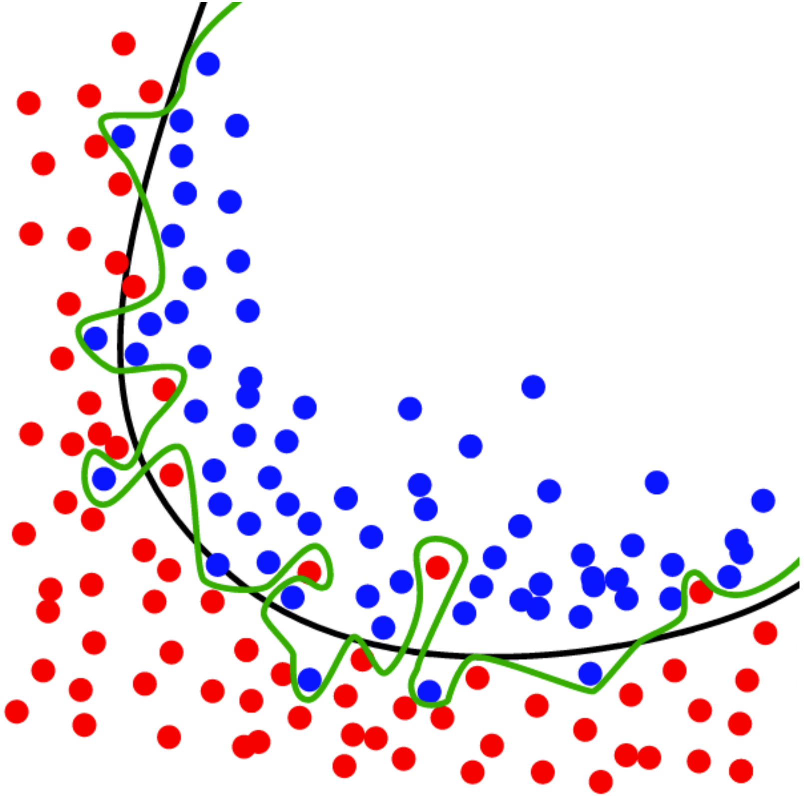

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TRAINING ERROR

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This phenomenon is called *overfitting*.

A: Training error is not a good estimate of OOS accuracy.

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NOTE

The generalization error gives a *high-variance estimate* of OOS accuracy.

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5) *Take the average generalization error as the estimate of OOS accuracy.*

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3) *Presents tradeoff between efficiency and computational expense.*
   - *10-fold CV is 10x more expensive than a single train/test split*
4) *Can be used for model selection.*