Training, validating and testing

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How do we know which rooted to pick? E.g. for linear regression we can choose the degree of polynomial features, the number of RBF basis functions, and the value of 2 for L, or L2 regularisation. How do we choose which of these to use? Classification: We could look at the loss (or another e.g. accuracy (metric such as MSE or RMSE) on the training I data. But this is problematic since the More complex/expressive model (e.g. high order polynomial, lower values of 25 will always do better (on the training data).

Idea: Use a held-out validation set (which you don't train on) and evaluate different model options on that.

(xe", y"), (xe", y"), (xe", y")

Training set

80%.

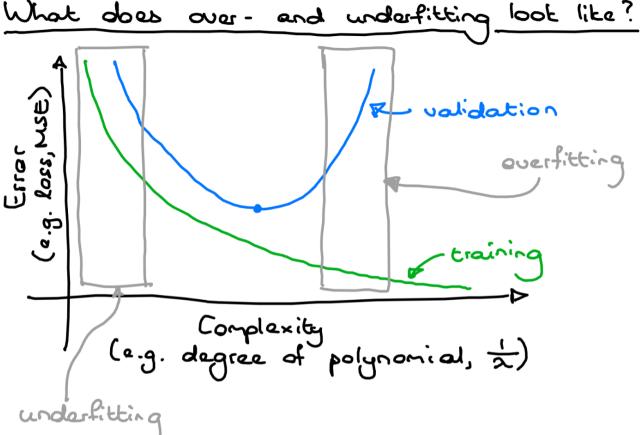
Fit noolels on this part

this part

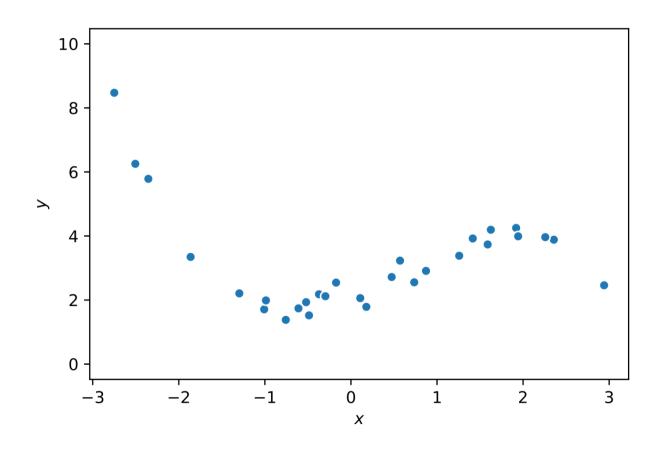
How well does the model generalize?
How well could you expect the model to perform on completely new data?
Could report validation metric, but this is likely to be optimistic (we actually had to fit some hyperparameters like I on the validation data).

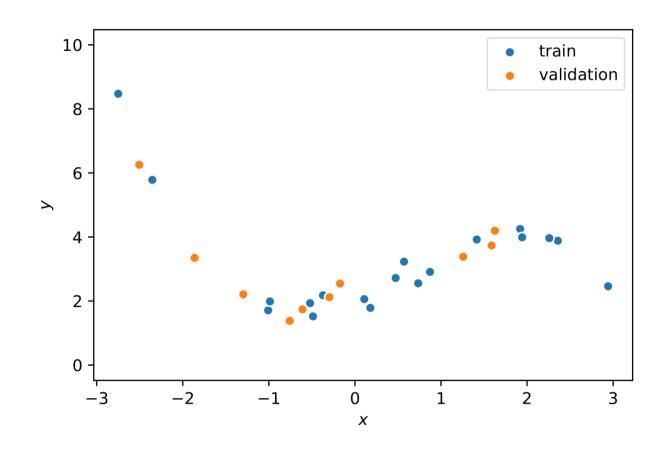
Idea: Report final performance on a completely held-out test set. Try to use this set as little as possible (ideally never) in model development.

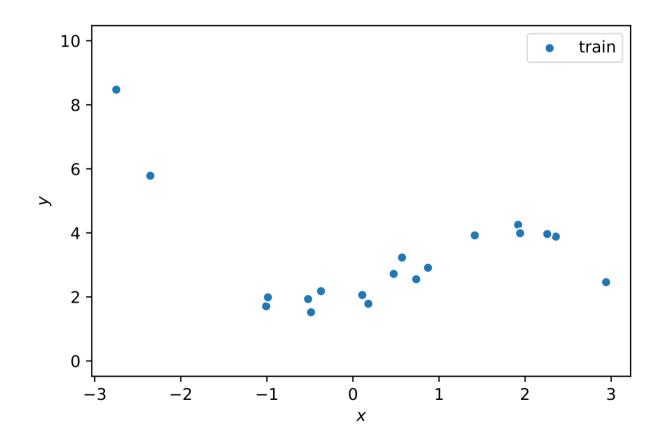
 $(\underline{x}^{(1)}, y^{(1)}), (\underline{x}^{(2)}, y^{(2)}), \dots (\underline{x}^{(n)}, y^{(n)})$ Training $(\underline{y}^{(n)}, y^{(n)}), \dots (\underline{y}^{(n)}, y^{(n)})$ $(\underline{y}^{(n)}, y^{(n)}), \dots (\underline{y}^{(n)}, y^{(n)})$ $(\underline{y}^{(n)}, y^{(n)}), \dots (\underline{y}^{(n)}, y^{(n)})$ $(\underline{y}^{(n)}, y^{(n)}), \dots (\underline{y}^{(n)}, y^{(n)})$



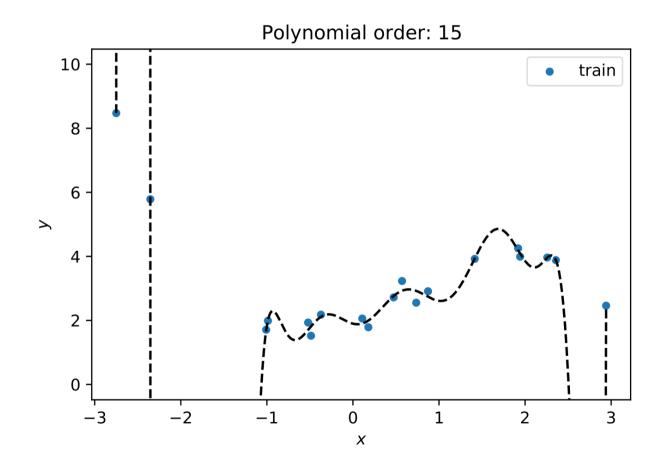
When reporting training loss as above, we don't include the regularization term so that it is comparable to the validation loss (where the regularization term is never included).

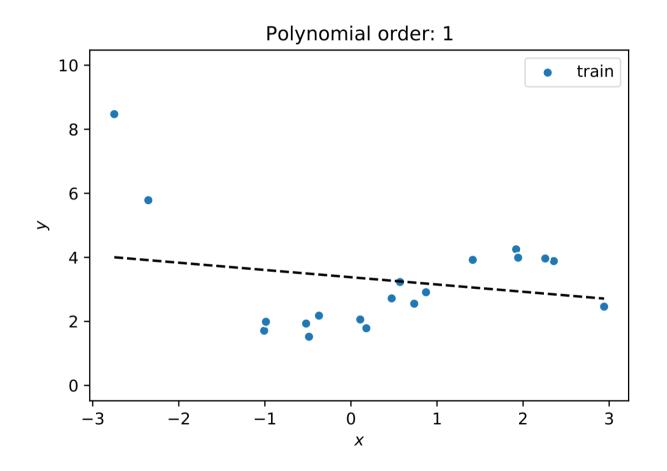


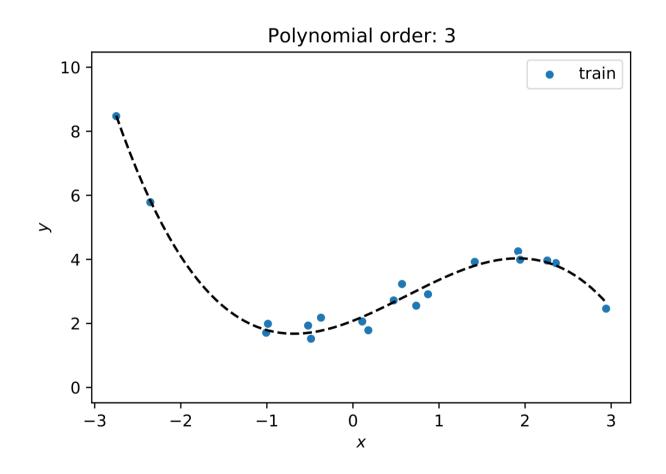


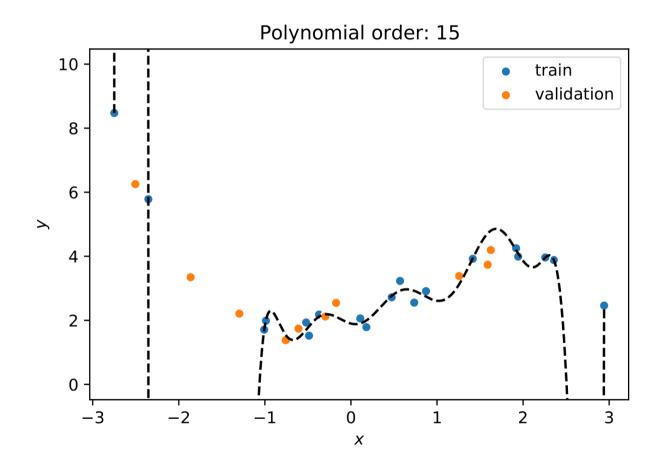


Let's fit some models on the training data

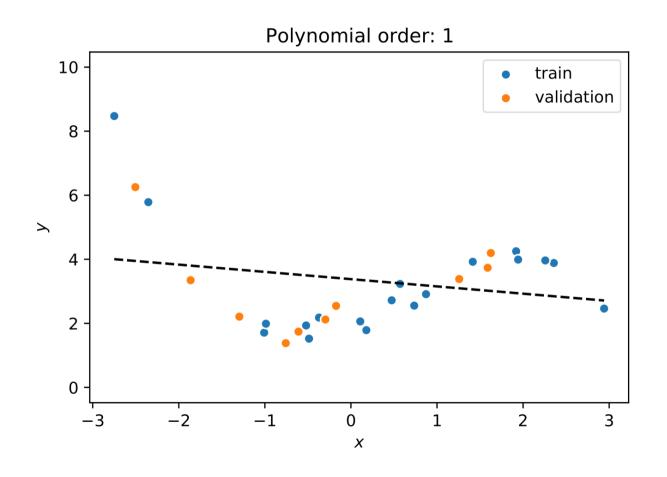




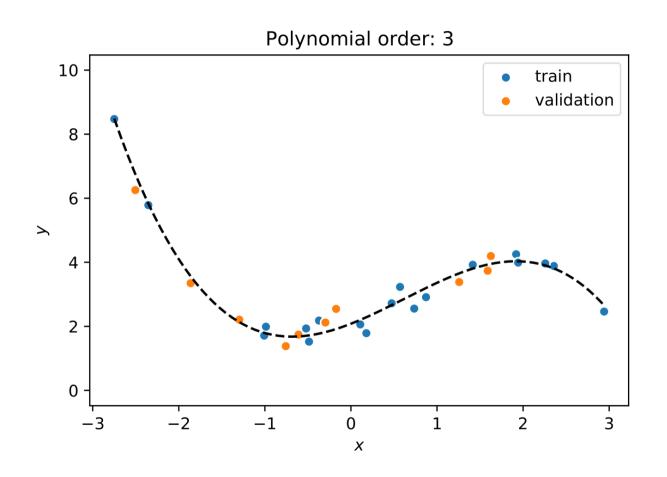




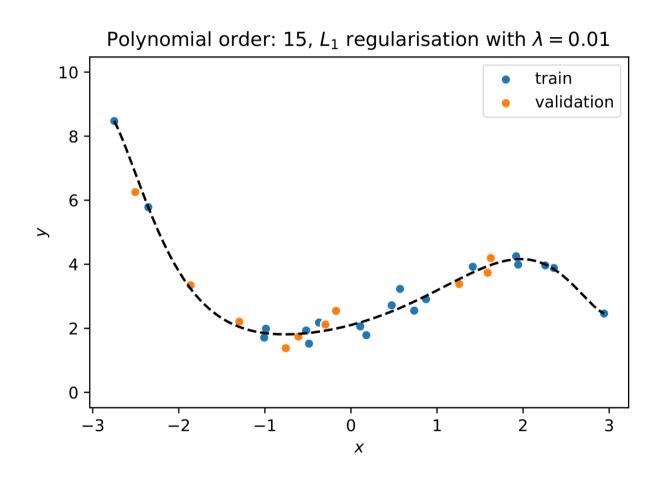
 $MSE_{train} = 0.0243$; $MSE_{val} = 456386.9249$ (overfitting, "high variance")



 $\mathrm{MSE}_{\mathrm{train}} = 2.5005; \ \mathrm{MSE}_{\mathrm{val}} = 2.0069$ (underfitting, "high bias")



 $MSE_{train} = 0.0600$; $MSE_{val} = 0.1056$ ("just right")



Training on test data is one of the worst mistakes you can make in machine learning