## **Polynomial Regression**

```
## Hyperparameter Selection

Best Degree: 7

Best Theta: [-0.53103609 -0.02168913  0.57052874 -1.71309263  0.0370365  0.6737321 -0.03256637 -0.03962692]

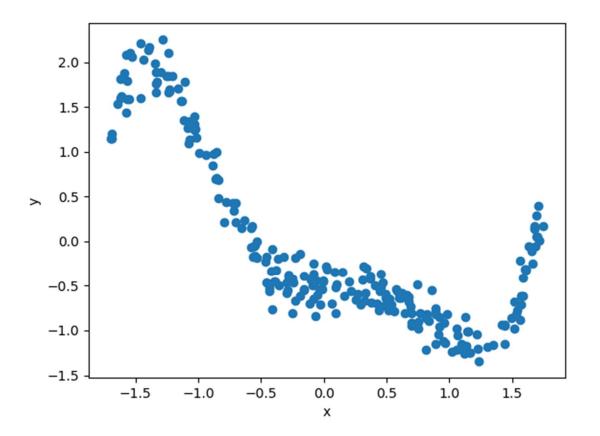
Best Theta: [-0.53103609 -0.02168913  0.57052874 -1.71309263  0.0370365  0.6737321 -0.03256637 -0.03962692]

Test Loss: 0.02125312187756854

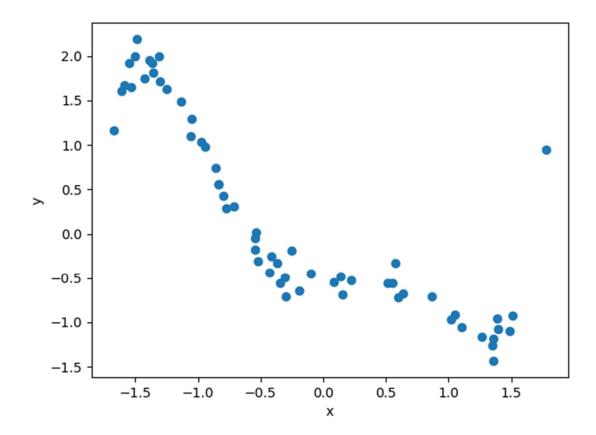
### Gradient Descent

Best Degree: 7

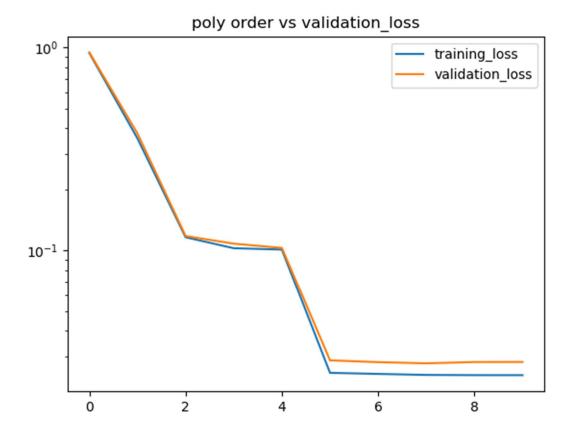
Best Theta: [-0.35529357 -0.4165501  0.15522872 -0.41374686  0.20231069 -0.29417689 -0.04526306  0.15937102]
```



A plot of the training portion of the generated dataset

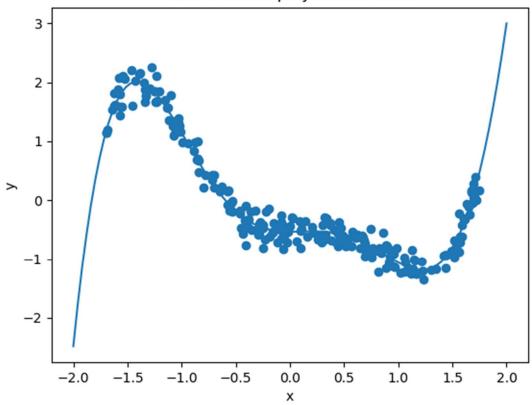


A plot of the test portion of the generated dataset

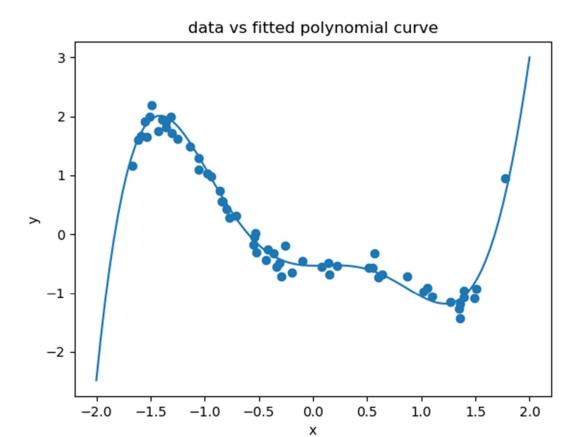


A plot of the order of the polynomial transformation compared to the training and validation losses; Degree 7 is found to be the best degree (since it has the minimum loss in validation). This is a bit odd considering the data was generated using a fifth-degree polynomial and would suggest that slight overfitting has occurred.

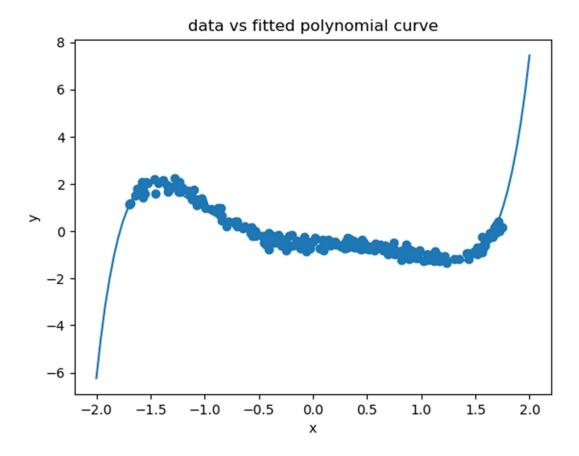
## data vs fitted polynomial curve



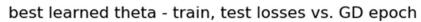
A plot of the best-fit polynomial curve over the training data

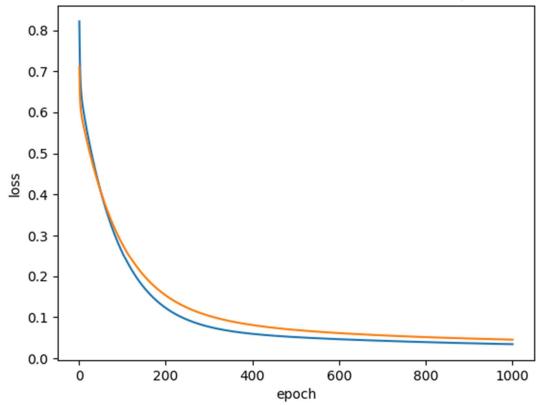


A plot of the best fit curve over the test data. The best-fit theta was derived using the normal equation with a degree of 7, since that was found to be the best degree during hyper-parameter tuning.

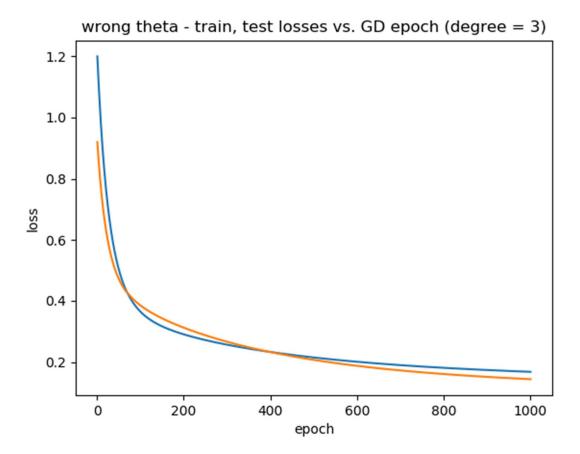


A plot of the curve found via gradient descent over the training data with optimal degree and theta. I'm not really sure what is meant by "we require you to generate a similar plot for one more hyperparameter degree d from part 2, that is not the best hyperparameter." This is pretty ambiguous.



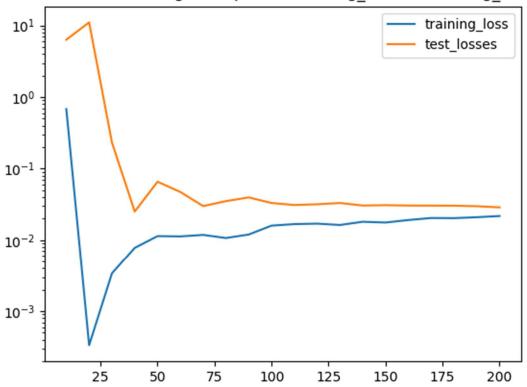


A plot of the gradient descent loss during the training with the optimal degree (degree = 7)



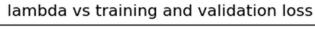
A plot of the gradient descent loss when the wrong degree is chosen (degree = 3). As you can see, the error to which the algorithm converges is an order of magnitude higher than the previous graph.

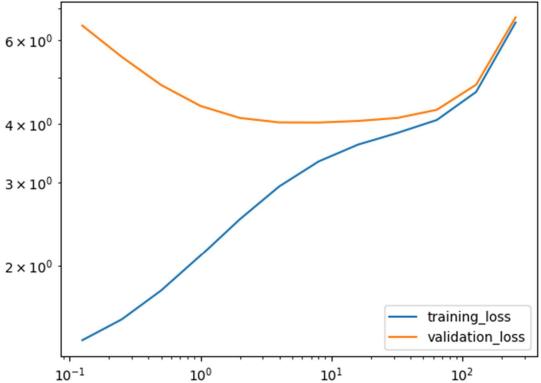
number of training examples vs training\_loss and testing\_loss



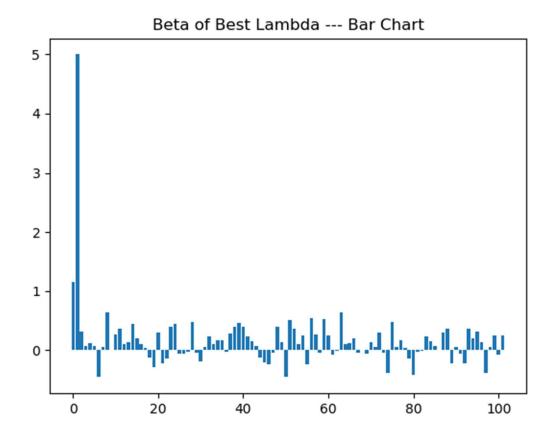
## **Ridge Regression**

```
Best Lambda: 8
L2 norm of normal beta: 30.2696547988007
L2 norm of best beta: 5.748383109215213
L2 norm of large lambda beta: 5.748383109215213
Average testing loss for normal beta: 11.031286619642902
Average testing loss for best beta: 4.655100367769717
Average testing loss for large lambda beta: 12.12642033283745
```





The plot shows that there is clearly a "golden zone" for lambda that produces the lowest average validation loss around 8.



A plot of the beta values. This makes a lot of sense given that the underlying distribution is 5x+3, with a bunch of random noise tacked on for the latter 100 or so variables. You can clearly see that the model "figured out" the underlying distribution (for the most part).