CSCI 181 / E-181 Spring 2014 Practical 2

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Warm-Up

Baseline

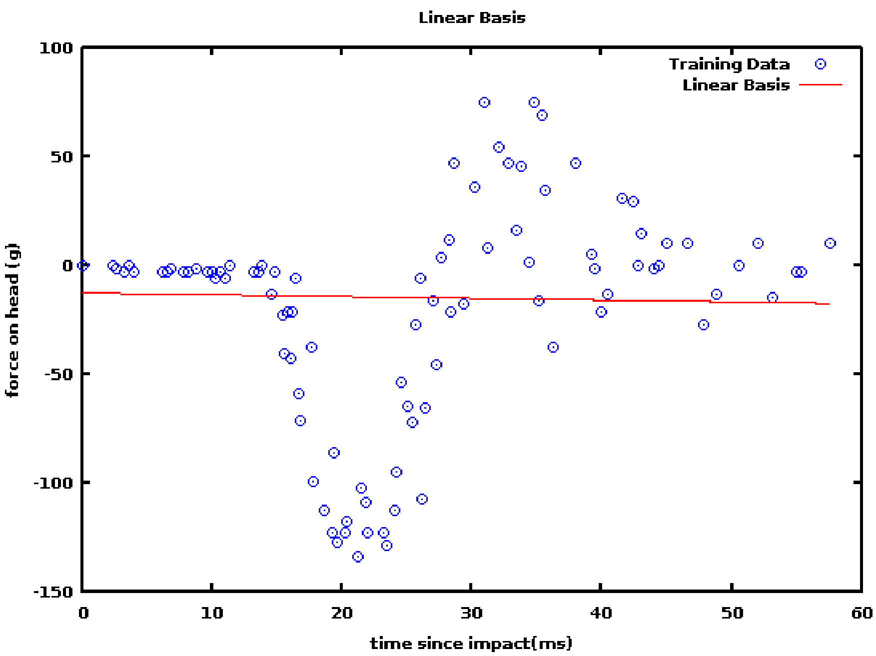

Figure 1: Warmup: Linear Basis

As a baseline, we first created a simple linear gradient descent with a flat slope and intercept.

We also used a polynomial basis, iterating with polynomials from n^2 up to n^{12} and selecting the lowest error. Unsurprisingly, n^{12} had the lowest error rate, but is likely highly overfit.

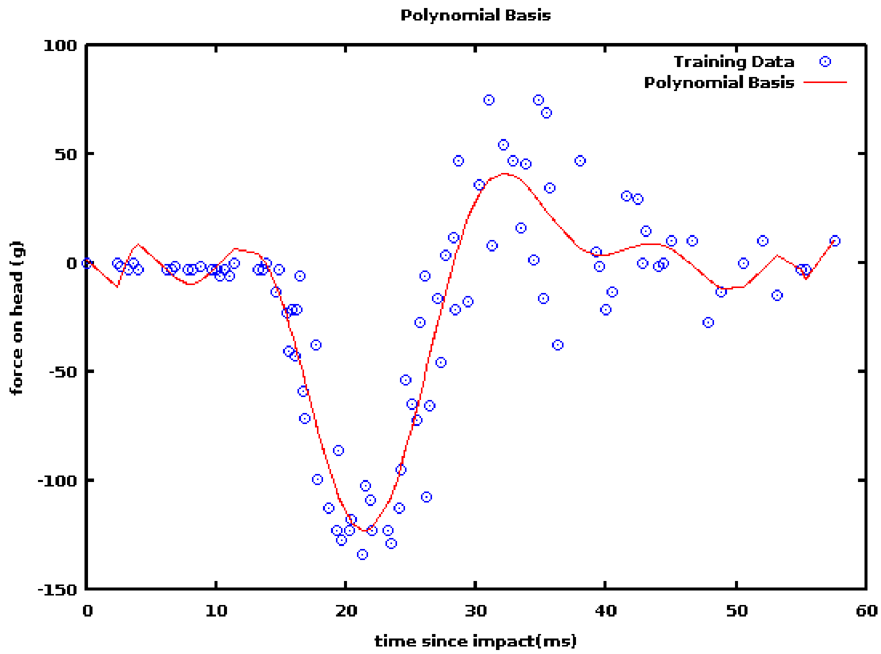

Figure 2: Warmup: Polynomial Basis n^{12}

Bayesian Linear Regression

Using Gaussian Likelihood and Prior, we solved for W using Moore Penrose.

$$W_{ML} = (\Phi^T \Phi)^{-1} \Phi^T t \tag{1}$$

This was simple to implement, especially in Octave/Matlab. However, without normalization the error rate was close to the baseline linear basis and significantly worse than the polynomial.

Locally Weighted Linear Regression

Locally Weighted Linear Regression[1] provided the lowest cost overall and a smooth fit to the data without overfitting given the profile of this dataset. A variety of K values were attempted. 0.001 never converged. Values from 0.5, 1.0, 5.0 and 10.0 did converge with 1.0 seemingly providing the best balance between fit and smoothness.

[1] *Machine Learning in Action* by Peter Harrington. © 2012 ISBN 978-1617290183

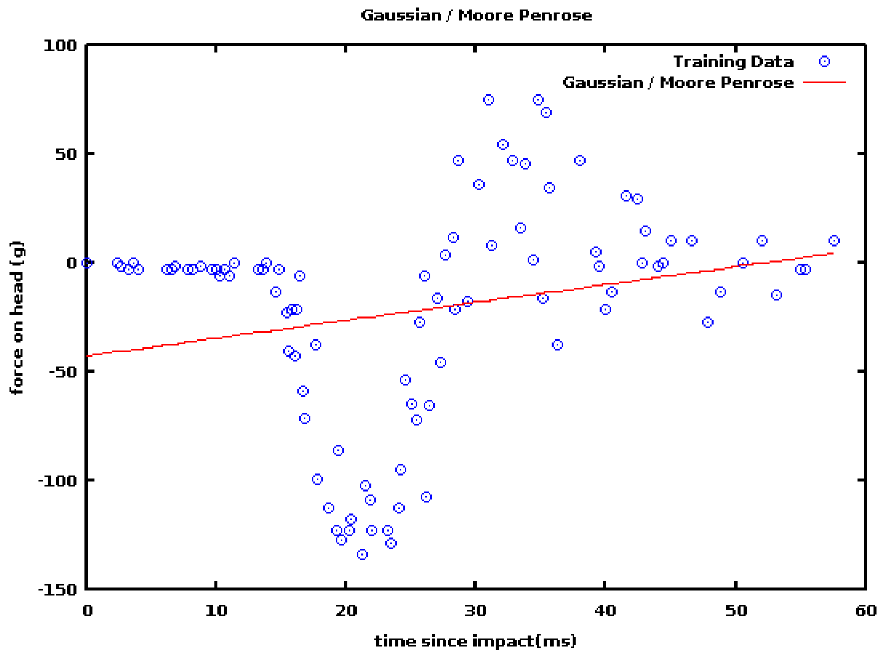

Figure 3: Warmup: Gaussian

Warmup Summary

Across all basis functions, overall error rate was calculated by sum-of-squares:

$$J = \frac{1}{2N} \sum_{i=1}^{N} (y_i - t_i)^2 \tag{2}$$

The following table summarizes our results. LWLR was reasonably simple to implement and provided the lowest cost. For this particular data set, it would be our basis function of choice.

Basis	Lowest Error
Linear Basis	1293.0
Gaussian Basis	1187.7
Polynomial Basis	211.9
LWLR Basis	185.6

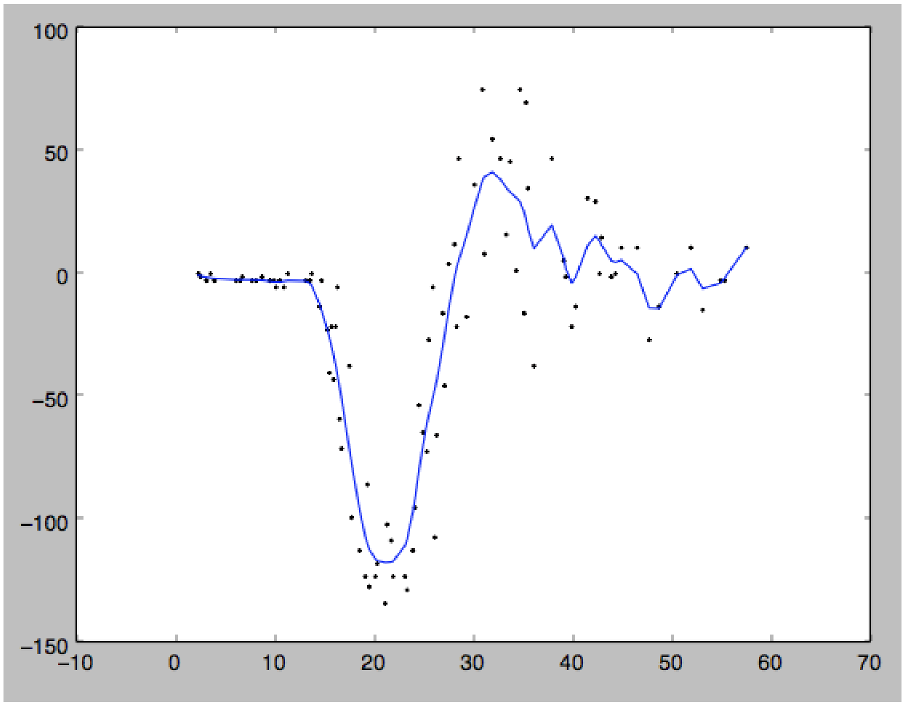

Figure 4: Warmup: Locally Weighted Linear Regression $K = 1$

Predicting Movie Opening Weekend Revenues

Subsection 1

Subsection 2

Conclusion