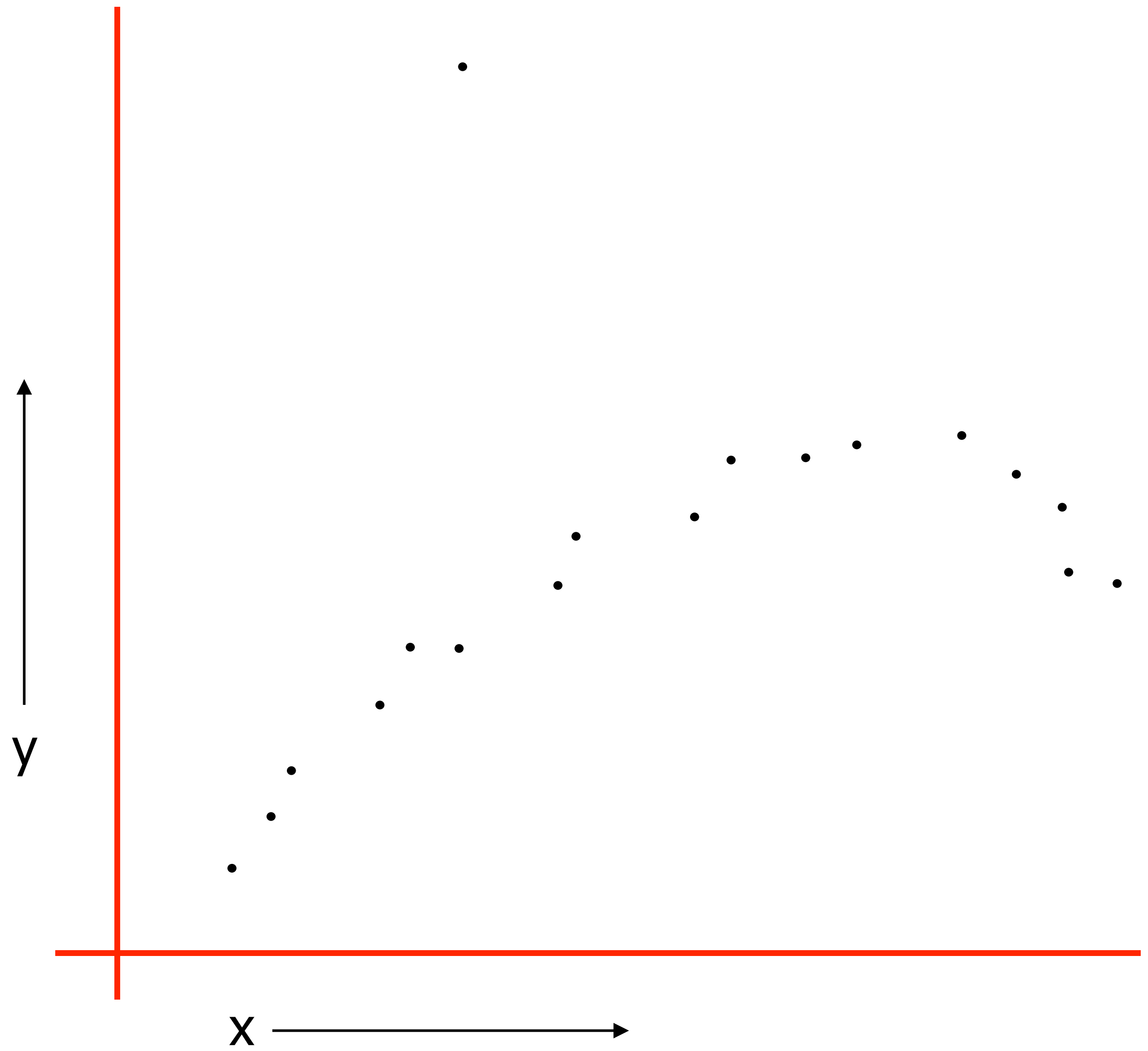
Robust Regression

Robust Regression



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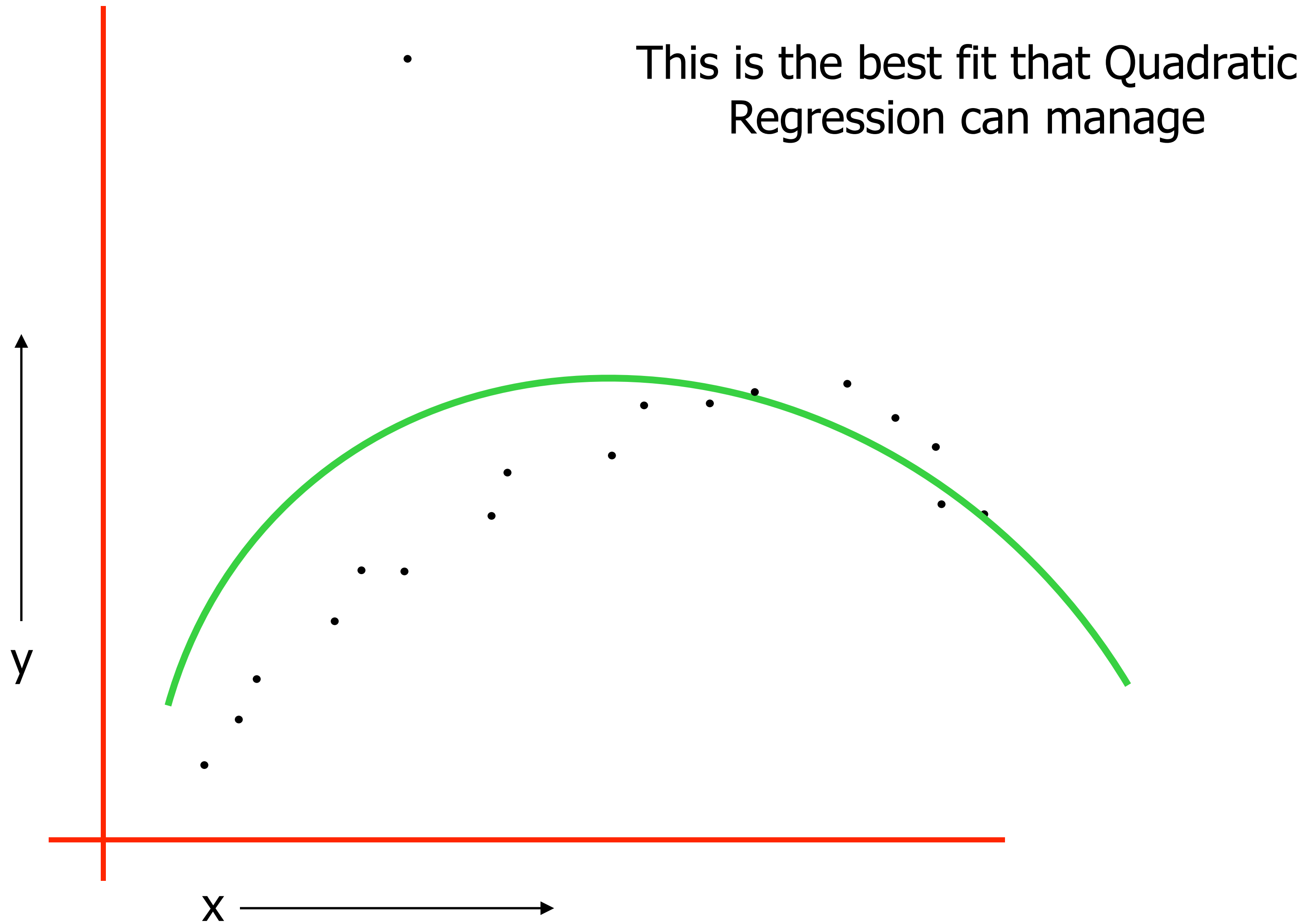

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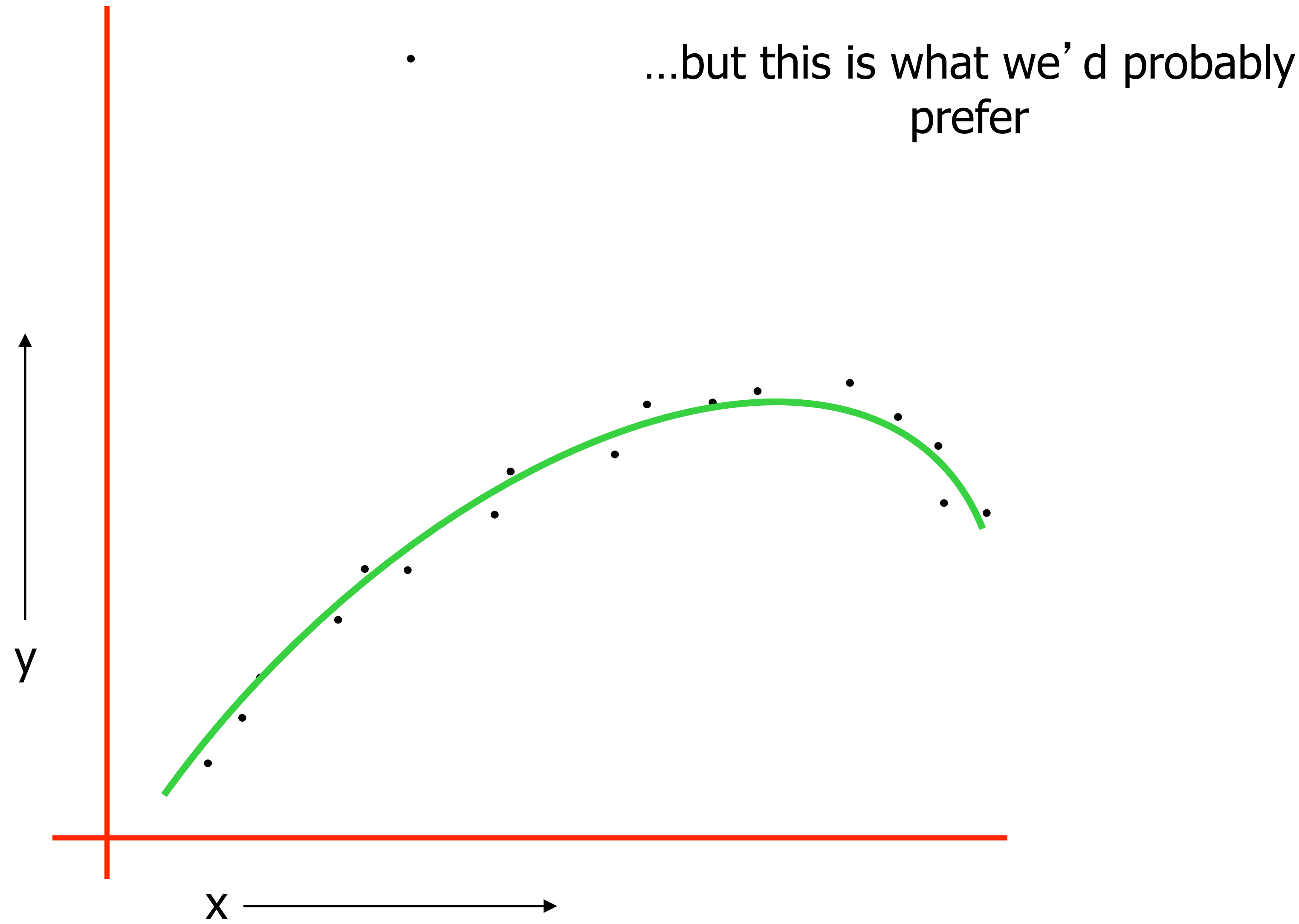
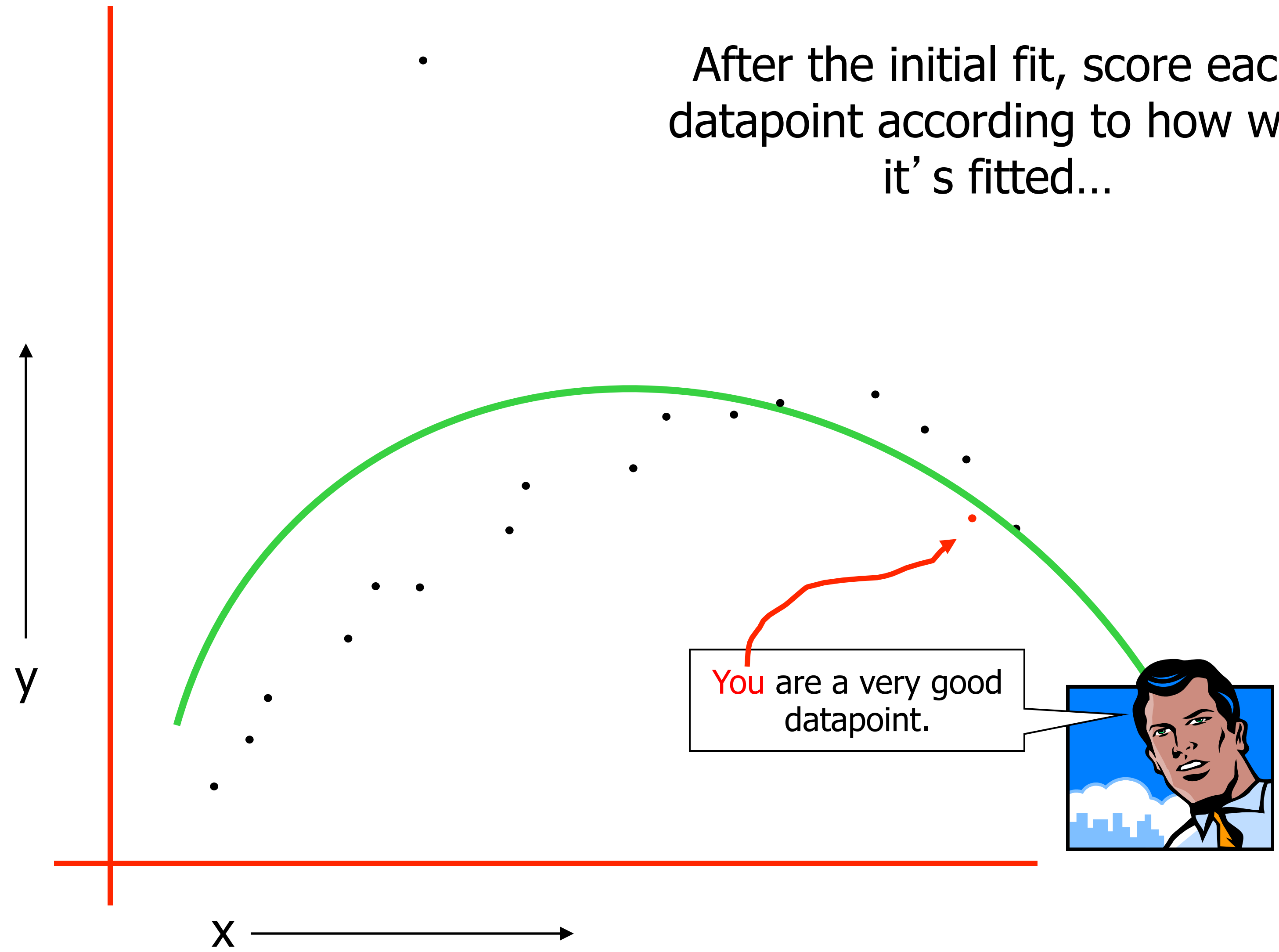


LOESS-based Robust Regression

After the initial fit, score each datapoint according to how well it’s fitted…



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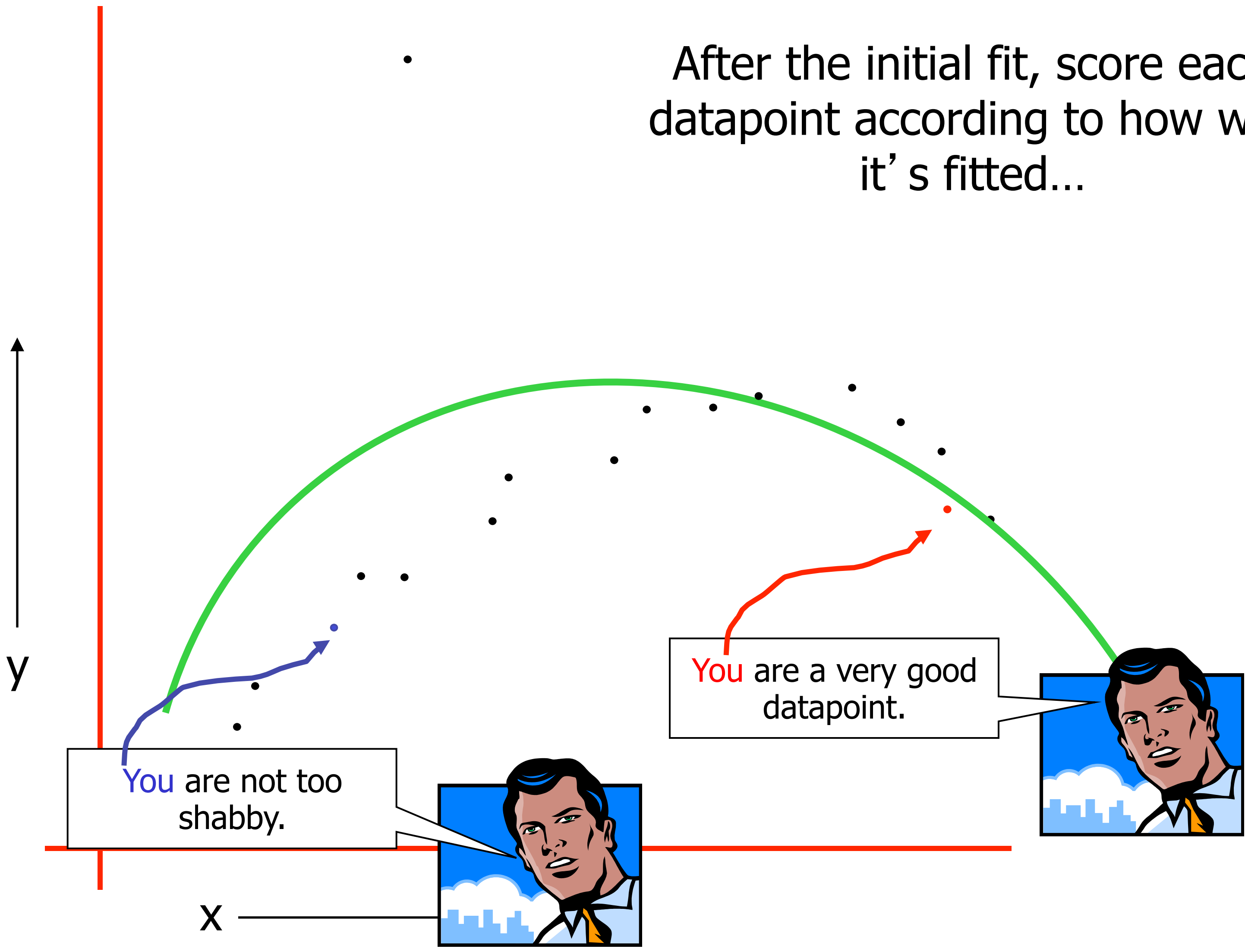

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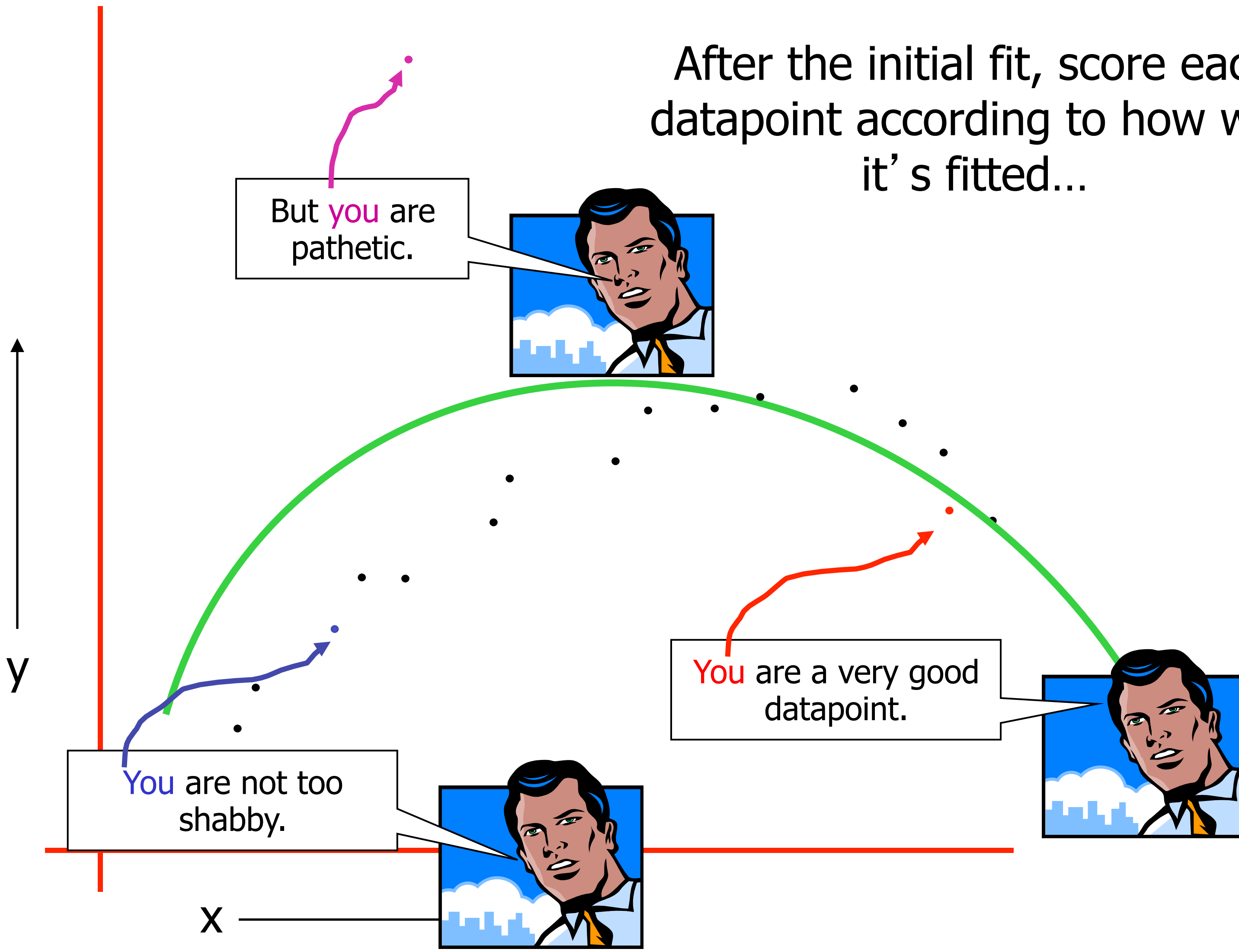
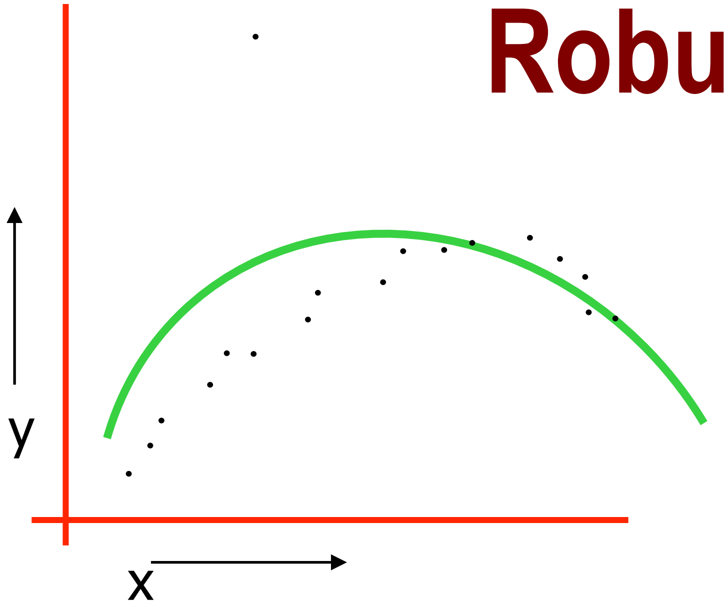


Robust Regression



For k = 1 to R…

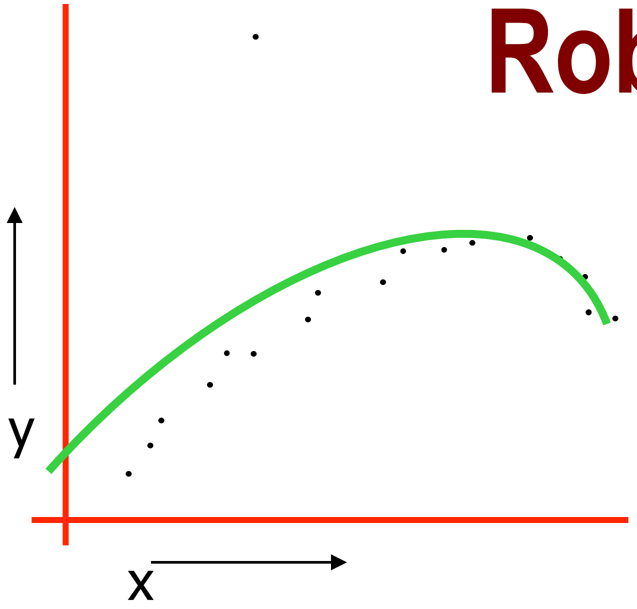
•Let (x_k, y_k) be the kth datapoint

•Let y^{est}_k be predicted value of y_k

•Let w_k be a weight for datapoint k that is large if the datapoint fits well and small if it fits badly:

$$w_k = KernelFn([y_k - y^{est}_k]^2)$$

Robust Regression



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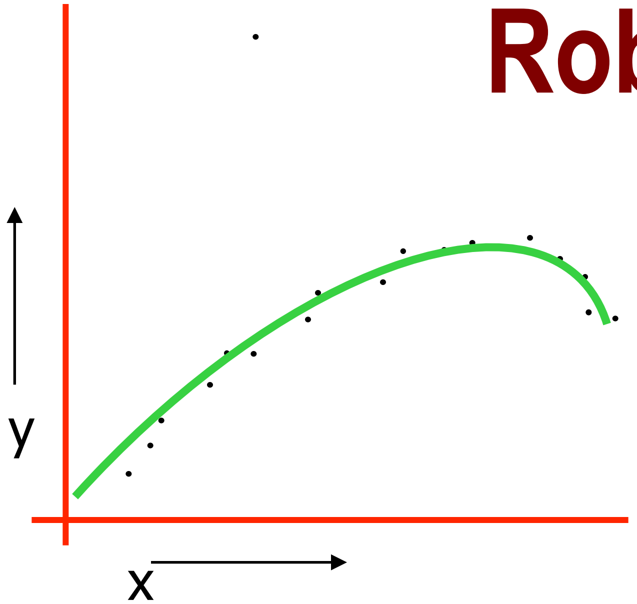
Then redo the regression using weighted datapoints.

Weighted regression was described earlier in the "vary noise" section, and is also discussed in the "Memory-based Learning" Lecture.

Guess what happens next?

Robust Regression



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Then redo the regression using weighted datapoints.

I taught you how to do this in the "Instance-based" lecture (only then the weights depended on distance in input-space)

Repeat whole thing until converged!

Robust Regression---what we're doing

What regular regression does:

Assume y_k was originally generated using the following recipe:
$y_k = \beta_0 + \beta_1 x_k + \beta_2 x_k^2 + N(0,\sigma^2)$

Computational task is to find the Maximum Likelihood β_0 , β_1 *and* β_2

Robust Regression---what we're doing

What LOESS robust regression does:

Assume y_k was originally generated using the following recipe:

With probability p:

$$y_k = \beta_0 + \beta_1 x_k + \beta_2 x_k^2 + N(0,\sigma^2)$$

But otherwise

$$y_k \sim N(\mu,\sigma_{huge}^2)$$

Computational task is to find the Maximum Likelihood β_0, β_1, β_2, p, μ and σ_{huge}

Robust Regression---what we're doing

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Computational task is to find the Maximum Li
β_1 , β_2 , p, μ and σ_{huge}

Mysteriously, the reweighting procedure does this computation for us.

Your first glimpse of two spectacular letters:

E.M.

Citations

Radial Basis Functions

T. Poggio and F. Girosi, Regularization Algorithms for Learning That Are Equivalent to Multilayer Networks, Science, 247, 978--982, 1989

LOESS

W. S. Cleveland, Robust Locally Weighted Regression and Smoothing Scatterplots, Journal of the American Statistical Association, 74, 368, 829-836, December, 1979