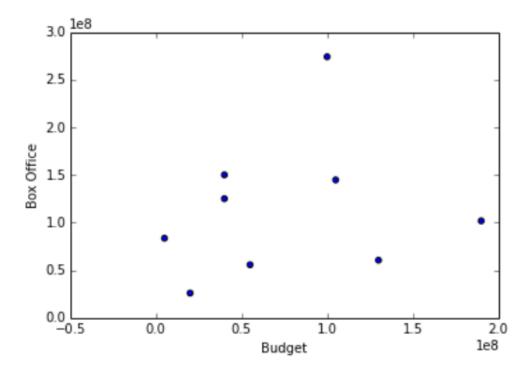
Linear Regression



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$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$y_{\beta}(x) = \beta_0^{\text{coef 0}} + \beta_1^{\text{coef 1}} x + \varepsilon$$

Gross of movie Budget of

Noise (random for movie each movie)

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$\beta_0 = 0$$

$$\beta_1 = 1.5$$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$\beta_0 = 0$$

$$\beta_0 = 1.5$$

$$\beta_0 = 0$$
 $\beta_0 = 120$ million $\beta_1 = 1.5$ $\beta_1 = 0.1$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$\beta_0 = 0$$

$$\beta_1 = 1.5$$

$$\beta_0 = 0$$

$$\beta_0 = 120 million$$

$$\beta_1 = 1.5$$

$$\beta_1 = 0.1$$

$$\beta_1 = 0.1$$

$$\beta_0 = 30$$
 million $\beta_1 = 2$

$$\beta_1 = 2$$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$\beta_0 = 0$$

$$\beta_0 = 0$$
 $\beta_0 = 120$ million
 $\beta_1 = 1.5$
 $\beta_1 = 0.1$

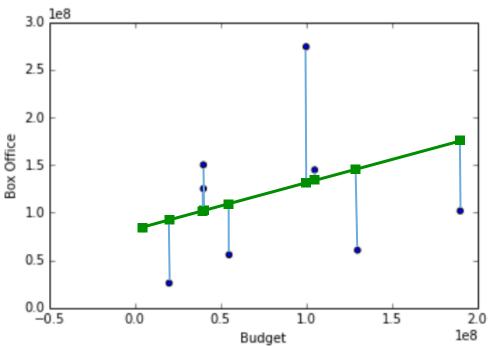
$$\beta_0 = 30$$
 million $\beta_1 = 2$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_0 = 0$ $\beta_0 = 120$ million $\beta_0 = 30$ million $\beta_1 = 0.5$ $\beta_1 = 1.5$ $\beta_1 = 0.1$ $\beta_1 = 2$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 80$$
 million $\beta_0 = 0$ $\beta_0 = 120$ million $\beta_0 = 30$ million $\beta_1 = 0.5$ $\beta_1 = 1.5$ $\beta_1 = 0.1$ $\beta_1 = 2$



$$y_{\beta}(x_{obs}^{(0)}) - y_{obs}^{(0)}$$

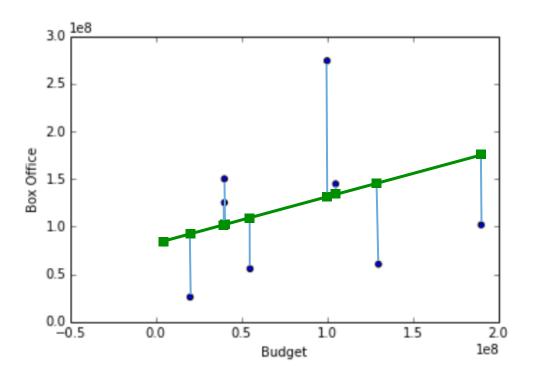
$$y_{\beta}(x_{obs}^{(1)}) - y_{obs}^{(1)}$$

$$y_{\beta}(x_{obs}^{(2)}) - y_{obs}^{(2)}$$

$$y_{\beta}(x_{obs}^{(3)}) - y_{obs}^{(3)}$$

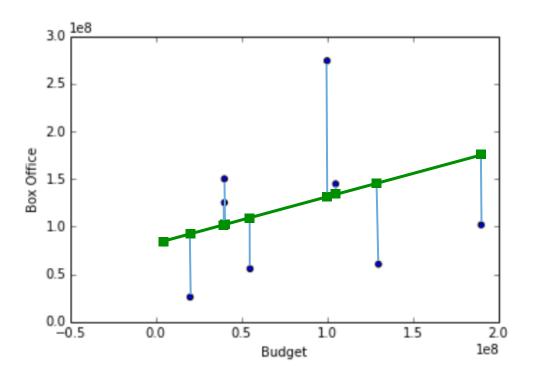
$$y_{\beta}(x_{obs}^{(3)}) - y_{obs}^{(3)}$$

Predicted value by model – Observed value $\beta 0 = 80M$, $\beta 1 = 0.5$



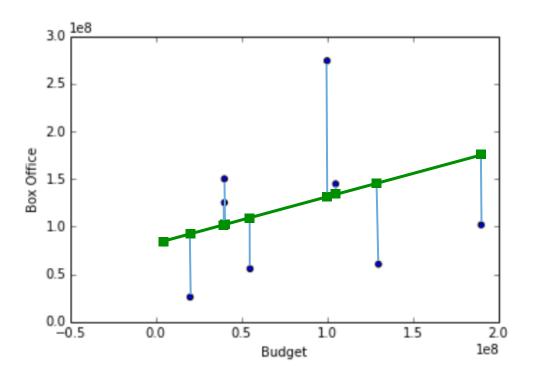
Predicted value by model – Observed value $\beta 0 = 80M$, $\beta 1 = 0.5$

$$y_{\beta}(x_{obs}^{(i)}) - y_{obs}^{(i)}$$



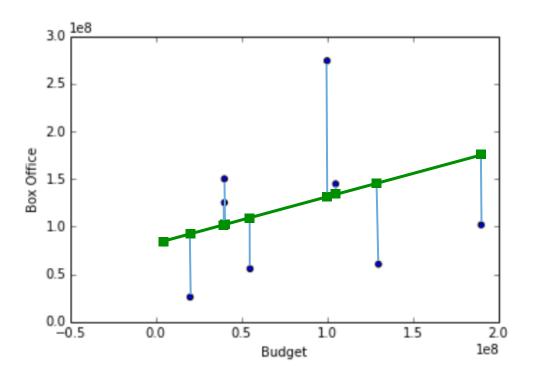
Predicted value by model – Observed value $\beta 0 = 80M$, $\beta 1 = 0.5$

$$(\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)}$$



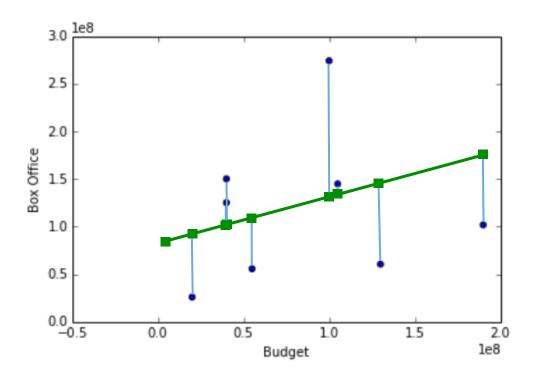
Predicted value by model – Observed value $\beta 0 = 80M$, $\beta 1 = 0.5$

$$\sum_{i=1}^{m} \left((\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2$$



Predicted value by model – Observed value $\beta 0 = 80M$, $\beta 1 = 0.5$

$$\min_{\beta_0, \beta_1} \sum_{i=1}^{m} \left((\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2$$



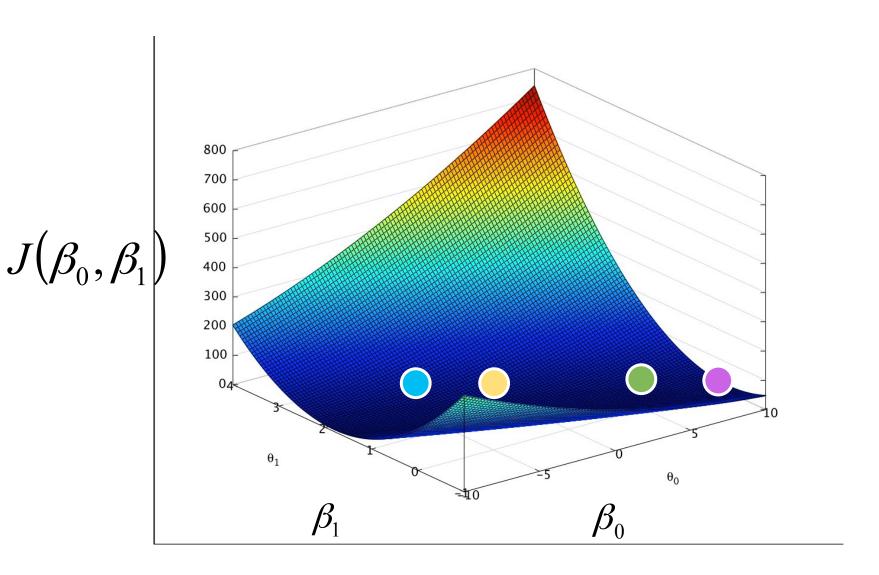
Cost function

Takes a model (specific parameter values), returns score

$$J(\beta_0, \beta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left((\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2$$

$$J(oldsymbol{eta}_0,oldsymbol{eta}_1)$$

$$J(\beta_0, \beta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left((\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2$$



$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

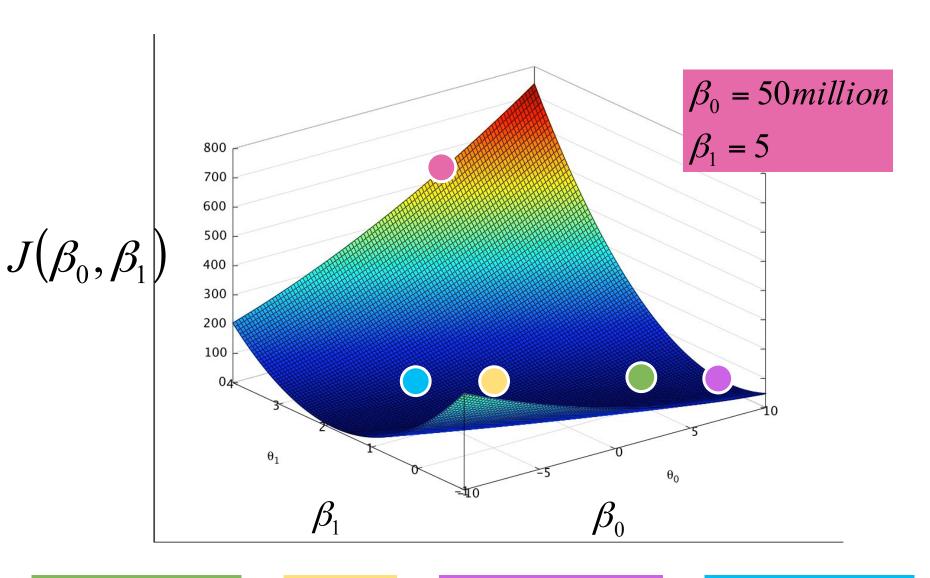
$$\beta_0 = 0$$
$$\beta_1 = 1.5$$

$$\beta_1 = 1.5$$

$$\beta_0 = 120 million$$
 $\beta_1 = 0.1$

$$\beta_0 = 30$$
 million $\beta_1 = 2$

$$\beta_1 = 2$$

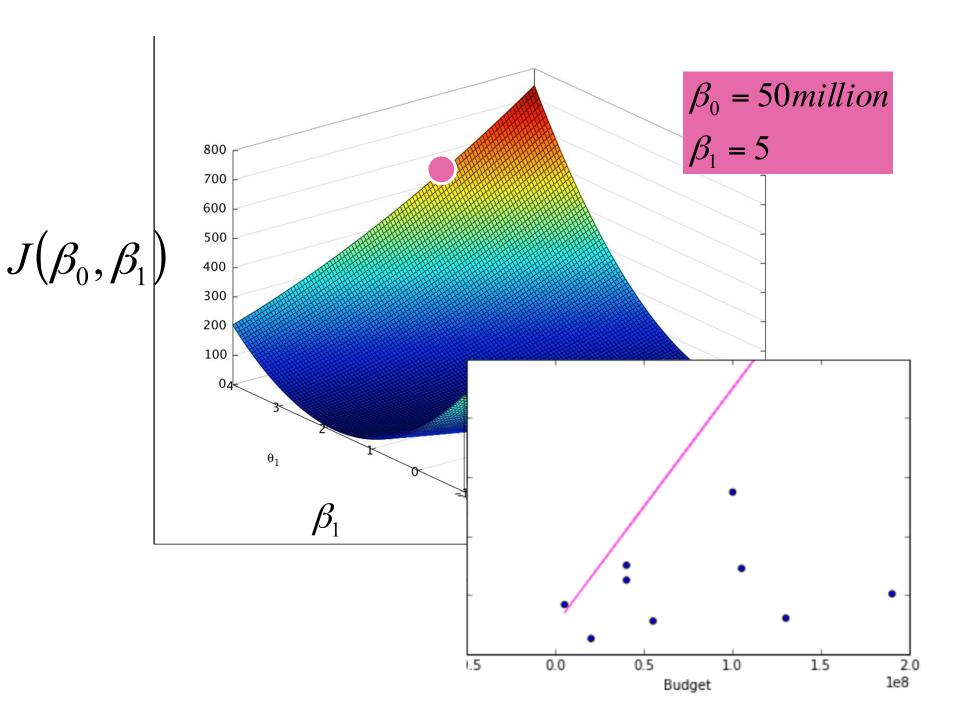


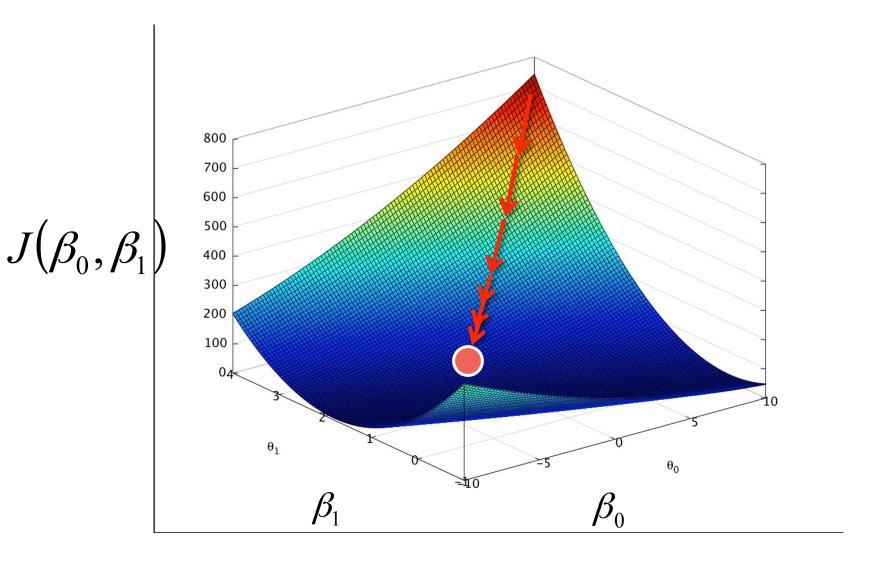
$$\beta_0 = 80$$
 million $\beta_1 = 0.5$

$$\beta_0 = 0$$
$$\beta_1 = 1.5$$

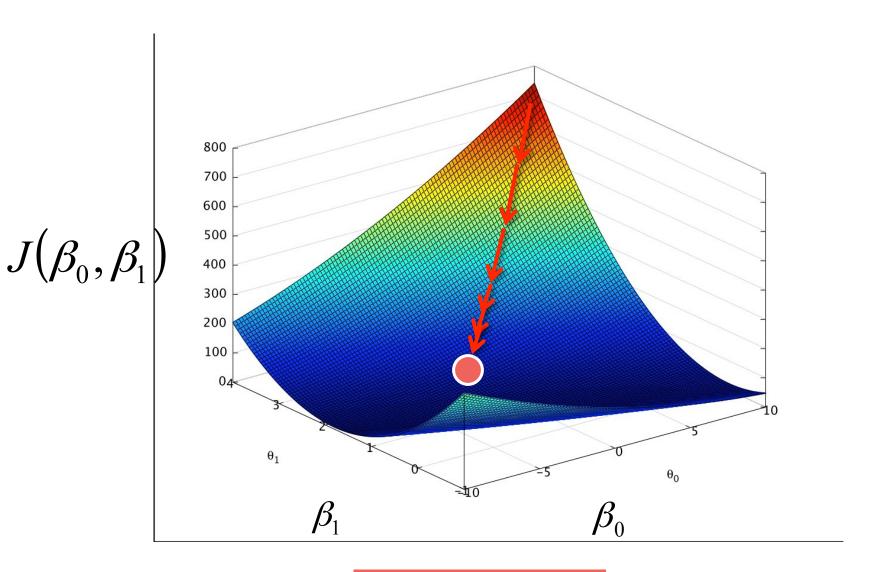
$$\beta_0 = 120 million$$
 $\beta_1 = 0.1$

$$\beta_0 = 30$$
 million $\beta_1 = 2$





import statsmodels.formula.api as sm
linmodel = sm.OLS(Y, X).fit()



$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$

$$\beta_1 = 0.1$$

Models and Randomness

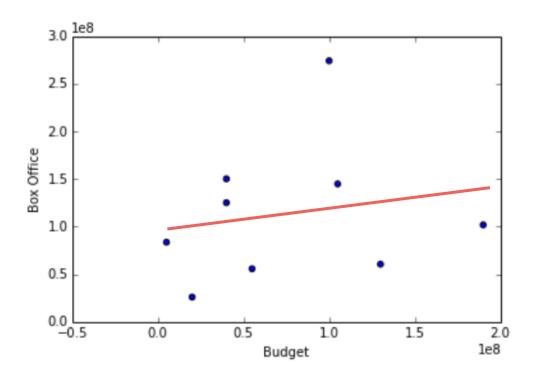


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$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

Random for each movie

$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$



$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

 $\beta_0 = 94.68$ million $\beta_1 = 0.1$

$$\beta_1 = 0.1$$

Random

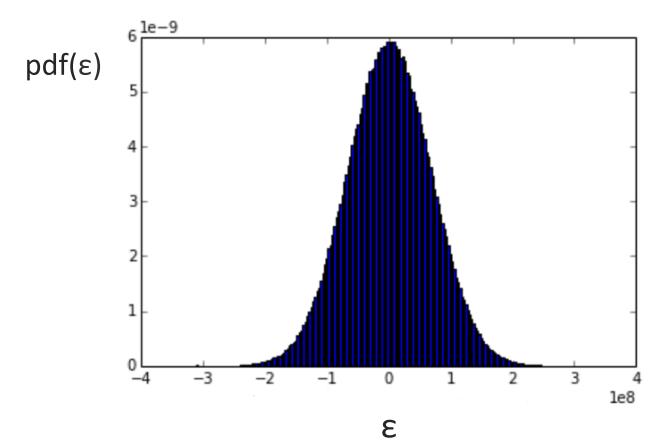
Normal distribution Mean=0 Stdev= \$67,762,000

$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

$$\beta_0 = 94.68 million$$
 $\beta_1 = 0.1$

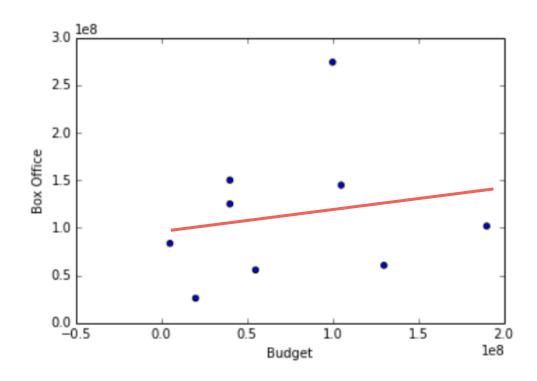
$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



(Note axes!)

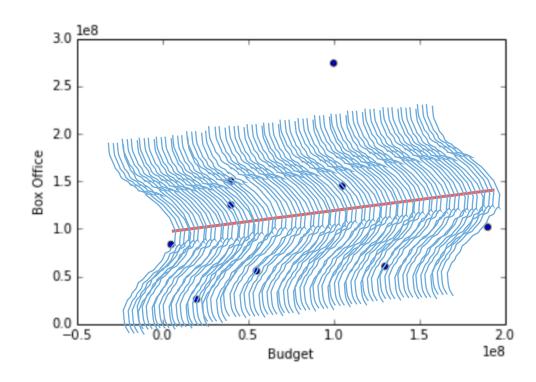
$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



$$\beta_0 = 94.68$$
 million $\beta_1 = 0.1$

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

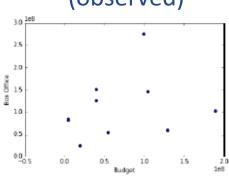


$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

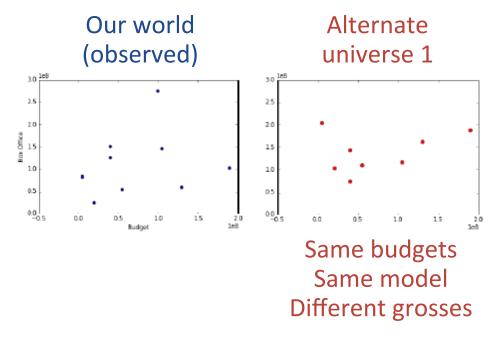
$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

return 94.68e6 + 0.248*budget +random.gauss(0,67762000)

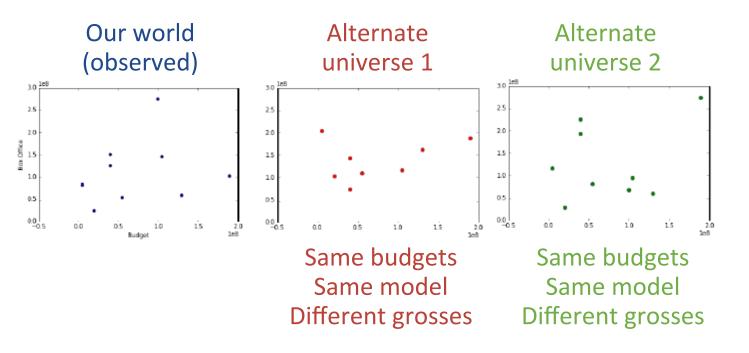
Our world (observed)



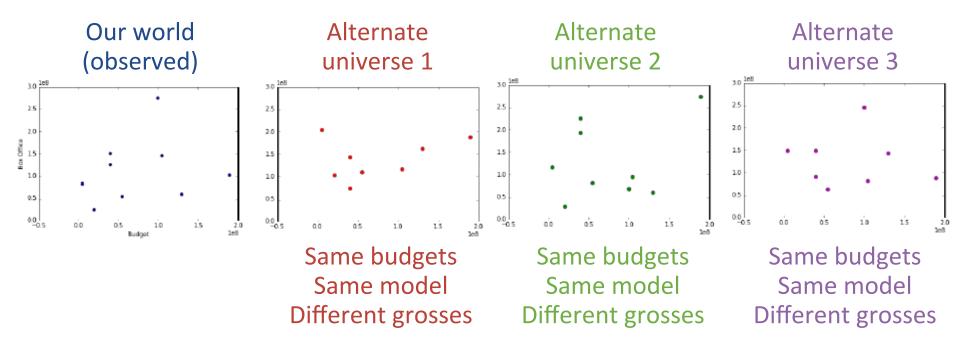
$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



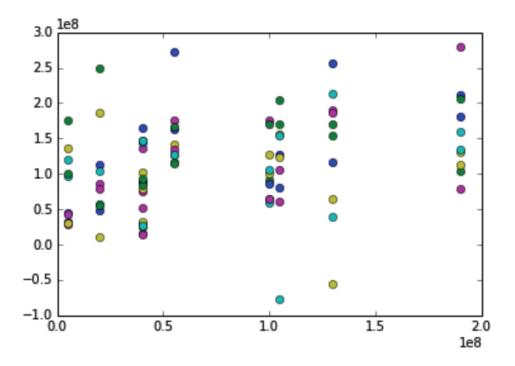
$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

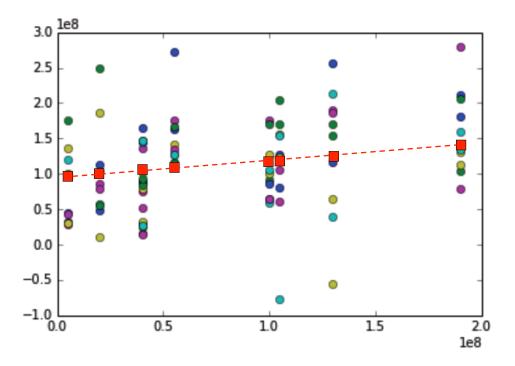


$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



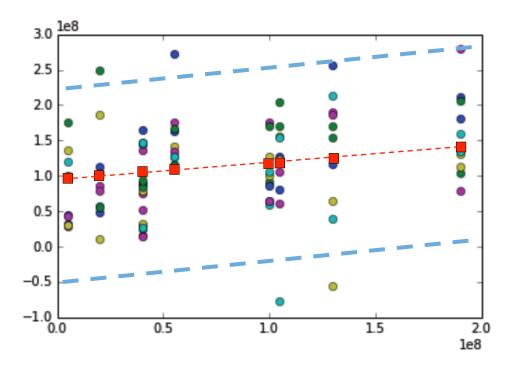
Possible Values in alternative universes

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



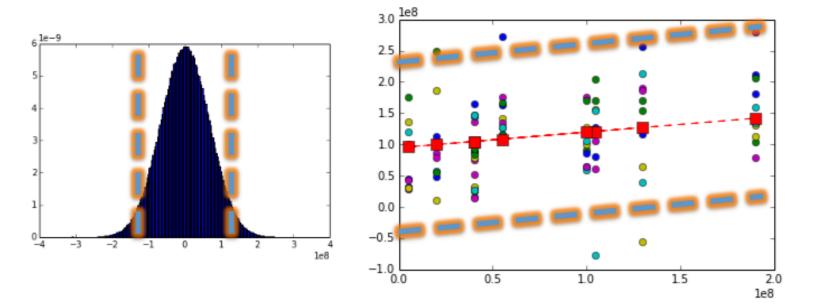
Expected value is $\beta 0+\beta 1x$ (without ϵ)

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



95% prediction interval

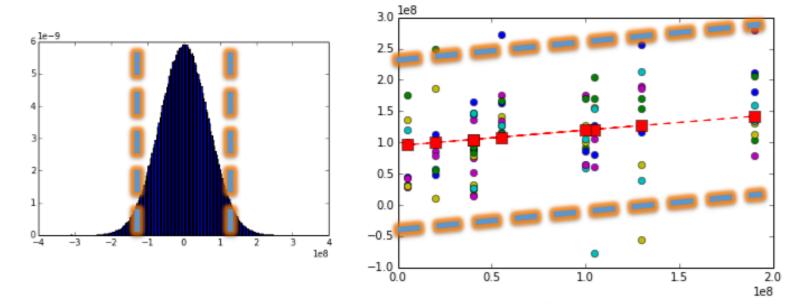
$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



95% prediction interval

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$

return random.gauss(94.68e6 + 0.248*budget, 67762000)



95% prediction interval

Multiple Linear Regression



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$$y_{\beta}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon$$

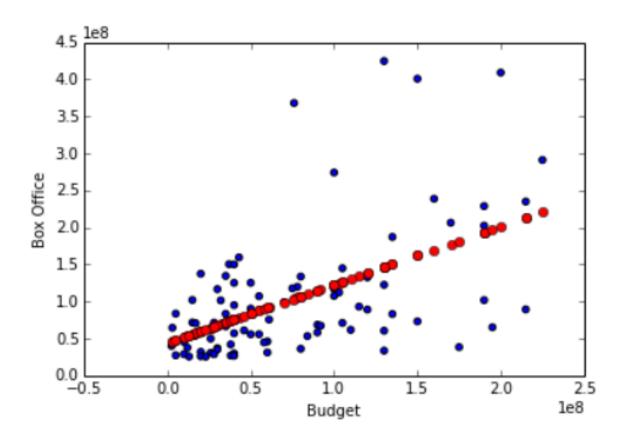
$$y_{\beta}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon$$

$$\min J(\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)$$

to find the best fitting model

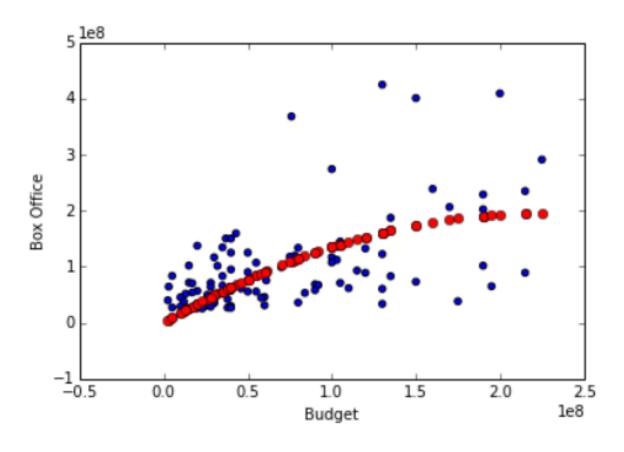
Polynomial regression

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \varepsilon$$



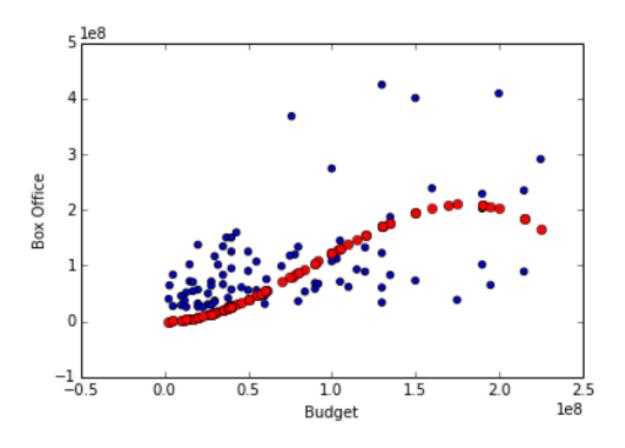
Polynomial regression

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$$



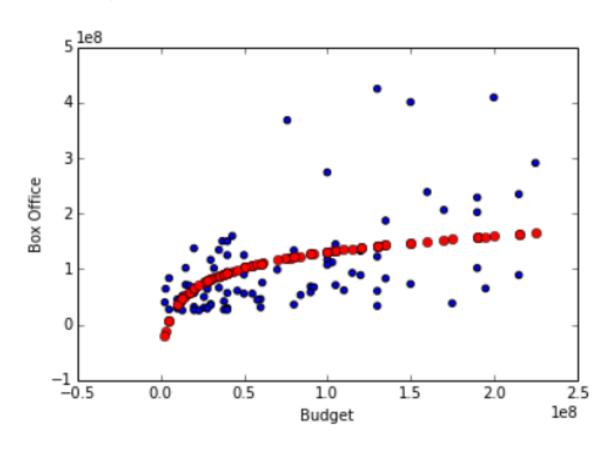
Polynomial regression

$$y_{\beta}(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \varepsilon$$



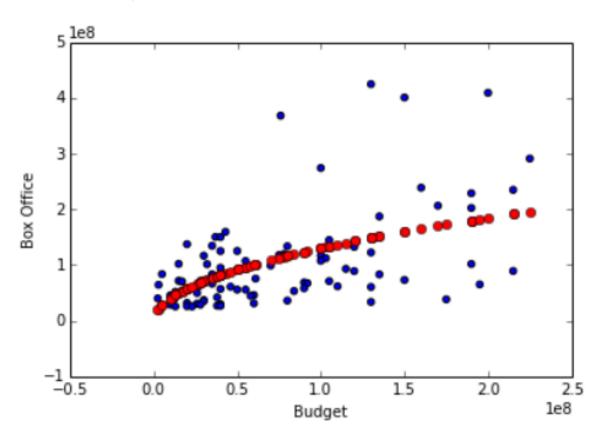
Other functional forms log

$$y_{\beta}(x) = \beta_0 + \beta_1 \log(x) + \varepsilon$$



Other functional forms square root

$$y_{\beta}(x) = \beta_0 + \beta_1 \sqrt{x} + \varepsilon$$



Possible to combine variables

$$y_{\beta}(x) = \beta_0 + \beta_1 \exp(x_1) + \beta_2 x_2 + \beta_3 x_2^2 + \beta_4 \log(x_3) + \varepsilon$$

Possible to combine variables

$$y_{\beta}(x) = \beta_0 + \beta_1 \exp(x_1) + \beta_2 x_2 + \beta_3 x_2^2 + \beta_4 \log(x_3) + \varepsilon$$

Interactions

(example: existence of both genres has an each extra effect, different than the sum of each)

$$y_{\beta}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$$

$$y_{\beta}(x) = \beta_0 + \beta_1 \exp(x_1) + \beta_2 x_2 + \beta_3 x_2^2 + \beta_4 \log(x_3) + \varepsilon$$

Linear Regression is not "linear" because we're fitting "a line."

We also fit many other forms.

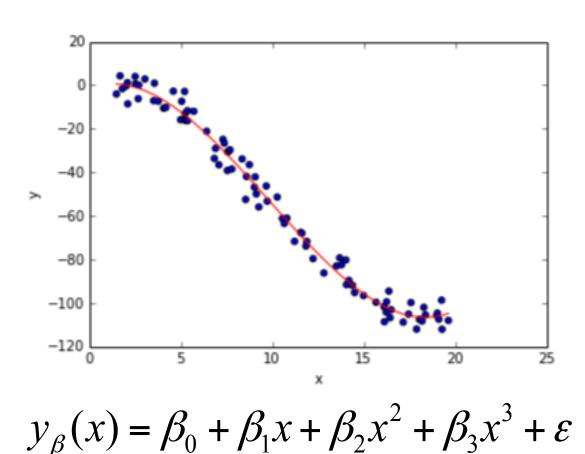
It's "linear" because the features are combined in a linear fashion ($\Sigma \beta_i f(x_i)$).

Linear

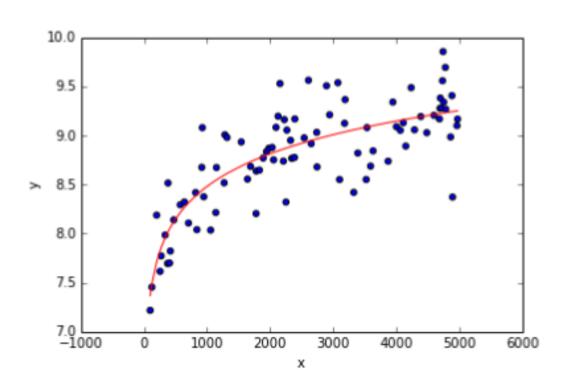
$$y_{\beta}(x) = \beta_0 + \beta_1 \exp(x_1) + \beta_2 x_2^{-1} + \varepsilon$$

Nonlinear
$$y_{\beta}(x) = \beta_0 + \beta_1 e^{\beta_2 x_1} + \frac{\beta_3 x_2}{(1 + \beta_4 x_2)} + \varepsilon$$

How to choose functional forms to try? Check one on one relationship of variable with outcome

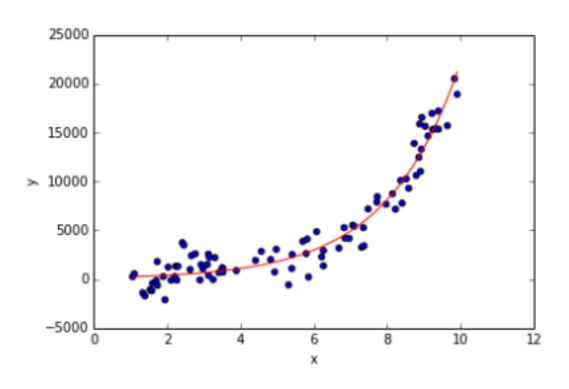


How to choose functional forms to try? Check one on one relationship of variable with outcome



$$y_{\beta}(x) = \beta_0 + \beta_1 \log(x) + \varepsilon$$

How to choose functional forms to try? Check one on one relationship of variable with outcome



$$\log(y_{\beta}(x)) = \beta_0 + \beta_1 x + \varepsilon$$