Regularization



OLS Regression Results

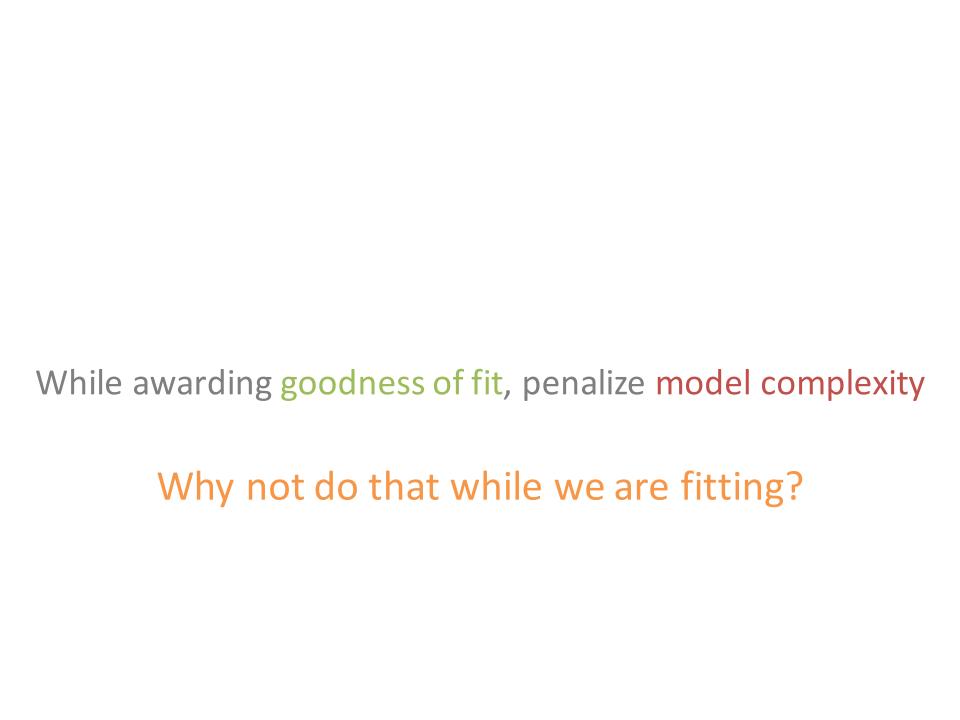
| Dep. Variable: | DomesticTotalGross | R-squared: | 0.286 |
|-------------------|--------------------|---------------------|----------|
| Model: | OLS | Adj. R-squared: | 0.278 |
| Method: | Least Squares | F-statistic: | 34.82 |
| Date: | Sun, 14 Sep 2014 | Prob (F-statistic): | 6.80e-08 |
| Time: | 21:59:46 | Log-Likelihood: | -1738.1 |
| No. Observations: | 89 | AIC: | 3480. |
| Df Residuals: | 87 | BIC: | 3485. |
| Df Model: | 1 | | |

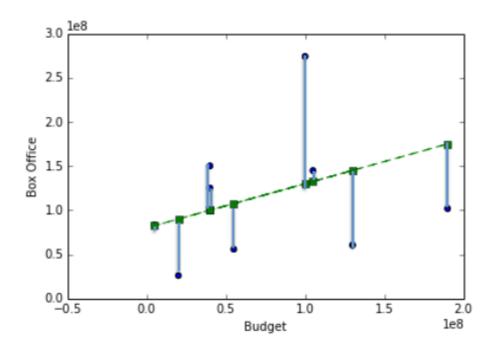
| | coef | std err | t | P> t | [95.0% Conf. Int.] |
|--------|----------|----------|-------|-------|--------------------|
| Budget | 0.7846 | 0.133 | 5.901 | 0.000 | 0.520 1.049 |
| Ones | 4.44e+07 | 1.27e+07 | 3.504 | 0.001 | 1.92e+07 6.96e+07 |

| Omnibus: | 39.749 | Durbin-Watson: | 0.674 |
|----------------|--------|-------------------|----------|
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 99.441 |
| Skew: | 1.587 | Prob(JB): | 2.55e-22 |
| Kurtosis: | 7.091 | Cond. No. | 1.54e+08 |

$$AIC = 2k - 2\ln(L)$$
parameters Log likelihood

While awarding goodness of fit, penalize model complexity

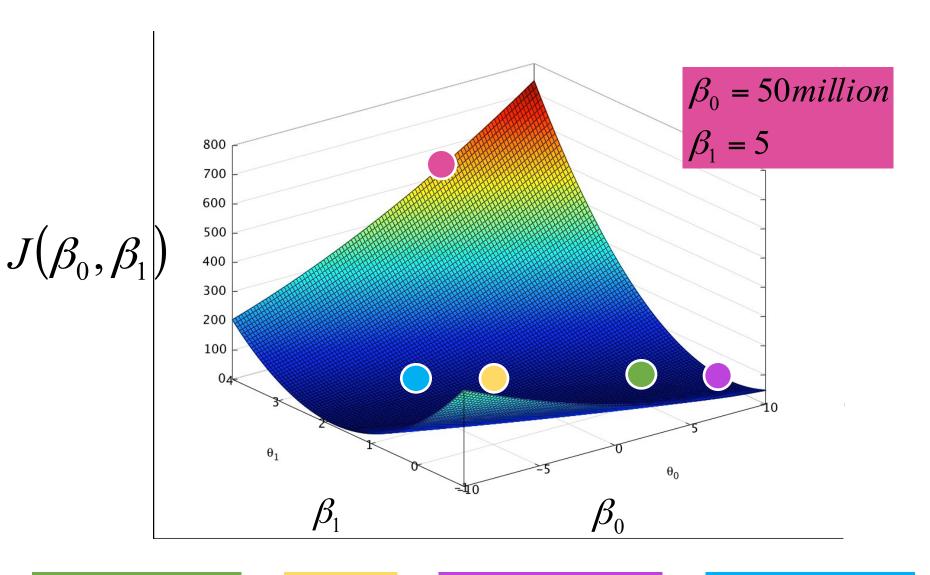




Cost function

Takes a model (specific parameter values), returns a score

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



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

$$\beta_0 = 0$$

$$\beta = 1.5$$

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

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

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

Cost function

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Cost function

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

Cost function Add a penalty for the size of each parameter!

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

L2 Regularization

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

Ridge Regression

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

Effect of λ ?

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

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

zero

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

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

very small

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

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

"just right"

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

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VERY LARGE

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

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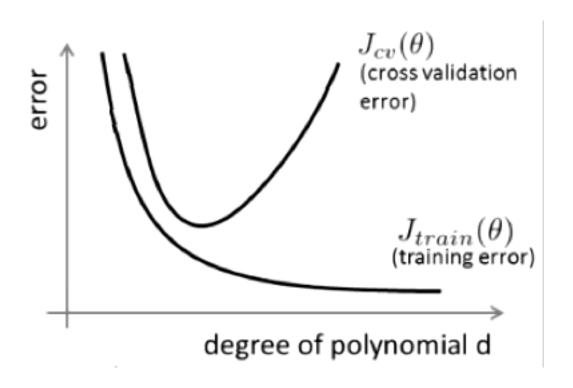
VERY LARGE

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

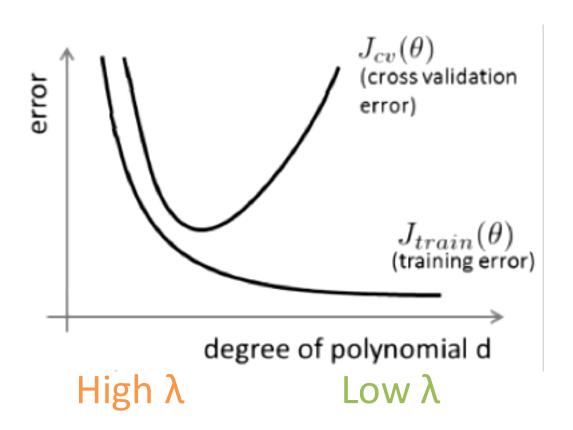
$$\stackrel{\approx 0}{\downarrow} \quad \stackrel{\approx 0}{\downarrow} \quad \stackrel{\approx 0}{\downarrow} \quad \stackrel{\approx 0}{\downarrow} \quad \stackrel{\approx 0}{\downarrow}$$

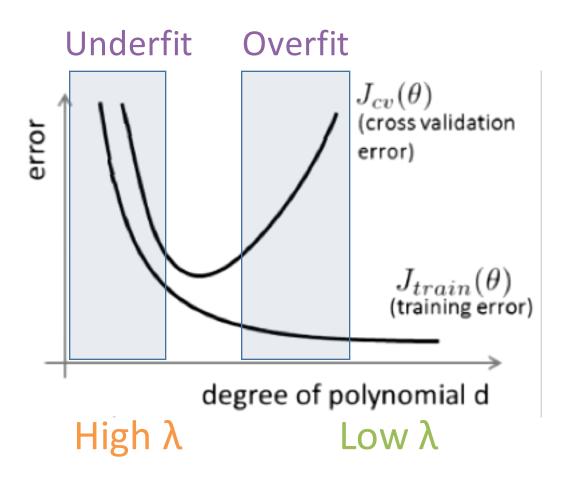
$$y_{\beta}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon$$

Error vs. regularization λ



Error vs. regularization λ





Ridge Regularization (L2)

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

Ridge Regularization (L2)

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

Lasso Regularization (L1)

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

Ridge Regularization (L2)

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

Lasso Regularization (L1)

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

Elastic Net (L1 + L2)

$$J(\beta_0, \beta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(y_{\beta}(x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2 + \lambda_1 \sum_{j=1}^{k} \left| \beta_j \right| + \lambda_2 \sum_{j=1}^{k} \beta_j^2$$

We were doing:

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X,Y)
```

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```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X, y)
```

To use Ridge Regularization:

```
from sklearn.linear_model import Ridge model = Ridge(1.0) model.fit(X, y) \lambda (sklearn Calls It alpha)
```

We were doing:

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X, y)
```

To use Lasso:

```
from sklearn.linear_model import Lasso model = Lasso(1.0) model.fit(X, y) \lambda (sklearn Calls It alpha)
```

We were doing:

from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X, y)

To use Elastic Net:

from sklearn.linear_model import ElasticNet
model = ElasticNet(1.0, l1_ratio = 0.5)
model.fit(X, y)

total weight for the full penalty term

ratio of I1/I2 penalty

My model is not awesome enough.

What do I do?

Try these and check test error (and AIC,BIC,etc.) again:

Use a smaller set of features

Regularization: Increase/decrease λ

Try adding polynomials

Check functional forms for each feature

Try including other features

Use more data (bigger training set)