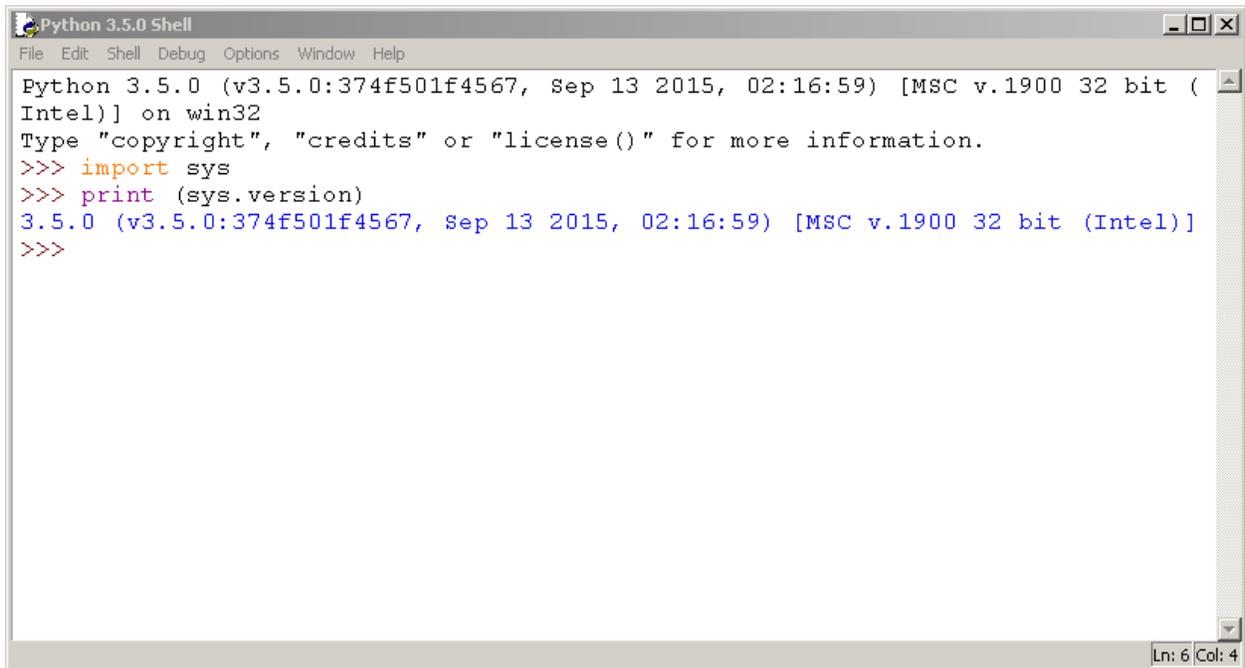
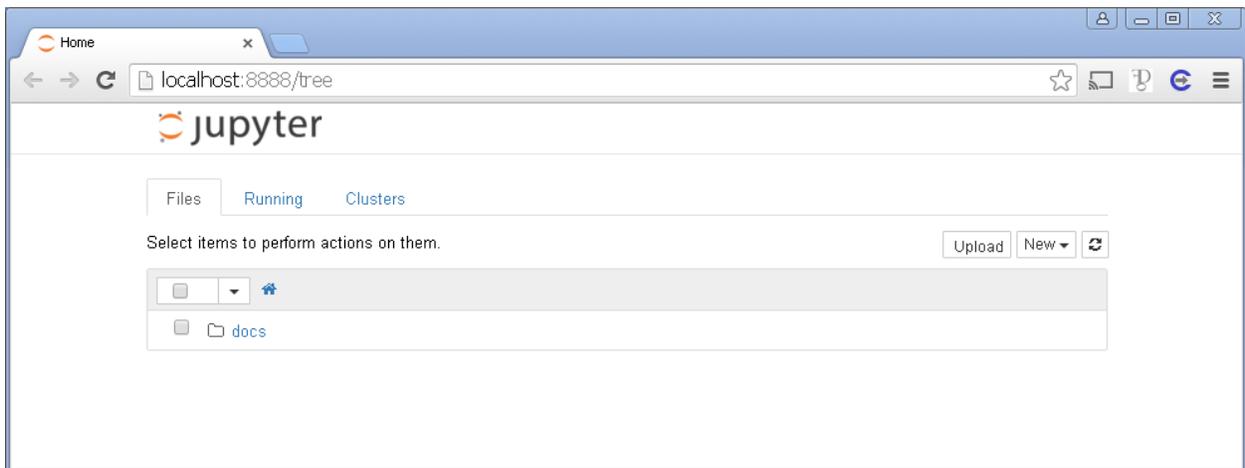


# Chapter 1: Regression – The Workhorse of Data Science



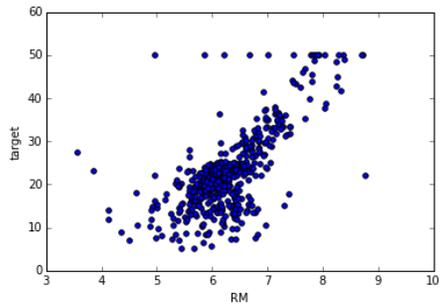
```
Python 3.5.0 Shell
File Edit Shell Debug Options Window Help
Python 3.5.0 (v3.5.0:374f501f4567, Sep 13 2015, 02:16:59) [MSC v.1900 32 bit (Intel)] on win32
Type "copyright", "credits" or "license()" for more information.
>>> import sys
>>> print (sys.version)
3.5.0 (v3.5.0:374f501f4567, Sep 13 2015, 02:16:59) [MSC v.1900 32 bit (Intel)]
>>>
```

Ln: 6 Col: 4



```
In [1]: import pandas as pd
        from sklearn.datasets import load_boston
        boston = load_boston()
        dataset = pd.DataFrame(boston.data, columns=boston.feature_names)
        dataset['target'] = boston.target
```

```
In [2]: %matplotlib inline
        # If you are using IPython, this will make the images available in the notebook
        scatter = dataset.plot(kind='scatter', x='RM', y='target')
```



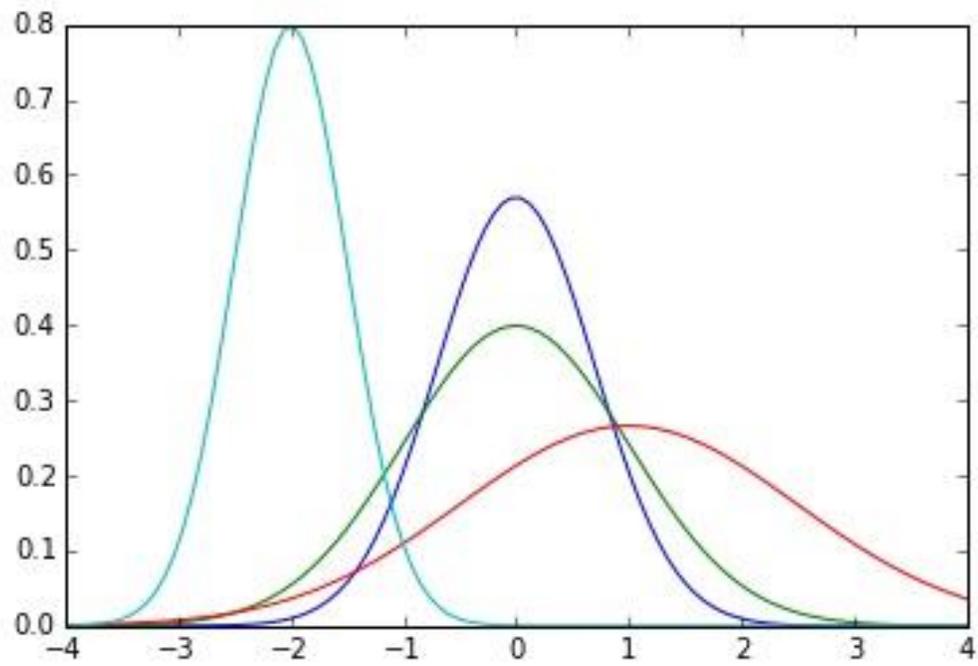
## Chapter 2: Approaching Simple Linear Regression

$$y = h(X)$$

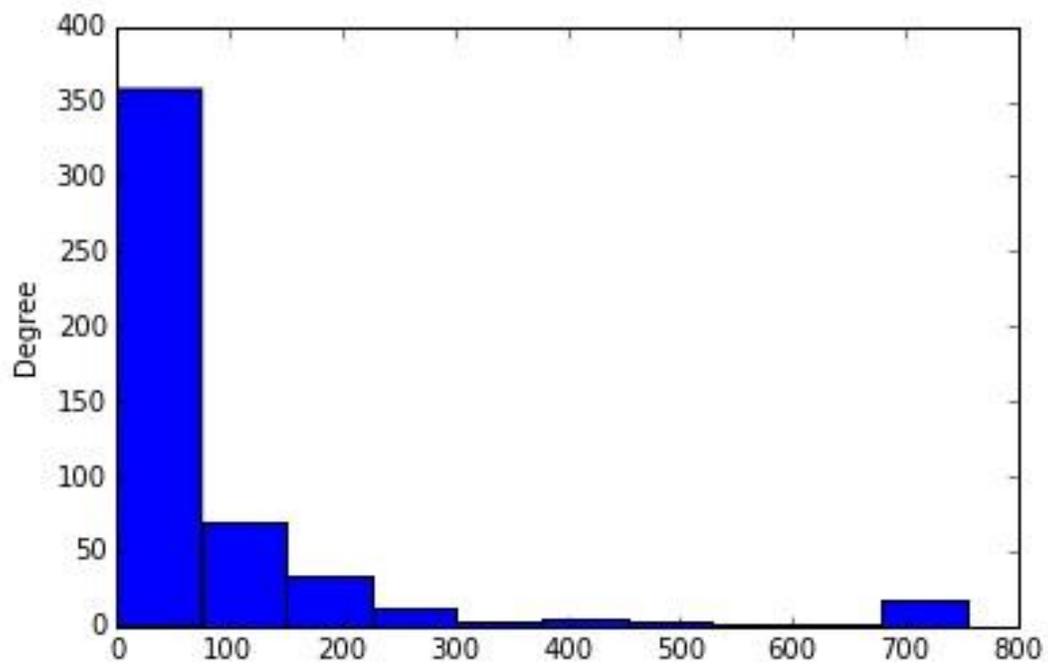
$$X = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{bmatrix}$$

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,p} \\ x_{2,1} & x_{2,2} & \dots & x_{2,p} \\ & & \cdot & \\ & & \cdot & \\ & & \cdot & \\ x_{n,1} & x_{n,2} & \dots & x_{n,p} \end{bmatrix}$$

$$f(x | \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$



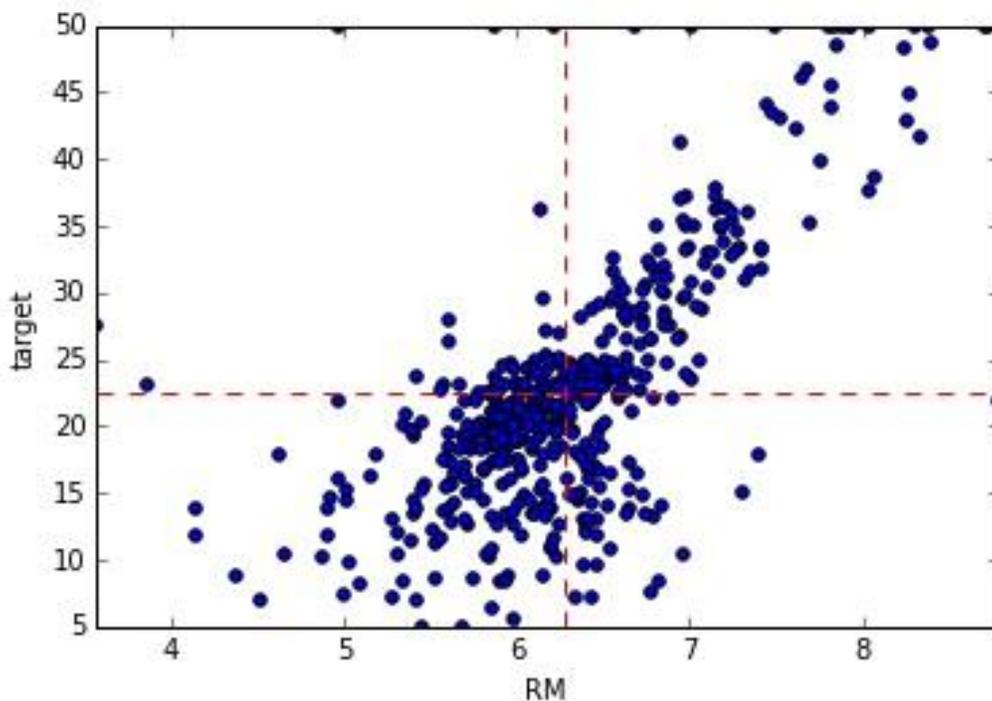
$$y = \bar{x}$$



$$x = \frac{x - \bar{x}}{\sigma_x}$$

$$\text{cov}(x_i, y) = \frac{1}{n} * \sum (x_i - \bar{x}_i) * (y - \bar{y})$$

$$r = \frac{1}{n} * \frac{\sum (x_i - \bar{x}_i) * (y - \bar{y})}{\sigma_{x_i} * \sigma_y}$$



$$y = \beta X + \beta_0$$

$$y = \beta X + \beta_0$$

$$y = \beta X$$

	const	RM
<b>0</b>	1	6.575
<b>1</b>	1	6.421
<b>2</b>	1	7.185
<b>3</b>	1	6.998
<b>4</b>	1	7.147

#### OLS Regression Results

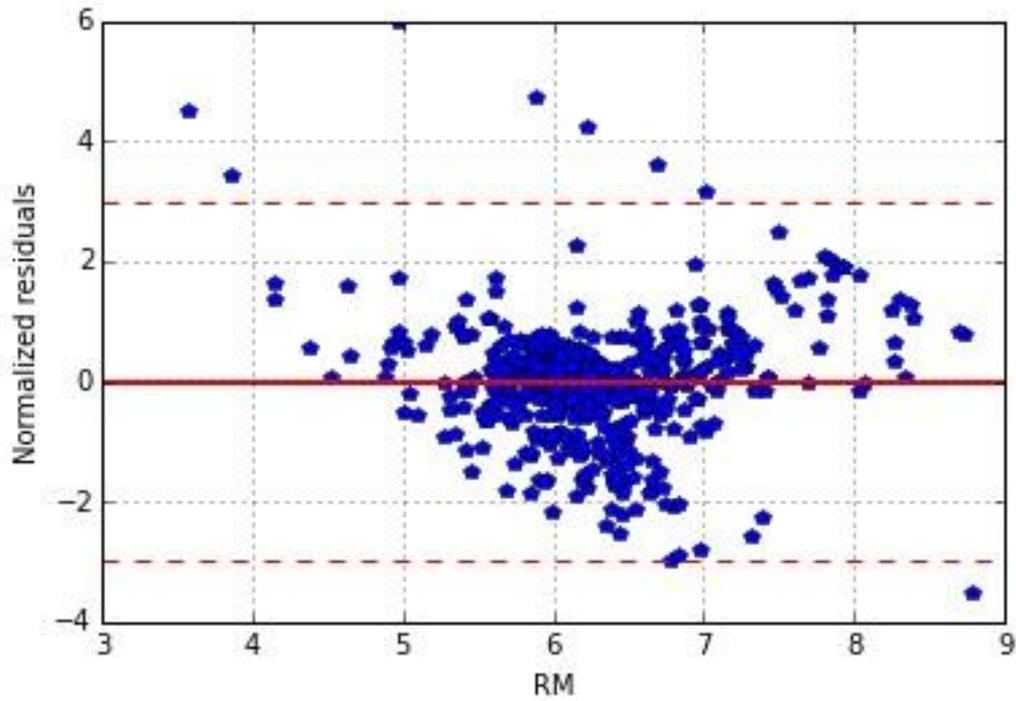
<b>Dep. Variable:</b>	target	<b>R-squared:</b>	0.484
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.483
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	471.8
<b>Date:</b>	Sat, 28 Nov 2015	<b>Prob (F-statistic):</b>	2.49e-74
<b>Time:</b>	21:02:32	<b>Log-Likelihood:</b>	-1673.1
<b>No. Observations:</b>	506	<b>AIC:</b>	3350.
<b>Df Residuals:</b>	504	<b>BIC:</b>	3359.
<b>Df Model:</b>	1		
<b>Covariance Type:</b>	nonrobust		

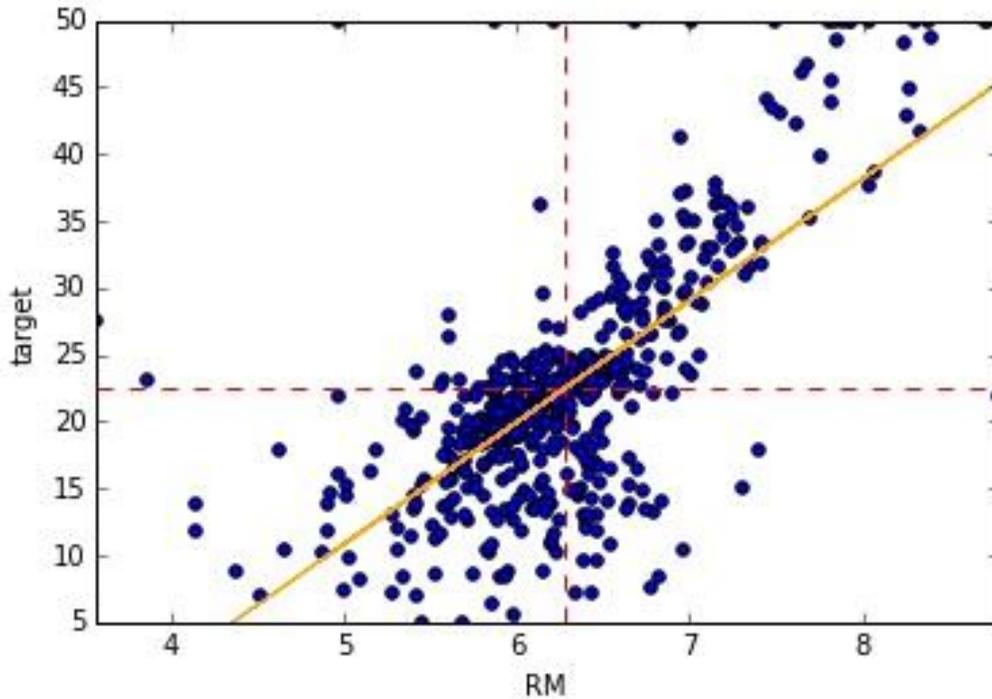
	coef	std err	t	P> t	[95.0% Conf. Int.]
<b>const</b>	-34.6706	2.650	-13.084	0.000	-39.877 -29.465
<b>RM</b>	9.1021	0.419	21.722	0.000	8.279 9.925

<b>Omnibus:</b>	102.585	<b>Durbin-Watson:</b>	0.684
<b>Prob(Omnibus):</b>	0.000	<b>Jarque-Bera (JB):</b>	612.449
<b>Skew:</b>	0.726	<b>Prob(JB):</b>	1.02e-133
<b>Kurtosis:</b>	8.190	<b>Cond. No.</b>	58.4

$$y = \beta X + \beta_0$$

$$y = 9.1021 * x_{RM} - 34.6706$$





$$y \approx h(X) = \beta X + \beta_0$$

$$\frac{1}{2n} * \sum (h(X) - y)^2$$

$$w = (X^T X)^{-1} X^T y$$

$$(X^T X)^{-1} * w = X^T y$$

$$J(w) = \frac{1}{2n} \sum (Xw - y)^2$$

$$w_j = w_j - \alpha * \frac{\partial}{\partial w} J(w)$$

$$w_j = w_j - \alpha * \frac{1}{n} \sum (Xw - y) * x_j$$

## Chapter 3: Multiple Regression in Action

### OLS Regression Results

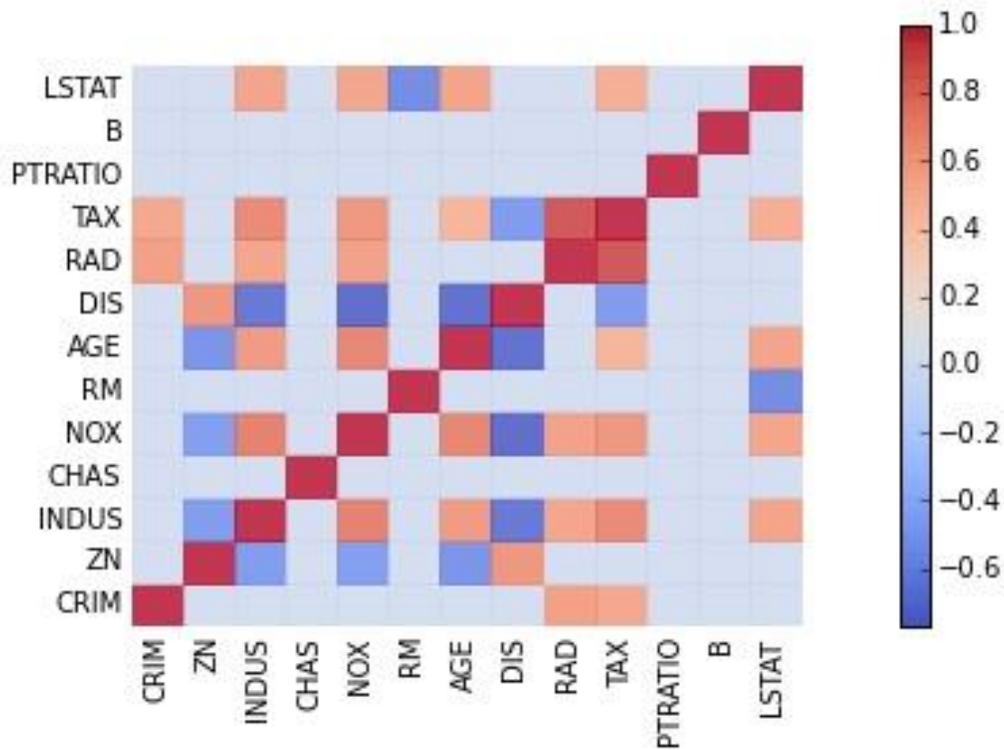
<b>Dep. Variable:</b>	y	<b>R-squared:</b>	0.741
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.734
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	108.1
<b>Date:</b>	Tue, 29 Sep 2015	<b>Prob (F-statistic):</b>	6.95e-135
<b>Time:</b>	21:45:28	<b>Log-Likelihood:</b>	-1498.8
<b>No. Observations:</b>	506	<b>AIC:</b>	3026.
<b>Df Residuals:</b>	492	<b>BIC:</b>	3085.
<b>Df Model:</b>	13		
<b>Covariance Type:</b>	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
<b>const</b>	36.4911	5.104	7.149	0.000	26.462 46.520
<b>CRIM</b>	-0.1072	0.033	-3.276	0.001	-0.171 -0.043
<b>ZN</b>	0.0464	0.014	3.380	0.001	0.019 0.073
<b>INDUS</b>	0.0209	0.061	0.339	0.735	-0.100 0.142
<b>CHAS</b>	2.6886	0.862	3.120	0.002	0.996 4.381
<b>NOX</b>	-17.7958	3.821	-4.658	0.000	-25.302 -10.289
<b>RM</b>	3.8048	0.418	9.102	0.000	2.983 4.626
<b>AGE</b>	0.0008	0.013	0.057	0.955	-0.025 0.027
<b>DIS</b>	-1.4758	0.199	-7.398	0.000	-1.868 -1.084
<b>RAD</b>	0.3057	0.066	4.608	0.000	0.175 0.436
<b>TAX</b>	-0.0123	0.004	-3.278	0.001	-0.020 -0.005
<b>PTRATIO</b>	-0.9535	0.131	-7.287	0.000	-1.211 -0.696
<b>B</b>	0.0094	0.003	3.500	0.001	0.004 0.015
<b>LSTAT</b>	-0.5255	0.051	-10.366	0.000	-0.625 -0.426

<b>Omnibus:</b>	178.029	<b>Durbin-Watson:</b>	1.078
<b>Prob(Omnibus):</b>	0.000	<b>Jarque-Bera (JB):</b>	782.015
<b>Skew:</b>	1.521	<b>Prob(JB):</b>	1.54e-170
<b>Kurtosis:</b>	8.276	<b>Cond. No.</b>	1.51e+04

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
CRIM	1.000000	-0.199458	0.404471	-0.055295	0.417521	-0.219940	0.350784
ZN	-0.199458	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537
INDUS	0.404471	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779
CHAS	-0.055295	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518
NOX	0.417521	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470
RM	-0.219940	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265
AGE	0.350784	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000
DIS	-0.377904	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881
RAD	0.622029	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022
TAX	0.579564	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456
PTRATIO	0.288250	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515
B	-0.377365	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534
LSTAT	0.452220	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339

	DIS	RAD	TAX	PTRATIO	B	LSTAT
CRIM	-0.377904	0.622029	0.579564	0.288250	-0.377365	0.452220
ZN	0.664408	-0.311948	-0.314563	-0.391679	0.175520	-0.412995
INDUS	-0.708027	0.595129	0.720760	0.383248	-0.356977	0.603800
CHAS	-0.099176	-0.007368	-0.035587	-0.121515	0.048788	-0.053929
NOX	-0.769230	0.611441	0.668023	0.188933	-0.380051	0.590879
RM	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808
AGE	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
DIS	1.000000	-0.494588	-0.534432	-0.232471	0.291512	-0.496996
RAD	-0.494588	1.000000	0.910228	0.464741	-0.444413	0.488676
TAX	-0.534432	0.910228	1.000000	0.460853	-0.441808	0.543993
PTRATIO	-0.232471	0.464741	0.460853	1.000000	-0.177383	0.374044
B	0.291512	-0.444413	-0.441808	-0.177383	1.000000	-0.366087
LSTAT	-0.496996	0.488676	0.543993	0.374044	-0.366087	1.000000



$$y = \beta_0 + \sum \beta_i x_i$$

$$y = \left( \hat{\beta}_0 - \sum \frac{\hat{\beta}_i * \bar{x}_i}{\delta_i} \right) + \sum \left( \frac{\hat{\beta}_i}{\delta_i} * x_i \right)$$

```

bias: 36.4911
CRIM: -0.1072
ZN: 0.0464
INDUS: 0.0209
CHAS: 2.6886
NOX: -17.7958
RM: 3.8048
AGE: 0.0008
DIS: -1.4758
RAD: 0.3057
TAX: -0.0123
PTRATIO: -0.9535
B: 0.0094
LSTAT: -0.5255

```

17.796 NOX  
 3.805 RM  
 2.689 CHAS  
 1.476 DIS  
 0.953 PTRATIO  
 0.525 LSTAT  
 0.306 RAD  
 0.107 CRIM  
 0.046 ZN  
 0.021 INDUS  
 0.012 TAX  
 0.009 B  
 0.001 AGE  
  
 3.749 LSTAT  
 3.104 DIS  
 2.671 RM  
 2.659 RAD  
 2.076 TAX  
 2.062 PTRATIO  
 2.060 NOX  
 1.081 ZN  
 0.920 CRIM  
 0.857 B  
 0.682 CHAS  
 0.143 INDUS  
 0.021 AGE  
  
 0.057 LSTAT  
 0.044 RM  
 0.029 DIS  
 0.028 PTRATIO  
 0.011 NOX  
 0.011 RAD  
 0.006 B  
 0.006 ZN  
 0.006 TAX  
 0.006 CRIM  
 0.005 CHAS  
 0.000 INDUS  
 0.000 AGE

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2$$

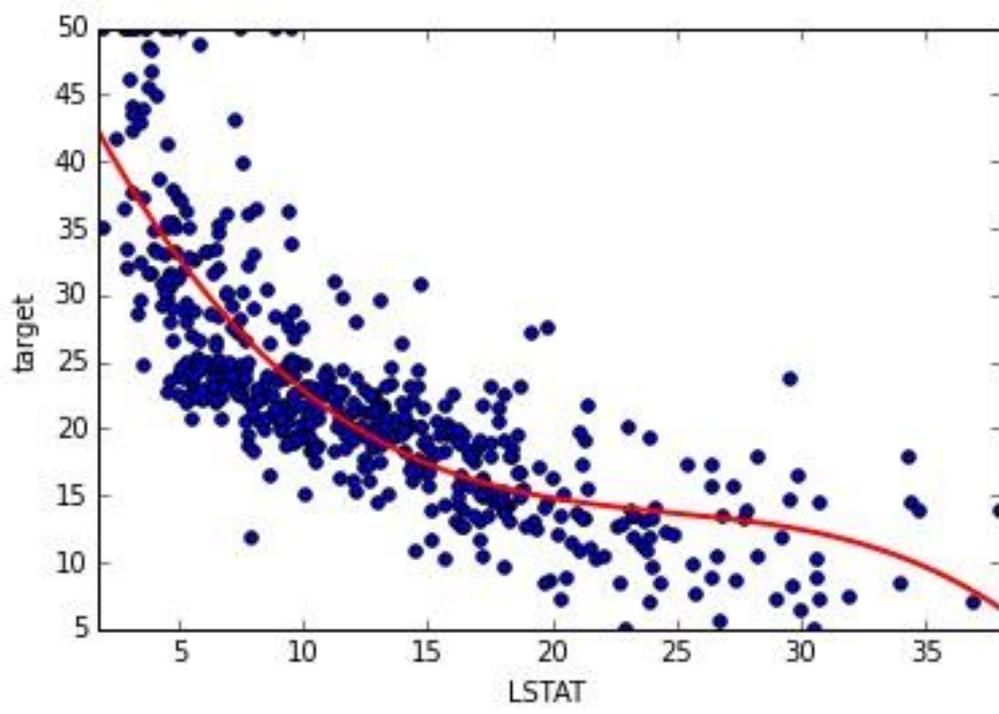
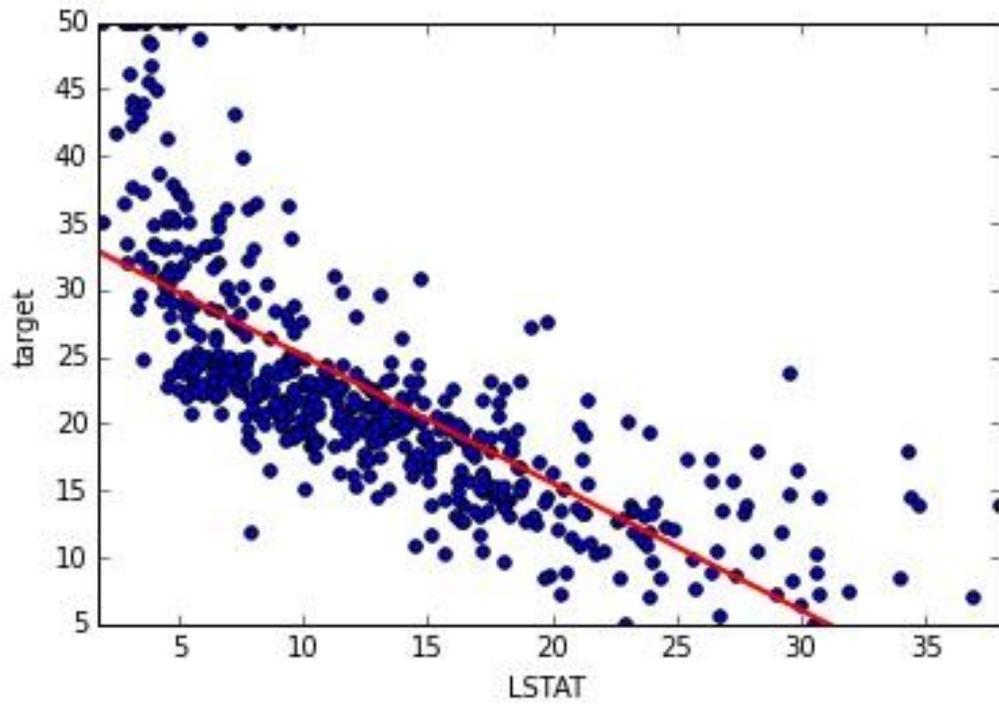
Adding interaction	CRIM *	CHAS R2: 0.011
Adding interaction	CRIM *	RM R2: 0.021
Adding interaction	ZN *	RM R2: 0.013
Adding interaction	INDUS *	RM R2: 0.038
Adding interaction	INDUS *	DIS R2: 0.013
Adding interaction	NOX *	RM R2: 0.027
Adding interaction	RM *	AGE R2: 0.024
Adding interaction	RM *	DIS R2: 0.018
Adding interaction	RM *	RAD R2: 0.049
Adding interaction	RM *	TAX R2: 0.054
Adding interaction	RM *	PTRATIO R2: 0.041
Adding interaction	RM *	B R2: 0.020
Adding interaction	RM *	LSTAT R2: 0.064

$$y = \beta_0 + \beta_1 x$$

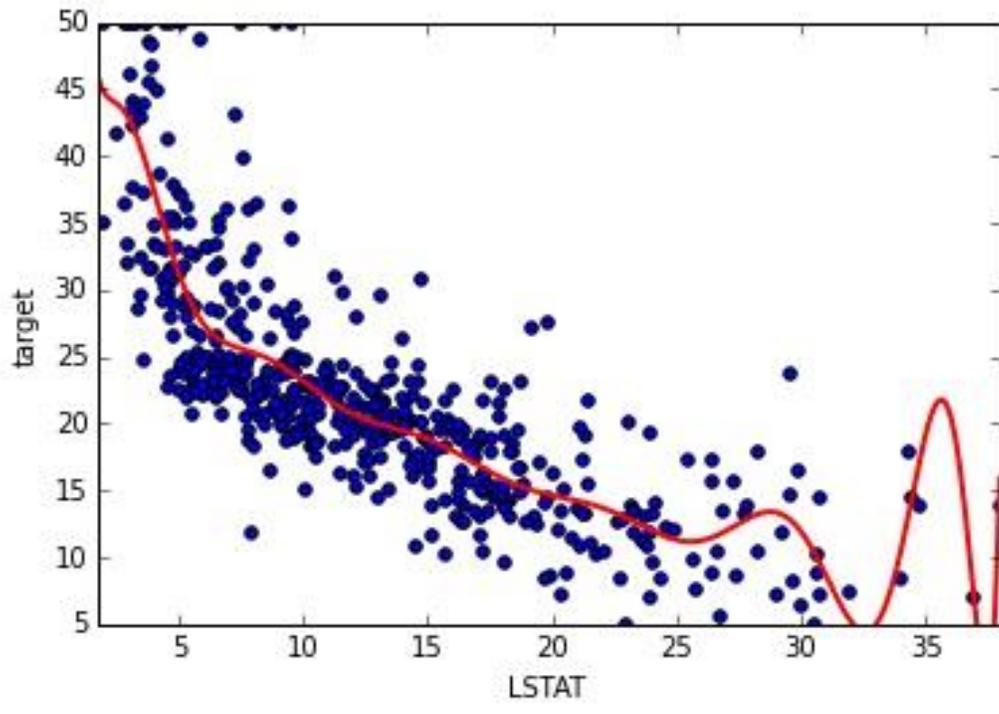
$$y = \beta_0 + \beta_1 x + \beta_3 x^2$$

$$y = \beta_0 + \beta_1 x + \beta_3 x^2 + \beta_4 x^3$$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \beta_4 x_1^2 + \beta_5 x_2^2$$

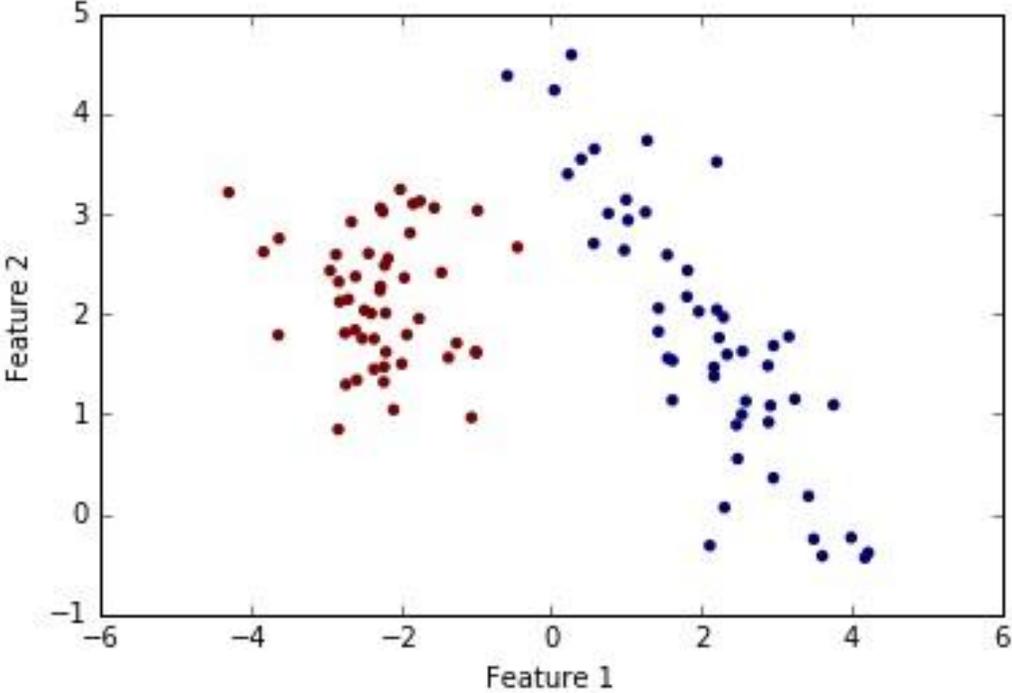
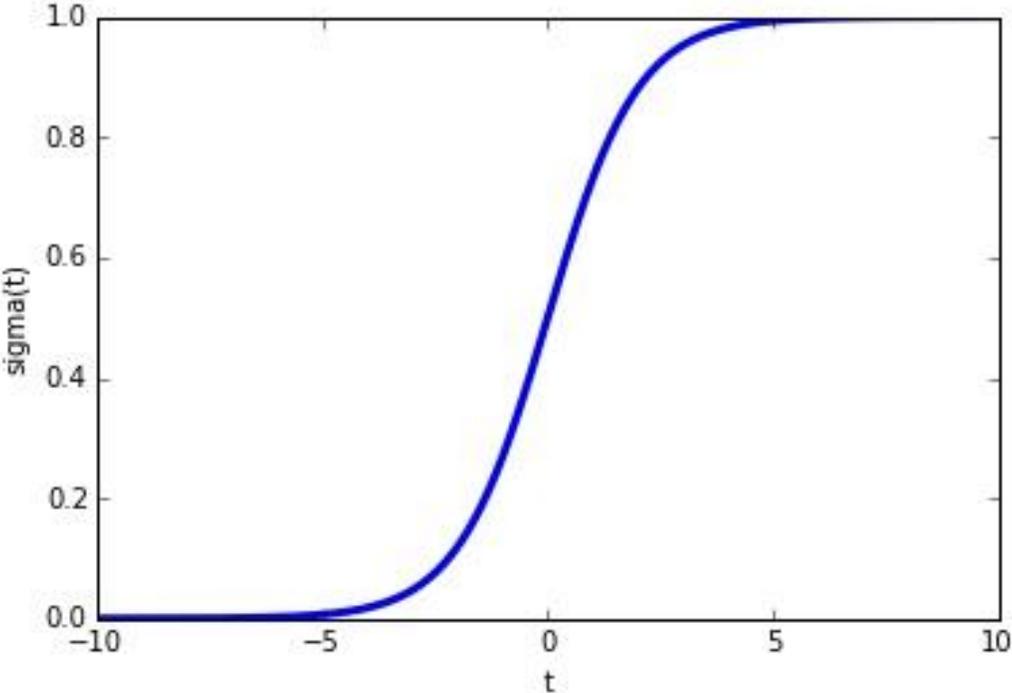


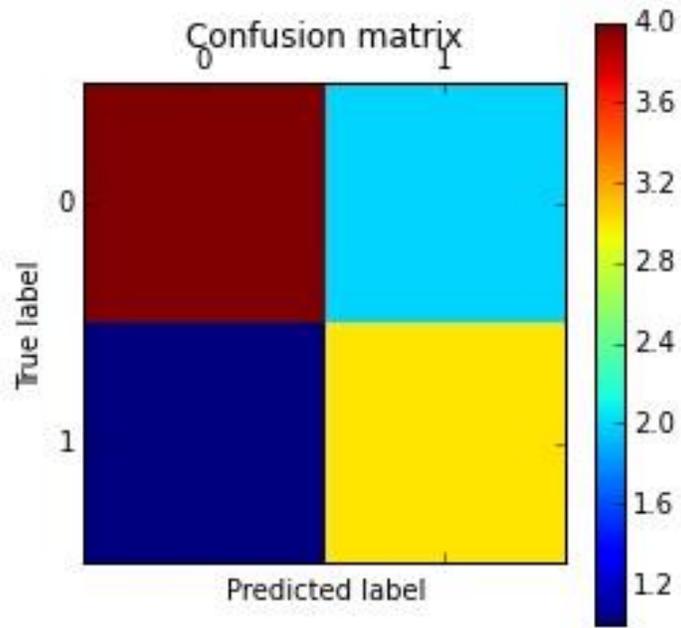
R2 degree - 1 polynomial :0.544  
R2 degree - 2 polynomial :0.641  
R2 degree - 3 polynomial :0.658  
R2 degree - 5 polynomial :0.682  
R2 degree - 15 polynomial :0.695



$\bar{x}$

# Chapter 4: Logistic Regression



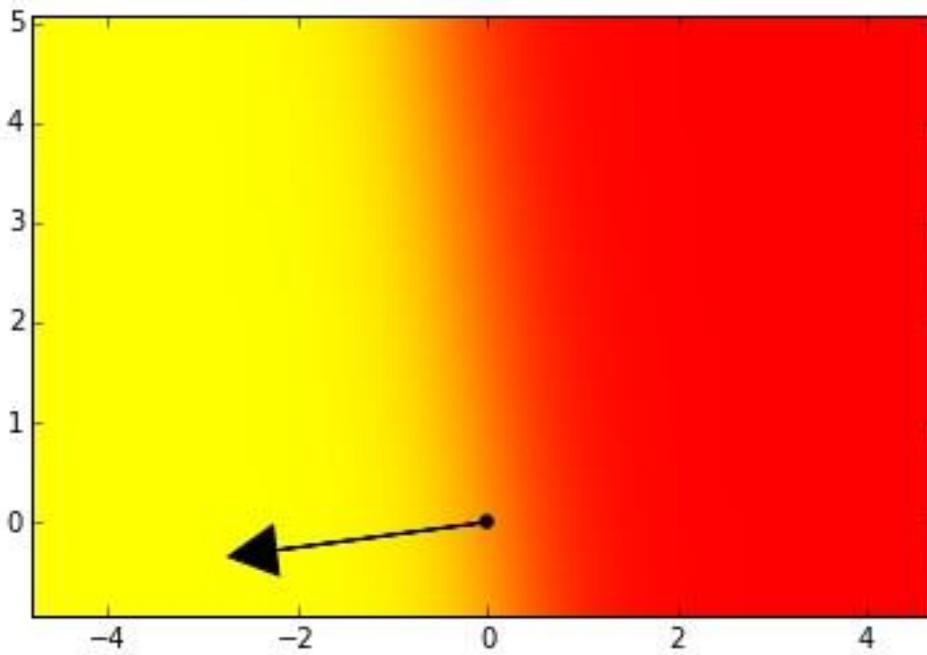
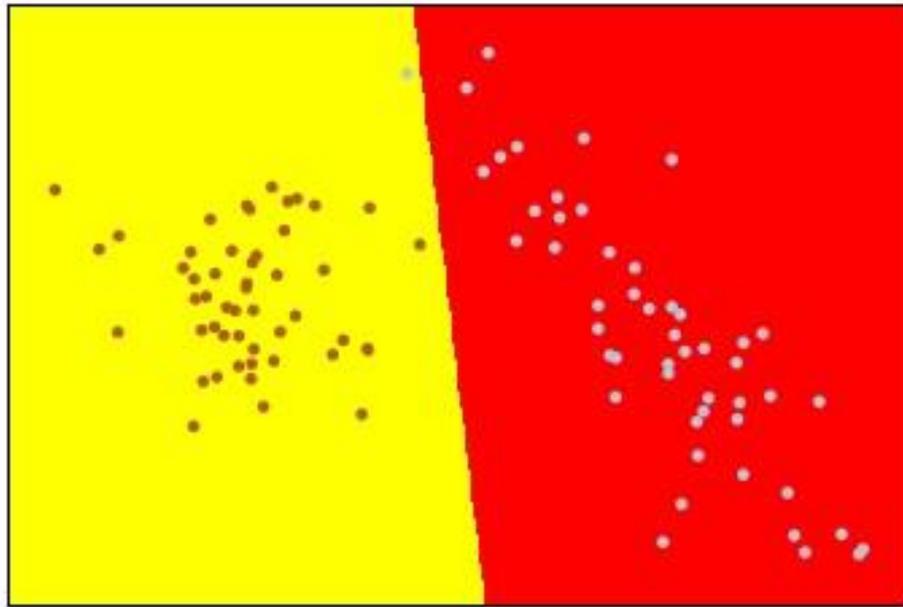


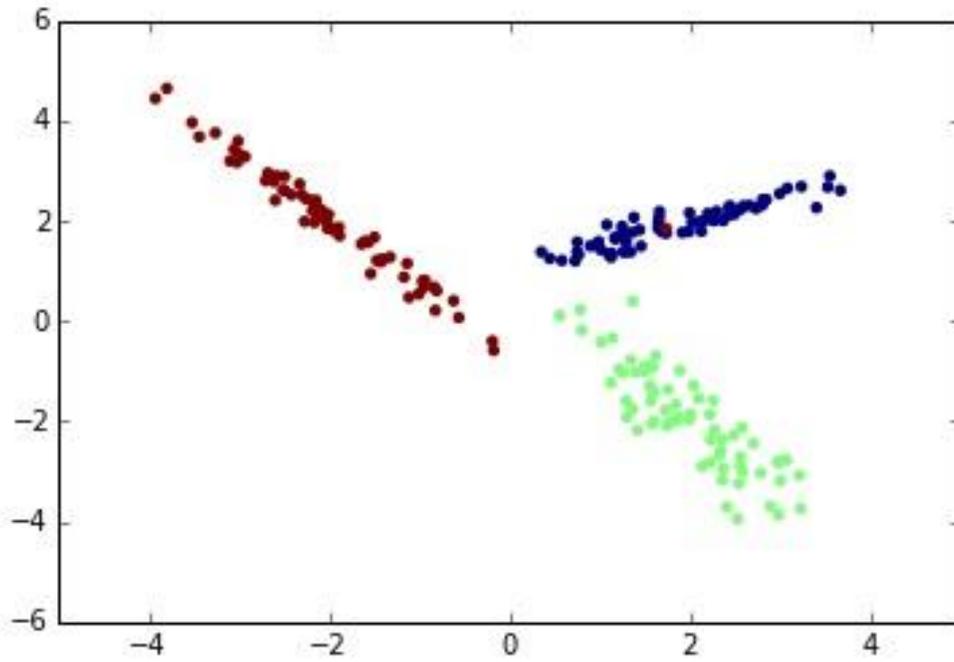
	precision	recall	f1-score	support
0	0.80	0.67	0.73	6
1	0.60	0.75	0.67	4
avg / total	0.72	0.70	0.70	10

```
array([ 0.,  1.,  1.,  0.,  1.,  1.,  0.,  1.,  0.,  0.,  0.,  0.,  1.,
        0.,  1.,  0.,  0.,  1.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  1.,  0.,  1.,  0.]
```

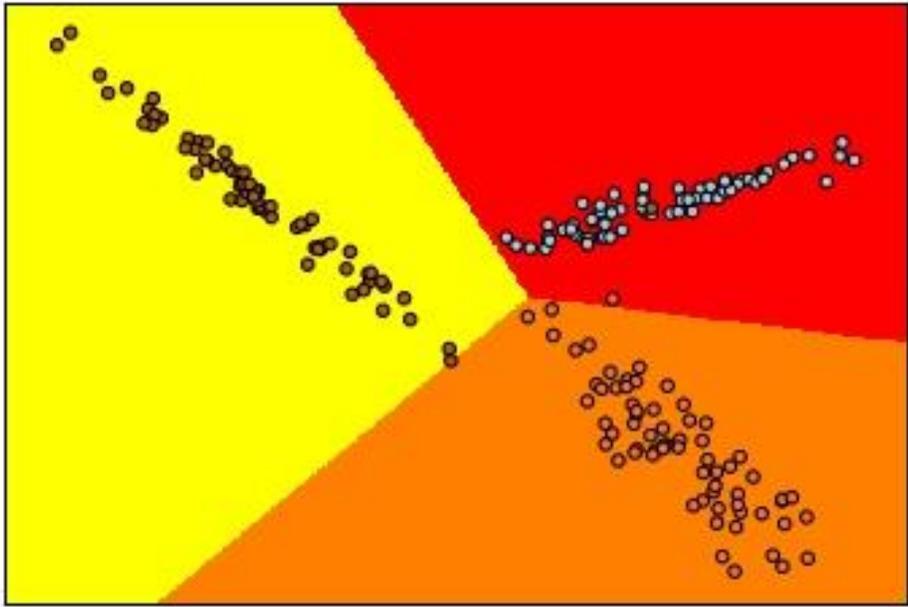
```
array([ 0.06688448,  1.01981921,  1.08597427, -0.15225094,  1.05856628,
        0.8156161 ,  0.04837505,  0.7997539 ,  0.18942251, -0.03658995,
       -0.0462575 , -0.09640911,  1.0253004 , -0.17062754,  1.13642842,
        0.14052848, -0.00703683,  0.90903158,  1.26997191,  0.03606483,
       -0.19047191,  0.22476337, -0.05936491, -0.18559975,  0.28378888,
        0.01139188, -0.03559395,  0.22742328,  0.07485246,  1.24545626,
        0.13924533,  1.09388935,  0.35341582])
```

	precision	recall	f1-score	support
0.0	1.00	0.95	0.98	22
1.0	0.92	1.00	0.96	11
avg / total	0.97	0.97	0.97	33





	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	24
1.0	1.00	1.00	1.00	22
2.0	1.00	1.00	1.00	20
avg / total	1.00	1.00	1.00	66



## Logit Regression Results

<b>Dep. Variable:</b>	y	<b>No. Observations:</b>	10000
<b>Model:</b>	Logit	<b>Df Residuals:</b>	9989
<b>Method:</b>	MLE	<b>Df Model:</b>	10
<b>Date:</b>	Fri, 01 Jan 2016	<b>Pseudo R-squ.:</b>	0.3671
<b>Time:</b>	11:48:59	<b>Log-Likelihood:</b>	-4386.8
<b>converged:</b>	True	<b>LL-Null:</b>	-6931.5
		<b>LLR p-value:</b>	0.000

	<b>coef</b>	<b>std err</b>	<b>z</b>	<b>P&gt; z </b>	<b>[95.0% Conf. Int.]</b>
<b>const</b>	0.4299	0.039	11.023	0.000	0.353 0.506
<b>x1</b>	0.0671	0.015	4.410	0.000	0.037 0.097
<b>x2</b>	-0.7828	0.019	-41.947	0.000	-0.819 -0.746
<b>x3</b>	0.1221	0.016	7.815	0.000	0.091 0.153
<b>x4</b>	0.2841	0.016	18.150	0.000	0.253 0.315
<b>x5</b>	0.1469	0.014	10.283	0.000	0.119 0.175
<b>x6</b>	-0.3414	0.019	-17.636	0.000	-0.379 -0.303
<b>x7</b>	0.0503	0.014	3.481	0.000	0.022 0.079
<b>x8</b>	-0.1393	0.014	-9.642	0.000	-0.168 -0.111
<b>x9</b>	0.1127	0.014	7.931	0.000	0.085 0.141
<b>x10</b>	-0.4792	0.018	-27.340	0.000	-0.514 -0.445

[0.42991394845314063,  
0.067077096874709585,  
-0.7827957661488677,  
0.12208730826867409,  
0.28410283693190336,  
0.14689340914475549,  
-0.34143434245188609,  
0.050310756492560317,  
-0.1393205915231476,  
0.11267402173781312,  
-0.47916904027905627]

[0.42571117875899561,  
0.092754663986175351,  
-0.78381378869544127,  
0.093708745822509473,  
0.1675646650527122,  
0.10596527209458738,  
-0.41091578158018643,  
0.062219832489940362,  
-0.19435965629236054,  
0.2353120824478212,  
-0.48793778455042086]

$$(x_i, y_i) : x_i \in \mathbb{R}^n, y_i \in \{0, 1\}$$

$$f : \mathbb{R}^n \rightarrow \{0, 1\}$$

$$f1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$P(y_i = "1" | x_i)$$

$$y = X \cdot w$$

$$P(y = 1 | x) = \sigma(W^T \cdot x)$$

$$\sigma(t) = \text{logit}^{-1}(t) = \frac{1}{1 + e^{-t}}$$

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = \log(p) - \log(1-p)$$

$$P(y = "1" | x) = \frac{1}{1 + e^{-t}}$$

$$P(y = "0" | x) = 1 - \frac{1}{1 + e^{-t}}$$

$$\log\left(\frac{P(y = "1" | x)}{P(y = "0" | x)}\right) = W^T \cdot x$$

$$\text{logit}(P(y = "1" | x)) = W^T \cdot x$$

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

$$\sigma'(t) = \frac{\partial}{\partial z} \frac{1}{1 + e^{-t}} = \frac{e^{-t}}{(1 + e^{-t})^2} = \left(\frac{1}{1 + e^{-t}}\right) \cdot \left(1 - \frac{1}{1 + e^{-t}}\right) = \sigma(t) \cdot (1 - \sigma(t))$$

$$\begin{aligned} L(W) &= P(Y | X; W) \\ &= \prod_i P(y_i | x_i; W) \\ &= \prod_i \left(\sigma(W^T \cdot x_i)\right)^{y_i} \cdot \left(1 - \sigma(W^T \cdot x_i)\right)^{1-y_i} \end{aligned}$$

$$\begin{aligned} \hat{L}(W) &= \log(L(W)) \\ &= \sum_i y_i \log\left(\sigma(W^T \cdot x_i)\right) + (1 - y_i) \log\left(1 - \sigma(W^T \cdot x_i)\right) \end{aligned}$$

$$\frac{\partial}{\partial w_k} \hat{L}(W) = \dots = \left(y - \sigma(W^T \cdot x)\right) \cdot x_k$$

$$W \leftarrow W + \alpha \nabla \hat{L}(W)$$

$$w_k \leftarrow w_k + \alpha \cdot \left(y - \frac{1}{1 + e^{-W^T \cdot x}}\right) \cdot x_k$$



## Chapter 5: Data Preparation

$$y = \beta_0 + \beta X$$

```
coefficients: [-0.10717  0.0464  0.02086  2.68856 -17.79576  3.80475  0.00075  
              -1.47576  0.30566 -0.01233 -0.95346  0.00939 -0.52547]  
intercept: 36.491
```

```
CRIM      0.00632  
ZN        0.00000  
INDUS     0.46000  
CHAS      0.00000  
NOX       0.38500  
RM        3.56100  
AGE       2.90000  
DIS       1.12960  
RAD       1.00000  
TAX      187.00000  
PTRATIO  12.60000  
B         0.32000  
LSTAT    1.73000  
target   5.00000  
dtype: float64
```

```
coefficients: [-0.10717  0.0464  0.02086  2.68856 -17.79576  3.80475  0.00075  
              -1.47576  0.30566 -0.01233 -0.95346  0.00939 -0.52547]  
intercept: 22.533
```

```
coefficients: [-0.92041  1.08098  0.14297  0.6822  -2.06009  2.67064  0.02112 -3.10445  
              2.65879 -2.0759  -2.06216  0.85664 -3.74868]  
intercept: 22.533
```

```
coefficients: [-9.53495  4.63952  0.56907  2.68856 -8.64874  19.857  0.07293  
              -16.22877  7.03007 -6.46058 -8.96256  3.72488 -19.04291]  
intercept: 26.613
```

Optimization terminated successfully.  
 Current function value: 0.206632  
 Iterations 9

Logit Regression Results

```

=====
Dep. Variable:                y      No. Observations:      506
Model:                        Logit   Df Residuals:          492
Method:                       MLE    Df Model:              13
Date:                          Tue, 20 Oct 2015  Pseudo R-squ.:        0.6289
Time:                          16:33:29    Log-Likelihood:       -104.56
converged:                      True    LL-Null:              -281.76
                                  LLR p-value:          9.147e-68
=====
  
```

	coef	std err	z	P> z	[95.0% Conf. Int.]	
const	-3.0541	0.356	-8.572	0.000	-3.752	-2.356
x1	-0.0949	0.389	-0.244	0.807	-0.857	0.667
x2	0.2543	0.252	1.008	0.314	-0.240	0.749
x3	-0.7570	0.403	-1.880	0.060	-1.546	0.032
x4	0.2452	0.205	1.195	0.232	-0.157	0.648
x5	-0.7924	0.519	-1.527	0.127	-1.810	0.225
x6	1.3244	0.318	4.168	0.000	0.702	1.947
x7	0.0982	0.313	0.314	0.754	-0.515	0.712
x8	-1.2390	0.345	-3.591	0.000	-1.915	-0.563
x9	2.7664	0.719	3.849	0.000	1.358	4.175
x10	-1.8228	0.680	-2.682	0.007	-3.155	-0.491
x11	-0.7635	0.264	-2.888	0.004	-1.282	-0.245
x12	-0.2062	0.349	-0.591	0.554	-0.890	0.477
x13	-2.6208	0.521	-5.031	0.000	-3.642	-1.600

Optimization terminated successfully.  
 Current function value: 0.556842  
 Iterations 5

Logit Regression Results

```

=====
Dep. Variable:                y      No. Observations:      506
Model:                        Logit   Df Residuals:          505
Method:                       MLE    Df Model:              0
Date:                          Tue, 20 Oct 2015  Pseudo R-squ.:        0.000
Time:                          16:33:29    Log-Likelihood:       -281.76
converged:                      True    LL-Null:              -281.76
                                  LLR p-value:          nan
=====
  
```

	coef	std err	z	P> z	[95.0% Conf. Int.]	
const	-1.1251	0.103	-10.886	0.000	-1.328	-0.923

probability of value above 25 using just a constant: 0.245

Optimization terminated successfully.  
 Current function value: 0.292346  
 Iterations 32

Logit Regression Results

```

=====
Dep. Variable:          y      No. Observations:          36
Model:                 Logit  Df Residuals:              29
Method:                MLE    Df Model:                  6
Date:                 Tue, 20 Oct 2015  Pseudo R-squ.:            0.5744
Time:                 16:33:30    Log-Likelihood:           -10.524
converged:            True      LL-Null:                  -24.731
                               LLR p-value:              7.856e-05
=====

```

	coef	std err	z	P> z	[95.0% Conf. Int.]	
const	0.2393	1.76e+07	1.36e-08	1.000	-3.44e+07	3.44e+07
outlook_overcast	2.9833	6.69e+07	4.46e-08	1.000	-1.31e+08	1.31e+08
outlook_rainy	-2.1746	6.69e+07	-3.25e-08	1.000	-1.31e+08	1.31e+08
outlook_sunny	-0.5695	6.69e+07	-8.51e-09	1.000	-1.31e+08	1.31e+08
temperature_cool	-2.1996	6e+07	-3.66e-08	1.000	-1.18e+08	1.18e+08
temperature_hot	0.3045	6e+07	5.07e-09	1.000	-1.18e+08	1.18e+08
temperature_mild	2.1344	6e+07	3.55e-08	1.000	-1.18e+08	1.18e+08
humidity_high	-2.0459	2.24e+07	-9.15e-08	1.000	-4.38e+07	4.38e+07
humidity_normal	2.2851	2.24e+07	1.02e-07	1.000	-4.38e+07	4.38e+07
windy_FALSE	1.3162	4.47e+07	2.94e-08	1.000	-8.77e+07	8.77e+07
windy_TRUE	-1.0770	4.47e+07	-2.41e-08	1.000	-8.77e+07	8.77e+07

Optimization terminated successfully.  
 Current function value: 0.292346  
 Iterations 8

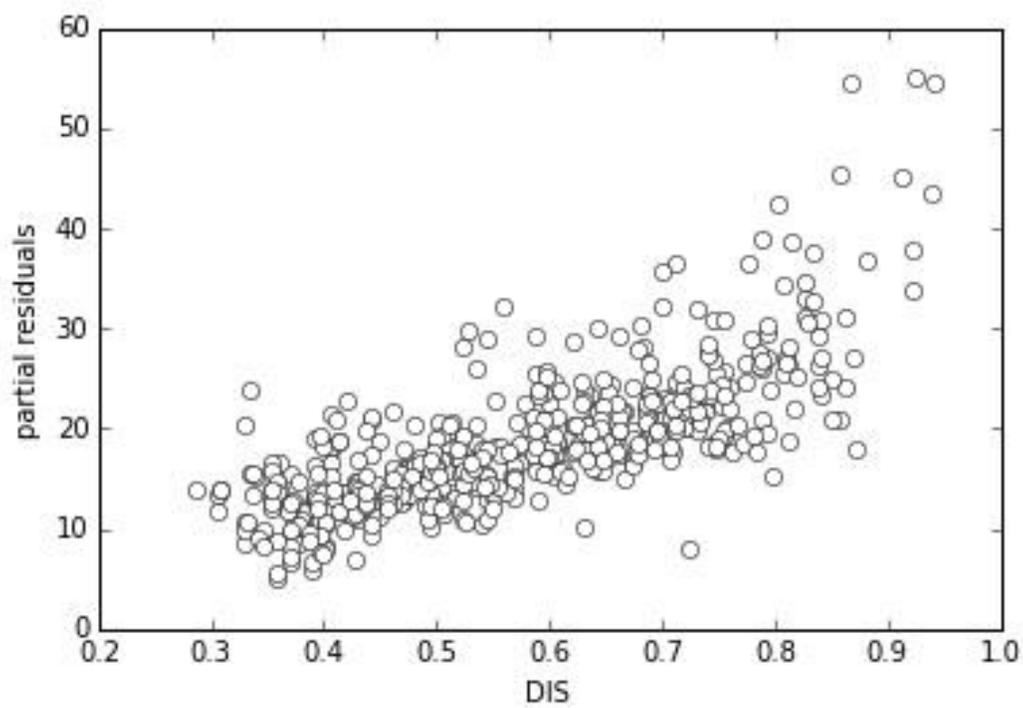
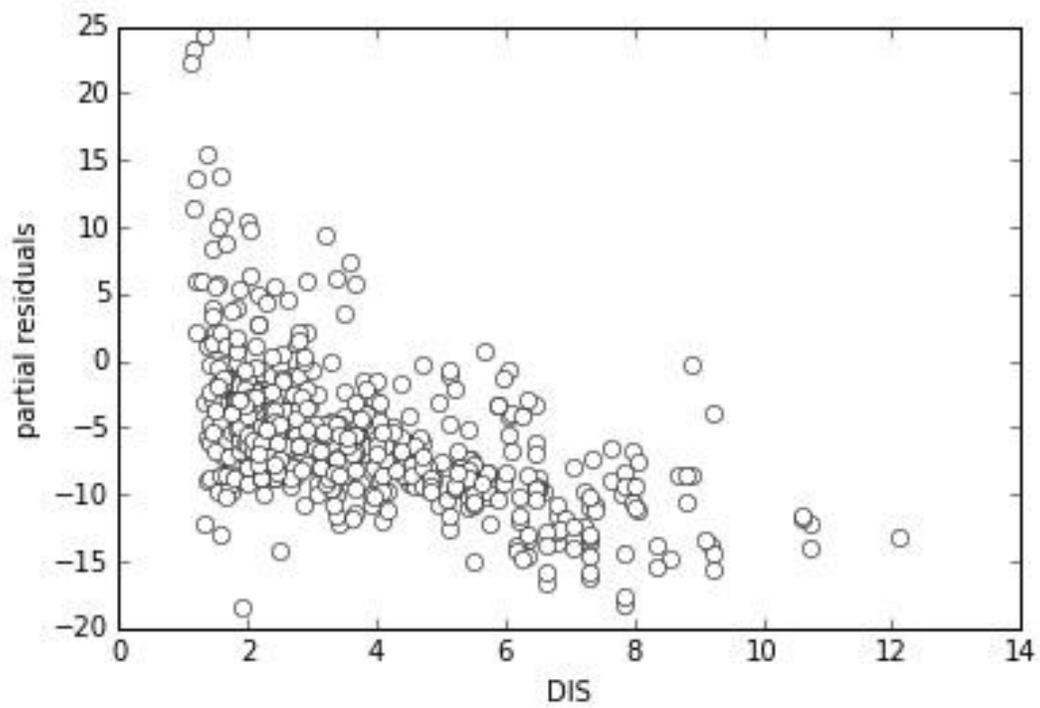
Logit Regression Results

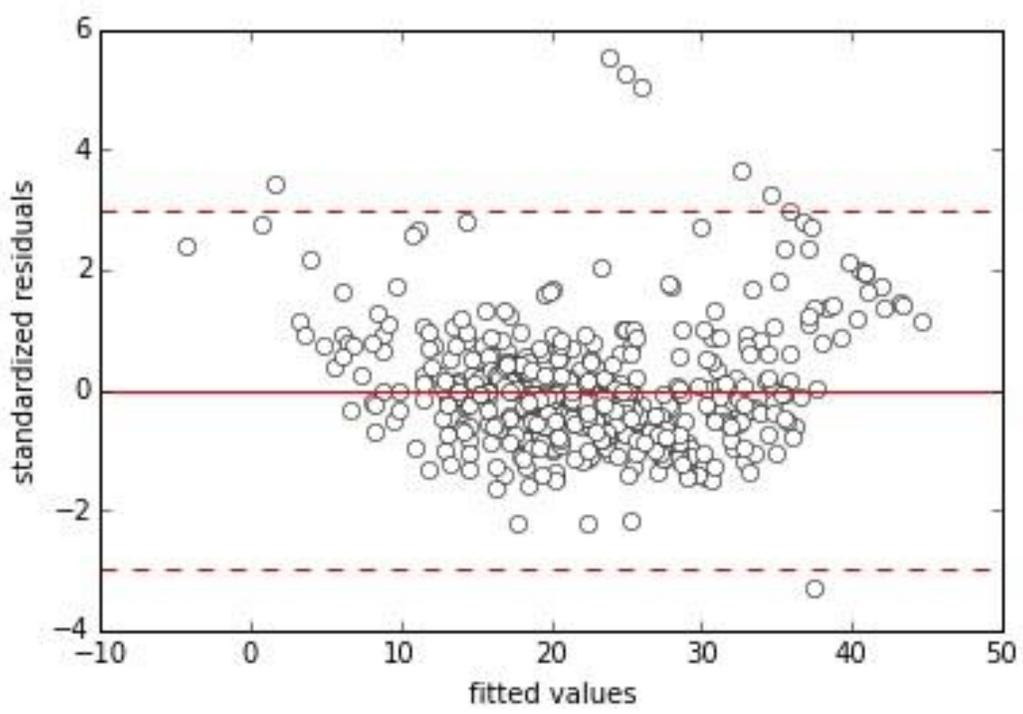
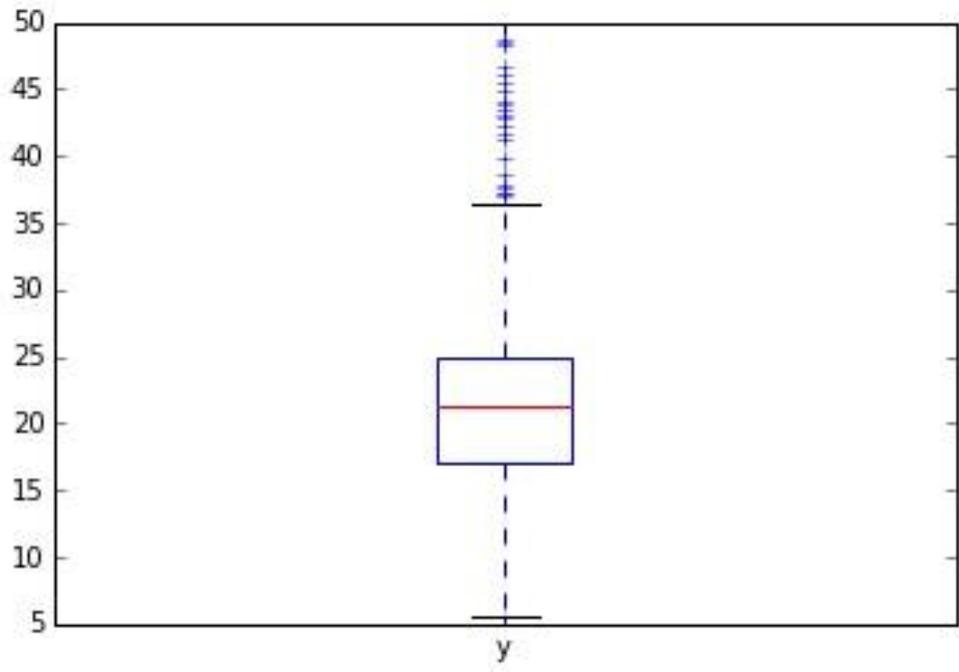
```

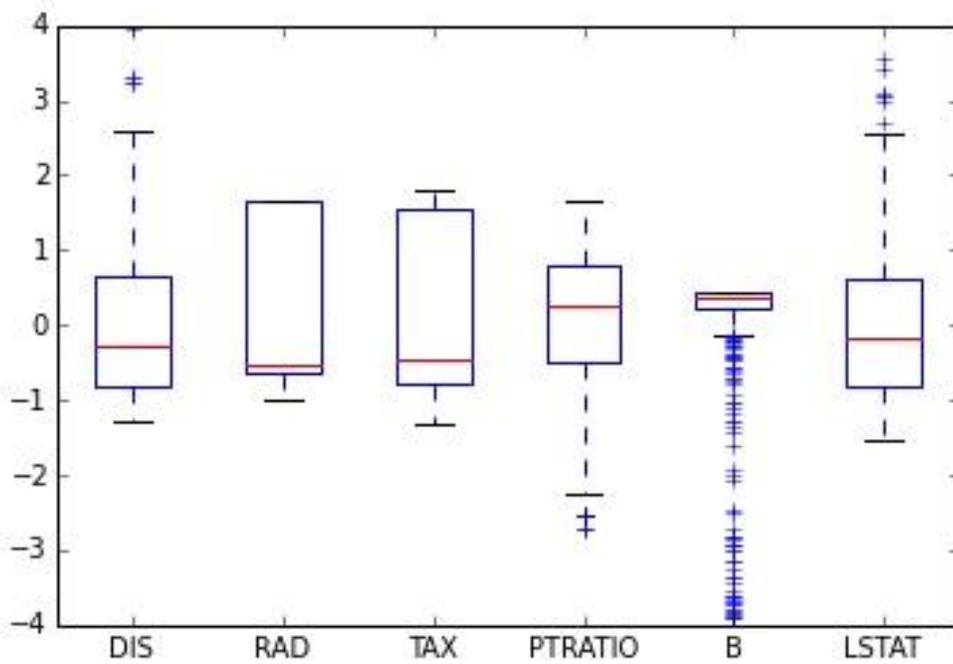
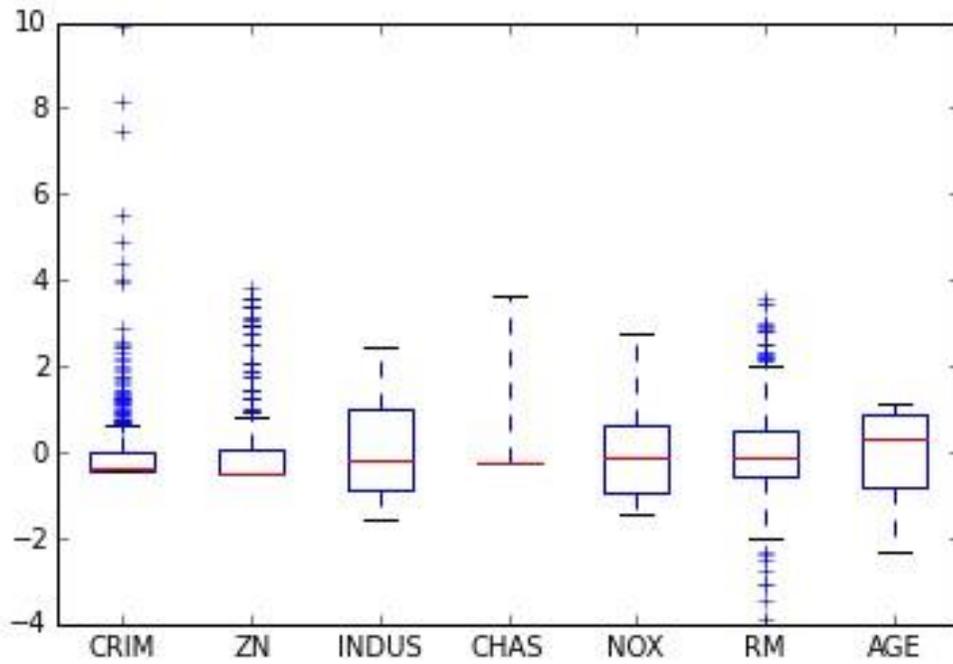
=====
Dep. Variable:          y      No. Observations:          36
Model:                 Logit  Df Residuals:              29
Method:                MLE    Df Model:                  6
Date:                 Tue, 20 Oct 2015  Pseudo R-squ.:            0.5744
Time:                 16:33:30    Log-Likelihood:           -10.524
converged:            True      LL-Null:                  -24.731
                               LLR p-value:              7.856e-05
=====

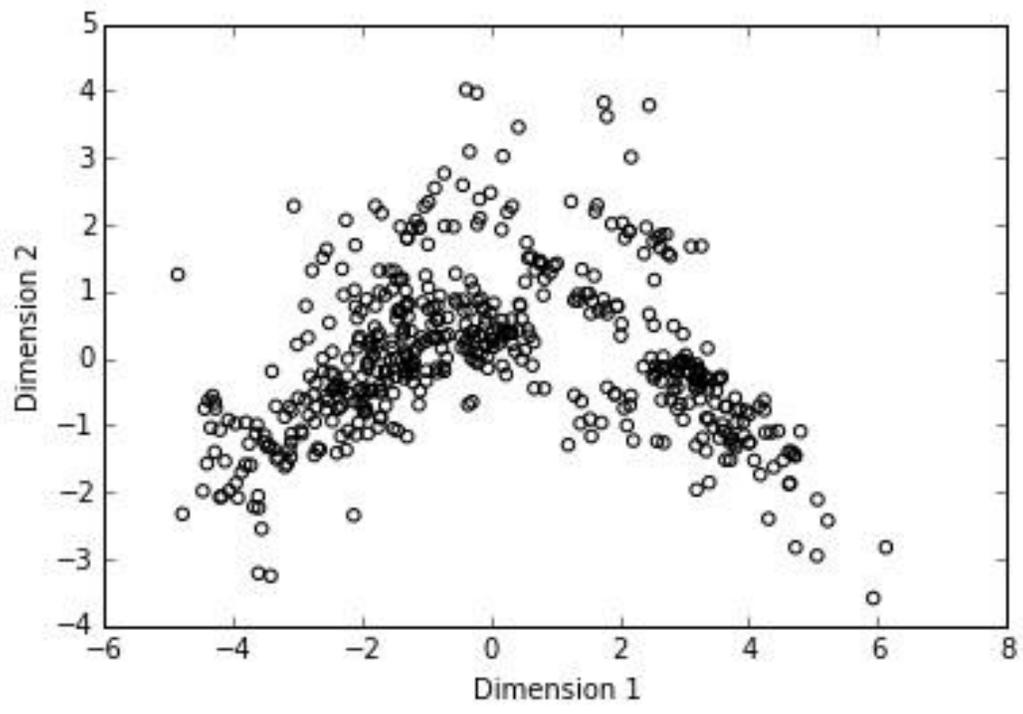
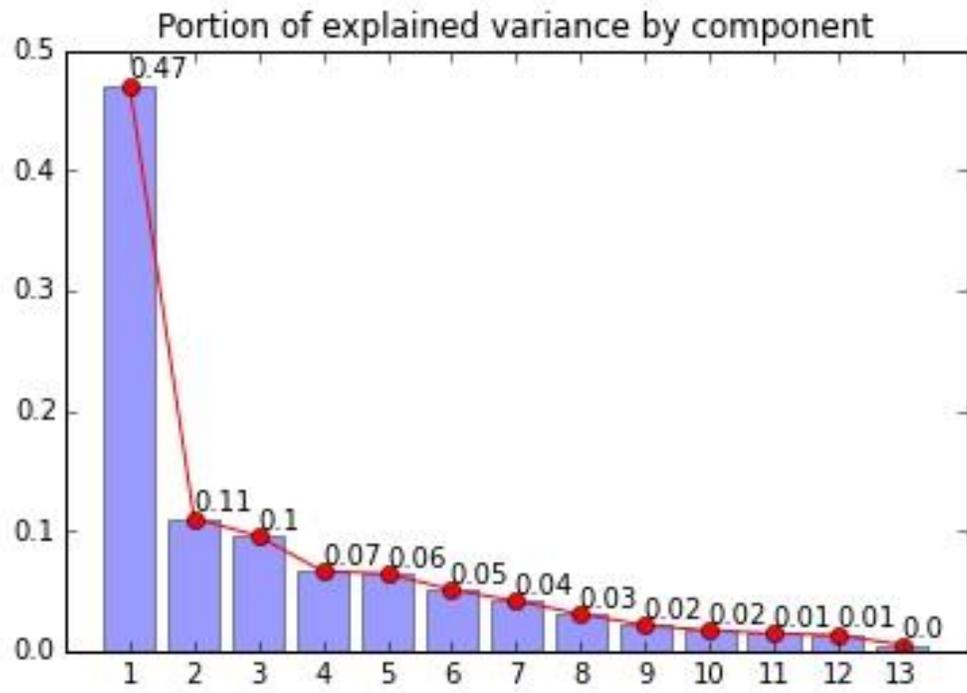
```

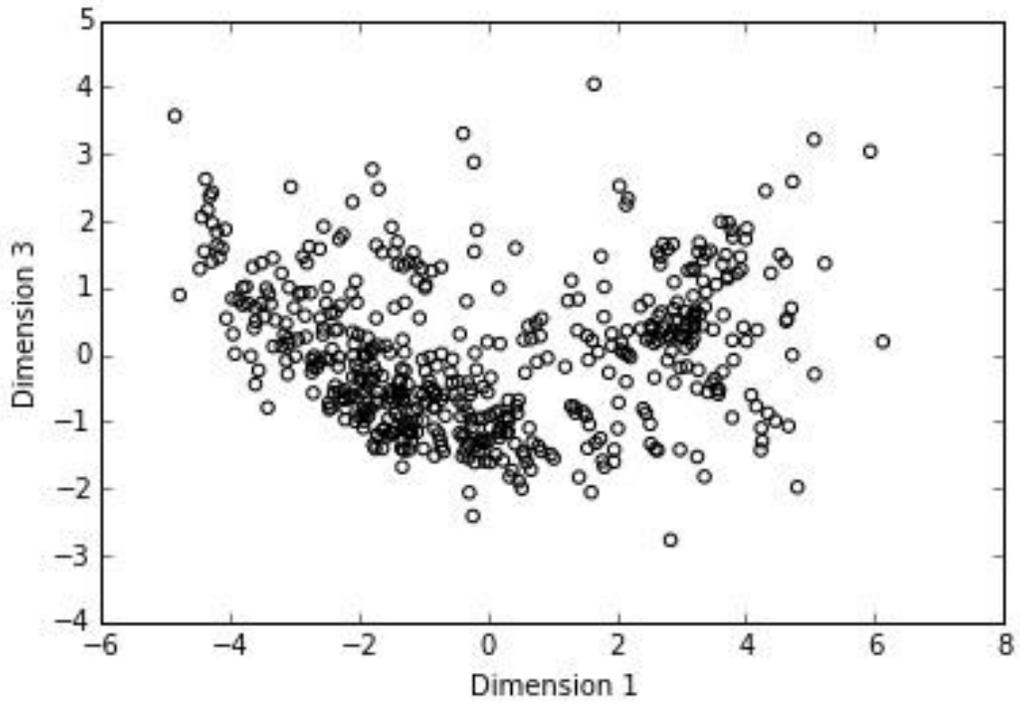
	coef	std err	z	P> z	[95.0% Conf. Int.]	
const	5.4055	2.196	2.462	0.014	1.102	9.709
outlook_overcast	3.5528	1.721	2.064	0.039	0.179	6.927
outlook_rainy	-1.6051	1.357	-1.183	0.237	-4.265	1.055
temperature_cool	-4.3340	1.867	-2.322	0.020	-7.993	-0.675
temperature_hot	-1.8299	1.478	-1.238	0.216	-4.727	1.067
humidity_high	-4.3310	1.645	-2.633	0.008	-7.555	-1.107
windy_TRUE	-2.3932	1.325	-1.807	0.071	-4.989	0.203





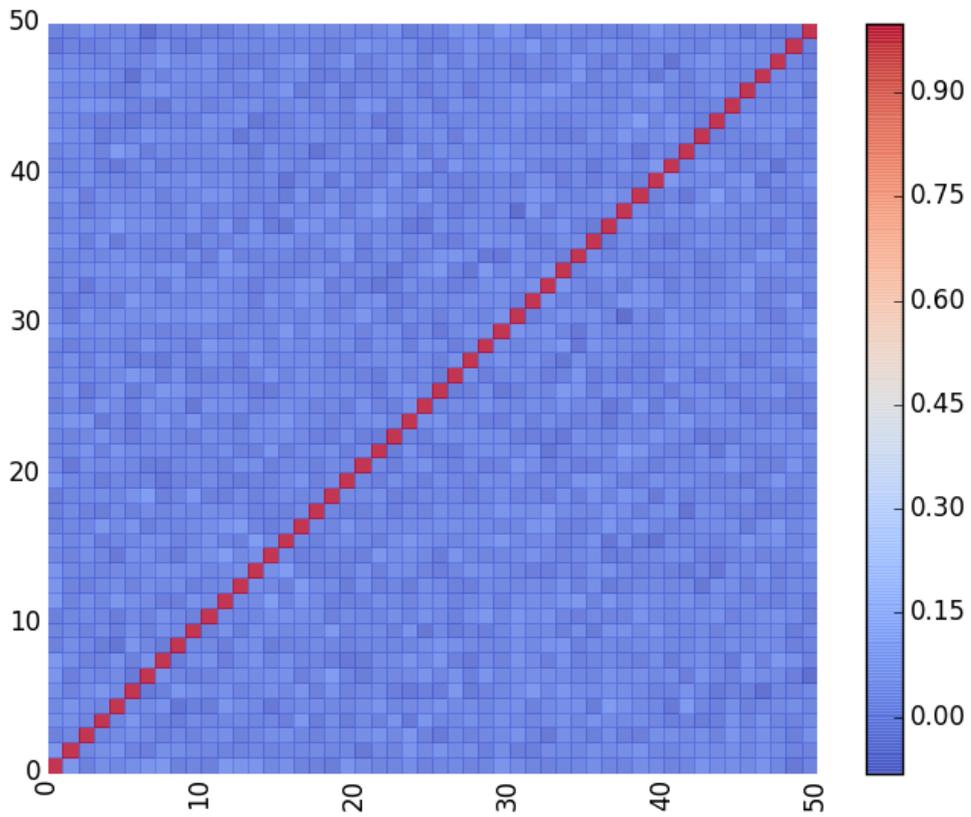


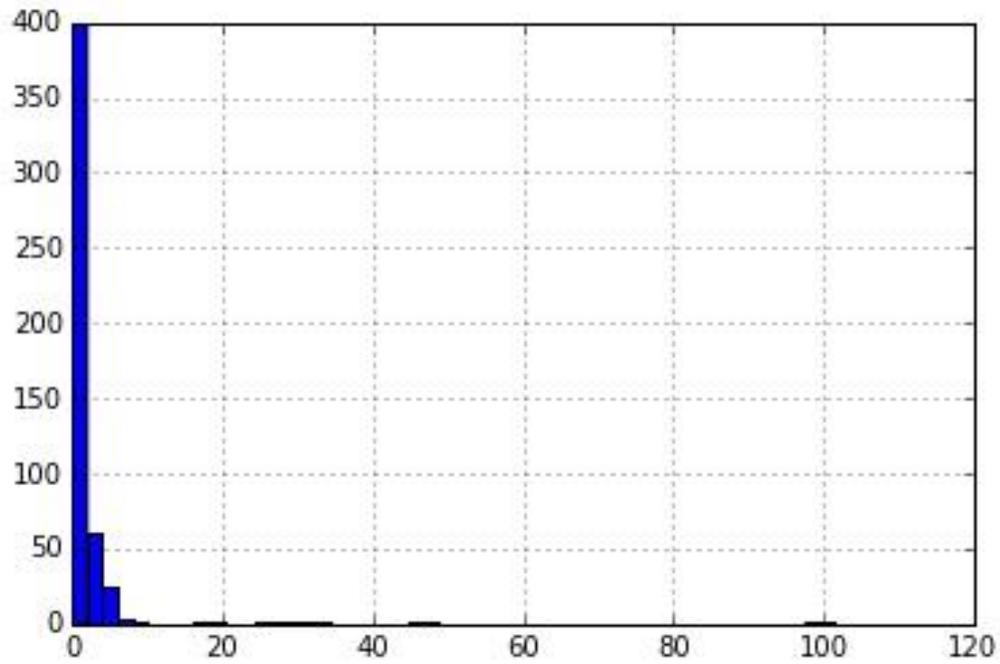




## Chapter 6: Achieving Generalization

```
[9, 3, 8, 5, 7, 0, 8, 3, 9, 3] [1, 2, 4, 6]  
[4, 7, 3, 5, 7, 1, 4, 3, 2, 1] [0, 8, 9, 6]  
[7, 8, 5, 3, 7, 5, 3, 6, 6, 3] [0, 1, 2, 9, 4]  
[1, 6, 7, 4, 3, 1, 9, 5, 4, 6] [0, 8, 2]  
[6, 3, 6, 1, 6, 6, 0, 7, 3, 8] [9, 2, 4, 5]
```

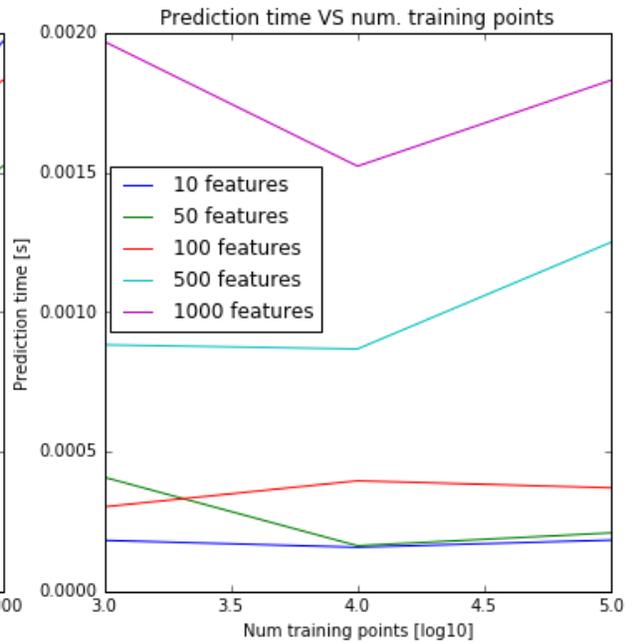
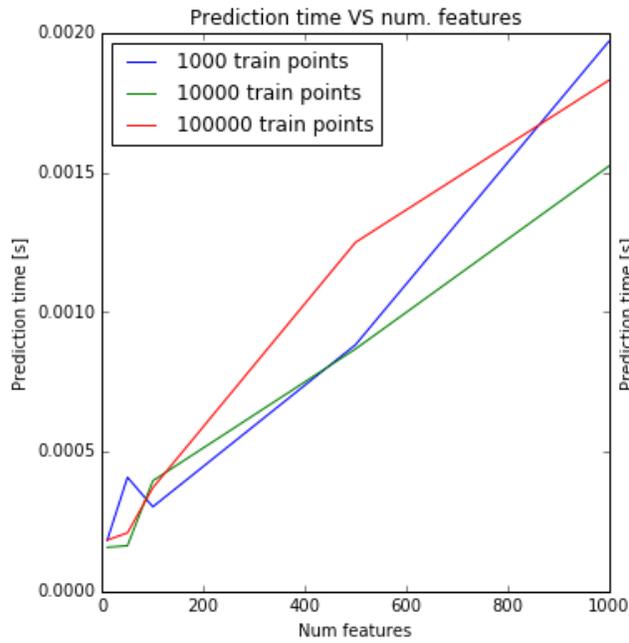
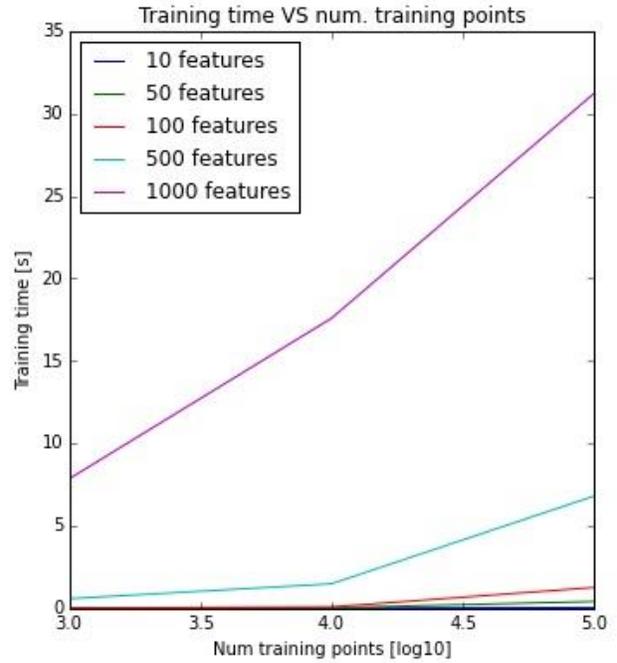
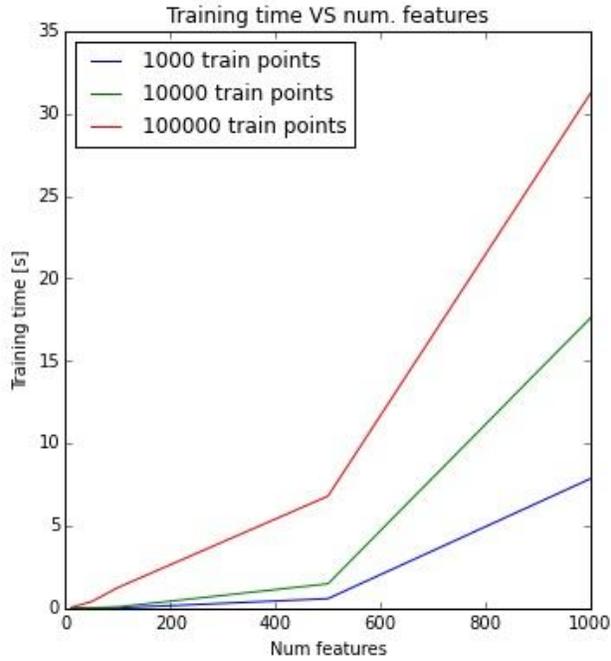


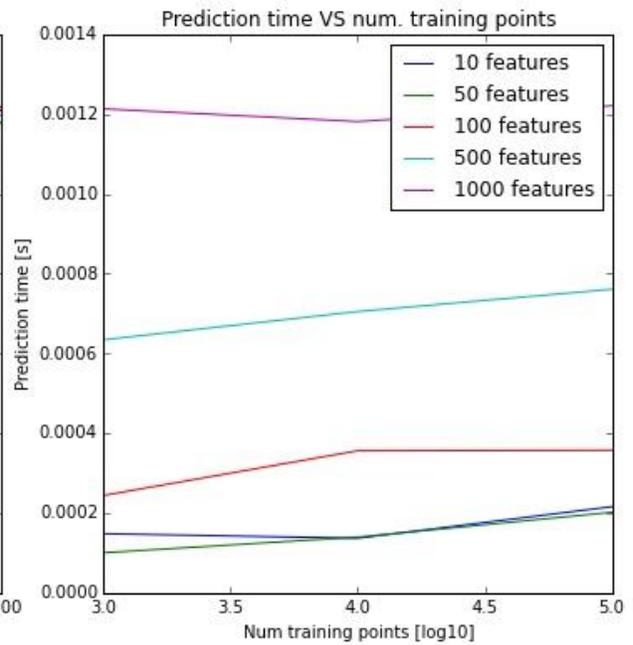
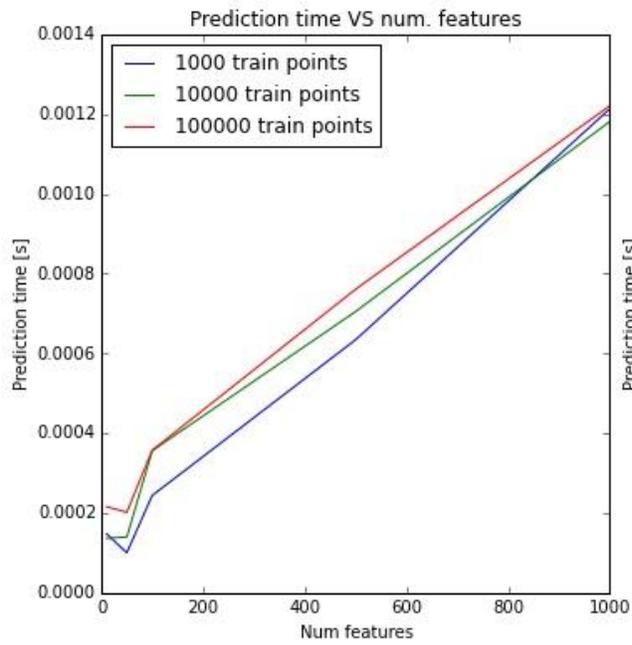
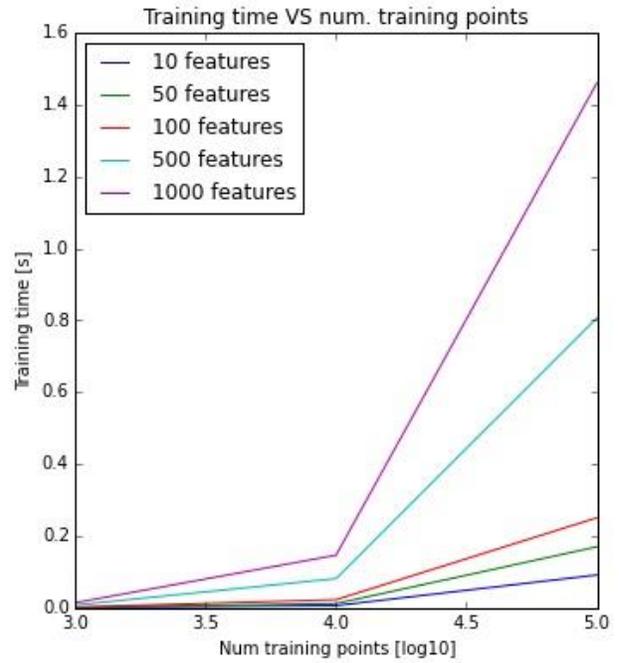
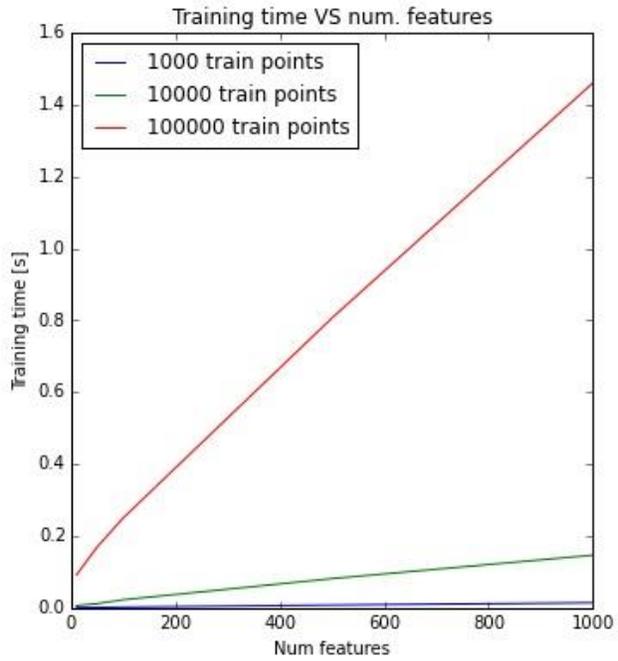


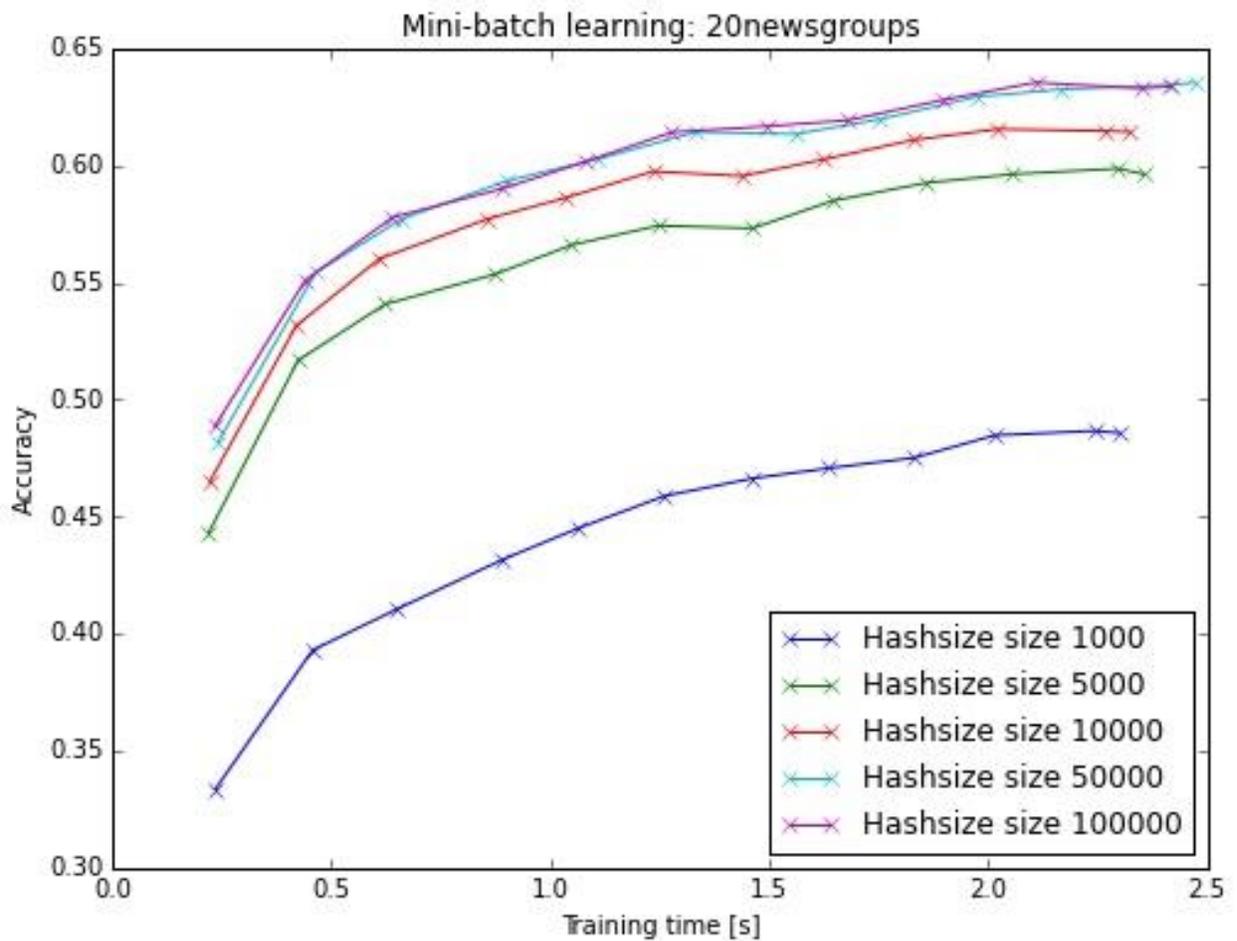
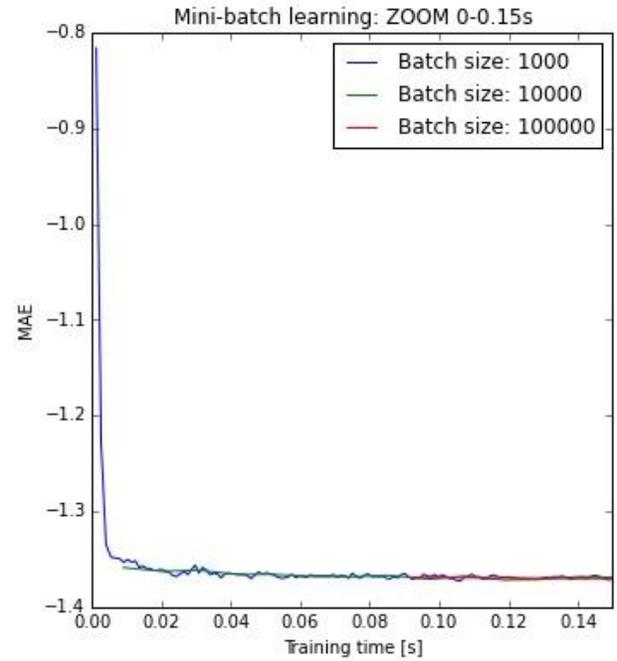
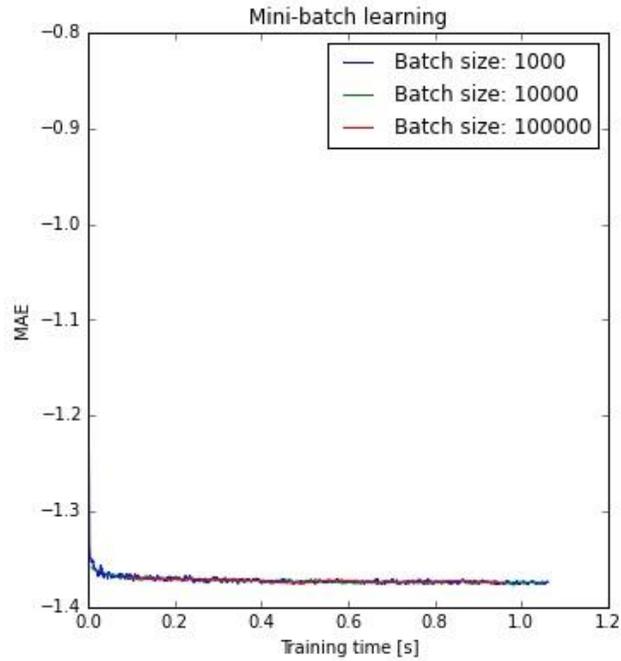
$$w_j = w_j - \frac{\alpha}{n} * \left( \sum (Xw - y) * x_j - \lambda * w_j^2 \right)$$

$$w_j = w_j - \frac{\alpha}{n} * \left( \sum (Xw - y) * x_j + \lambda * |w_j| \right)$$

# Chapter 7: Online and Batch Learning





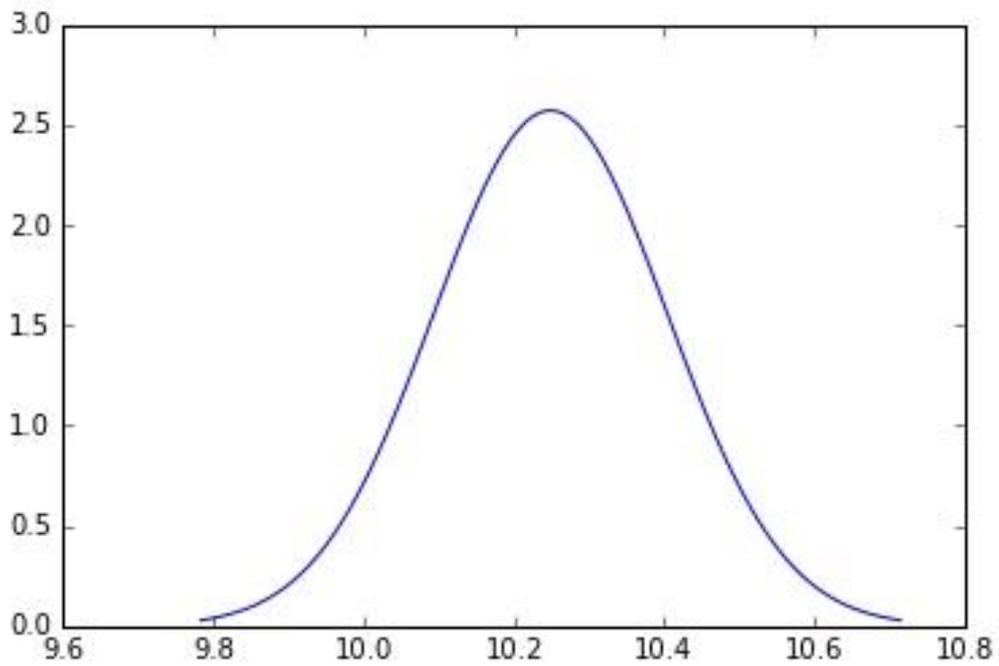
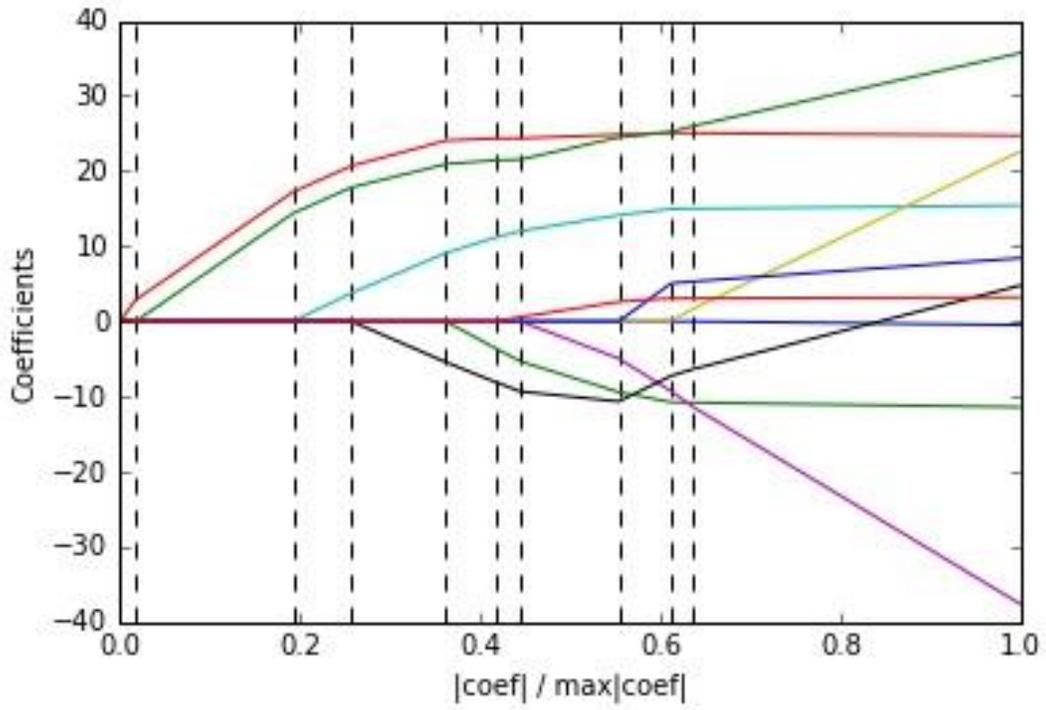


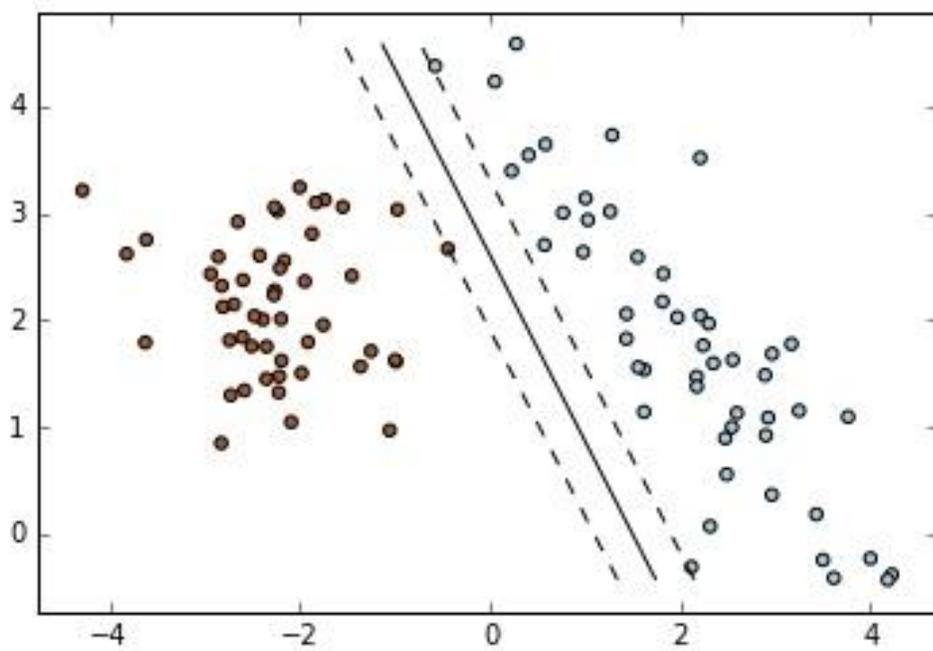
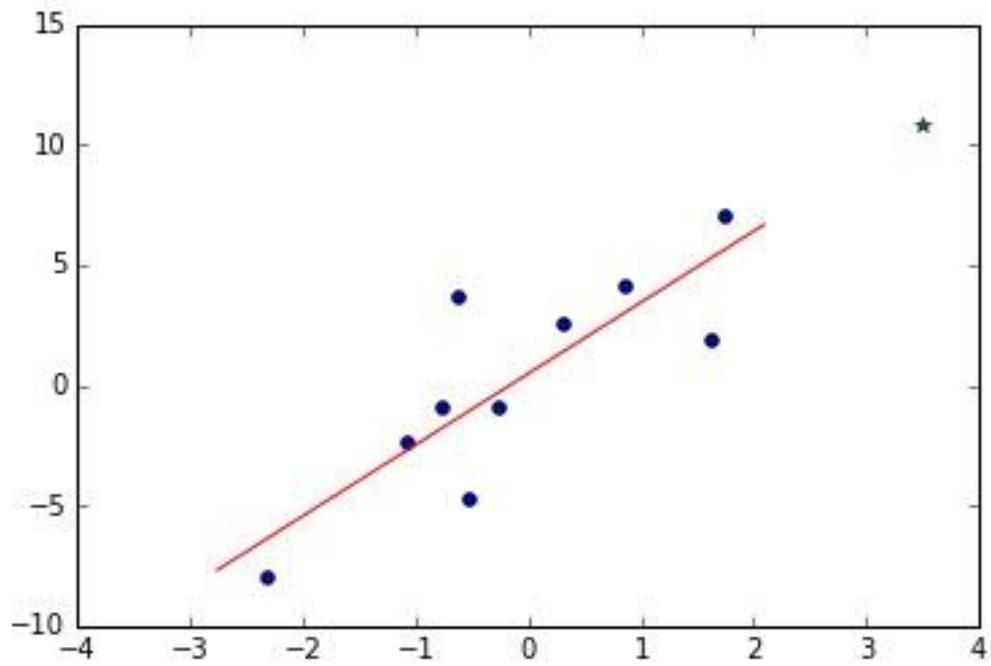
Report: Mini-batch size 1000  
First output after [s]: 0.0007998943328857422  
First model MAE [log10]: -0.942320304943  
Total training time [s]: 1.3718714714050293  
Final MAE [log10]: -1.24036819201

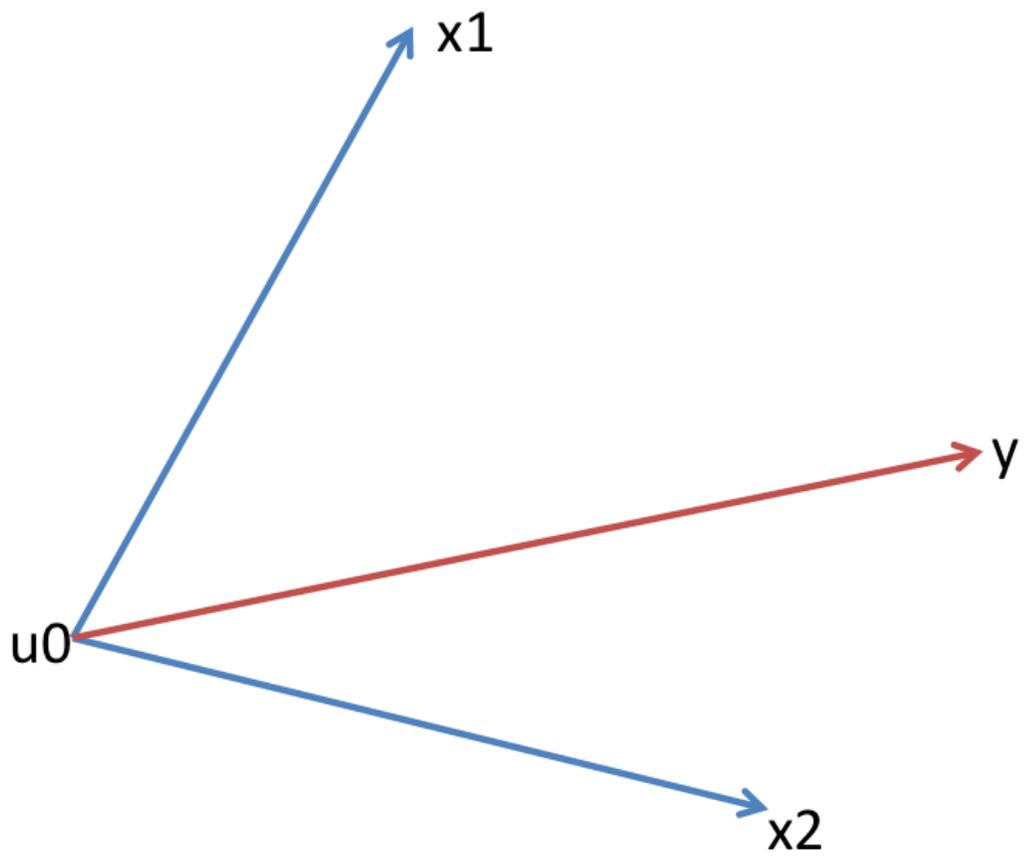
Report: Mini-batch size 10000  
First output after [s]: 0.007853984832763672  
First model MAE [log10]: -1.23171862851  
Total training time [s]: 1.308701992034912  
Final MAE [log10]: -1.24038903474

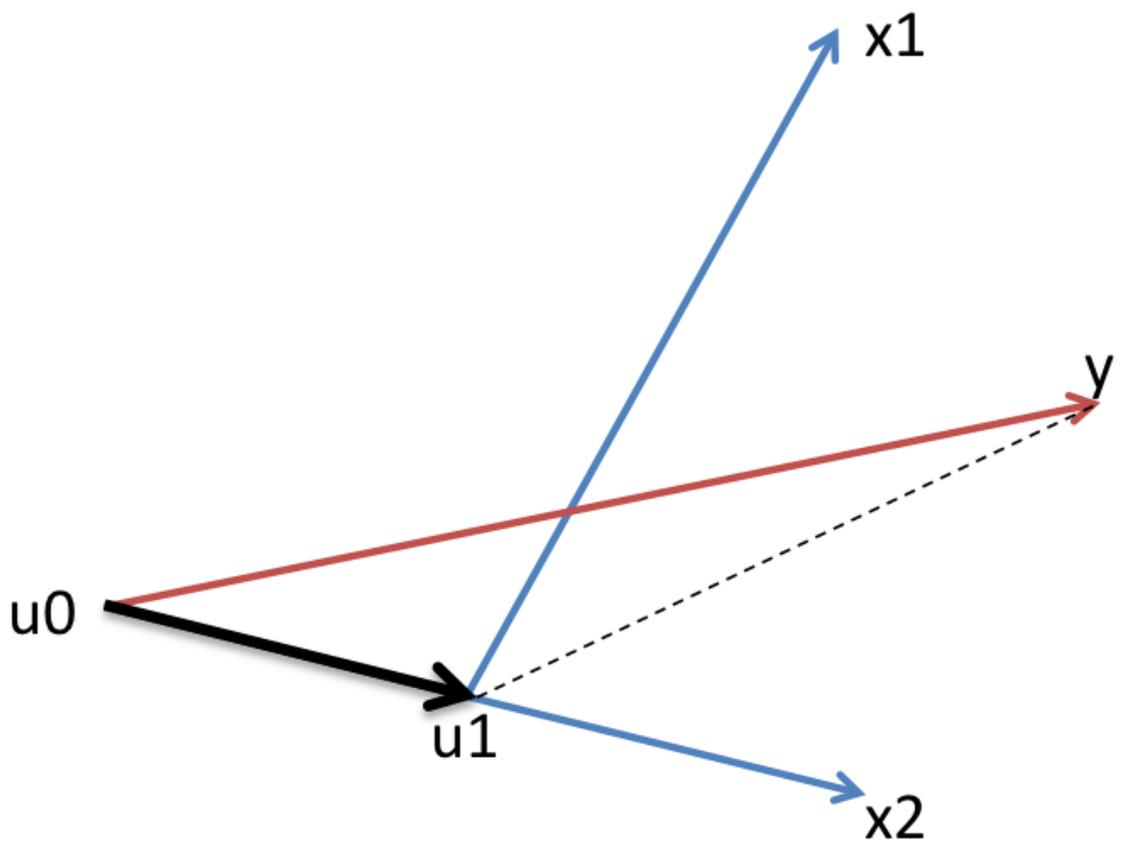
Report: Mini-batch size 100000  
First output after [s]: 0.05989503860473633  
First model MAE [log10]: -1.24053929732  
Total training time [s]: 1.1995868682861328  
Final MAE [log10]: -1.24053790326

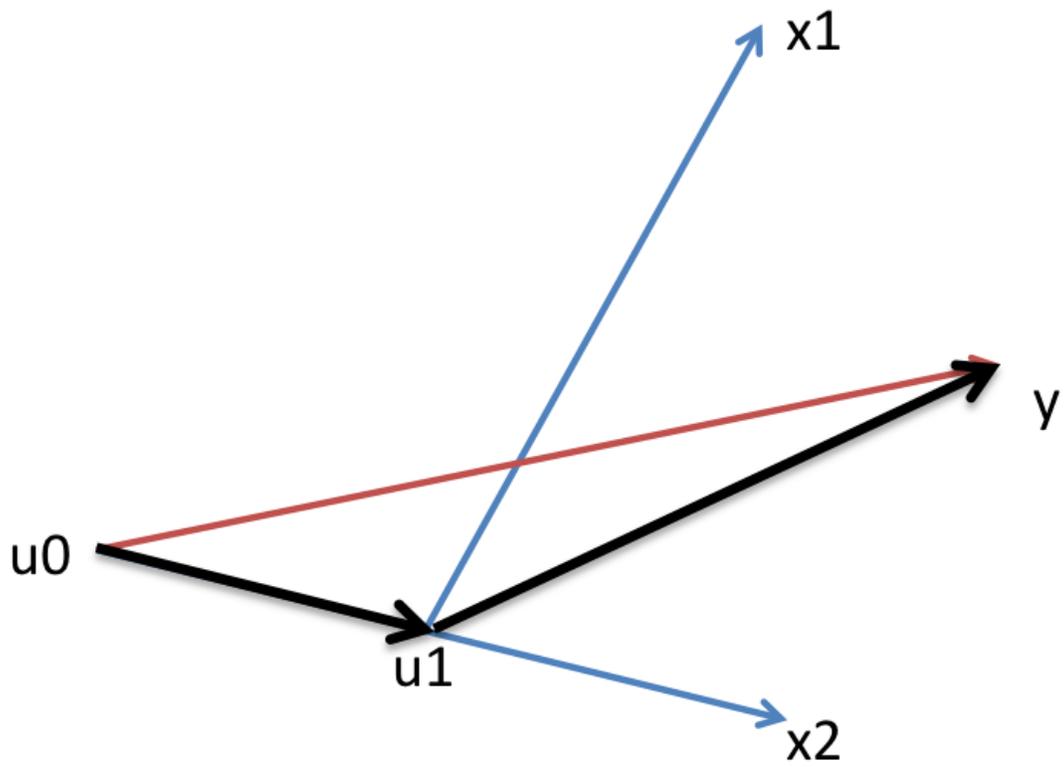
## Chapter 8: Advanced Regression Methods











Step	Added	Dropped	Active set size	C
0	2		1	19960.733269
1	8		2	18696.7980058
2	3		3	9521.69759738
3	6		4	6645.07641798
4	1		5	2735.84447649
5	9		6	1866.54369652
6	4		7	1449.91074453
7	7		8	420.081823008
8	5		9	115.157274041
9	0		10	106.993857228

```
[ (0.52639646470399315, 'LSTAT'),  
  (0.27921428015177541, 'RM'),  
  (0.054353831310065687, 'DIS'),  
  (0.031820451224154722, 'CRIM'),  
  (0.029793467094947356, 'NOX'),  
  (0.021350472586185009, 'PTRATIO'),  
  (0.015375071104791901, 'AGE'),  
  (0.015233565046354791, 'TAX'),  
  (0.01095820296701624, 'B'),  
  (0.0075592385798185944, 'INDUS'),  
  (0.0055375893522671962, 'RAD'),  
  (0.001348634019939781, 'ZN'),  
  (0.0010587318586900362, 'CHAS') ]
```

```
[ (0.26442820639779868, 'LSTAT'),  
  (0.21170609523931225, 'RM'),  
  (0.11520512234965929, 'DIS'),  
  (0.078532434845484278, 'TAX'),  
  (0.075850985431776763, 'PTRATIO'),  
  (0.0756604687541029, 'NOX'),  
  (0.052097327327291075, 'B'),  
  (0.041177393920216847, 'CRIM'),  
  (0.034255068725583829, 'AGE'),  
  (0.023541808250096587, 'INDUS'),  
  (0.012189199051061582, 'CHAS'),  
  (0.011705380397086919, 'RAD'),  
  (0.0036505093105288107, 'ZN') ]
```

$$\text{loss}(x) = \max(0.1 - l \cdot w \cdot x)$$

# Chapter 9: Real-world Applications for Regression Models

