Linear Regression: What do these numbers mean?

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

y

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Ordinary Least Squares

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m

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Residual degrees of freedom

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Residual degrees of freedom = number of observations - number of parameters (including intercept)

Model degrees of freedom

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R^2

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Best model minimizes

$$\sum_{i=1}^{m} \left(y_{\beta}(x^{(i)}) - y_{obs}^{(i)} \right)^2$$

Sum of Squared Error
SSE

Variance of observed points (times m) is

$$\sum_{i=1}^{m} \left(\overline{y}_{obs} - y_{obs}^{(i)} \right)^2$$

Total Sum of Squares
SST

$$R^2 = 1 - \frac{SSE}{SST}$$

Sum of Squared Error
SSE

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Randomness left in the model

Variation in the data

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Randomness left in the model

Variation in the data

SSE/SST is the portion of variation left unexplained by the model (handled by ε)

$$R^2 = 1 - \frac{SSE}{SST}$$

Randomness left in the model

Variation in the data

R^2 is the portion of variation explained by the model (R^2 is between 0 and 1)

(as long as the model has smaller residuals than the mean-only model)

OLS Regression Results

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F-test

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Null hypothesis:

This data can be modeled by setting all β values to zero

(and the linear relationship we've found is purely due to chance)

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If p-value <0.05, we can reject the null hypothesis.

Data is too extreme to fit this model just by chance.

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This data can be modeled by setting all β values to zero

(and the linear relationship we've found is purely due to chance)

If p-value <0.05, we can reject the null hypothesis.

Data is too extreme to fit this model just by chance.

Doesn't mean the model is "true"

OLS Regression Results

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Log L

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Likelihood is a different cost function

$$L(\beta_0, \beta_1) = p(y_{obs} | \beta_0, \beta_1)$$

$$p(\beta_0, \beta_1 | y_{obs}) = \frac{p(y_{obs} | \beta_0, \beta_1) p(\beta_0, \beta_1)}{p(y_{obs})}$$

Likelihood is a different cost function

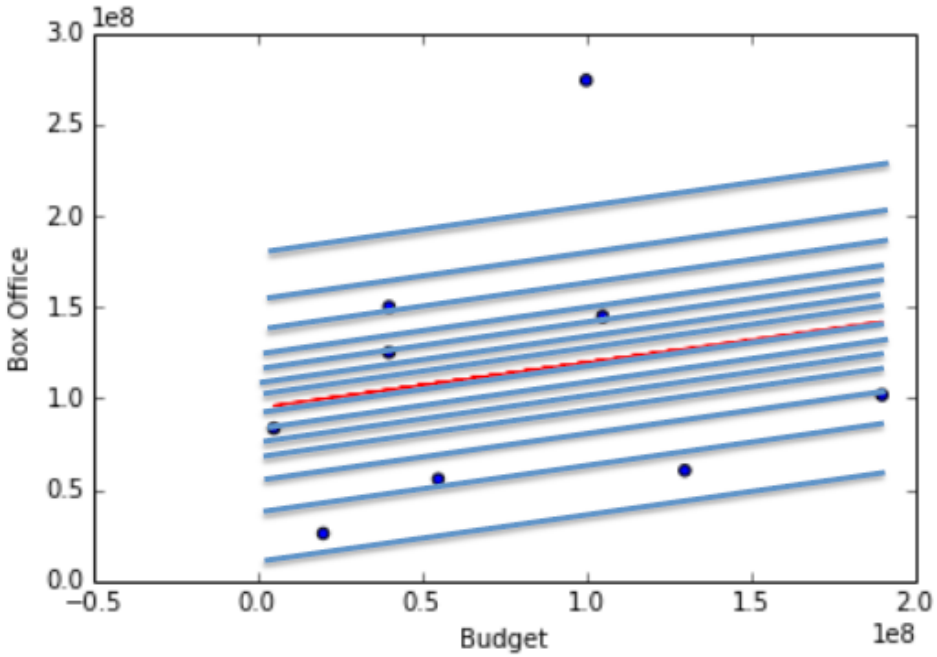
$$L(\beta_0, \beta_1) = p(y_{obs} | \beta_0, \beta_1)$$

For a given model (pair of β_0 And β_1 values), Likelihood is the prob. Of getting exactly this set of observed y values

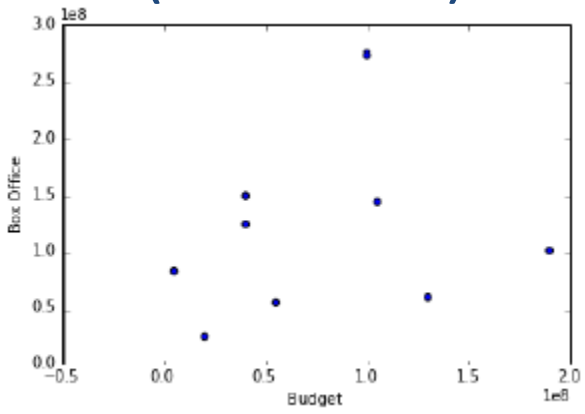
The model with maximum likelihood is the best fit.

Likelihood is a different cost function

$$L(\beta_0, \beta_1) = p(y_{obs} | \beta_0, \beta_1)$$



Our world (observed)



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β_1

β_0

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Standard error of the coefficient

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95% conf interval for coefficient's value

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t-test

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This specific β value is zero

(and the data can be created by such a model (with the other β values intact)

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(and the data can be created by such a model (with the other β values intact)

If p-value <0.05, we can reject the null hypothesis.

This variable DOES contribute to the model.

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(and the data can be created by such a model (with the other β values intact)

If p-value <0.05, we can reject the null hypothesis.
This variable DOES contribute to the model.

Note: DOES or DOESN'T. Not how much.

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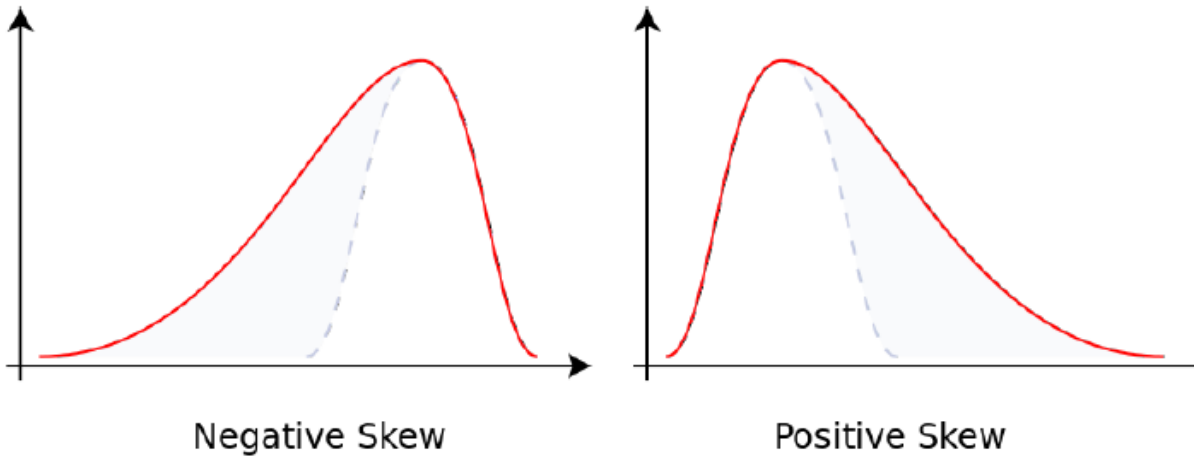
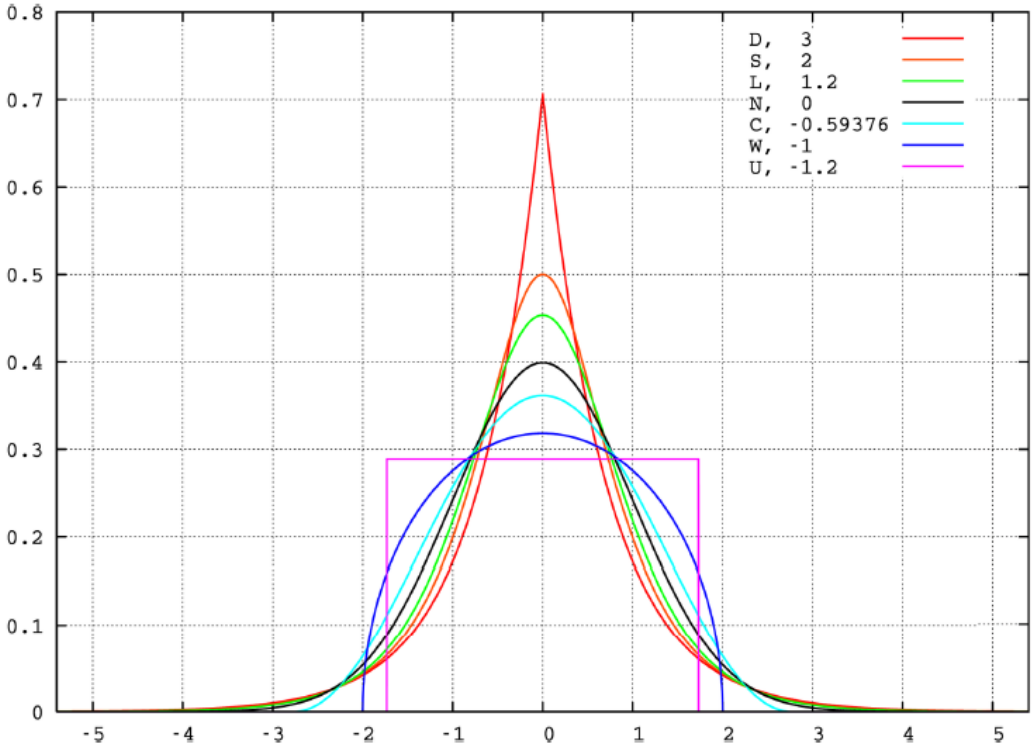
Skew & Kurtosis

Skew
(asymmetry)



Kurtosis
(peakness)



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Normality test

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Null hypothesis:

ε is normally distributed.

(no skew, no excess kurtosis)

If p-value <0.05, we can reject the null hypothesis.

ε does not exactly follow a normal distribution as we assumed

We may need to look closer.

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Another normality test

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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

Autocorrelation test

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
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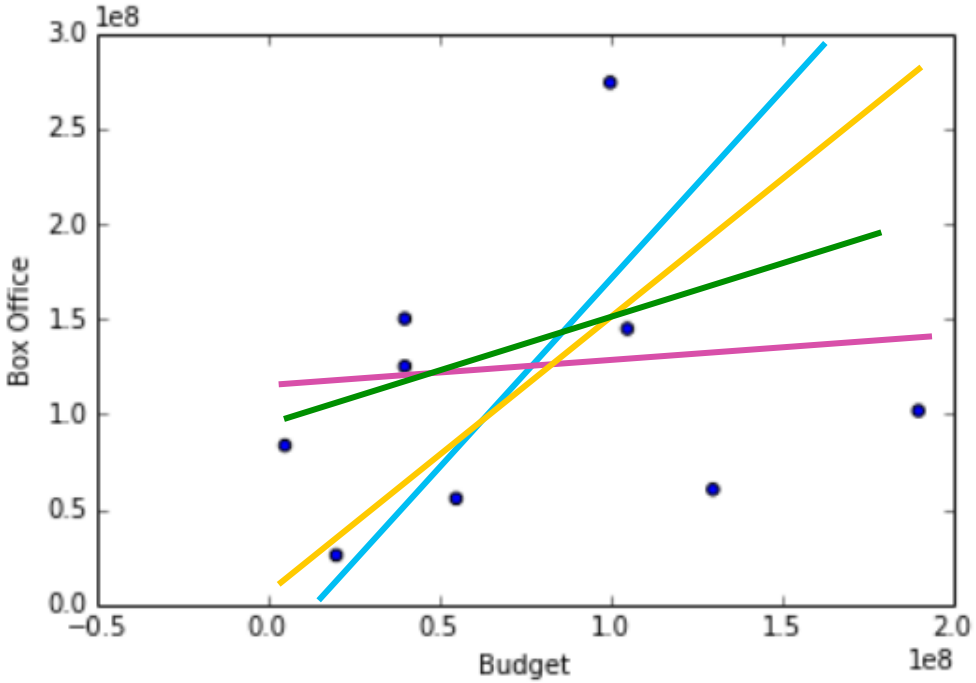
Sensitivity of prediction to small errors in input

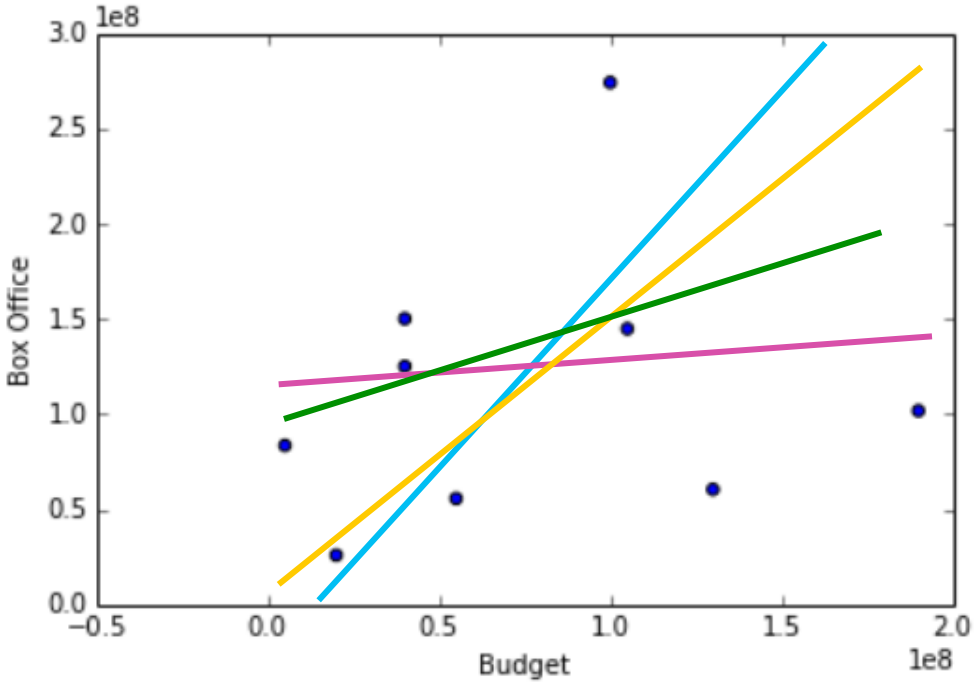
Model Selection I

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



For models with the same amount of parameters, easy:

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

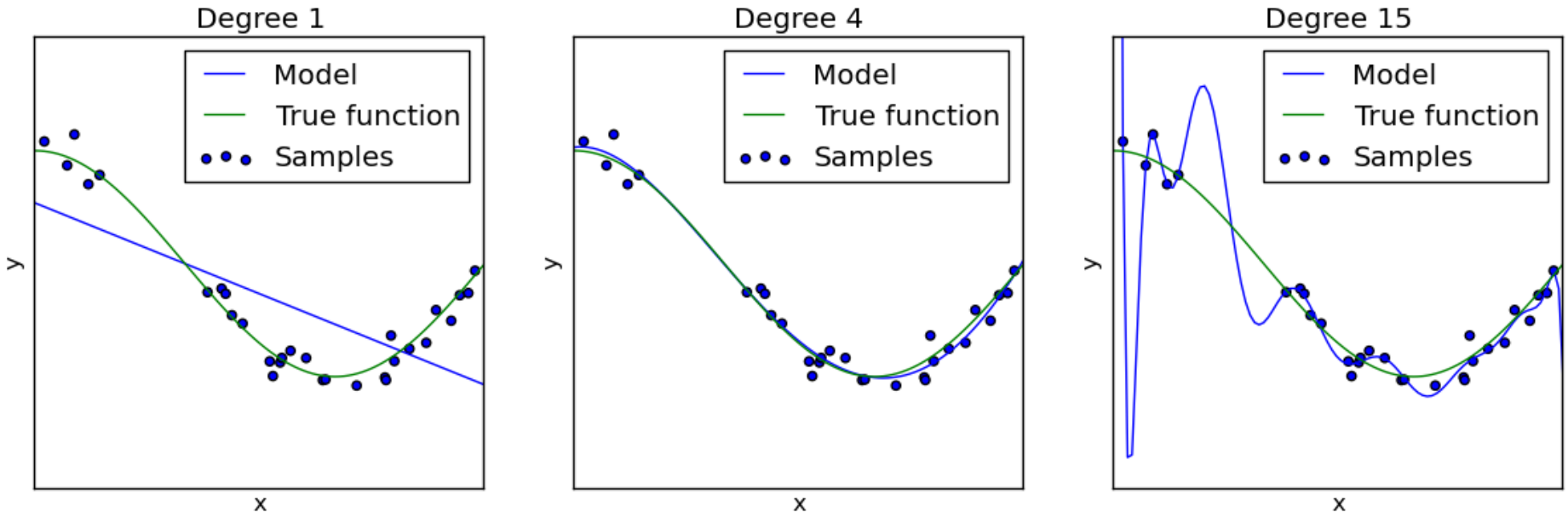


For models with the same amount of parameters, easy:

Take the one with the better cost function

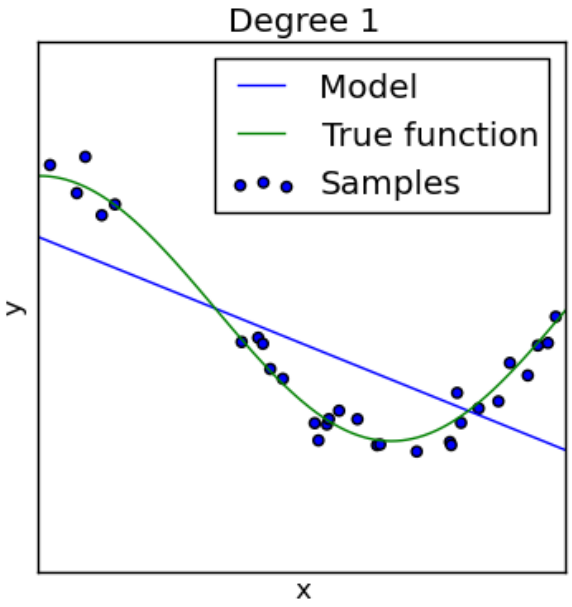
Log-Likelihood:	-1753.0

For models of different complexity: Beware under/overfitting

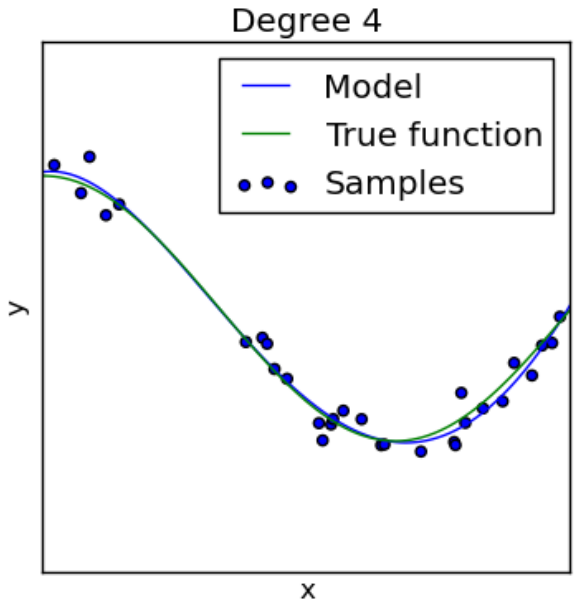


For models of different complexity: Beware under/overfitting

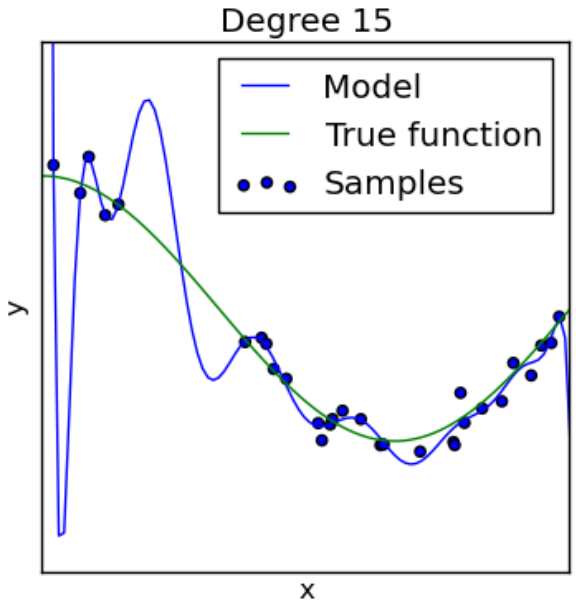
Underfitting



Just Right

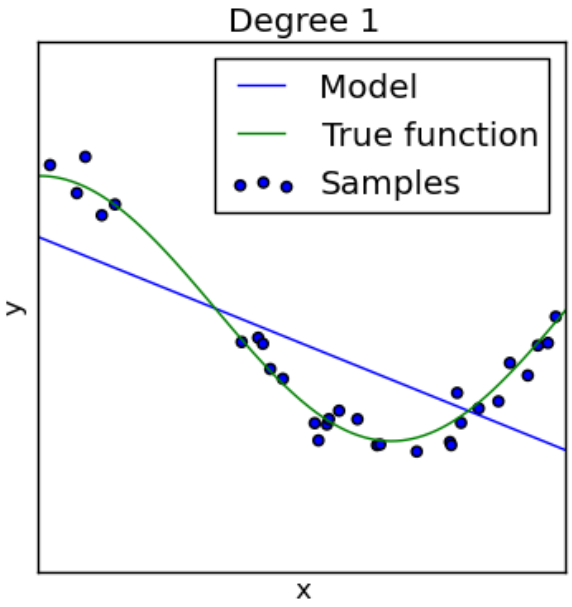


Overfitting



In machine learning, this is also called Bias/variance tradeoff

High bias
Low varience



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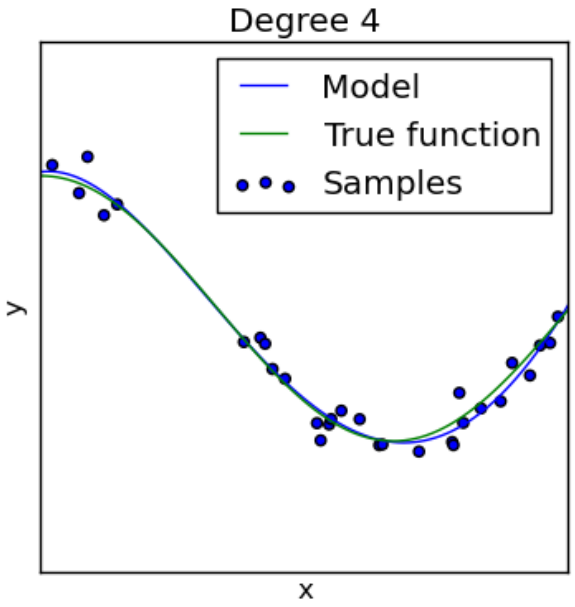
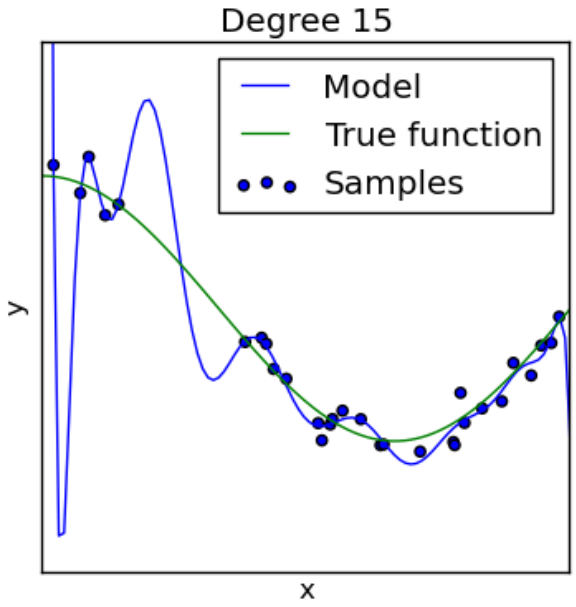


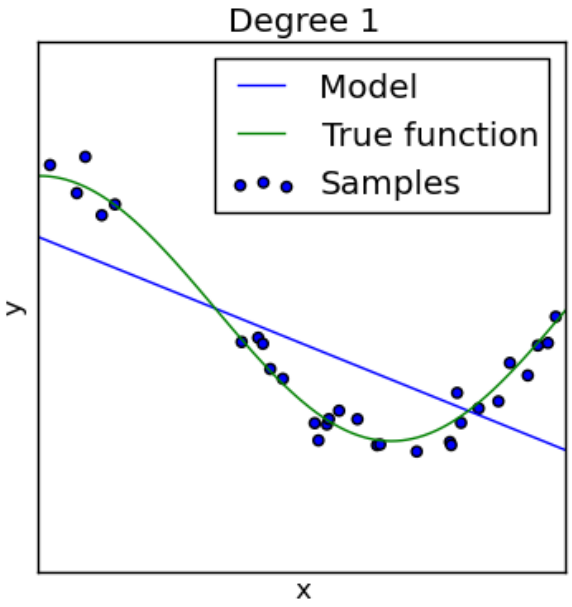
Low bias
High varience

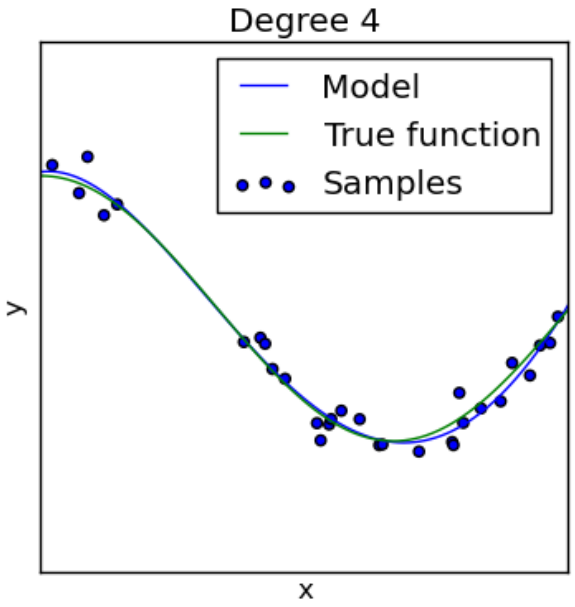


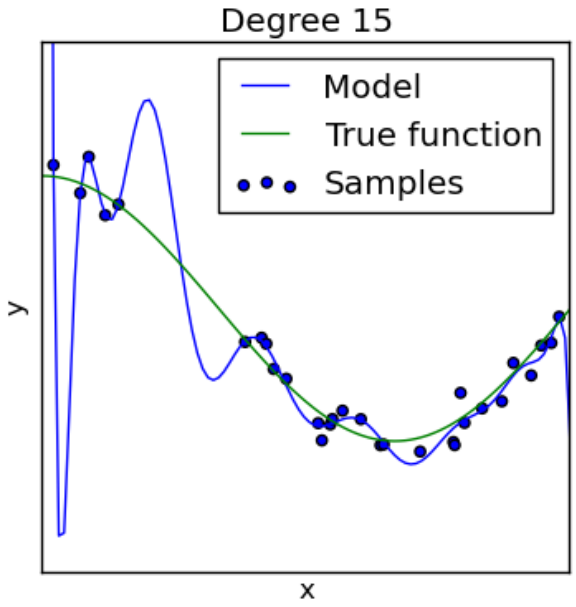
First training poorly, predictions bad

Just Right

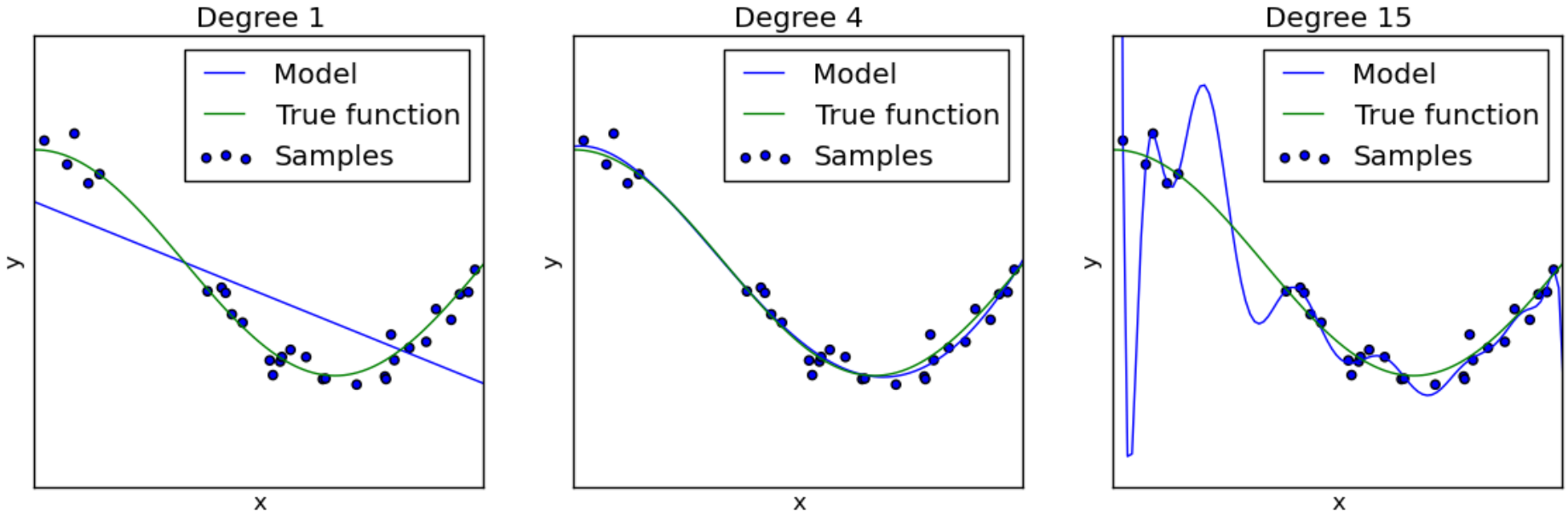
First training very well, can't generalize





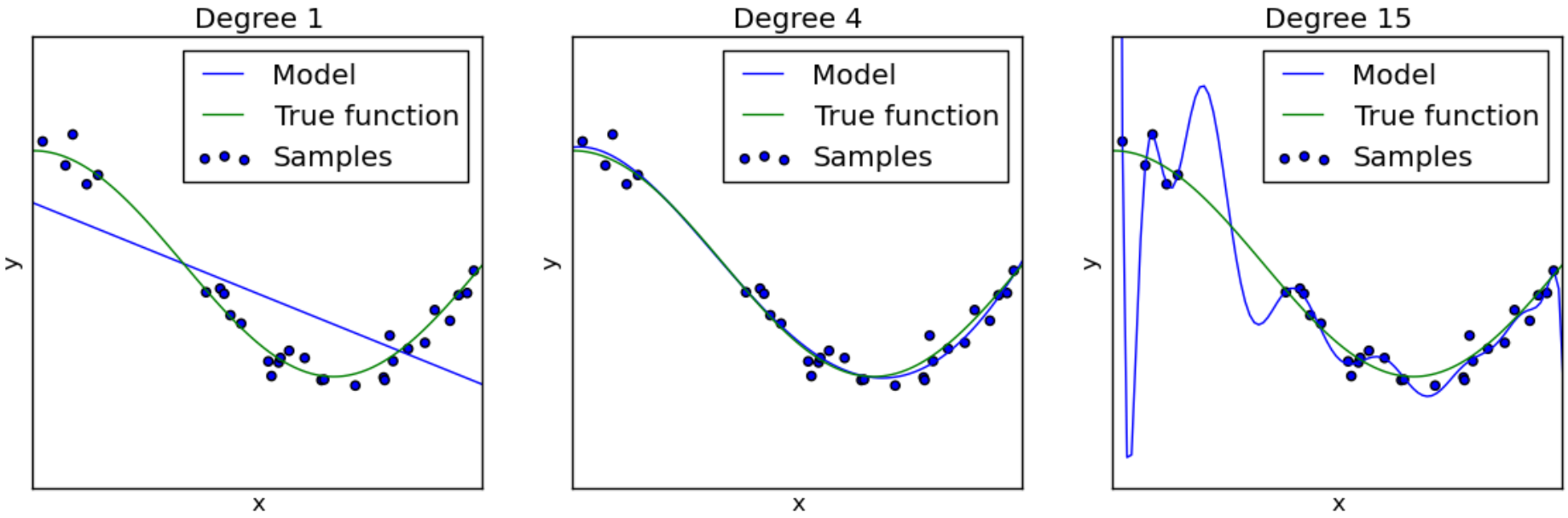


First and third will do poorly in the test set



Challenge: Fit a training set, calculate mean squared error on your test set (scikit learn)

There are a few metrics that try to measure this (without even looking at a test set yet)



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No. Observations:	89	**AIC:**	3480.
Df Residuals:	87	**BIC:**	3485.
Df Model:	1		

Adjusted R^2

	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

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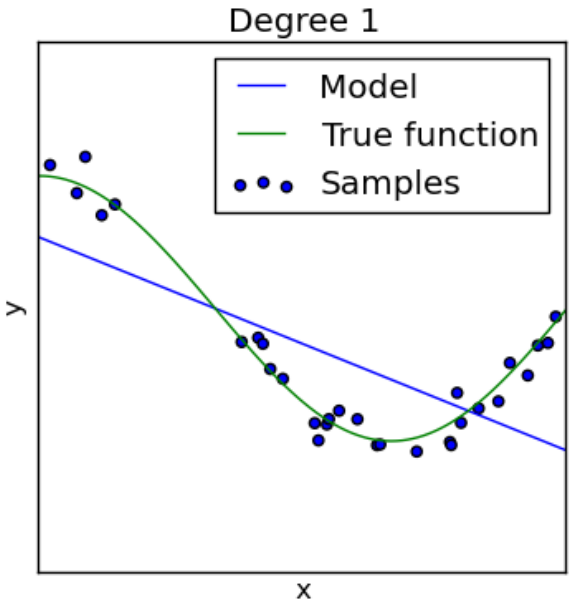
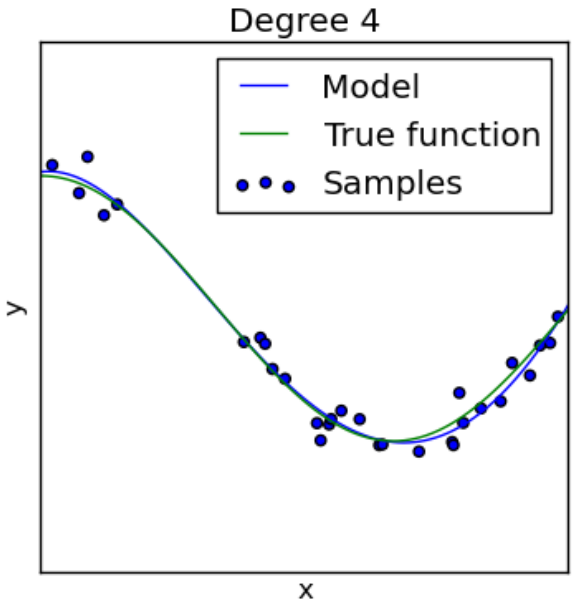
Skew:	1.587	**Prob(JB):**	2.55e-22
Kurtosis:	7.091	**Cond. No.**	1.54e+08

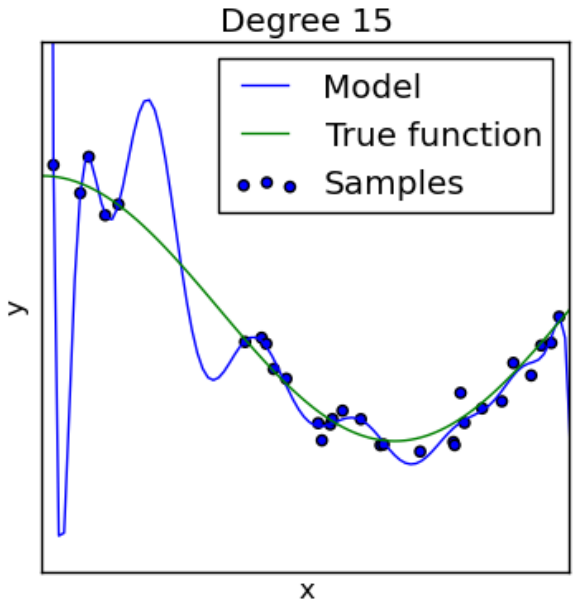
Low R^2



Higher R^2

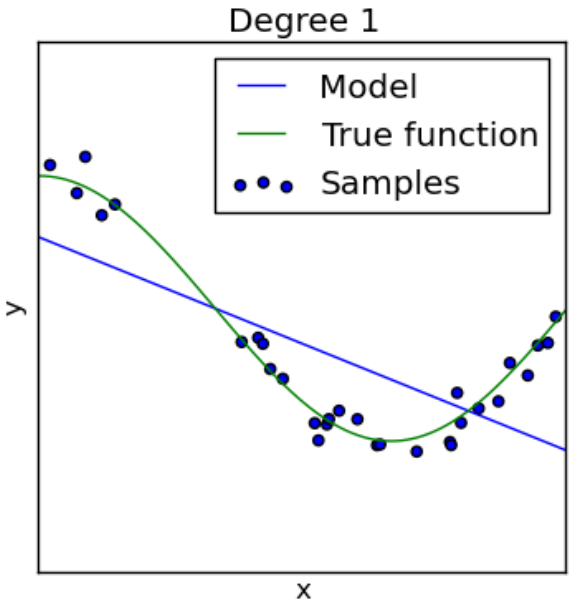


Highest R^2



$$\overline{R}^2 = 1 - \frac{SSE / df_e}{SST / df_t}$$

Low R^2



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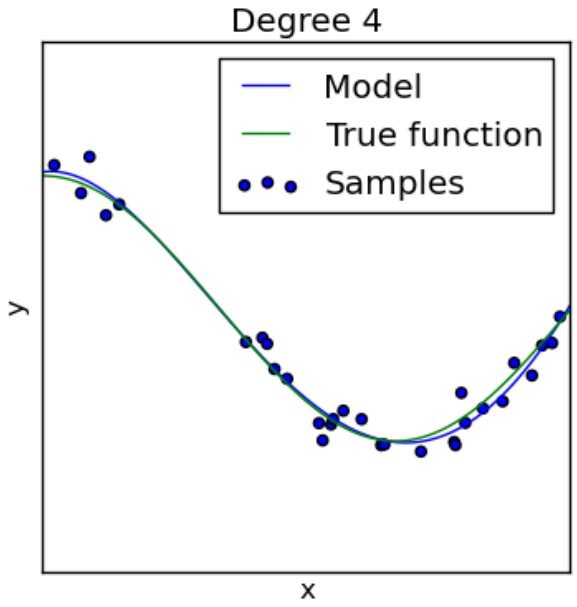

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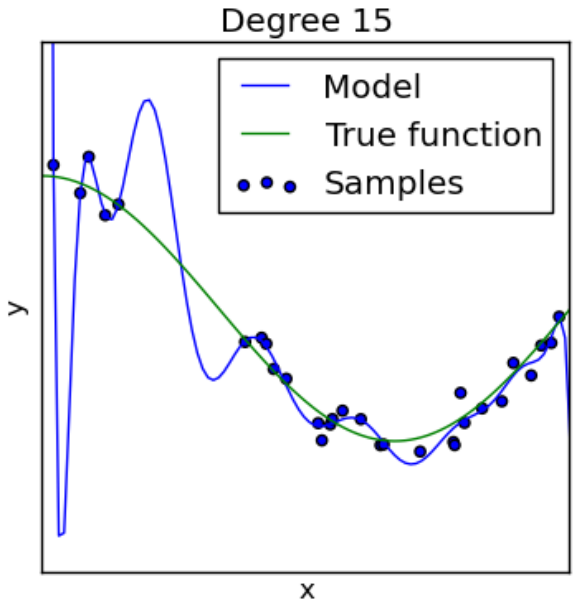


$$\overline{R}^2 = 1 - \frac{SSE / df_e}{SST / df_t}$$

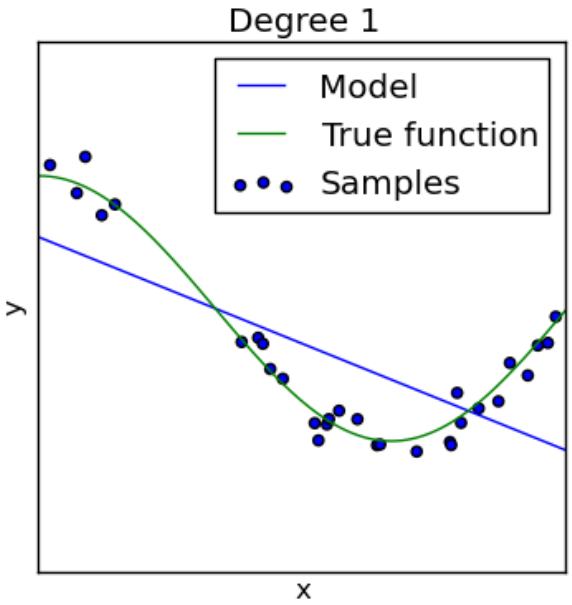
$df_e \rightarrow m - k - 1$

$df_t \rightarrow m - 1$

m= # points

k = # parameters

Low R^2



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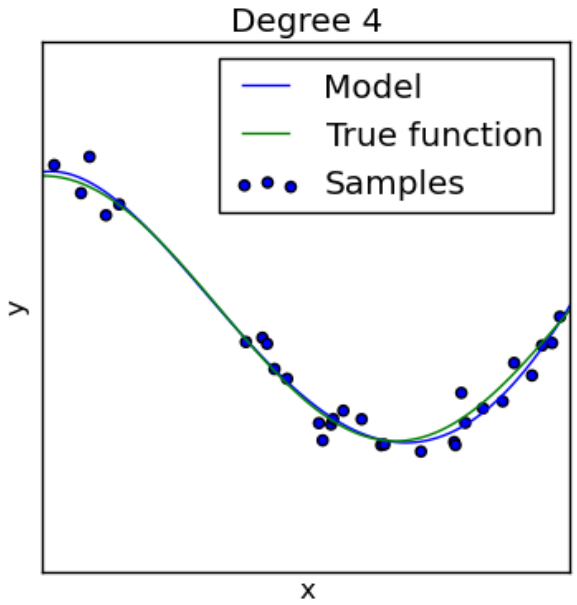

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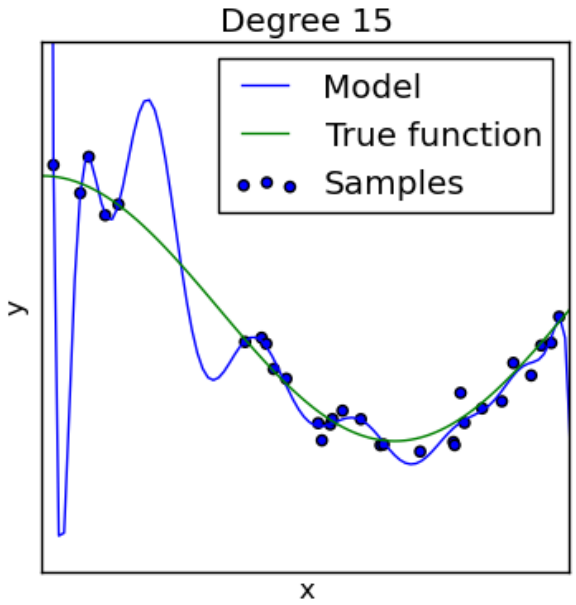

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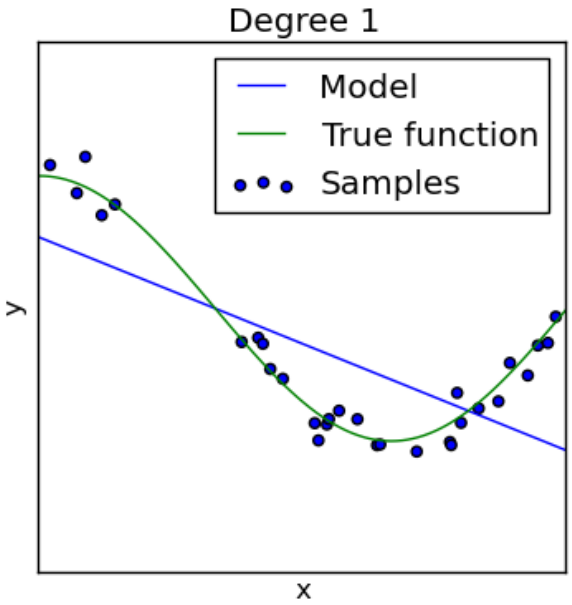
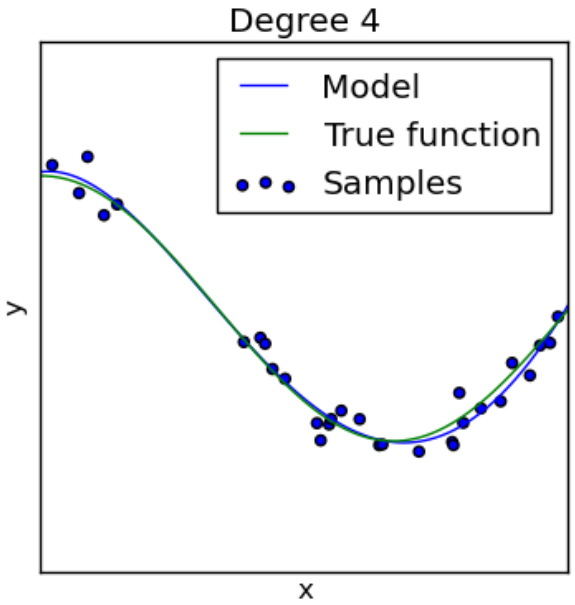
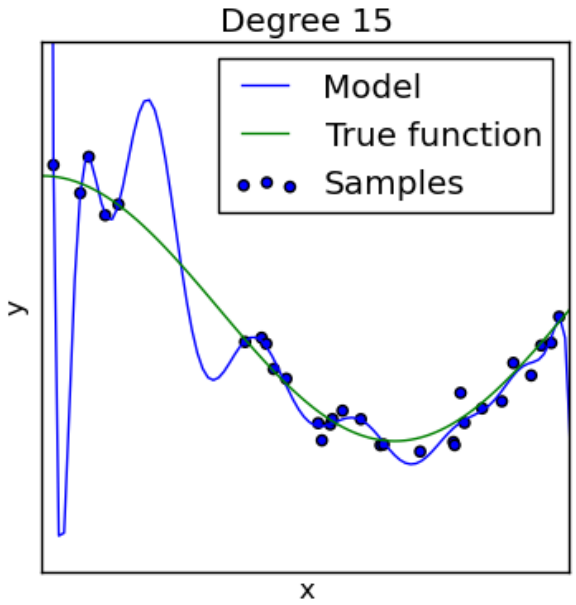
Low adj. R^2



Max. adj R^2



Low adj. R^2



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Akaike Information Criterion

	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
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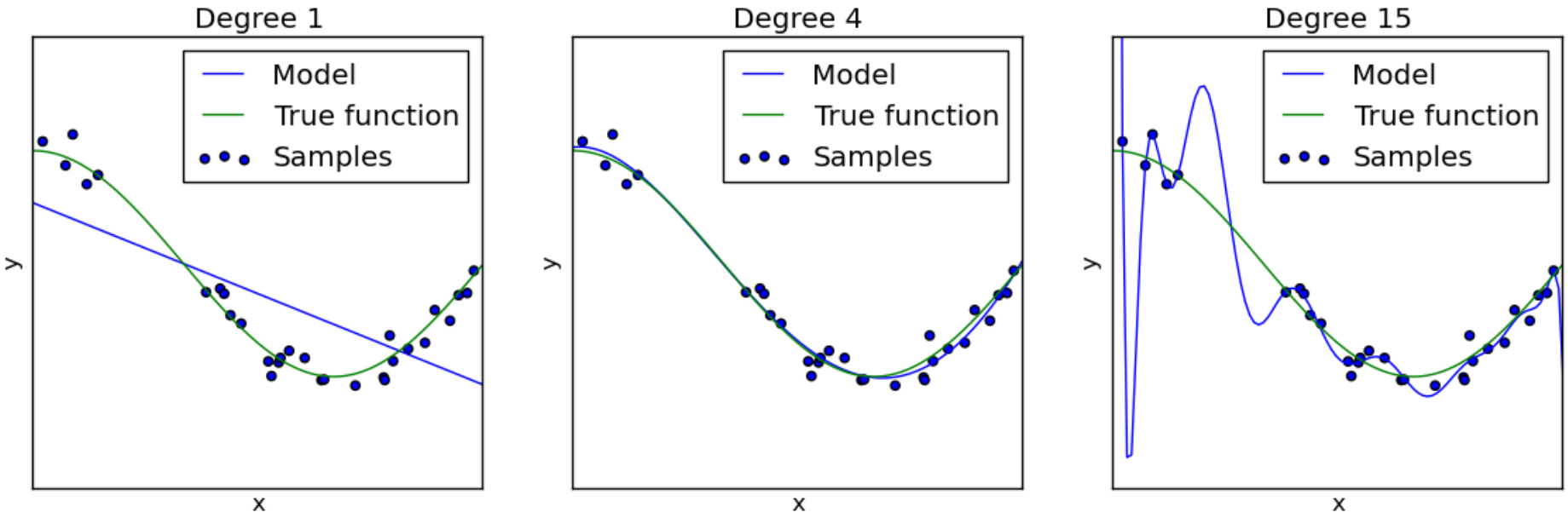
Skew:	1.587	**Prob(JB):**	2.55e-22
Kurtosis:	7.091	**Cond. No.**	1.54e+08

$$AIC = 2k - 2\ln(L)$$

parameters

Log likelihood



$$AIC = 2k - 2\ln(L)$$

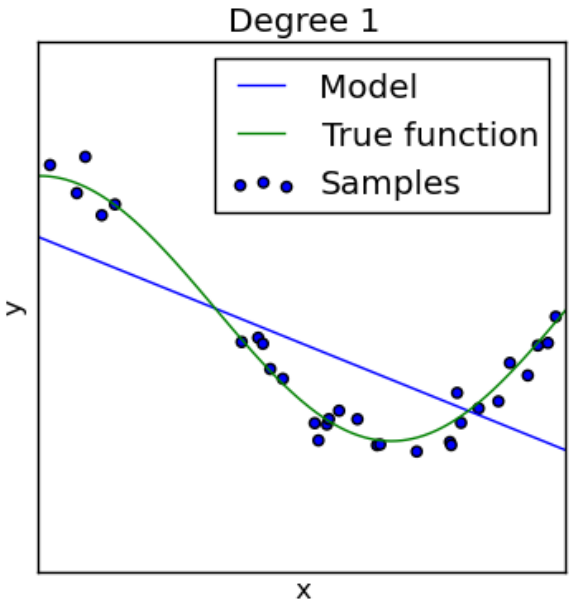
parameters

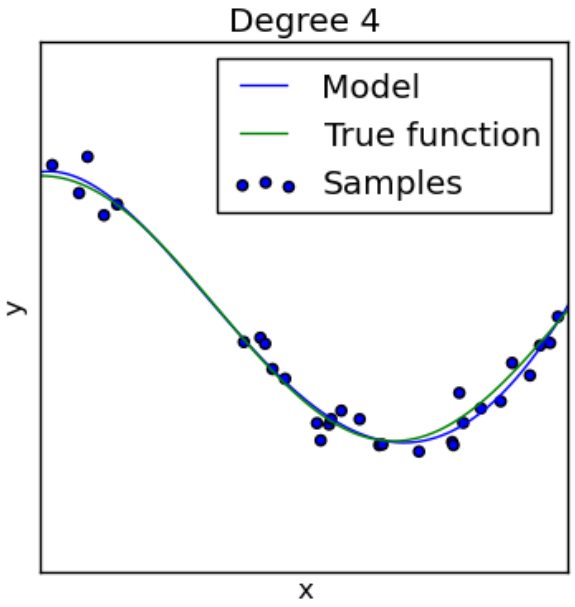
Log likelihood

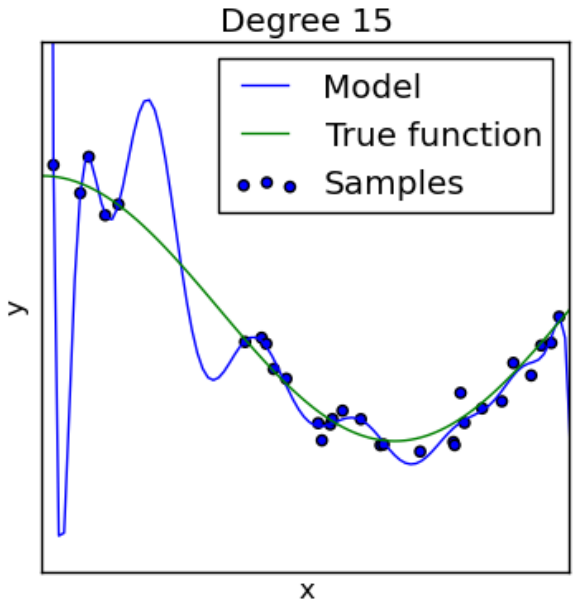
Higher AIC

Min. AIC

Higher AIC







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No. Observations:	89	**AIC:**	3480.
Df Residuals:	87	**BIC:**	3485.
Df Model:	1		

Bayesian Information Criterion

	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

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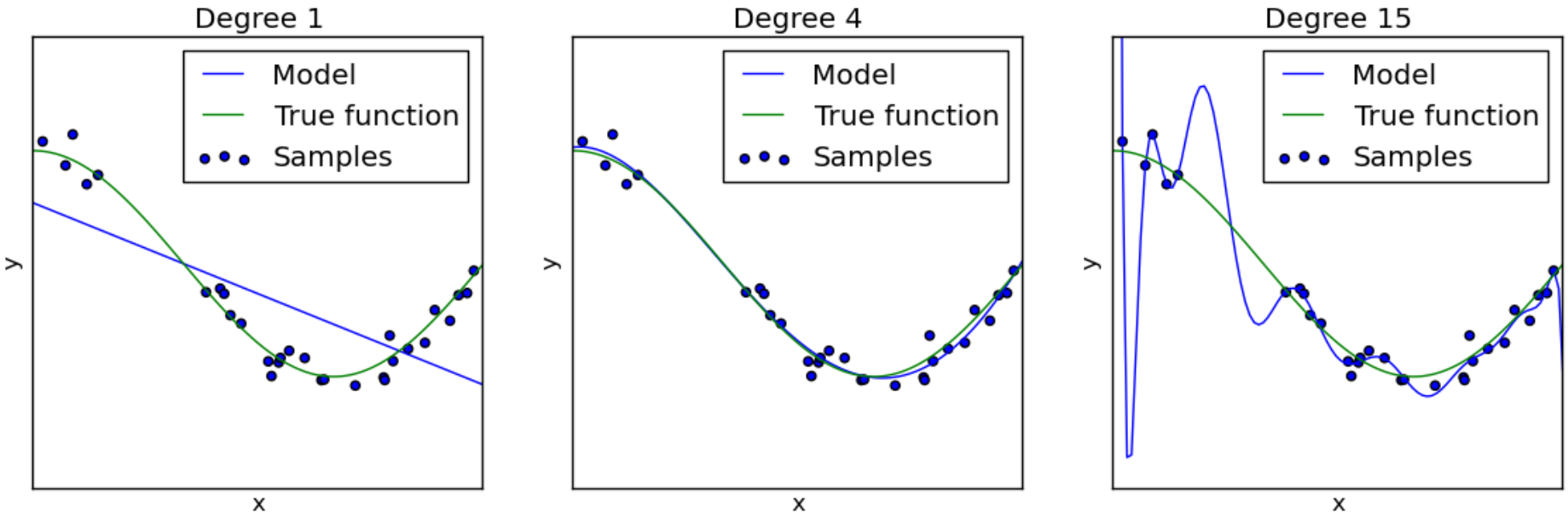
Kurtosis:	7.091	**Cond. No.**	1.54e+08

$$BIC = k\ln(m) - 2\ln(L)$$

parameters

points

Log likelihood



$$BIC = k\ln(m) - 2\ln(L)$$

parameters

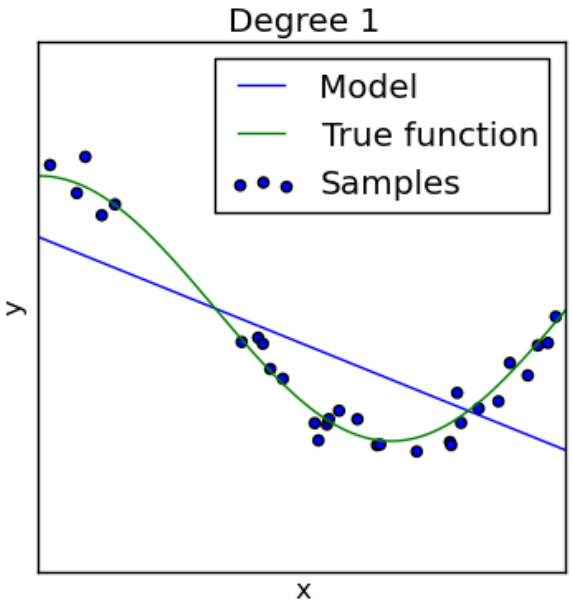
points

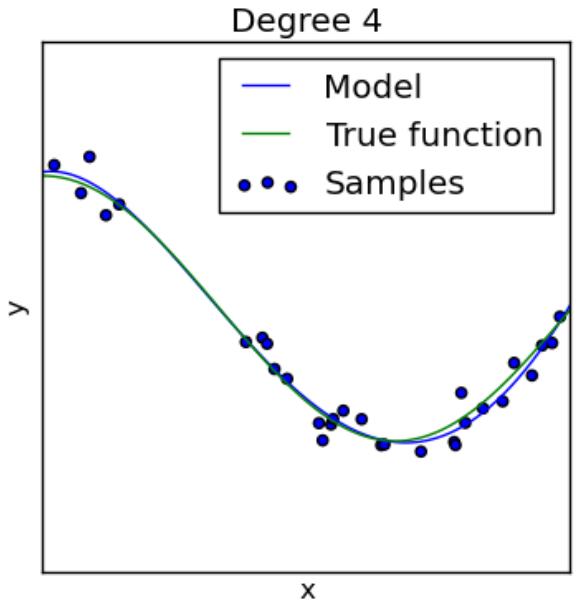
Log likelihood

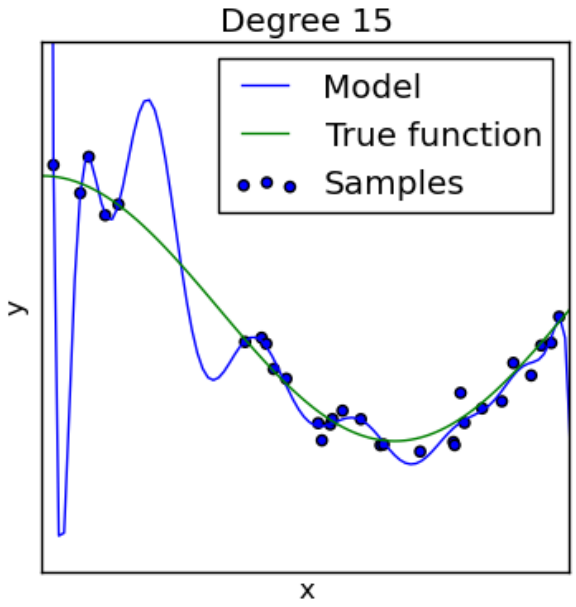
Higher BIC

Min. BIC

Higher BIC







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

Try adding polynomials

Check functional forms for each feature

Try including other features

Use more data (bigger training set)

Regularization (tomorrow)

Try some other model (later)