What do these numbers mean?

METIS

datascope

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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

Ordinary Least Squares

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
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Residual degrees of freedom

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
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Kurtosis:	7.091	**Cond. No.**	1.54e+08

Residual degrees of freedom = number of observations - number of parameters

Model degrees of freedom

OLS Regression Results

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R^2

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
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The cost (error) of the model: $$\sum_{i=1}^{m}\left(y_{\beta}(x^{(i)})-y_{obs}^{(i)}\right)^2$$

Sum of Squared Error

SSE

Varience of observed points (times m): $$\sum_{i=1}^{m}\left(\bar{y}_{obs}-y_{obs}^{(i)}\right)^2$$

Total Sum of Squares

SST

Sum of Squared Error

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

Total Sum of Squares

Randomness
left in the model

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

Variation in the data

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

Randomness left in the model

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

Variation in the data

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

Randomness left in the model

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

Variation in the data

Another way of thinking about R^2

Errors of **my** model: $$\sum_{i=1}^{m}\left(y_\beta(x^{(i)})-y_{obs}^{(i)}\right)^2$$

SSE

Errors of the "**mean**" model: $$\sum_{i=1}^{m}\left(\overline{y}_{obs}-y_{obs}^{(i)}\right)^2$$
(always predict average value)

SST

Another way of thinking about R^2

Errors of **my** model

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

Errors of **mean** model

OLS Regression Results

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OLS Regression Results

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F-test

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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
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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)

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)

If p-value <0.05, we can reject the null hypothesis.
Data is too extreme to fit this model <u>just by chance.</u>

OLS Regression Results

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Log L

	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
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Likelihood is a different cost function

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

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

Likelihood is a different cost function

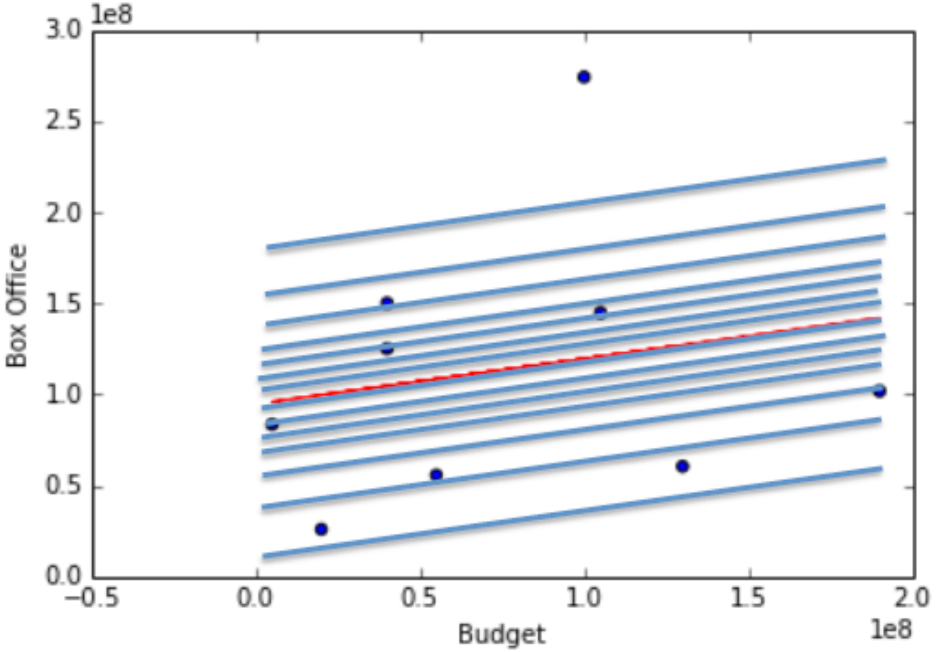
$$L(\beta_0, \beta_1) = p(y_{obs} | \beta_0, \beta_1)$$

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

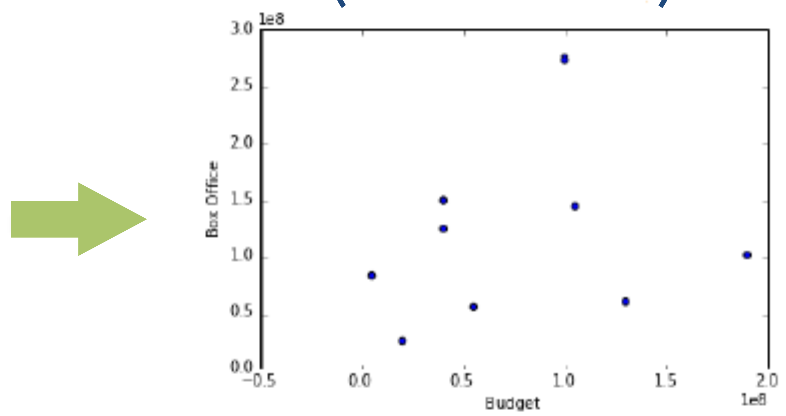
The model with maximum likelihood is the best fit.

Likelihood is a different cost function

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



Our world
(observed)



OLS Regression Results

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		coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
β_1	**Budget**	0.7846	0.133	5.901	0.000	0.520 1.049
β_0	**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

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Df Model:	1		

Standard error of the coefficient

	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

OLS Regression Results

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95% conf interval for coefficient's value

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Skew:	1.587	**Prob(JB):**	2.55e-22
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t-test

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

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

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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)

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.

OLS Regression Results

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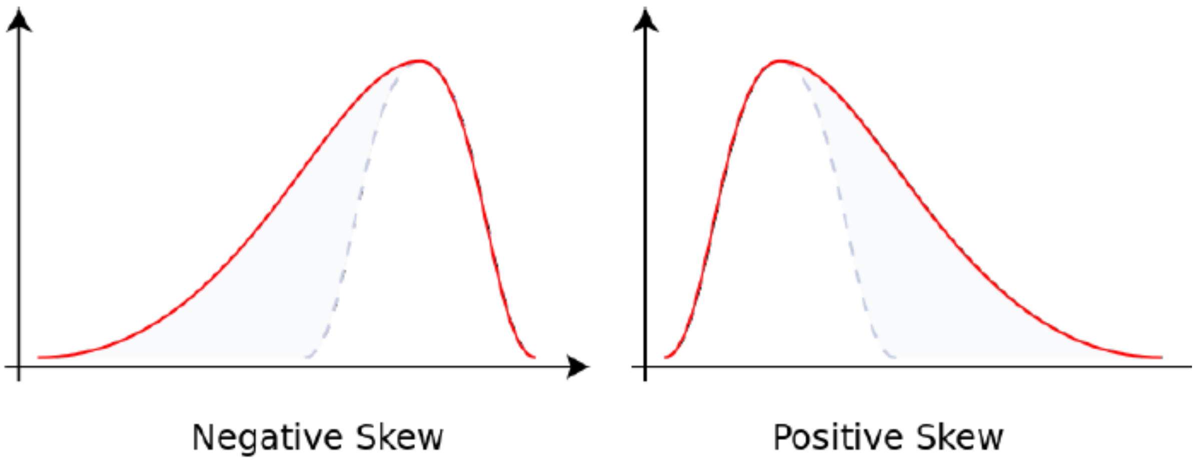
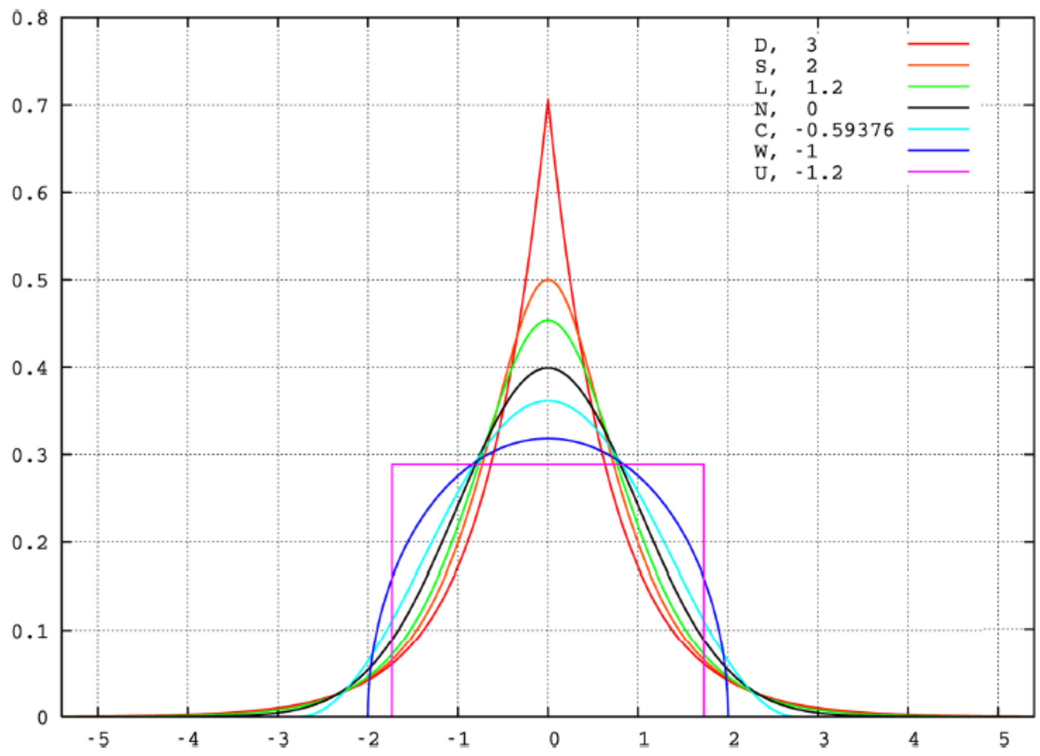
Skew & Kurtosis

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.

OLS Regression Results

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Another normality test

OLS Regression Results

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

Autocorrelation test

OLS Regression Results

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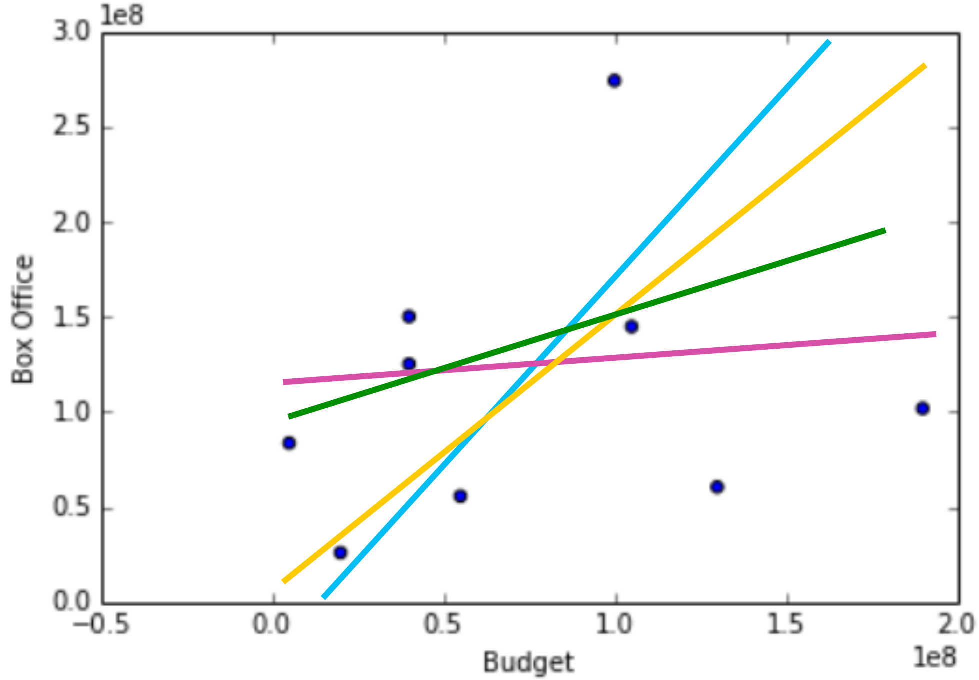
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	99.441
Skew:	1.587	**Prob(JB):**	2.55e-22
Kurtosis:	7.091	**Cond. No.**	1.54e+08

Sensitivity of prediction to small errors in input

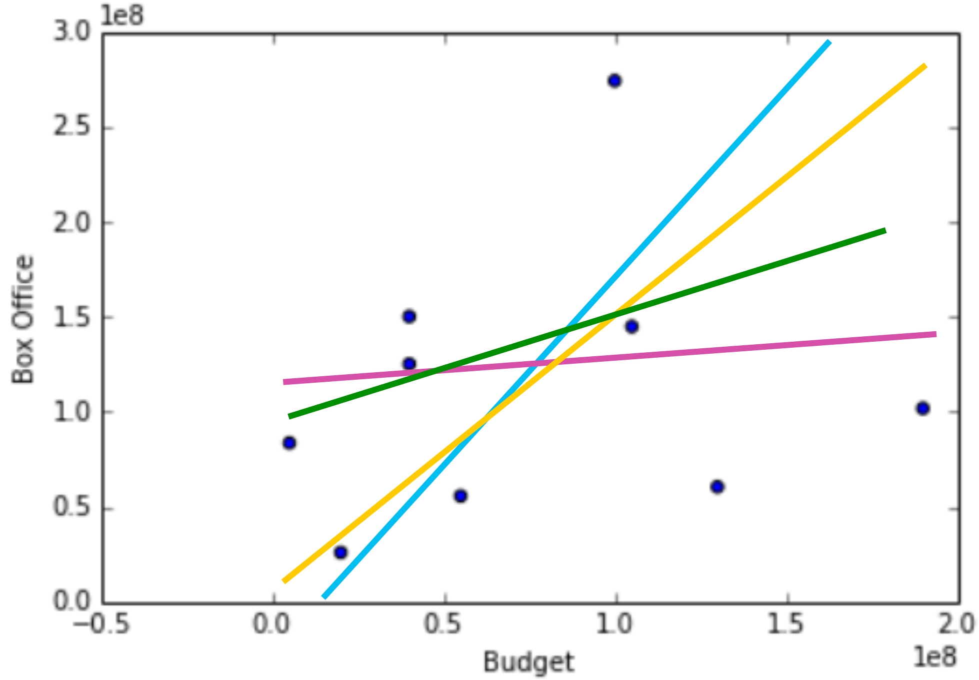
Model Selection

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



For models with the same amount of parameters, easy:

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

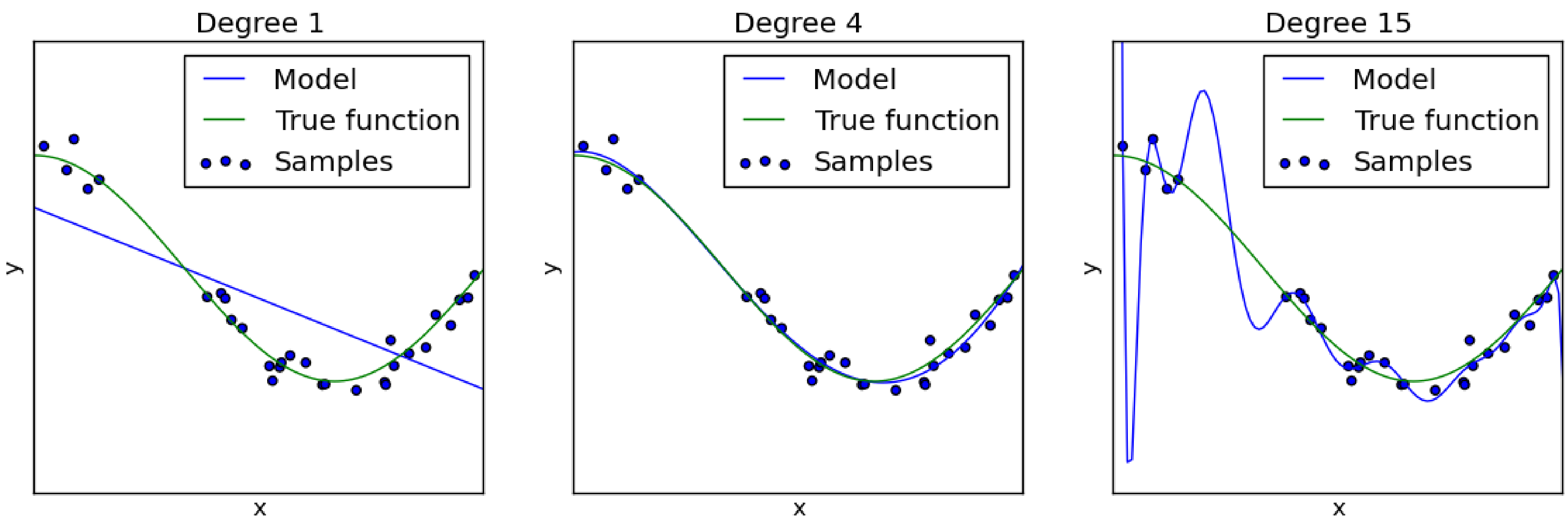


For models with the same amount of parameters, easy:

Take the one with the better cost function

Log-Likelihood:	-1753.0

For models of different complexity: Beware under/overfitting



$y = b_0+b_1x$

$y = b_0+b_1x+b_2x^2+b_3x^3+b_4x^4$

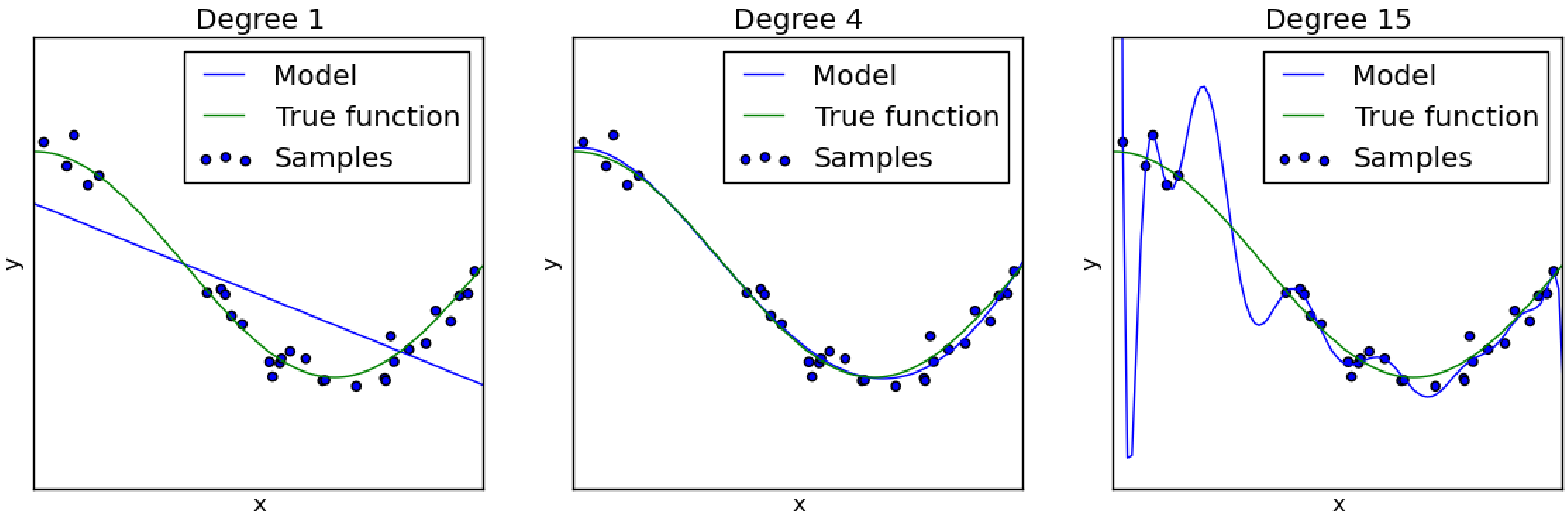
$y = b_0+b_1x+b_2x^2+ \ldots$

$+b_3x^3+b_4x^4+\ldots$

$+b_{13}x^{213}+b_{14}x^{14}+b_{15}x^{15}$

For models of different complexity: Beware under/overfitting

Underfitting | Just Right | Overfitting

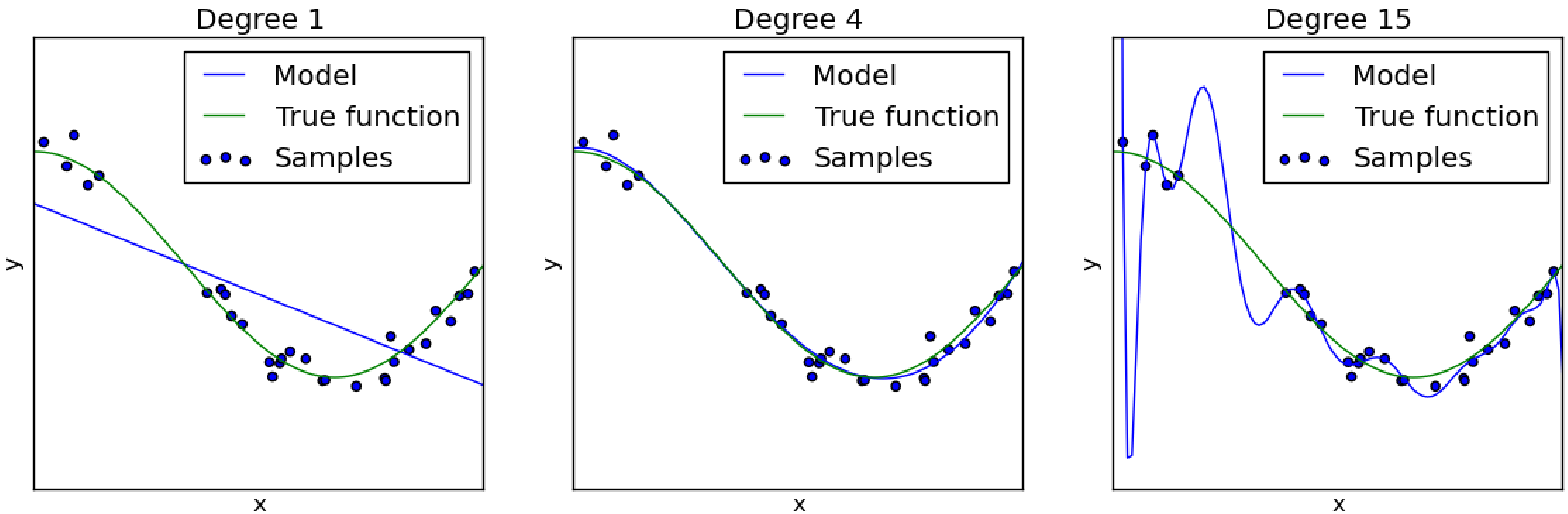


In machine learning, this is also called Bias/variance tradeoff

High bias
Low varience

Just Right

Low bias
High varience

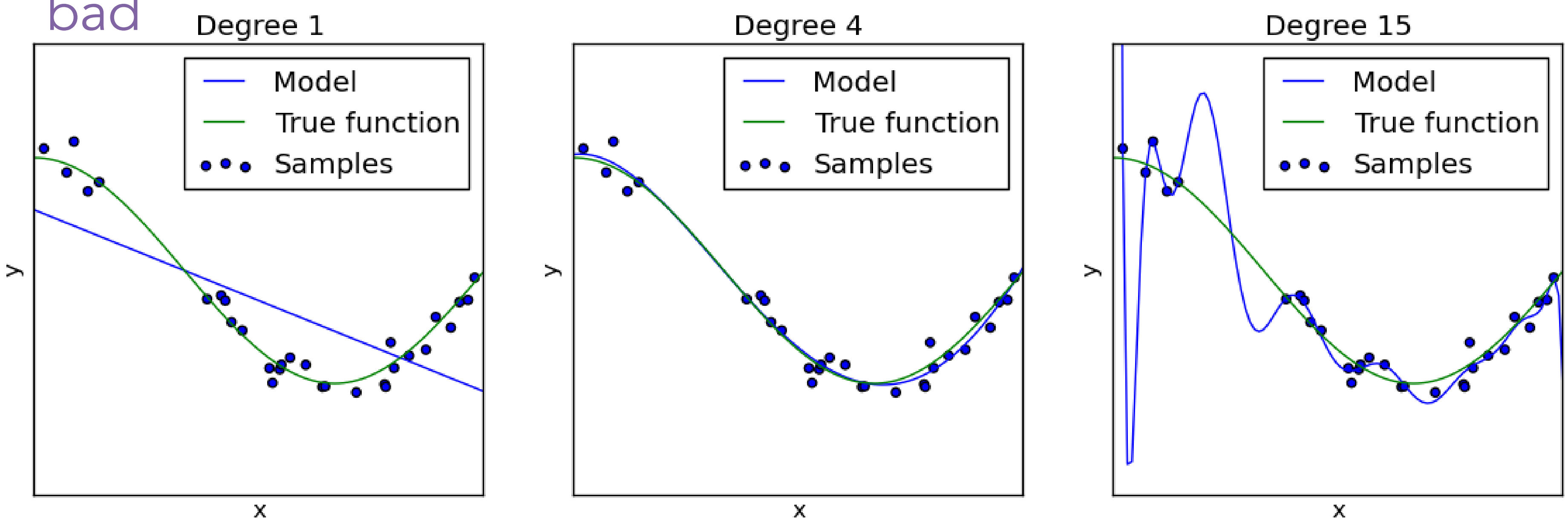


First and third will do poorly with incoming new data

First training poorly, predictions bad

Just Right

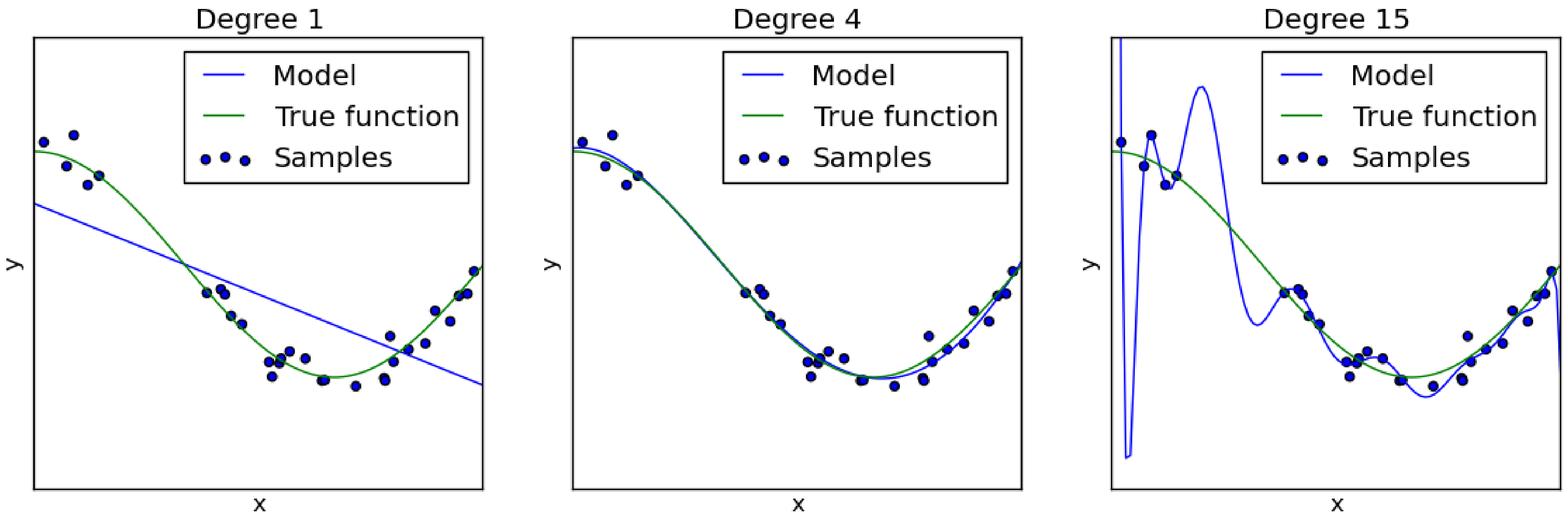
First training very well, can't generalize



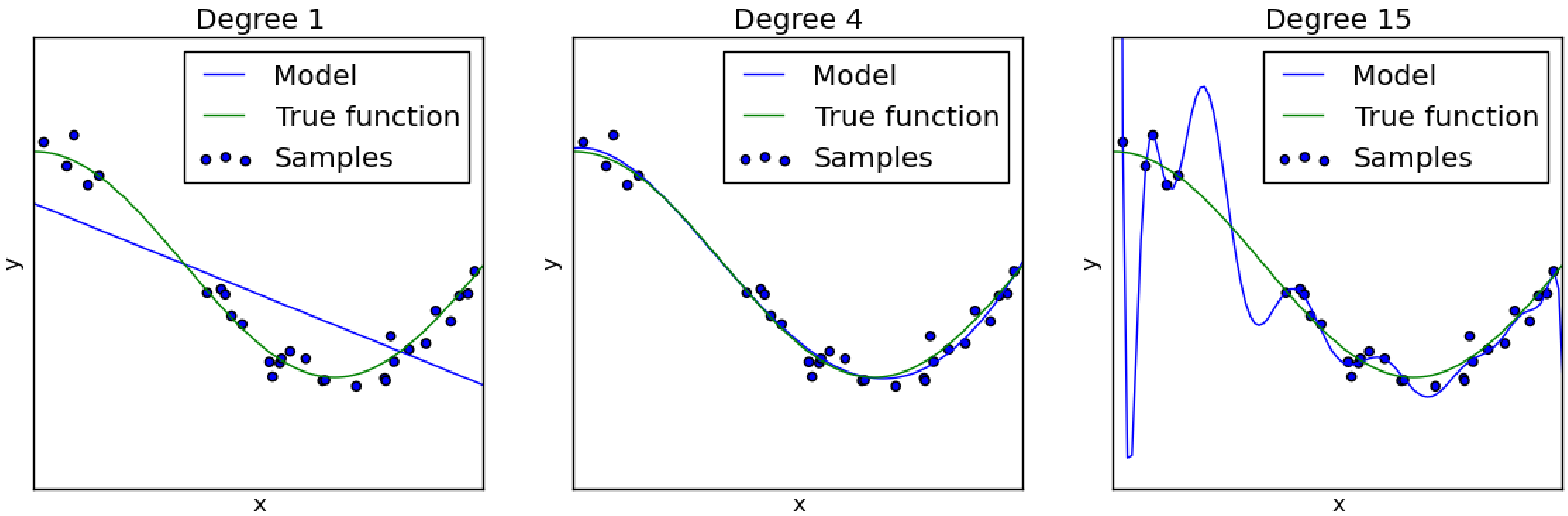
Solution:

Fit to~75% of data (training set)

Evaluate on remaining ~25% (test set)



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



OLS Regression Results

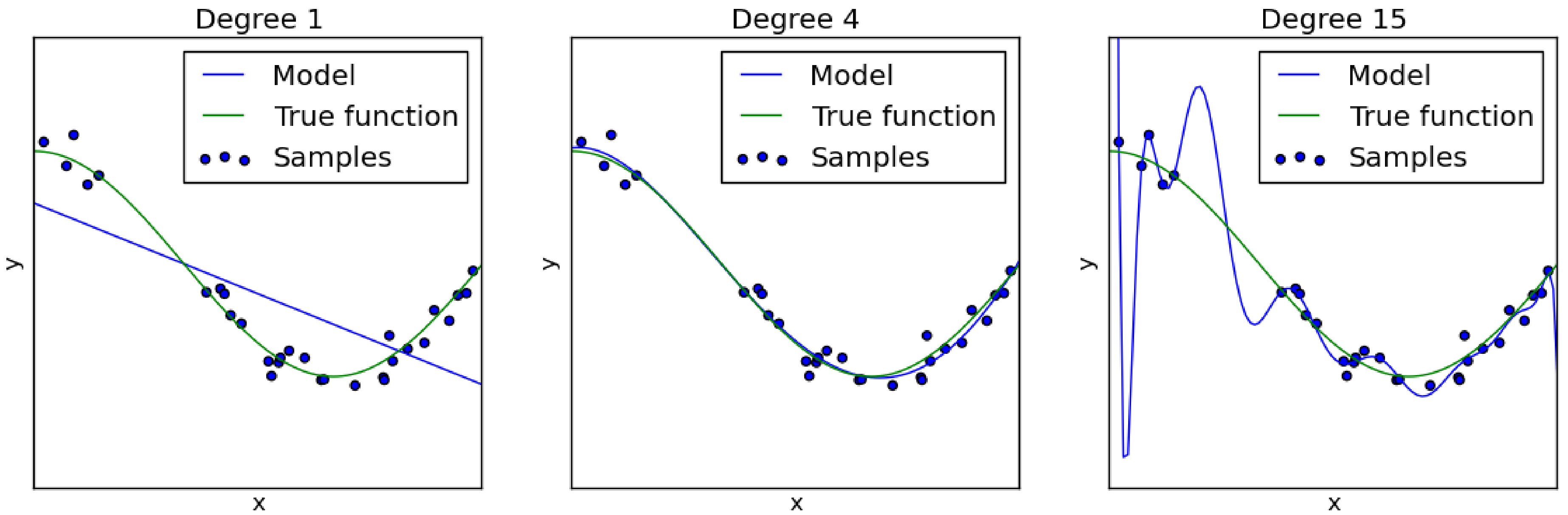
Dep. Variable:	DomesticTotalGross	**R-squared:**	0.286
Model:	OLS	**Adj. R-squared:**	0.278
Method:	Least Squares	**F-statistic:**	34.82
Date:	Sun, 14 Sep 2014	**Prob (F-statistic):**	6.80e-08
Time:	21:59:46	**Log-Likelihood:**	-1738.1
No. Observations:	89	**AIC:**	3480.
Df Residuals:	87	**BIC:**	3485.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

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

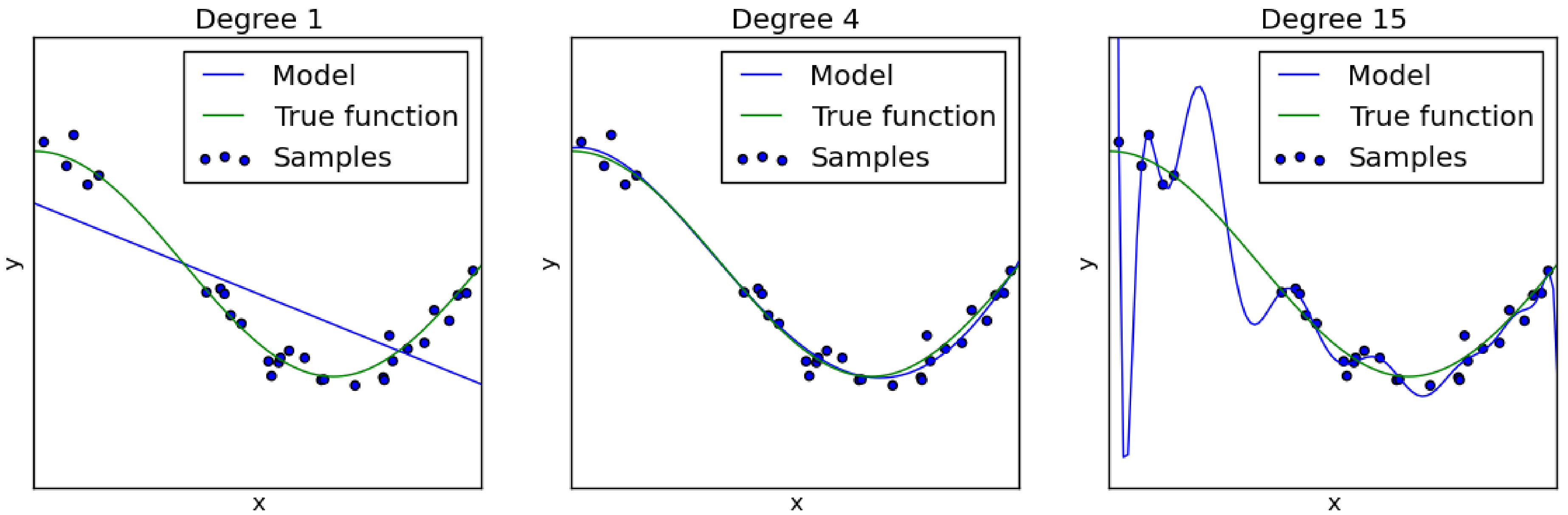
Omnibus:	39.749	**Durbin-Watson:**	0.674
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	99.441
Skew:	1.587	**Prob(JB):**	2.55e-22
Kurtosis:	7.091	**Cond. No.**	1.54e+08

Low R^2 | Higher R^2 | Highest R^2



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

Low R^2 | Higher R^2 | Highest R^2



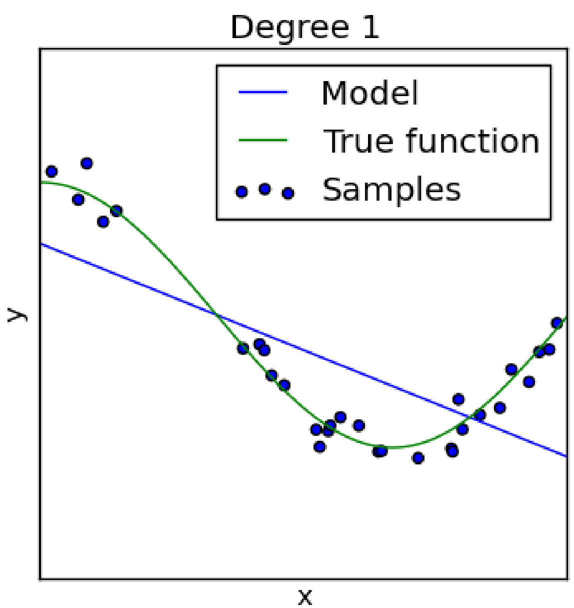
$$\overline{R}^2 = 1 - \frac{SSE/df_e}{SST/df_t}$$

$$df_e \rightarrow m - k - 1$$

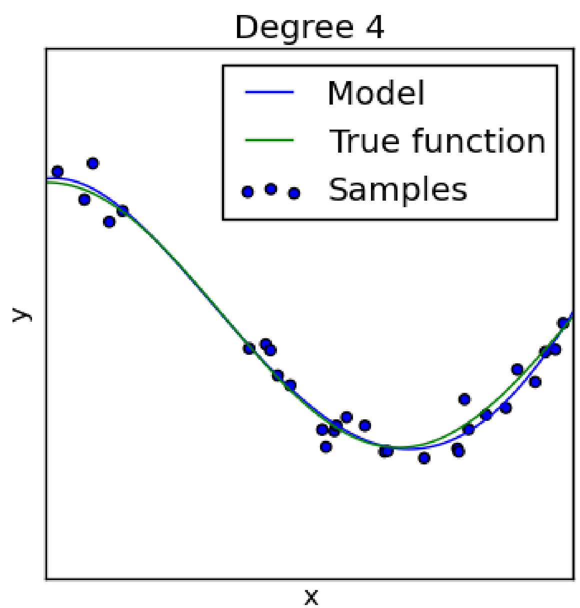
$$df_t \rightarrow m - 1$$

m= # points
k = # parameters

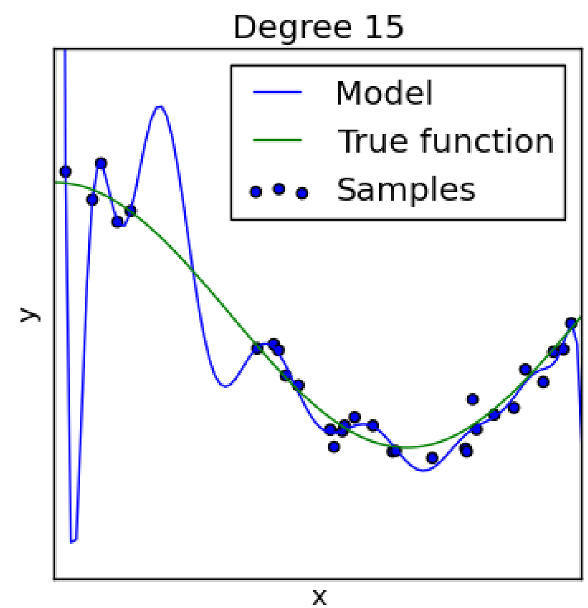
Low R^2



Higher R^2



Highest R^2



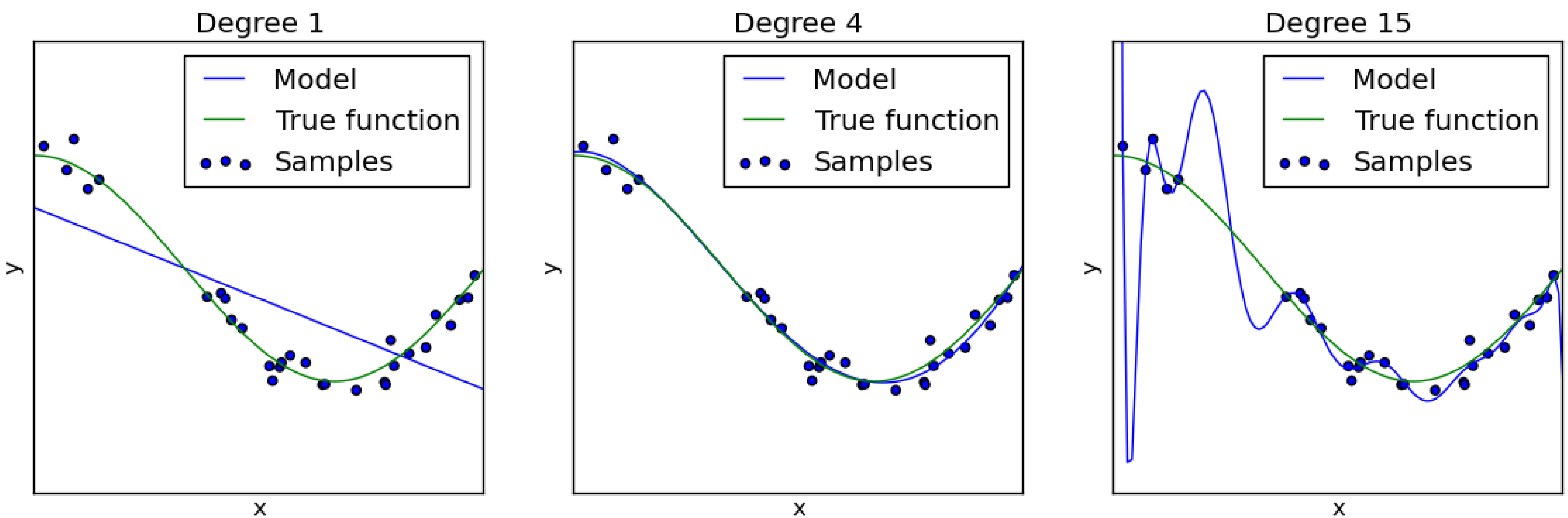
$$\overline{R}^2 = 1 - \frac{SSE / df_e}{SST / df_t}$$

$df_e \rightarrow m - k - 1$

$df_t \rightarrow m - 1$

m= # points
k = # parameters

Low adj. R^2 | Max. adj R^2 | Low adj. R^2



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

Akaike Information Criterion

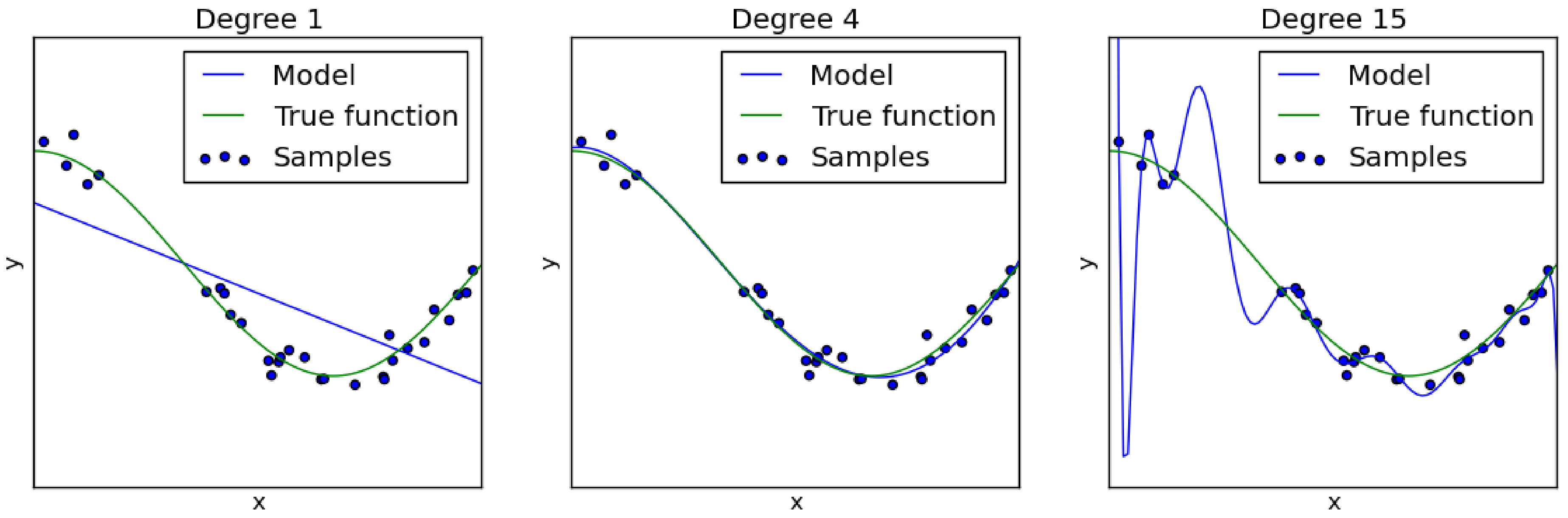
	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
Budget	0.7846	0.133	5.901	0.000	0.520 1.049
Ones	4.44e+07	1.27e+07	3.504	0.001	1.92e+07 6.96e+07

Omnibus:	39.749	**Durbin-Watson:**	0.674
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

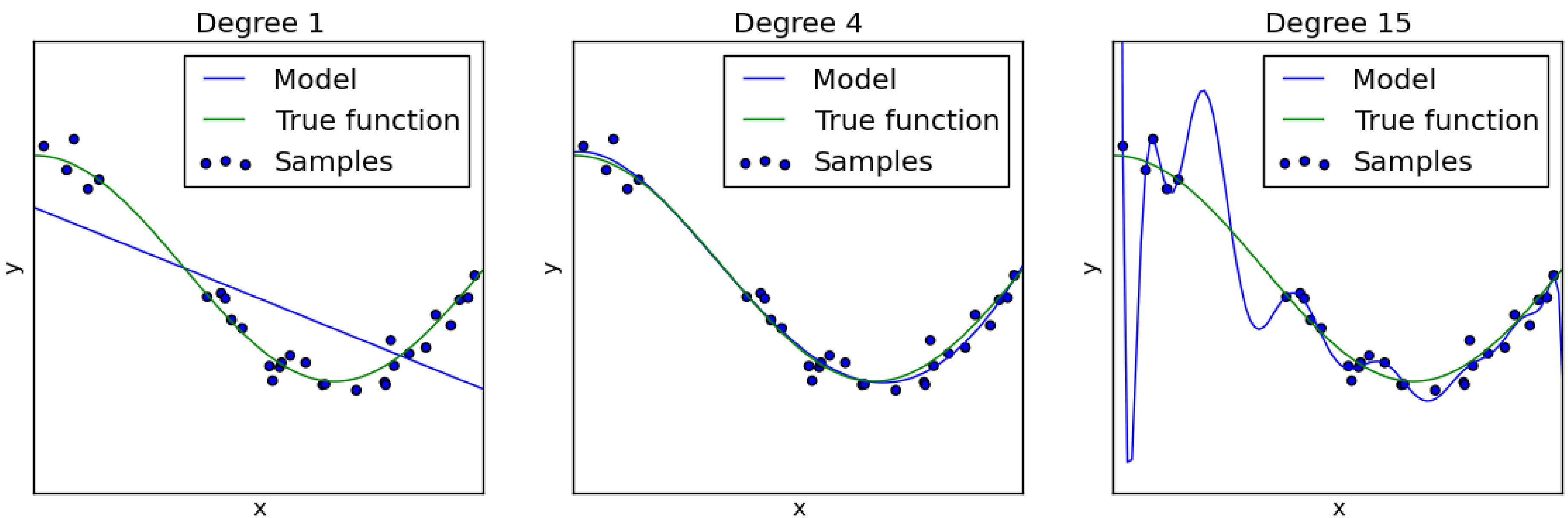
Log likelihood



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

parameters

Log likelihood



Higher AIC Min. AIC Higher AIC

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		

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

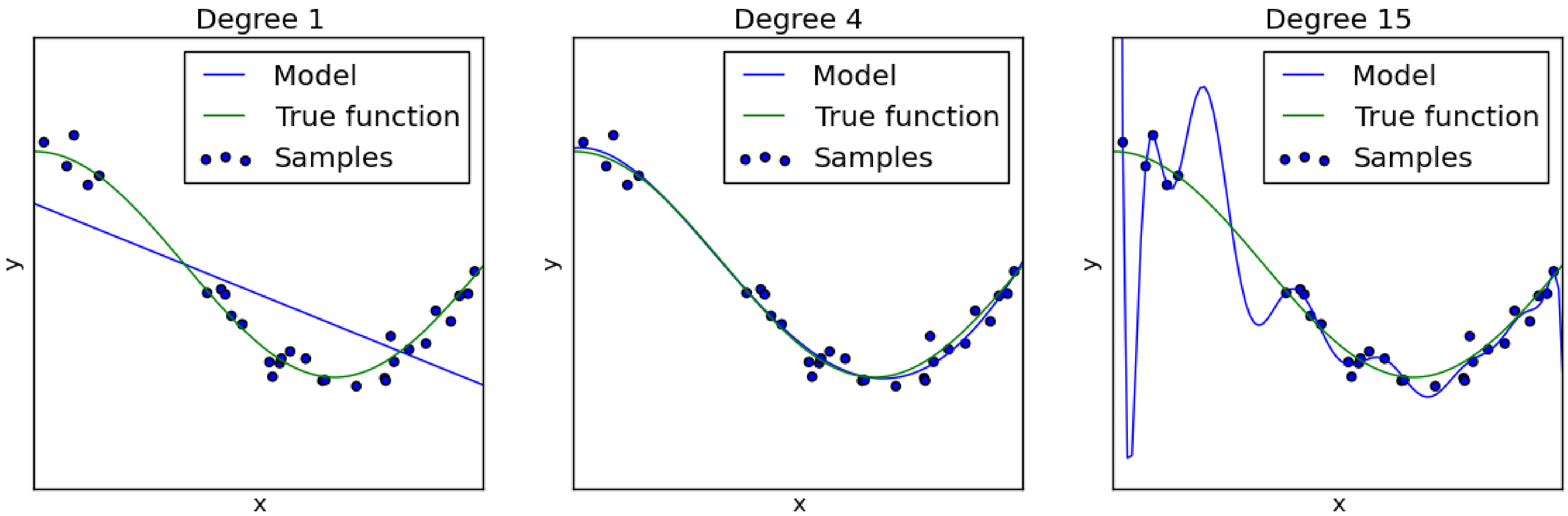
Omnibus:	39.749	**Durbin-Watson:**	0.674
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	99.441
Skew:	1.587	**Prob(JB):**	2.55e-22
Kurtosis:	7.091	**Cond. No.**	1.54e+08

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

parameters

points

Log likelihood

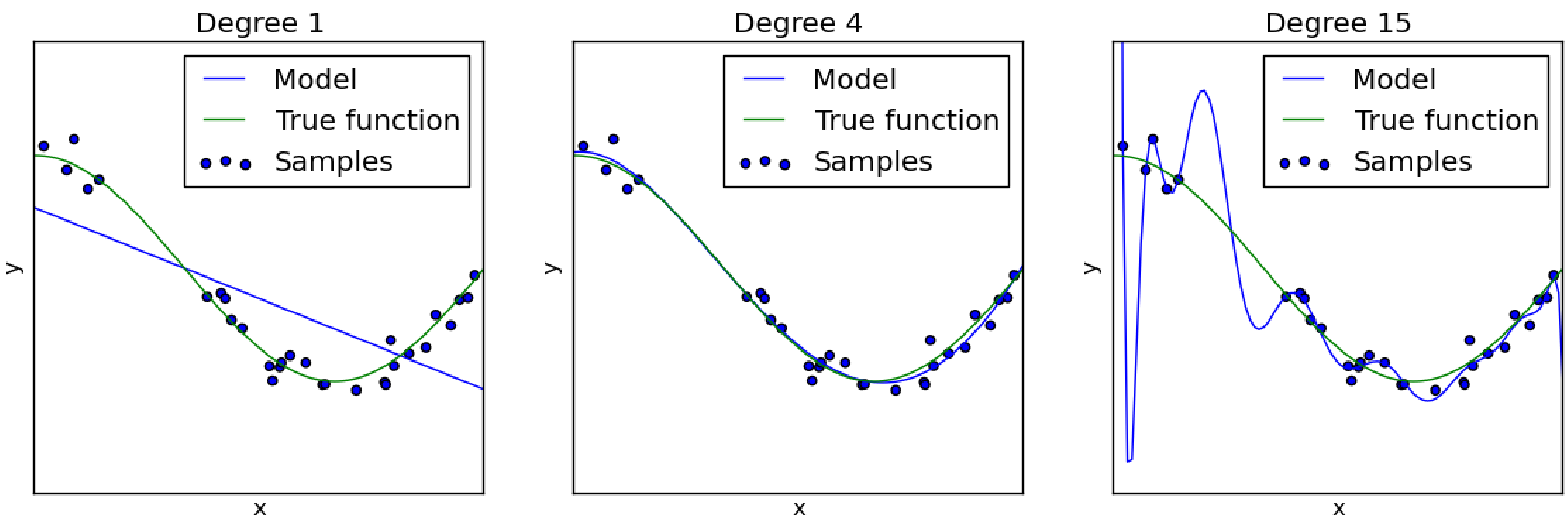


$$BIC = k\ln(m) - 2\ln(L)$$

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)