Linear Regression Metrics

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Intro

Metrics

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

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Ordinary Least Squares

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Residual degrees of freedom

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Model degrees of freedom

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R^2

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t statistic

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p-Value

Skew & Kurtosis

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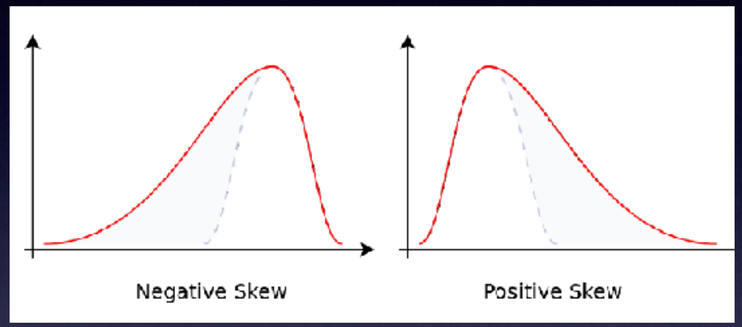
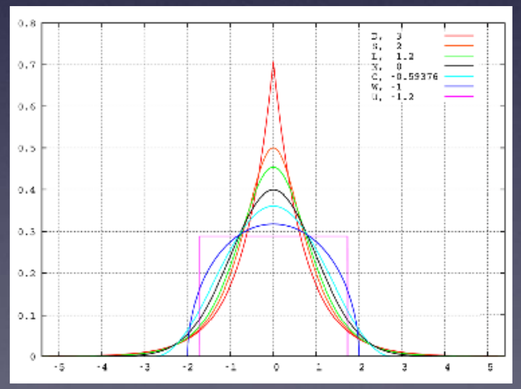
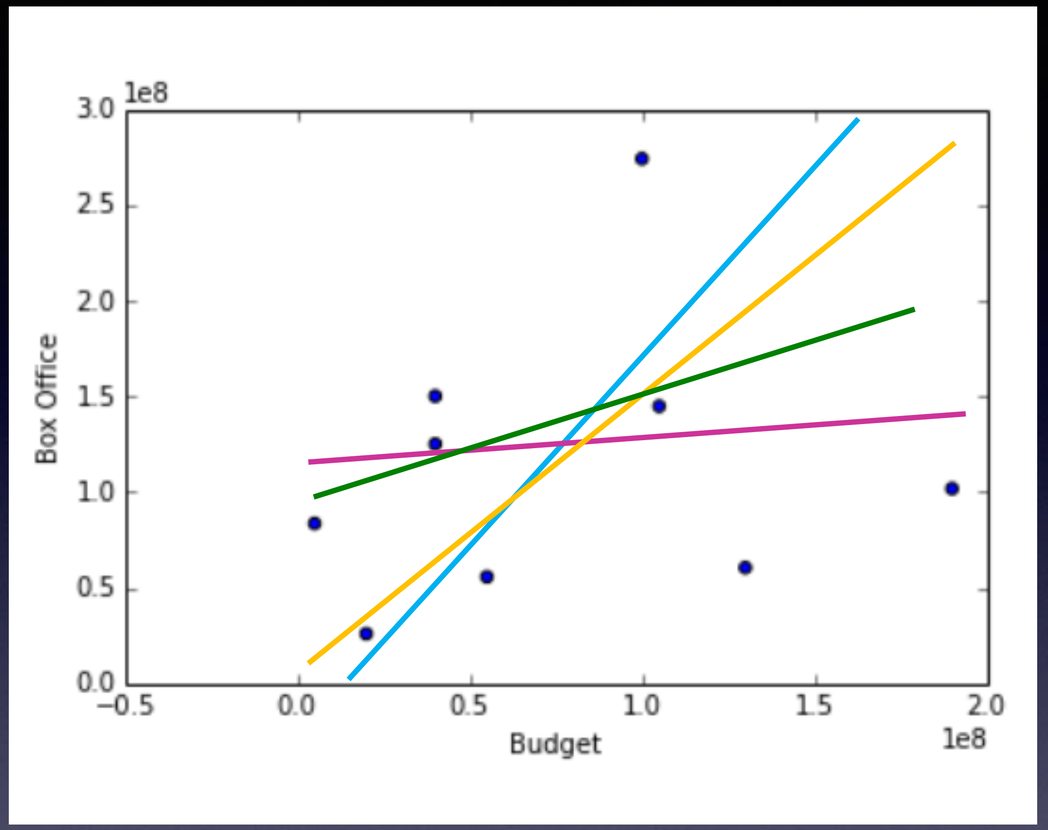
Skew (asymmetry)



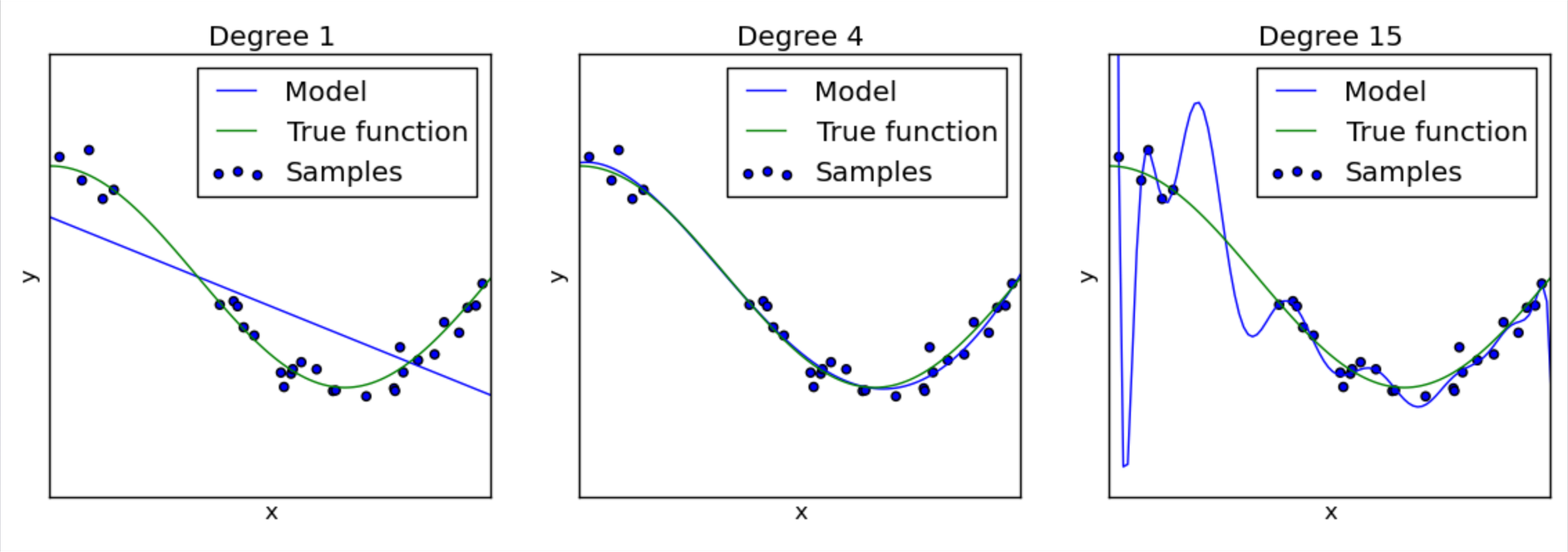
Kurtosis (peakness)



Model Evaluation

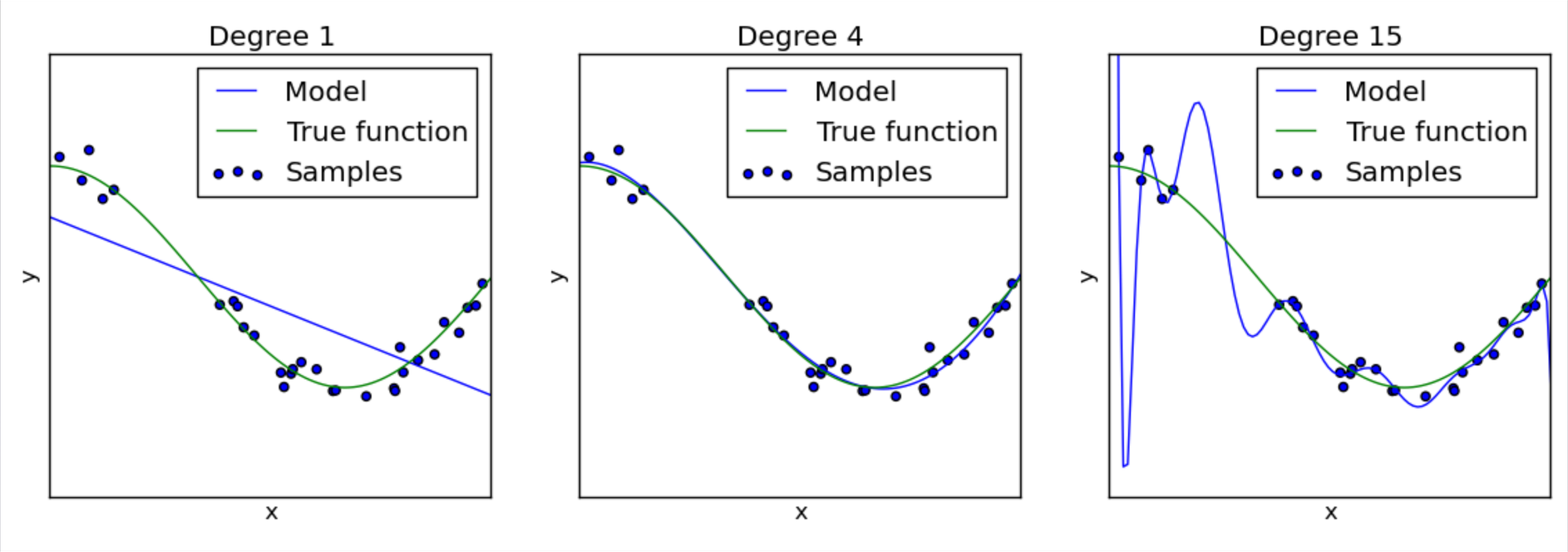


For models with the same amount of parameters, easy:
Take the one with the lowest least squares (as in OLS)



Underfitting Just Right Overfitting

For models of different complexity: Beware under/overfitting

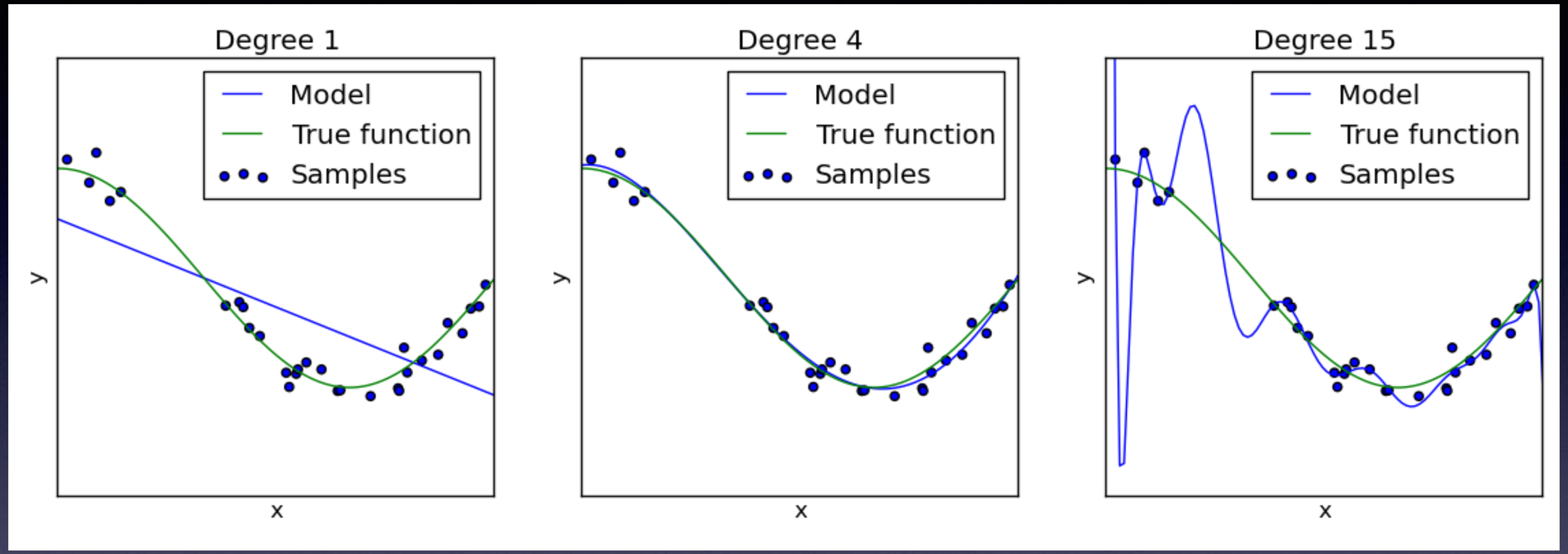


High bias
Low varience

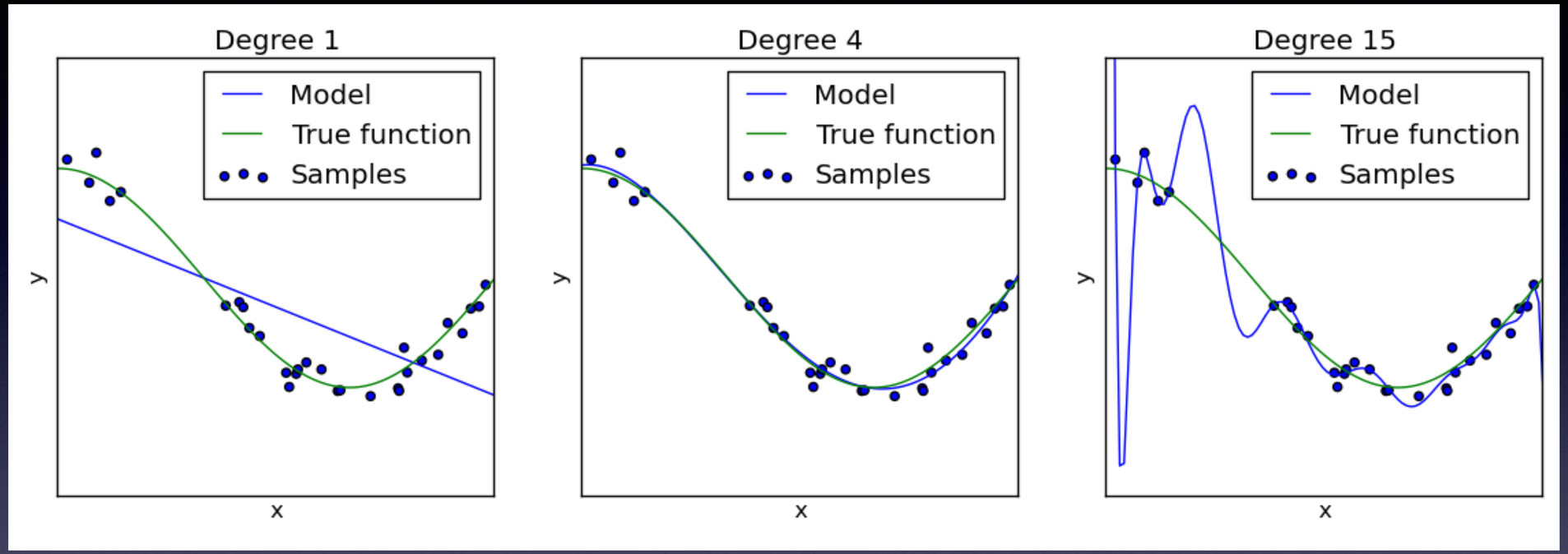
Just Right

Low bias
High varience

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



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



Low adj R^2 Higher adj R^2 Low adj R^2

Approaches for future model iterations

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
Try some other model

Recap

OLS Metrics

- **Metrics:** There are many, many metrics
- **Statsmodels:** provides great statistics for evaluating the model you've trained
- **Rabbit hole:** Choose and evaluate one or two metrics. Everything else is a nice to have until you have strong baseline and first iteration models.