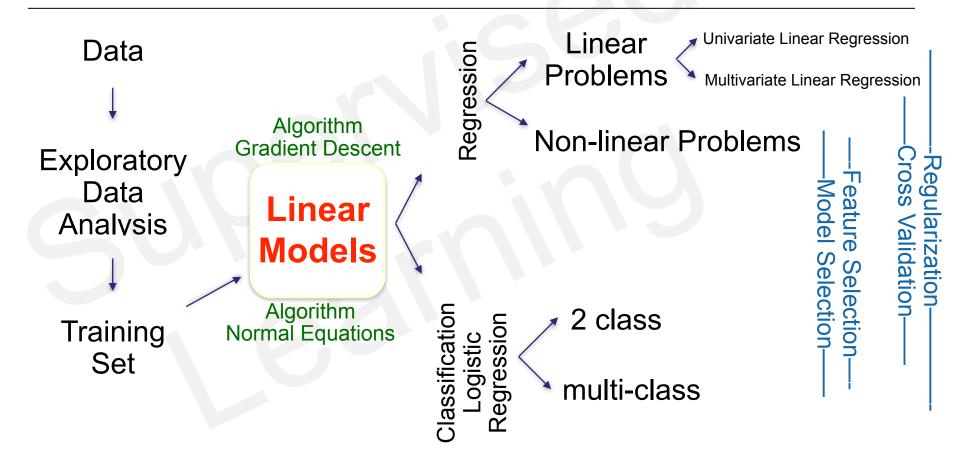
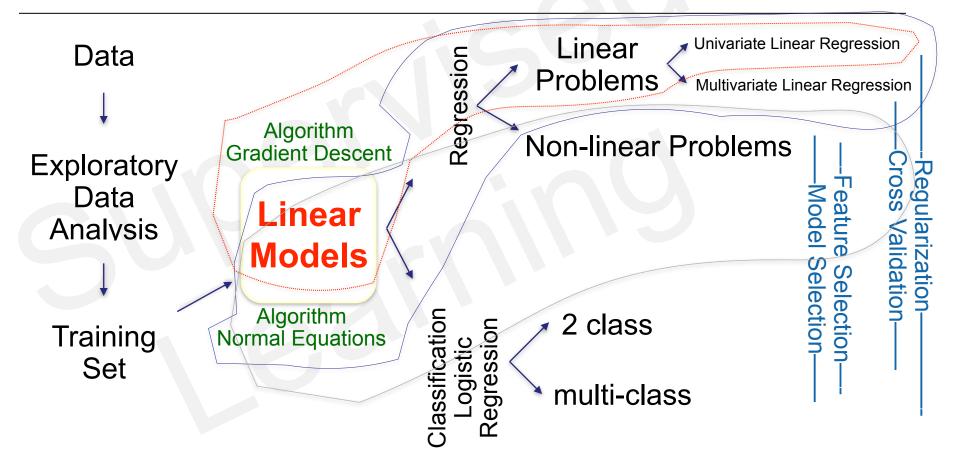
# INTRO TO DATA SCIENCE LECTURE 6: LINEAR MODELS & Non-Linear Functions

#### WHERE ARE WE ON THE DATA SCIENCE ROAD-MAP?



#### WHERE ARE WE ON THE DATA SCIENCE ROAD-MAP?



$$y = \theta_0 + \theta_1 x$$

**Univariate Linear Regression** 

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 \dots \theta_n x_n$$
 Multivariate Linear Regression

$$y = \theta_0 + \theta_1 z_1 + \theta_2 z_2 + \theta_3 z_3 \dots \theta_n z_n$$

 $z_1 = x_1$ 

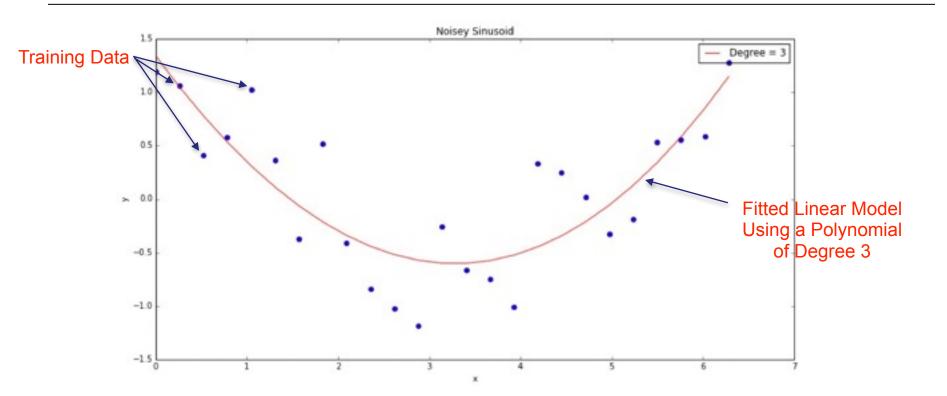
 $z_2 = x_2$ 

 $z_3 = x_1 x_2$ 

 $z_4 = x_1^2$ 

 $z_5 = x_2^2$ 

This is still linear in the parameters but allows modeling of non-linear combinations of features



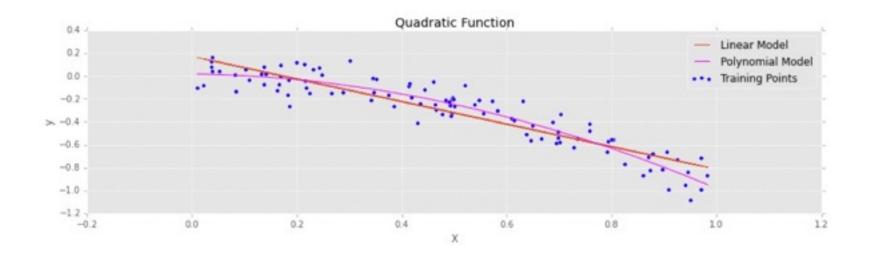
#### **KEY CONCEPTS - CREATING NON-LINEAR FEATURES IN PYTHON**

- Sklearn has 'PolynomialFeatures()' in the preprocessing module
- http://scikit-learn.org/dev/modules/preprocessing.html#preprocessing
- Polynomial Features converts an input array into an array consisting of:
  - the original features, e.g. x1, x2
  - · interaction terms e.g. x1 \* x2
  - · power terms e.g. x1 \* x1
- There is an option to use only the interaction features

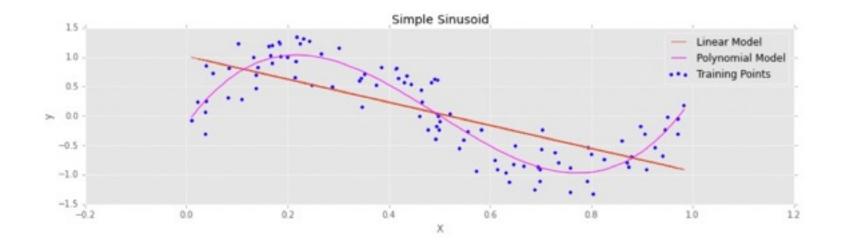
#### **KEY CONCEPTS - CREATING NON-LINEAR FEATURES IN PYTHON**

- Usually this is used in conjunction with the 'pipeline'
- http://scikit-learn.org/stable/modules/generated/ sklearn.pipeline.Pipeline.html#sklearn.pipeline.Pipeline
- In general I tend to use the 'make\_pipeline' function, to combine preprocessing and a linear model into a consolidated model
  - e.g. make\_pipeline(PolynomialFeatures(degree\_of\_polynomial\_required),
    LinearRegression())

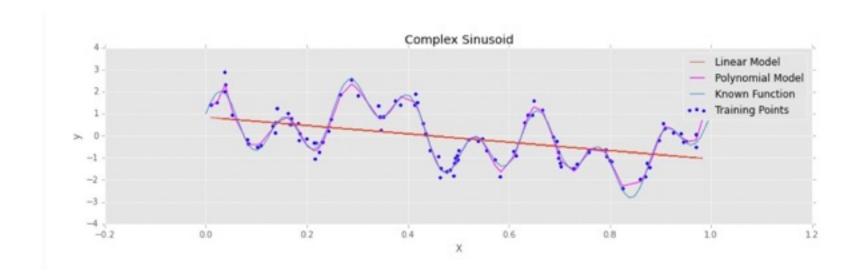
Random points generated using a quadratic function and added noise Ideal polynomial to fit is of degree 2



Random points generated using a simple sinusoid and added noise Ideal polynomial to fit is of degree 3

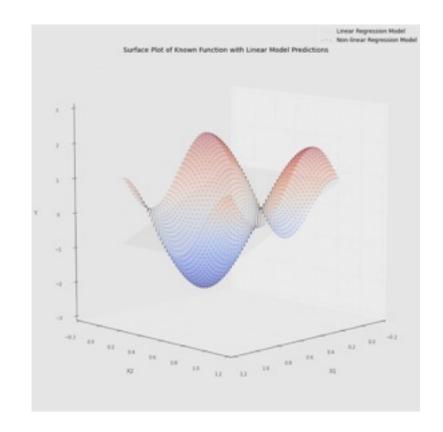


Random points generated using a complex sinusoid and added noise Ideal polynomial to fit is of degree ?



# Multivariate Regression

A 2D polynomial with a fit using multivariate linear regression and non-linear regression



#### **KEY CONCEPTS - FEATURE SELECTION & MODEL SELECTION**

## **Model Selection**

- To (hopefully) improve our model we add non-linear components
  - · e.g.1 House price might be related to the square of the number of baths
  - · e.g.2 In a polynomial regression we have x1 \* x1, x2 \* x2 terms
- In polynomial regression we determine the complexity of the model by the degree of the polynomial

#### **KEY CONCEPTS - FEATURE SELECTION & MODEL SELECTION**

## **Feature Selection**

- Choosing which input features can be successfully modeled to outputs
  - · e.g.1 What features of the a house optimally predict it's price
  - e.g.2 In a polynomial regression problem there is just x1, x2, ..., xN

#### **KEY CONCEPTS - MODEL SELECTION AND THE CONCEPT OF FIT**

# "Essentially, all models are wrong, but some are useful"

# George Box, statistician

(and who has been referred to as one of the greatest statistical minds of the 20th Century

#### **KEY CONCEPTS - HOW DO WE TEST FIT?**

- One way would be to measure the mean squared error
  - · Take the data
  - · Fit the model
  - Train the model until a suitable reduction in MSE is achieved
- The problem with this is that the model will be 'tuned' to the dataset it was trained on and may not 'generalize' well
- In the next class we will discuss this in great detail

#### **KEY CONCEPTS - HOW DO WE TEST FIT?**

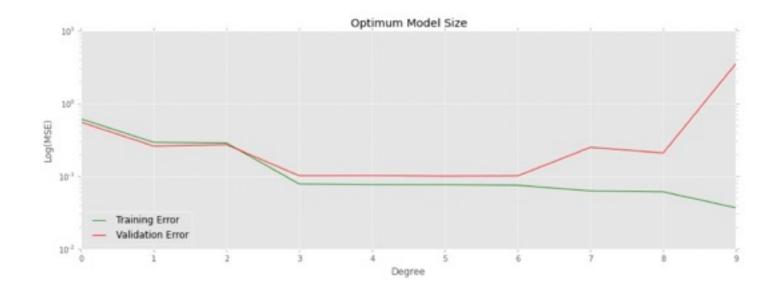
- What does it mean to 'generalize'?
- A machine learning algorithm generalizes well when it performs well on unseen data
- Objectively this can be measured using the cost function when the ML algorithm is run on <u>unseen data</u>
- In order to achieve this we must first partition the data

- Data Partitioning
- Ideally we have enough data to divide the dataset into 3 subsets,
  - 1. training set,
  - 2. validation set and
  - 3. test set.
- If the original dataset is large these may be 3 equal subsets
- Often, however, they may be equal in size

- The training set is used to train the model, BUT
- Feature & Model selection are optimized by the model's performance on the validation set
  - because we want the model to generalize
- This process is called <u>validation</u> or <u>cross validation</u>
- The test set is used to test the final model and report results
- The test set is not used to influence model construction in any way

- A common data science community 'belief' is that most practitioners do not worry about an independent 3rd set
- The Python data science stack is, as you will see, designed around a partition into only 2 sets - training and test
- http://scikit-learn.org/stable/modules/generated/sklearn.cross\_validation.train\_test\_split.html#sklearn.cross\_validation.train\_test\_split
- The story goes that most people train using the training set, and optimize their models using the validation set, and report their results using that same validation set
- OK for class... but beware...

- If the dataset is small however, equal separation into 3 groups maybe impossible.
- The training set usually contains the largest proportion of the data, e.g.60%
- The validation set usually contains the majority of the remaining data, e.g.20%
- The test often contains the remainder of the data, 'just-enough' e.g.20%



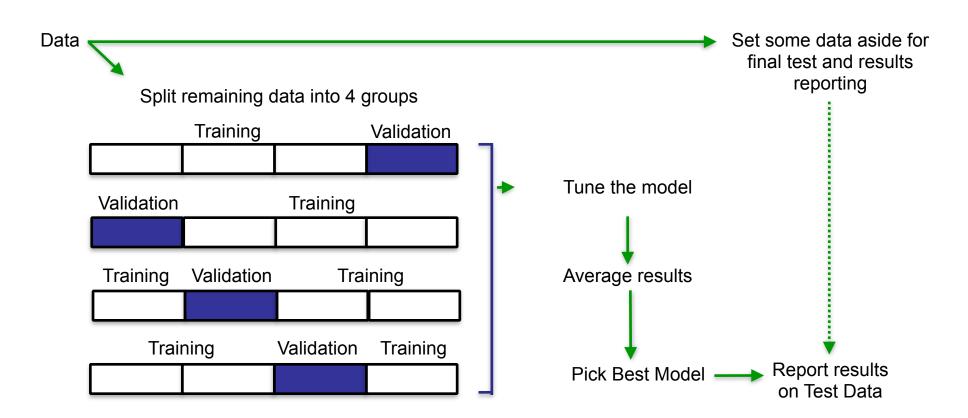
#### **KEY CONCEPTS - CROSS VALIDATION**

- What happens when data is scarce?
- We would still like to use the majority of the data to train our model on
- However, we need a way to tune the model using some 'independent' data that the model has not been exposed to
- ...and some data should be held back for an independent test from which to report results

#### **KEY CONCEPTS - S-FOLD CROSS-VALIDATION**

- Split the training data in to 'S' folds (e.g. S=4, 4-fold cross-validation)
- Use the 3 groups of data to train, 1 to validate
- Repeat, swapping the groups around
- Average the performance
- In the case of 4-fold cross validation there will be 4 models, each trained on 3/4 of the data and each tested on the 1/4 of the data that was held out. Held-out data being different each time

#### **KEY CONCEPTS - CROSS-VALIDATION**



#### **KEY CONCEPTS - OTHER WAYS TO ASSESS FIT**

- Historically various 'information criteria' have been proposed in an attempt to assess model fit without the need for validation.
   Two of the most well know are:
- 1. Akaike Information Criteria (AIC)
- 2. Bayesian Information Criteria (BIC)
- In general they tend to favor overly simple models.

#### **KEY CONCEPTS - STATSMODELS**

- For those seeking more statistical information on model fit there is a python library called 'Statsmodels'
- http://statsmodels.sourceforge.net/

#### **ASSESSING MODEL FIT: STATSMODELS**

#### **OLS Regression Results**

Dep. Variable:	у	R-squared:	0.858			
Model:	OLS	Adj. R-squared:	0.858			
Method:	Least Squares	F-statistic:	3015.			
Date:	Wed, 08 Oct 2014	Prob (F-statistic):	1.19e-213			
Time:	18:57:43	Log-Likelihood:	-867.25			
No. Observations:	500	AIC:	1736.			
Df Residuals:	499	BIC:	1741.			
Df Model:	1					

	coef	std err	t	P> t	[95.0% Conf. Int.]
x1	5.8530	0.107	54.911	0.000	5.644 6.062

#### **KEY CONCEPTS - FEATURE SELECTION**

# TO BE CONTINUED...