# INTRO TO DATA SCIENCE

### LECTURE 5: REGRESSION AND REGULARIZATION

Paul Burkard 07/07/2015

#### **LAST TIME:**

- WHAT IS WEB SCRAPING?
  - HOW DO WE DO IT IN PYTHON?
  - HTML, XML, JSON, WEB APIS
- WHAT IS THE UNIX COMMAND LINE?
  - WHAT ARE SOME COMMON COMMANDS?

#### **AGENDA**

#### **TODAY:**

- I. LINEAR REGRESSION
- II. MODEL EVALUATION: CROSS-VALIDATION
- III. REGULARIZATION

HANDS-ON: LINEAR REGRESSION AND REGULARIZATION

#### **LEARNING GOALS**

- ▶ What is Linear Regression?
  - What are the inputs and outputs?
  - What are some potential use cases?
- ▶ What is **Overfitting**?
  - How to we control for it?
  - What is Cross-Validation?
  - What is **Regularization**?
- ▶ Intro to **sklearn**, **patsy**, and **statsmodels**

# I. LINEAR REGRESSION

#### INTRO TO REGRESSION

Q: What is a regression model?

A: A functional relationship between input & response variables

The simple linear regression model captures a linear relationship between a single input variable x and a response variable y:

$$y = \alpha + \beta x + \varepsilon$$

#### INTRO TO REGRESSION

Q: What do the terms in this model mean?

$$y = \alpha + \beta_1 x_1 + \dots + \beta_n x_n + \varepsilon$$

A: y = response variable (the one we want to predict)

x =input variable (the one we use to train the model)

 $\alpha$  = intercept (where the line crosses the y-axis)

 $\beta$  = regression coefficients (the model "parameters")

 $\varepsilon$  = residual (the prediction error)

#### **TYPES OF LEARNING PROBLEMS**

	continuous	categorical
supervised	???	???
unsupervised	???	???

#### **TYPES OF LEARNING PROBLEMS**

	continuous	categorical
supervised	regression	classification
unsupervised	dim reduction	clustering

## ASIDE: LINEAR ALGEBRA INTRO

We can extend this model to several input variables, giving us the multiple linear regression model:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \quad \mathbf{X} = \begin{pmatrix} \mathbf{x}_1^{\mathrm{T}} \\ \mathbf{x}_2^{\mathrm{T}} \\ \vdots \\ \mathbf{x}_n^{\mathrm{T}} \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}, \quad \boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}, \quad \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}.$$

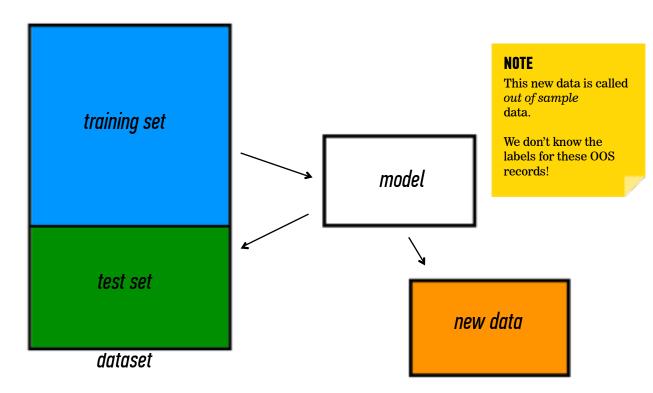
# II. CROSS-VALIDATION

	continuous	categorical
supervised	regression	classification
unsupervised	dim reduction	clustering
unsupervised	dim reduction  NOTE Remember	

#### **SUPERVISED LEARNING PROBLEMS**

### Q: What steps does a supervised learning problem require?

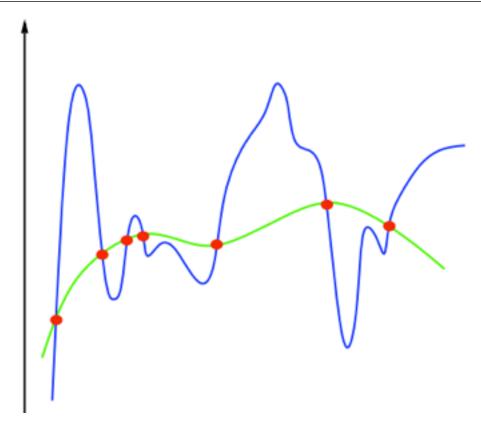
- 1) split dataset
- 2) train model
- 3) test model
- 4) make predictions



Q: What can go wrong if we don't follow these steps?

A: Overfitting!

- If we test our model against the training set it might perform quite well on the training set, but fail to **generalize** to new data
- The model might be overly **complex** and tailored to the training data



- Q: How can we avoid overfitting?
- A: One way is **Cross-Validation**

- Pre-splitting the dataset into train/test sets is one form of crossvalidation
- There are plenty of others (**k-fold**, **leave-one-out**, etc)

### Steps of **k-fold Cross-Validation**:

- Partition dataset into k random, equal-sized subsets
- For each subset, hold it out as the test set and train on the rest
- Report the average of the testing performances as the model's estimated generalization performance

### III. REGULARIZATION

#### **REGULARIZATION**

- Q: What is regularization?
- A: Any built-in method to **reduce complexity** of a model in an effort to **lower the risk of overfitting**

Q: How do we define the complexity of a regression model?

A: One method is to define complexity as a function of the size of the coefficients.

Ex 1:  $\sum |\beta_i|$  this is called the L1-norm

Ex 2:  $\sum \beta_i^2$  this is called the L2-norm

The basic **Ordinary Least Squares** solution to regression problems can also be expressed as:

**OLS:** Choose  $\beta$  s.t.  $min(\|y - x\beta\|^2)$ 

Here, the function in parenthesis is called the **Cost Function** and in general it is what you want to minimize when searching for solutions to machine learning problems.

### Thus, the regularization problems can be expressed as:

```
OLS: min(\|y - x\beta\|^2)
L1 regularization: min(\|y - x\beta\|^2 + \lambda\|\beta\|)
L2 regularization: min(\|y - x\beta\|^2 + \lambda\|\beta\|^2)
```

- We are no longer just minimizing error but also an additional term.
- Thus, large values of  $\beta$  will be discouraged

These measures of complexity lead to the following regularization techniques:

L1 regularization: 
$$y = \sum \beta_i x_i + \epsilon \quad st. \quad \sum |\beta_i| < s$$

L2 regularization: 
$$y = \sum \beta_i x_i + \epsilon \quad st. \quad \sum \beta_i^2 < s$$

**Regularization** refers to the method of preventing overfitting by explicitly controlling model complexity.

These measures of complexity lead to the following regularization techniques:

**Lasso** regularization: 
$$y = \sum \beta_i x_i + \epsilon st. \sum |\beta_i| < s$$

**Ridge** regularization: 
$$y = \sum \beta_i x_i + \epsilon \quad st. \quad \sum \beta_i^2 < s$$

**Regularization** refers to the method of preventing **overfitting** by explicitly controlling model **complexity**.

Q: What problems might we see?

*A:* 

- 1) Correlated predictor variables
- 2) Large number of parameters allow us to overfit

#### INTRO TO REGRESSION

Q: What can we do about this?

A:

1) Drop correlated predictors

2) Get more data

Q: Do regression models have to depend linearly on input variables?

A: NO

We can use almost any transformation of a single input variable (aka  $f(x_i)$ ) as a separate input variable, as long as we don't mix them (aka  $f(x_i, x_j)$ )

Some nonlinear laws in nature:

$$F = G \frac{m_1 m_2}{r^2} \qquad F = \frac{1}{4\pi\varepsilon_0} \frac{qQ}{r^2} = k_e \frac{qQ}{r^2} \,,$$

$$x(t) = A\cos(\omega t + \phi),$$