

# Business Intelligence and Data Management

*academic year 2019-2020*

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## Lecture 5

*topic:* Regression Analysis

*material:* Chapters 6 (book “Data Mining for Business Intelligence”)

## Summary from previous lectures

### Data Mining:

- Provides results useful for **decision making**
- Process involves multiple steps:  
Business understanding → Data preparation →  
**Model building** → Testing & Evaluation → Deployment
- Various options for the model:
  - Regression
  - Clustering
  - Decision trees
  - Association rules
  - etc.



# Summary of previous lectures / Agenda

Date		Lecture contents	Lecturer	Lab topics	Test
<b>Jan-27</b>	1	Intro. to BI+ Data Management	Caron		
Jan-30				SQL-1	1
<b>Jan-28</b>	2	Data warehousing	Caron		
Feb-06				SQL-2	2
<b>Feb-03</b>	3	OLAP business databases & dashboard	Caron		
<b>Feb-13</b>				SQL-3 & OLAP	3a & 3b
<b>Feb-10</b>	4	Data mining introduction	Ioannou		
	5	Regression models	Ioannou		
<b>Feb-17</b>	6	Naïve Bayes	Ioannou		
	7	k nearest neighbors	Ioannou		
Feb-20				Bayes & neighbors	4
<b>Feb-27</b>	8	Performance measures	Ioannou		
<b>Mar-02</b>	9	Decision trees	Ioannou		
Mar-05				Dec. trees	5
<b>Mar-09</b>	10	Association rules	Ioannou		
Mar-11,12&13				Ass. Rules	6
<b>Mar-16</b>	11	Clustering (+20 mins exam preparation)	Ioannou		
Mar-19				Clustering	7

Data Mining

# Motivation

## Data Mining:

Provides results useful for decision making

- Examples:
  - Store X wants to know the amount of water bottles to place in the fridge during June
  - The tax office wants to detect if the family income relates to the overall monthly spending of families
  - The university wants to find out if reducing the lab sessions will result in lower course grades
  - The university wants to find out if the color of the student hair affects the final exam score

# Variables

- Store X wants to know the amount of water bottles to place in the fridge each week
- Variables are any measurement on the records
- **Dependent** variables (denoted as Y):
  - The ones **we want to explain** / predict
  - Their value depend on something else
  - Example? **amount of water bottles to place for June**
- **Independent** variables (denoted as X):
  - The variables that explain / justify the dependent ones
  - Example? **mean temperature from past years with the expected temperature, i.e., forecast; stock control information for the stock of a new store; etc.**

# Relationships

- Store X wants to know the amount of water bottles to place in the fridge each week
- Variables are any measurement on the records
- A relationship shows the variable association
- Examples?
  - Place more water bottles in the fridge during Summer
  - Special events near the store don't affect something
  - Etc.

# Definition

Regression Analysis: fit a relationship between a numerical outcome variable and a set of predictors

- Numerical outcome variable  $Y$   
also called response, target, or **dependent variable**
- Set of predictors  $X_1, X_2, \dots, X_n$   
also referred to as **independent variables**, input variables, regressors, or covariates

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## **Linear** Regression Model

↳ arranged in, or extending, along  
a straight or nearly straight line



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## **Single** Linear Regression Model

↳ one independent predictor, i.e., single variable  $X$

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Single Linear Regression Model

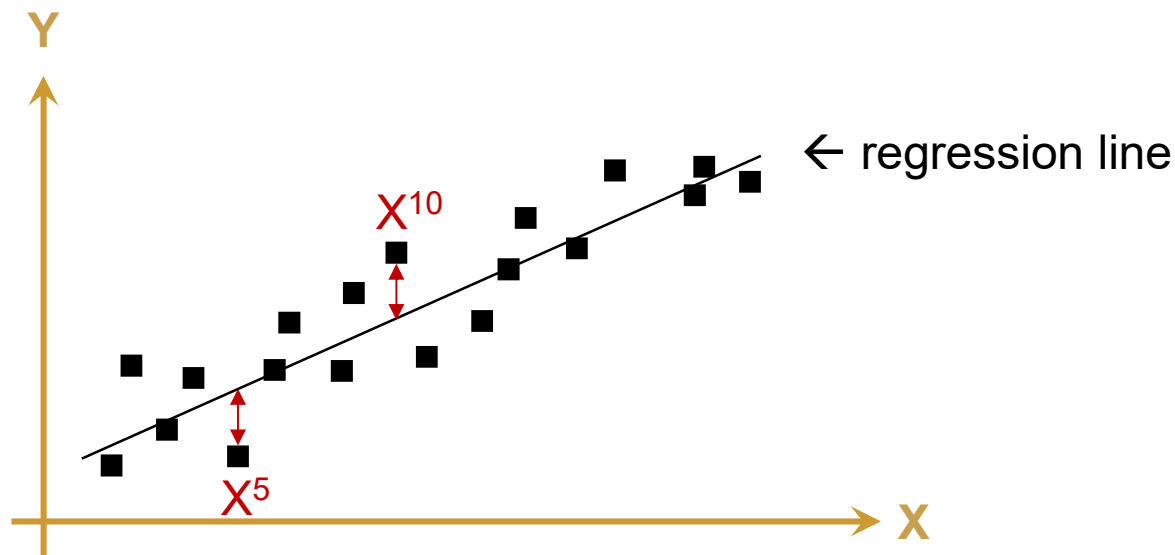
**Multiple** Linear Regression Model

↳ two or more predictors, i.e.,  $X_1, X_2, \dots$

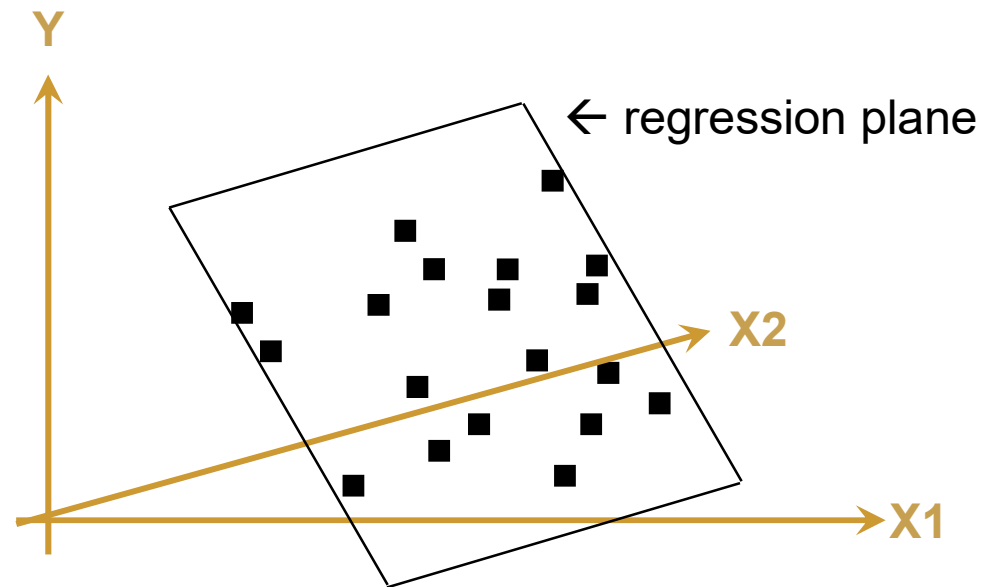
# Single / Multiple Linear Regression

# Intuition for Single Linear Regression

- Fitting a linear relationship (i.e., equation) between:
  - a numerical outcome (i.e., variable  $Y$ ) and
  - one predictor (i.e., variable  $X$ )
- Not all points go through the line  
→ Error, i.e., deviation of data from line



# Intuition for Multiple Linear Regression



- Fitting a linear relationship (i.e., equation) between:
  - a numerical outcome (i.e., variable  $Y$ ) and
  - two or more predictors (i.e., variables  $X_1, X_2, \dots$ )



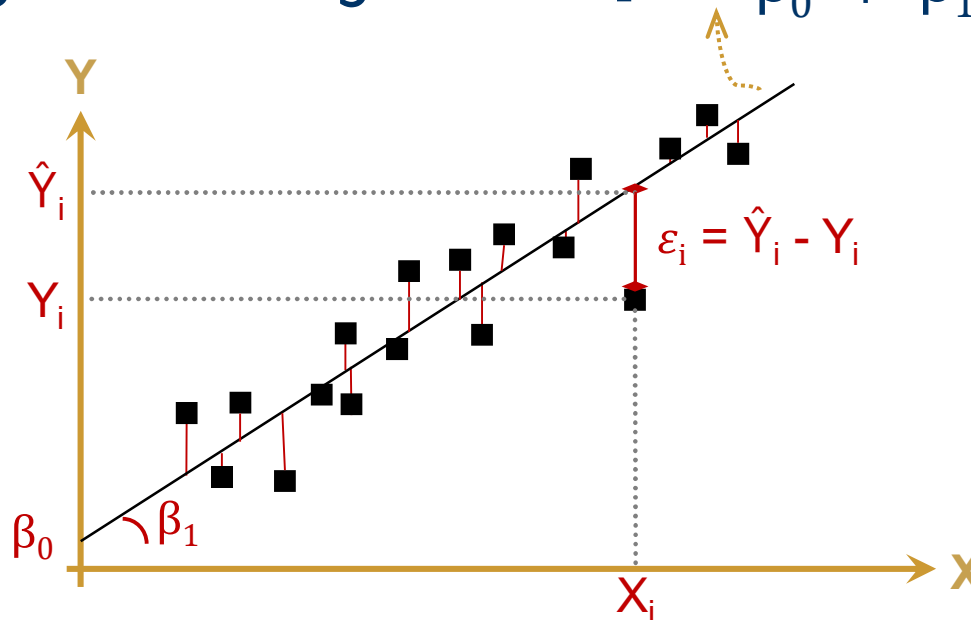
# Linear Regression Model

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \dots + \varepsilon$$

- $\varepsilon$  is a term that represents the errors associated with the model
- $\beta_0, \beta_1, \dots$  are the regression coefficients (parameters)
- **Values for attribute  $X_1$**  are  $X_{11}, X_{12}, \dots, X_{1i}, \dots$  where  $i$  is a “counter” representing the  $i$ th observation for the particular data collection

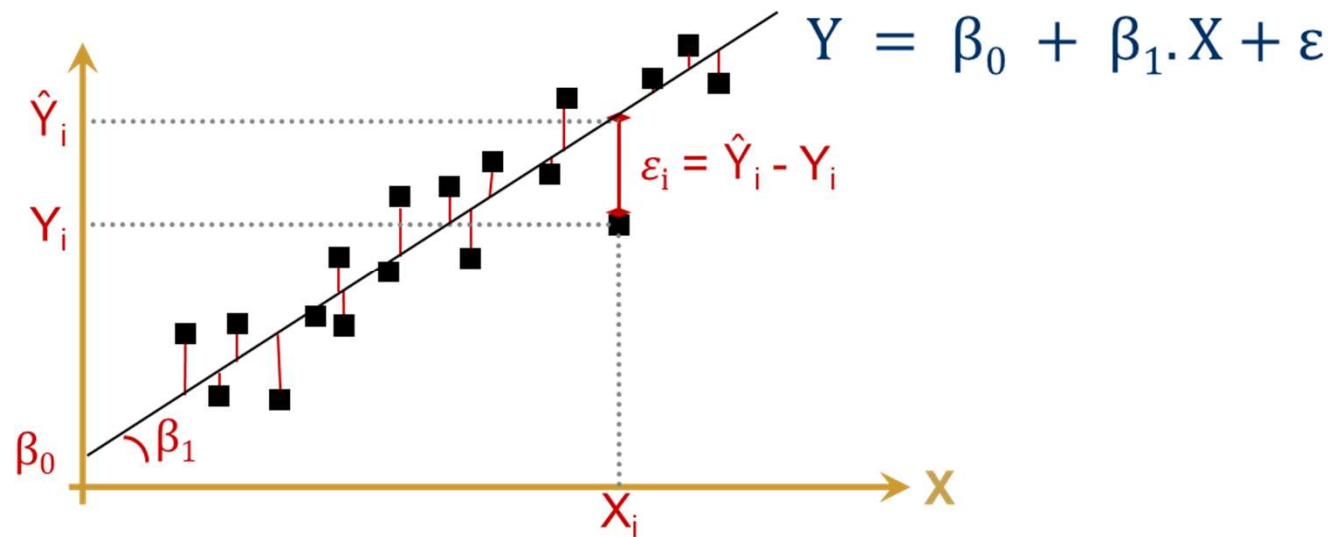
# Graphical Visualization

- Single Linear Regression:  $Y = \beta_0 + \beta_1 \cdot X + \varepsilon$



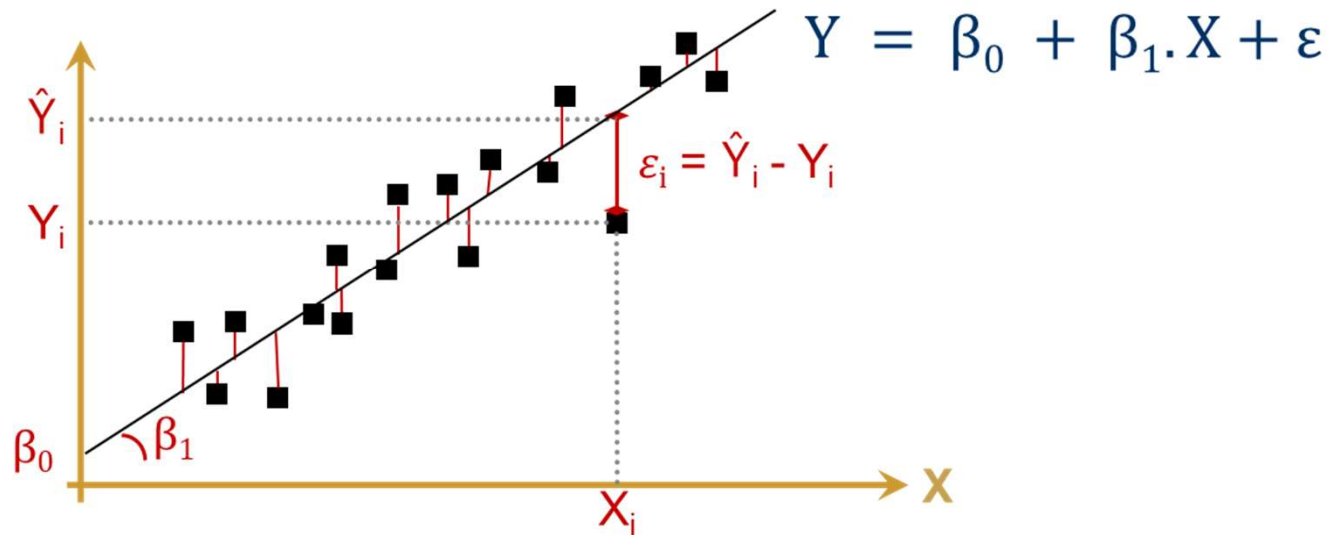
- $\beta_0$  the value of our dependent variable when the independent one is equal to zero, i.e., value of  $Y$  when  $X=0$
- $\beta_1$  the slope of the regression line
- $\varepsilon_i$  corresponds the difference between the observations and the predictions of our model, i.e., distance from the line

# Ordinary Least Squares (OLS)



- Method for **estimating the unknown parameters** in a linear regression model
- It **minimizes the errors** associated with predicting values for the dependent variable  $Y$
- It uses a least squares criterion because without square we would allow positive and negative deviations from the model to cancel each other out

# Ordinary Least Squares (OLS)



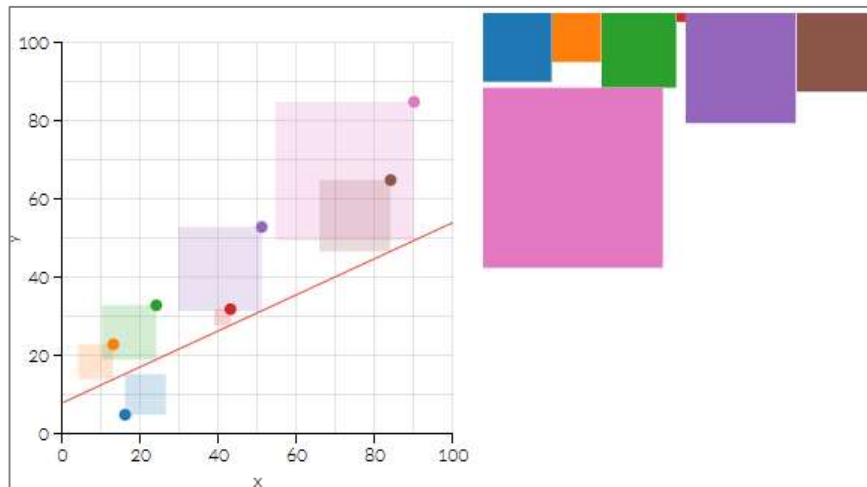
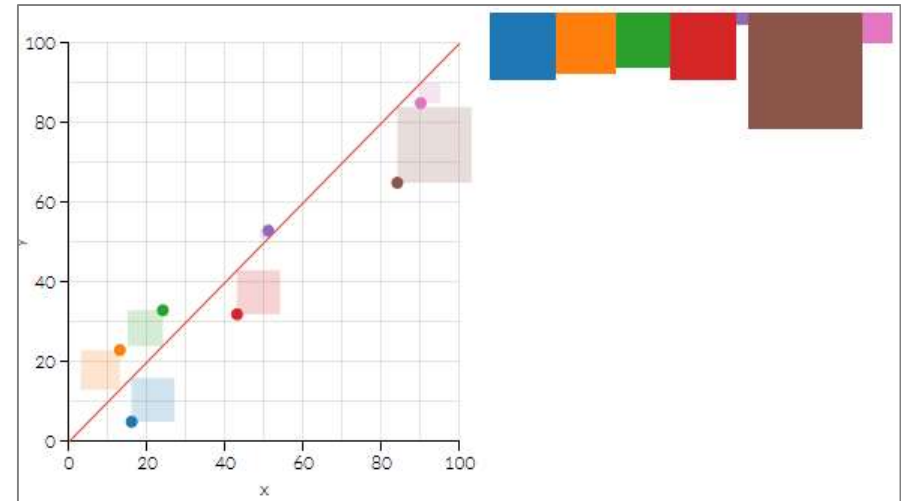
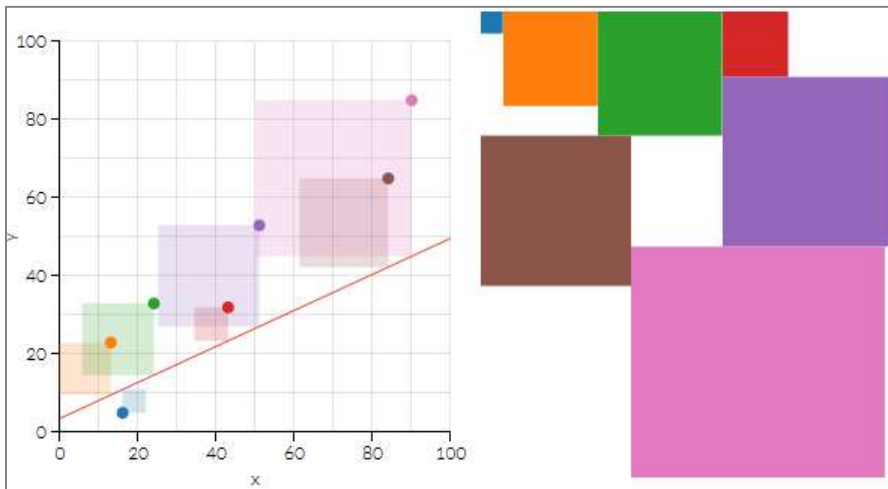
- Find  $\beta_0$  and  $\beta_1$  such that total error is minimal
- This criterion is very common and for example also used in Neural Network models
- Error for  $Y_i$  is  $\varepsilon_i$  and the value of  $\varepsilon_i$  is equal to  $\hat{Y}_i - Y_i$

$$\begin{aligned} \rightarrow \min \sum_{i=1}^n (\varepsilon_i)^2 &= \min \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \\ &= \min \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2 \end{aligned}$$

# Graphical Visualization

OLS: choose betas so that the total area of all the squares is as small as possible

$$\sum_{i=1}^n (\varepsilon_i)^2 = \min \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2$$



Plots taken from here:

<http://setosa.io/ev/ordinary-least-squares-regression/>

the site contains interactive plots to understand the concepts!



# Explanatory vs. Predictive

# Objectives for single/multiple regression

Two popular but different objectives behind fitting a regression model:

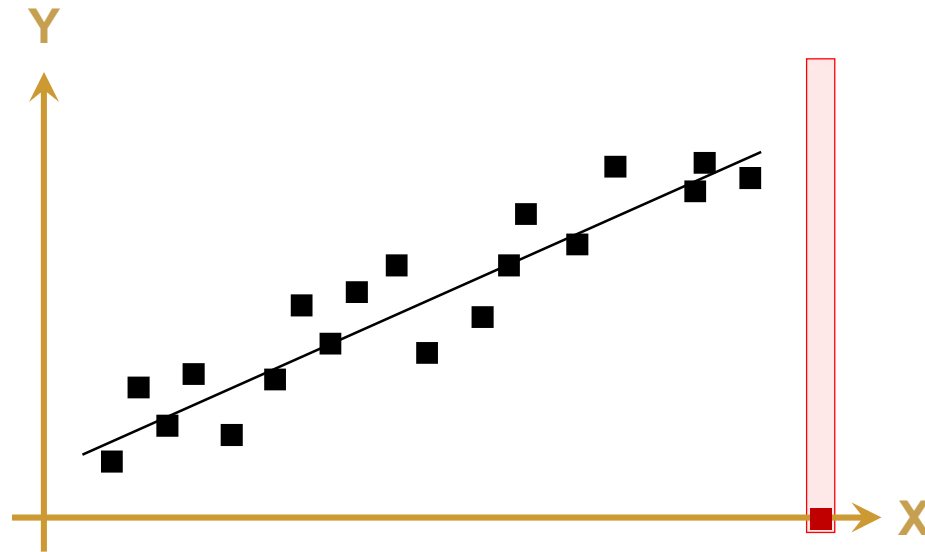
## 1. Predictive

- Detect the outcome value for new records, given their input values

## 2. Explanatory or descriptive

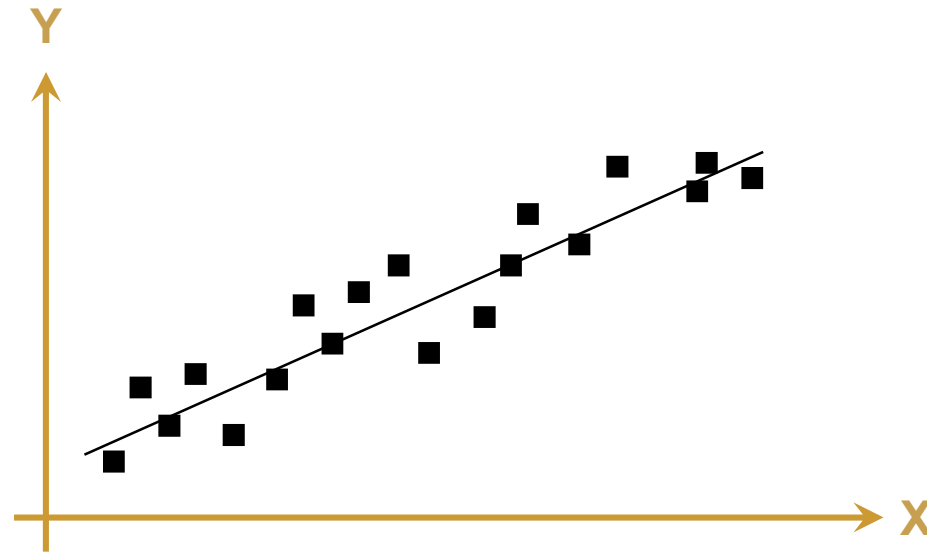
- Quantifying / explaining the average effect of inputs on an outcome
- Data are treated as a random sample from a larger population of interest

# Predictive



- Given a new value for  $X$ , estimate the value for  $Y$

# Explanatory



- Generate statements useful for decision making  
E.g., a unit increase in X is associated with  
an average increase of 2 points in Y