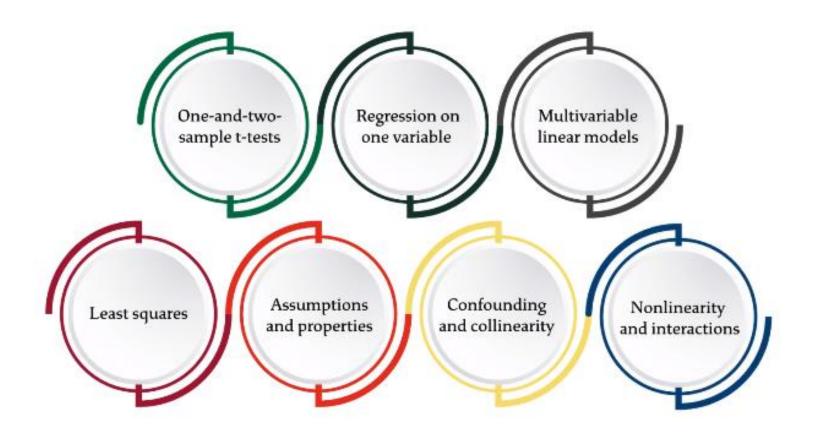


## Module 4: Linear Regression





#### Introduction to Linear Models







#### What is Statistic?

# Statistics is the study of random variables, such as:

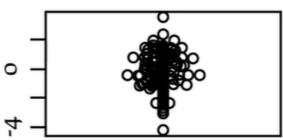
- Weight
- Body mass index (BMI)
- Eyesight



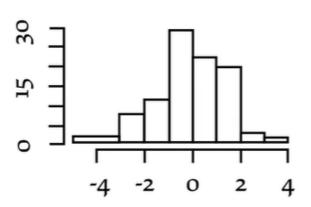


## Visualizing a Distribution

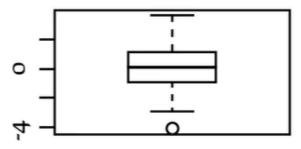




Histogram



**Boxplot** 









### Simple Statistical Model

Where,

Y = Random variable

 $\mu$  = Average or central tendency

ε = Error or distribution around the central tendency

$$E[Y] = \mu$$

OR

$$Y = \mu + \varepsilon$$

What can you do with this simple model? It can be used to test if  $\mu$  is equal to a particular value, such as  $\mu = 0$ 





### Paired or One-Sample t-Test

Assumption: Observations are independent

$$\frac{1}{n}\sum_{i=1}^{n}X_{i}\sim N(\mu,\sigma/\sqrt{n})$$

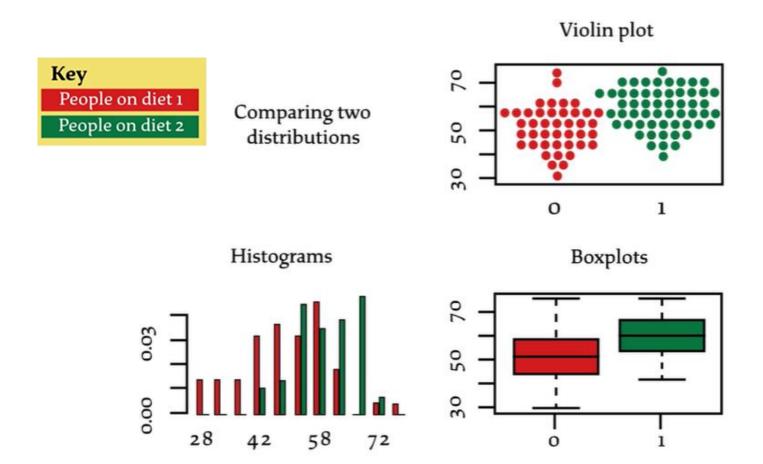


- In large samples, the z-test and t-test are identical
  In small samples, the t-test is preferred





## Paired or One-Sample t-Test







## Two-Sample t-Test

$$\frac{\frac{1}{n_1} \sum_{i=1}^{n} X_{1i} - \frac{1}{n_0} \sum_{i=1}^{n} X_{0i}}{\sqrt{\hat{\sigma}_0^2/n_0 + \hat{\sigma}_1^2/n_1}}$$



#### Here are the observations of a two-sample t-test:

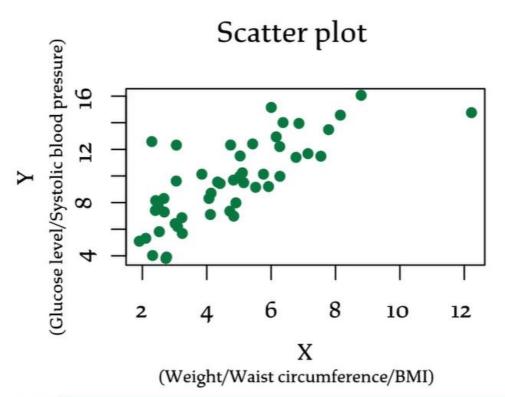
- If the value is close to zero, the null hypothesis is true
- If the value is far away from zero, the null hypothesis should be rejected







## Model Relating Two Variables





Linear model is the simplest way to relate two variables









## Expressing a Linear Model

Where,

E = Average

Y = Dependent variable

X = Independent variable

*b* = Slope/Coefficient

?

How does the average of Y depend on X?

$$E[Y|X] = a + bX$$

$$Y = a + bX + \epsilon$$





## Estimation by Least squares

## Using the least squares approach to estimate the slope (b)

Where,

*b* = Parameter/Coefficient

y = Dependent variable

x =Independent variable

 $\sum_{i=1}^{n} \left[ y_i - (a + bx_i) \right]^2$ 



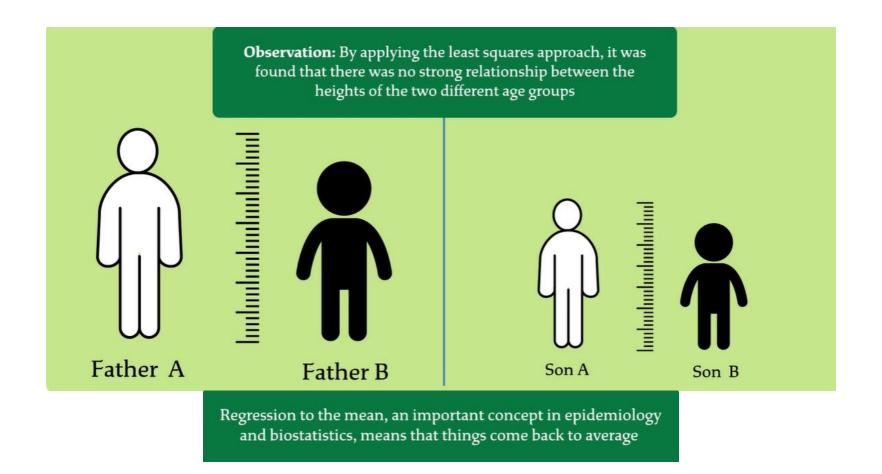
Minimize the sum of the squared distances between the observed values

The least squares approach is always preferred over the least absolute deviations approach





## Galton's Application of Least Squares









#### Estimation by Least Squares

Where,

b = Parameter/Coefficient/Slope

Y = Dependent variable

X = Independent variable

$$\sum_{i=1}^{n} [y_i - (a + bx_i)]^2$$

$$= \sum_{i=1}^{n} (y_i - a - bx_i)^2$$

Taking a derivative

$$\hat{b} = \frac{1}{\hat{\sigma}_{x}^{2}} \sum_{i=1}^{n} (x_{i} - \bar{x}) (y_{i} - \bar{y}) / n$$

$$= \frac{1}{\hat{\sigma}_{x}^{2}} \sum_{i=1}^{n} (x_{i} - \bar{x}) y_{i} / n$$

Parameter  $\hat{a} = \overline{y} - \hat{b}\overline{x}$  (of no use)





#### Standard Error of the Estimate

#### Where,

 $\hat{\sigma}$  = Variation of the dependent variable

 $\hat{\sigma}_{\rm X}$  = Variation of the independent variable

n = Sample size

$$\sigma(\hat{b}) = \frac{\hat{\sigma}}{\mathbf{n}\hat{\sigma}_{\mathbf{X}}}$$





#### Key Points in Statistic

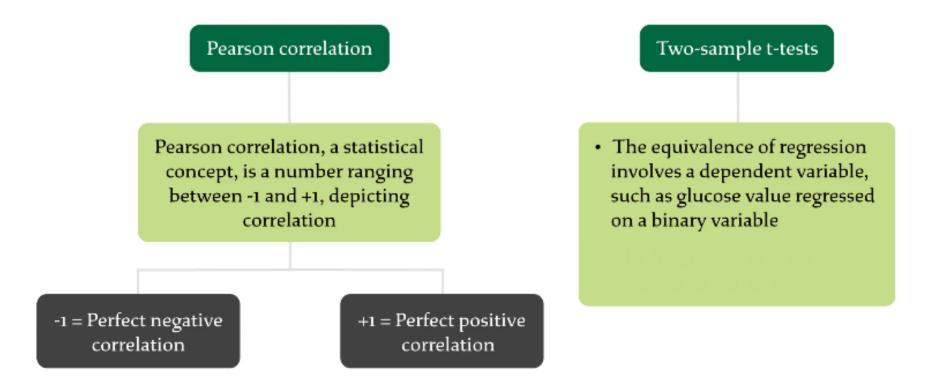
- Sample size has an inverse relationship to the standard error
- Confidence intervals are the intervals around the standard error or margin of error
- The value of confidence intervals is usually 95%







#### Equivalence of Regression





#### Multivariable Model

#### Where,

Y = Dependent variable (mortality rate)

X = Independent variable(government spend on healthcare/welfare)

$$E[Y|X_1,...,X_k] = b_0 + b_1X_1 + b_2X_2 + ... + b_kX_k$$



A linear model is the simplest way to connect one or more variables to a dependent variable





## Design Matrix

Healthcare spend (per person)	Welfare spend (per person)	Spend on policy	Average income



A design matrix is an abstract yet efficient model









## Testing

- Key concept in statistics
- Often referred to as the Wald test
- Uses slope estimations and divides it by the standard error calculation

$$\hat{b}_{j}^{2}/\sigma^{2}(\hat{b})_{jj}$$





#### Wald Test

#### Versions of the Wald test

- Z-test
- F-test/t-test

Wald test for multiple parameters:

$$(L\hat{b})^T L^t [\operatorname{Cov}(\hat{b})L]^{-1}(L\hat{b})$$



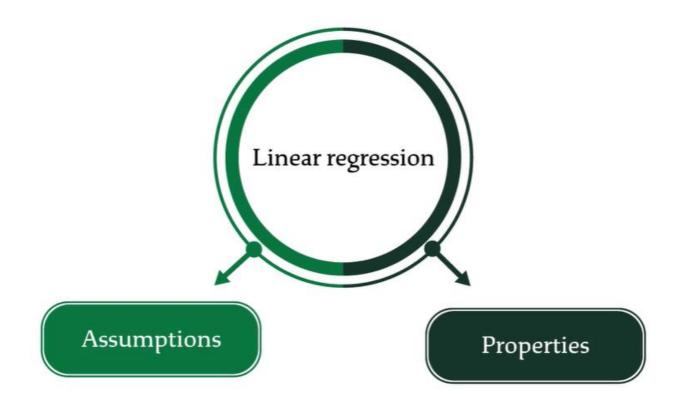
For large samples, both can be used



For small samples, t-test is preferred

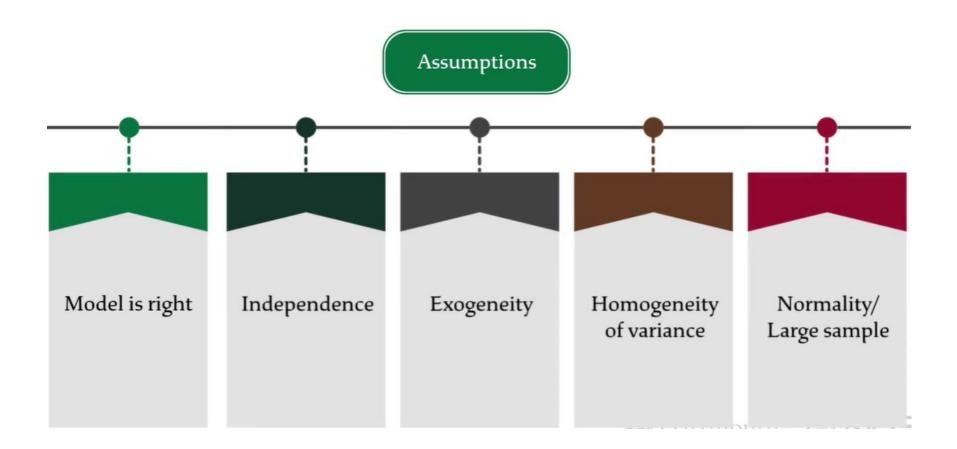






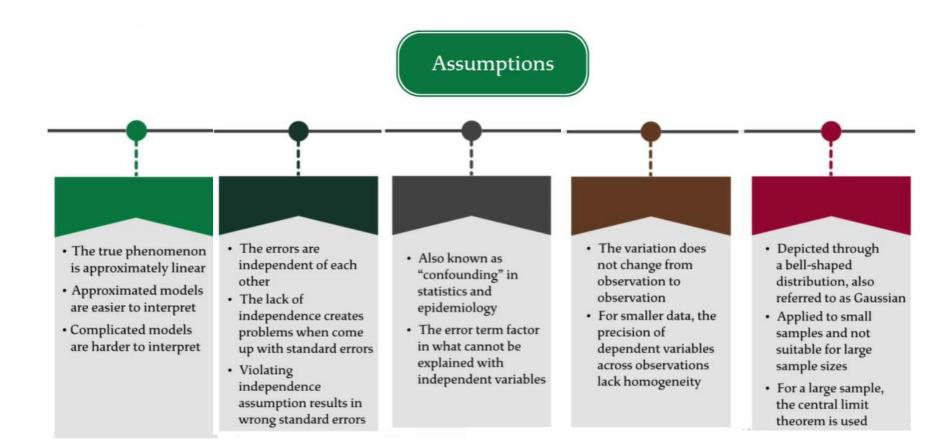






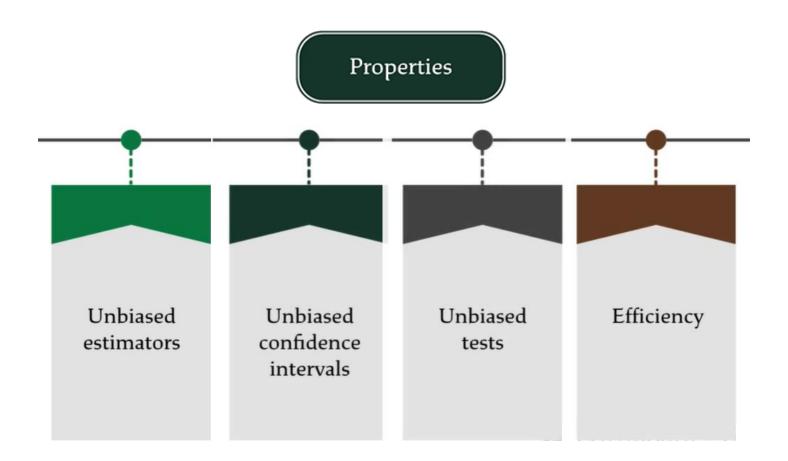






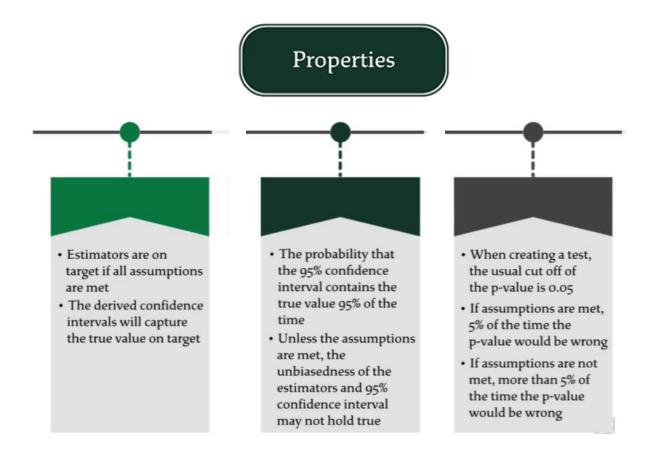
















## Categorical variables as Indicators

Dependent variable

Categorical variable

Y

 $\mathbf{X}$ 

Systolic blood pressure

Race

Whites

Blacks

**Asians** 

Native Americans/Pacific Islanders



Create indicator variables to capture the information in a categorical variable



To perform linear regression and least squares, a linear model creates an indicator variable for each group except the referent group







### Categorical Variables as Indicators

Dependent variable

Y

Systolic blood pressure

For each indicator variable, R creates a variable with a value of 1 or 0 in the background

K(variable) = 0 or 1

Person is not Black

Person is Black

Categorical variable

X

Race

Whites

**Blacks** 

**Asians** 

Native Americans/Pacific Islanders



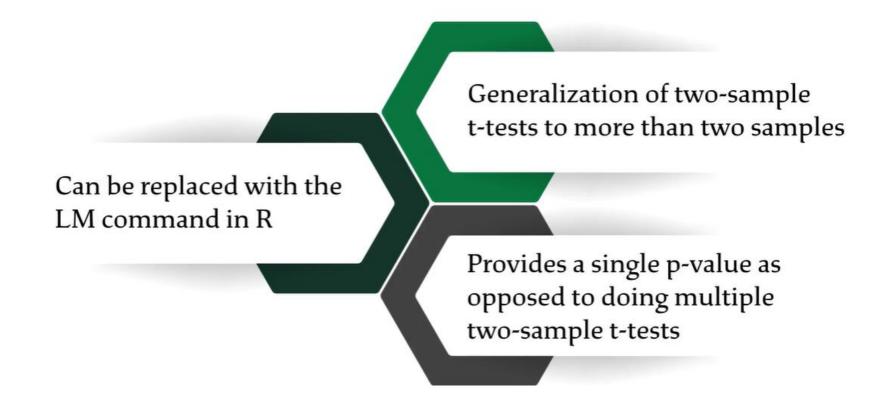
In a linear model, indicator variables split up the categorical variables when considering the referent group







#### **ANOVA Features**





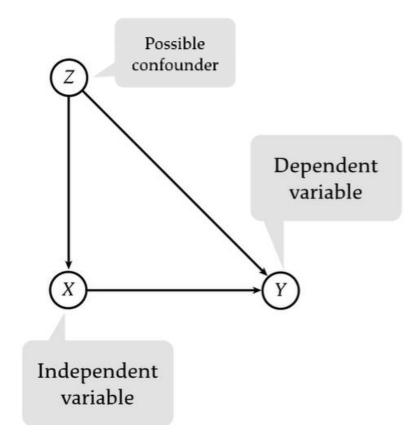
#### Analysis of Covariance

- Is a generalization of ANOVA
- Requires one more covariant to be added
- Is a linear model with a single categorical variable and a single continuous variable





#### Directed Acyclic Graphs (DAG)



D—Directed = Arrows go in **one direction** 

A—Acyclic = **No loops** 

This DAG helps to understand confounding

Key question: How does X affect Y?

A confounder is a variable that affects both the exposure of interest X and the dependent variable Y







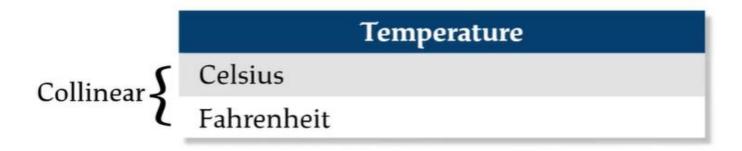
#### Cofounded Results

- Refer to the output of the related study
- Have significant limitations when interpreted
- Are difficult to share with other researchers and media





#### Collinear Variables: Example

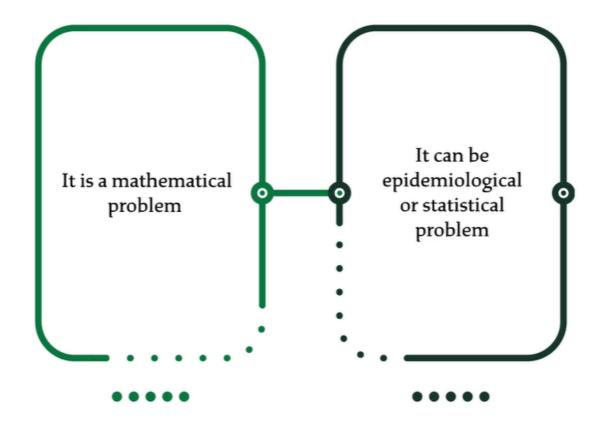


- · Variables are said to be collinear if they are highly correlated
- Collinearity provides the third variable given the other two





## Collinearity







#### Collinearity

To be modeled: Impact of weight on health outcomes

To be measured: Whether people will have a stroke in the next ten years

Data set (as independent variables):

- Body mass index (BMI)
- Weight
- Circumference

Highly correlated variables







#### Collinearity

To be modeled: Impact of education on health outcomes

To be measured: Whether people will have a stroke in the next ten years

#### Data set:

- · Years of education ·
- Highest degree

Coefficients of these will be difficult to interpret

In order to interpret a variable in a multi-variable model, all other variables are held constant







## Interpreting Coefficients from a Multi-Variable Model

- Coefficient corresponds to how much you can expect a dependent variable to change if you change this independent variable by one unit, keeping all the other variables constant
- Interpretations are difficult with highly collinear variables

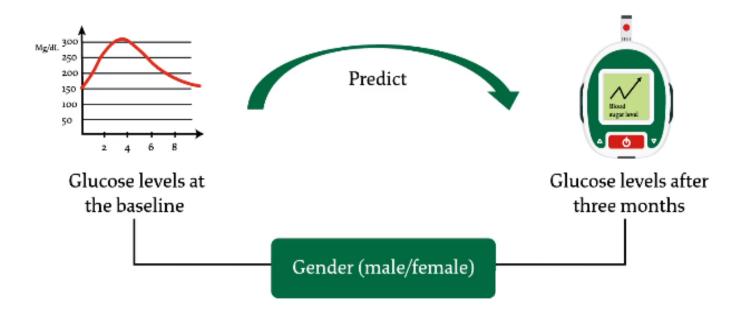




#### Nonlinearity

Nonlinearity refers to creating an interaction between two variables.

Does being female affect how your glucose control today affects your glucose control three months from now?







#### Nonlinear Effects

#### Where,

*Y* = Dependent variable

 $a_0$  = Intercept term

 $X_1$  = First variable

 $X_2$  = Second variable

Interaction term

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_{12} X_1 X_2 + \epsilon$$



In a linear model, a nonlinear effect can also be accommodated





#### **Interactions**

#### Variable/Term

Gender/Sex

Race

#### To measure

Glucose control at baseline Glucose control at follow up

#### Interaction

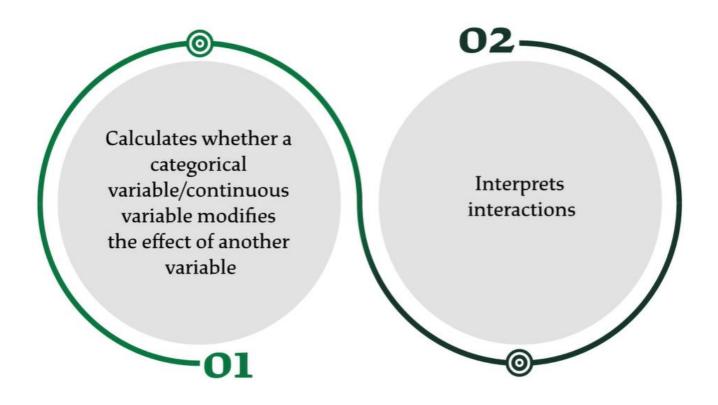
Does gender/sex modify the effect of glucose control?

Does race interact with glucose control?





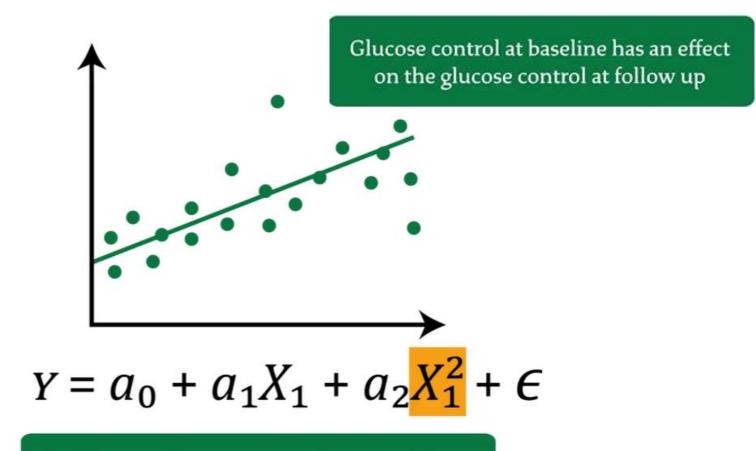
#### **Effect Modification**







#### Nonlinear Effects

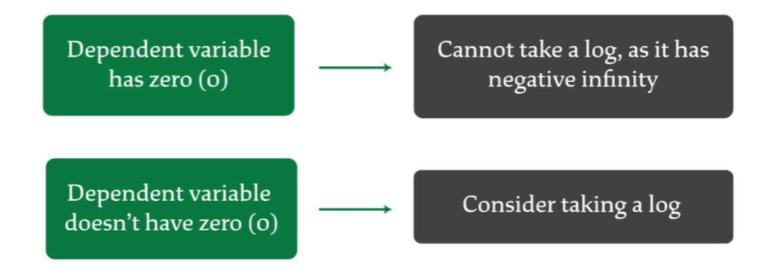


Coefficient ≠ Non-zero or significantly different from non-zero = Quadratic effect/Nonlinearity





## Transformation: Log Transform





When a log is transformed, the interpretation of coefficients comes down to a percentage scale







