

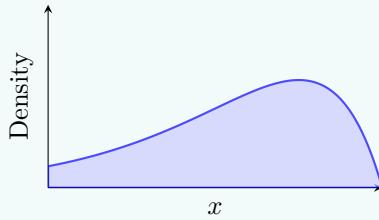
# STAT 151A Lecture 3

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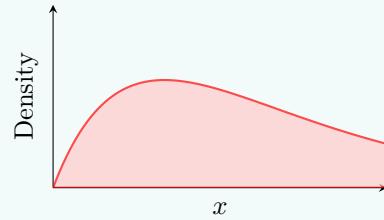
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## Method 0.1 (Transforming to fix skewness)

Left Skew (Negatively Skewed)



Right Skew (Positively Skewed)



Will want to compress distances between values log will compress for right skew and  $e^x$  will compress for left skew

To pick a specific transform  $f(x)$  use  $\frac{f(\text{Upper Quartile}) - f(\text{Median})}{f(\text{Median}) - f(\text{Lower Quartile})} = 1$

## Example 0.2 (Kleiber Data Box Cox Transformation)

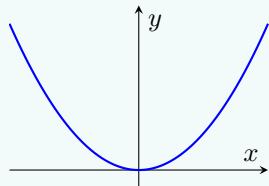
Transform	$\frac{f(\text{UQ}) - f(\text{Med})}{f(\text{Med}) - f(\text{LQ})}$
$x$	2.5
$\sqrt{x}$	1.23
$\sqrt[3]{x}$	0.96
$\log$	0.58

### Remark 0.3 (Transforming Nonlinear Relationships)

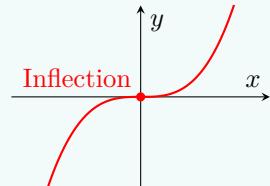
2 things we need:

1. “Simple” - direction of curvature (2nd derivative) does not change

Simple: Quadratic

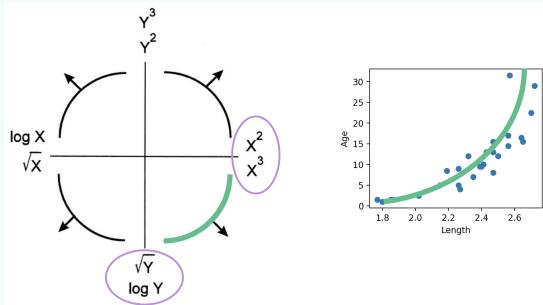


Not Simple: Cubic



2. Monotone - strictly increasing or decreasing

### Remark 0.4 (Transformations)



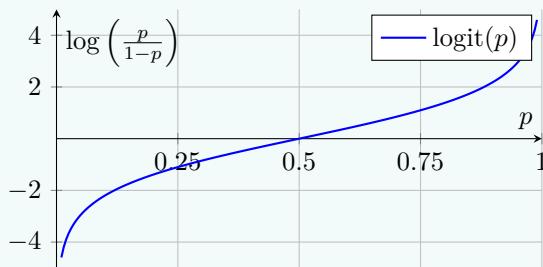
Transform  $y$  or transform  $x$

What about data where  $y \in (0, 1)$ ?

Issues:

- Scale, power transformations decrease instead of increase, negative values, all values are huge (rescale)
- Density (Binary) apply  $\text{logit}(p) \rightarrow \log\left(\frac{p}{1-p}\right)$

Logit Function



Caution: Not always necessary and hurts interpretability

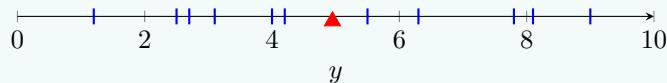
### **Remark 0.5 (Revisit mean and SD using regression)**

We can think of the mean, sd, and simple regression in 4 forms: Graphically, Optimization, Probabilistically, Vector Spaces  $y_1, \dots, y_n$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i, SD = s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2}$$

Graphically, the mean is the “balance point” of these plots, SD: How spread out are the points

Rugplot of Sample Data



### Optimization

$$\min_c \sum_{i=1}^n (y_i - c)^2 \rightarrow \frac{\partial}{\partial c} \sum_{i=1}^n (y_i - c)^2 = 0 \rightarrow \hat{c} = \bar{y}$$

$\bar{y}$  is the minimizer of the squared error

$$\sum (y_i - c)^2 = \sum (y_i - \bar{y} + \bar{y} - c)^2 = \sum (y_i - \bar{y})^2 + \sum (c - \bar{y})^2$$

SD? Minimized objective value is  $\sum (y_i - \bar{y})^2 = (n-1)s^2$  SD tells us how good of a miniizer  $\bar{y}$  is

### Probability

RV  $Y_i = \mu + \varepsilon_i$  where  $\mathbb{E}(\varepsilon_i) = 0$ ,  $\text{Var}(\varepsilon_i) = \sigma^2$  and  $\mu$  is a parameter

If  $y_1, \dots, y_n$  are random variables from the random variable model, then can we use them to estimate  $\mu$ ?

Yes and  $\bar{y}$  is a “good” estimator of  $\mu$

What about  $\sigma^2$ ?  $s^2$  is a good estimator for  $\sigma^2$