# Categorical Response and Probability Distributions

Demetris Athienitis



## Section 1

Terminology

Probability Distributions

# Categorical data

#### Definition

A categorical variable is any variable whose measurement scale consists of a set of categories

- Nominal variables: Unordered categories
- Ordinal variables: Ordered categories

#### Remark

Methods developed for ordinal variables utilize ordering information and therefore can not be used for nominal variables. Alan Agresti has a supplemental book *Analysis of Categorical Ordinal Data*.

## Examples

- Nominal data
  - Favorite color: Red, green, yellow, etc.
  - Type of music: Rap, pop, country, etc.
- Ordinal data
  - Rate your pain on a scale of 0-10
  - Political beliefs: Liberal, moderate, conservative

# Response variables vs. explanatory

Frequently we distinguish between response and explanatory variables.

- Explanatory variables are used to explain changes in the response variable.
- Explanatory variables also referred to as *independent* variables or *predictors*. Response variables are referred to as *dependent* variables.
- We focus on methods where the response (or dependent) variable is categorical and the explanatory variables are either categorical or continuous.

## Section 2

Terminology

Probability Distributions

# Probability distributions for categorical data

There are two very important classes of categorical distributions (for this class)

- Bernoulli, Binomial, Multinomial distributions
- Poisson distribution (to be seen later)

### Bernoulli distribution

Y be a random variable that only takes two values

$$Y = egin{cases} 1 & ext{with probability } \pi \ 0 & ext{with probability } 1-\pi \end{cases}$$

The PMF defined as

$$P(Y = y) \equiv p(y) = \pi^{y}(1 - \pi)^{1 - y}, \qquad y = 0, 1 \quad 0 \le \pi \le 1$$

- Denote by  $Y \sim \mathsf{Bernoulli}(\pi)$
- $E(Y) = \pi$  and  $V(Y) = \pi(1-\pi)$

#### Example

Suppose we roll a die and let Y be an indicator of whether a 5 is rolled

$$Y = \begin{cases} 1 & \text{if outcome is 5} \\ 0 & \text{otherwise} \end{cases}$$

Then,  $Y \sim \text{Bernoulli}(1/6)$  with mean 1/6 and variance 5/36.

### Binomial distribution

Let  $Y_1, Y_2, \ldots, Y_n$  be Bernoulli random variables such that

- 1 the random variables are independent of each other

Now let  $Y = \sum_{i=1}^n Y_i \sim \mathsf{Binomial}(n,\pi)$  where the PMF is given by

$$p(y) = \binom{n}{y} \pi^{y} (1 - \pi)^{n-y}, \quad y = 0, 1, \dots, n$$

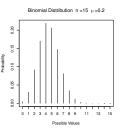
where 
$$\binom{n}{y} = \frac{n!}{y!(n-y)!}$$

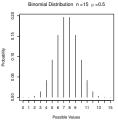
## Binomial distribution

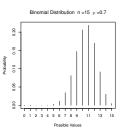
Using the rules for means and variances we can see that

- $E(Y) = n\pi$
- $V(Y) = n\pi(1-\pi)$

Let's look at the PMF for the binomial for different  $\pi$  values







### Example

- A die is rolled 4 times and the number of 5s is observed (y)
- $Y \sim \text{Binomial}(4, 1/6)$  and therefore the PMF is

	p(y)
0	0.4823
1	0.3858
2	0.1157
3	0.0154
4	8000.0

Find the probability that there is at least one 5

$$P(Y \ge 1) = 1 - P(X < 1) = 1 - P(X = 0) = 0.5177$$

In R, one would simple use

1-pbinom(0,4,1/6)

### Binomial random variables

Interest frequently lies in the proportion of successes

$$\hat{\pi} = \frac{Y}{n} = \frac{\sum Y_i}{n}$$

Using the rules of means and variances we can see

$$E(\hat{\pi}) = \pi$$

$$V(\hat{\pi}) = \frac{\pi(1-\pi)}{n}$$

#### Multinomial random variables

An extension of a binomial with categories  $c \geq 2$ 

- Probability  $\pi_i$  of being in category i, such that  $\sum_{i=1}^c \pi_i = 1$
- The probability that  $y_1$  are category 1,  $y_2$  are category 2, etc. is

$$P(Y_1 = y_1, ..., Y_c = y_c) = \left(\frac{n!}{y_1! y_2! ... y_c!}\right) \pi_1^{y_1} \pi_2^{y_2} ... \pi_c^{y_c}$$

where 
$$n = \sum_{i=1}^{c} y_i$$

### We learned

- What is a categorical response variable
- Binomial distribution