

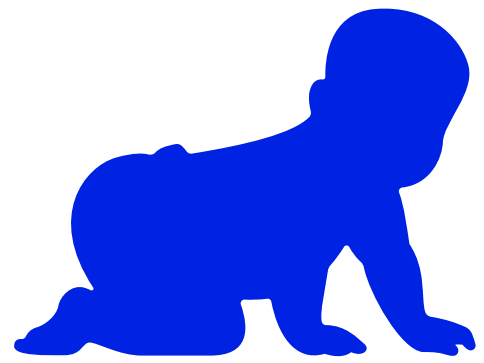
# ORDINAL REGRESSION MODELS

What is an ordinal variable?

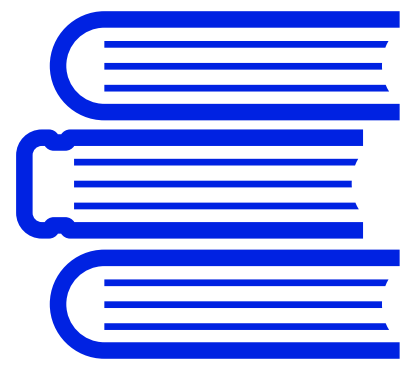
Quantitative variables

# Quantitative variables

Discrete



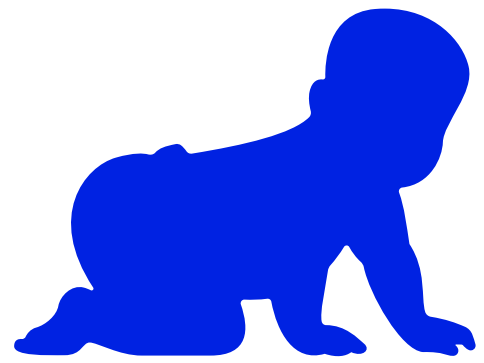
Number of  
children



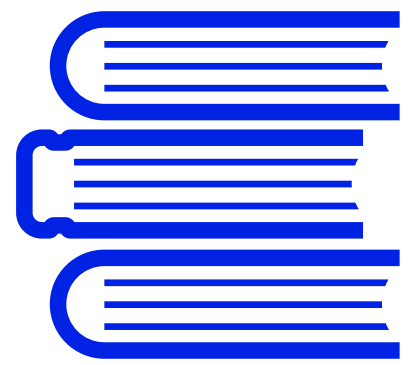
Books  
read

# Quantitative variables

Discrete

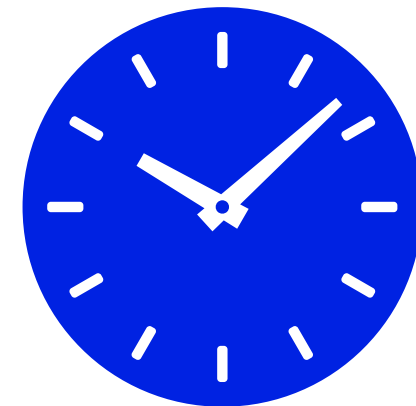


Number of  
children

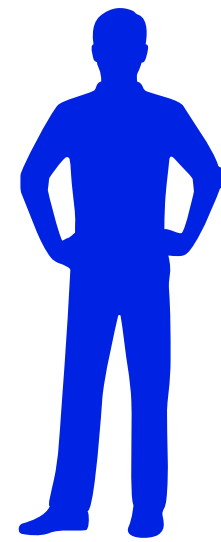


Books  
read

Continuous



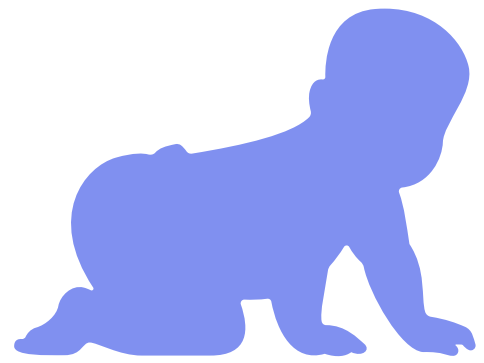
Time



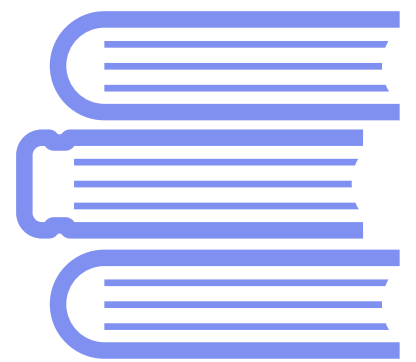
Age

## Quantitative variables

Discrete



Number of  
children

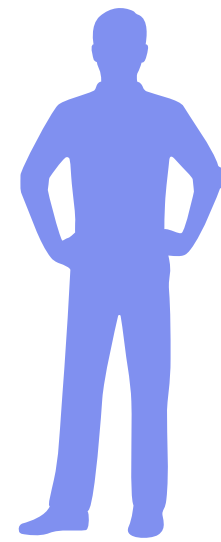


Books  
read

Continuous



Time

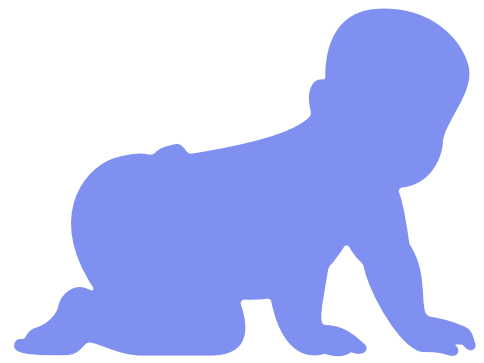


Age

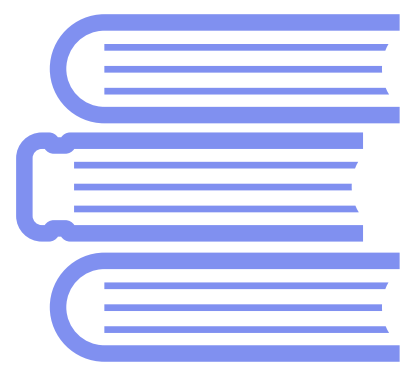
## Categorical variables

## Quantitative variables

### Discrete



Number of  
children

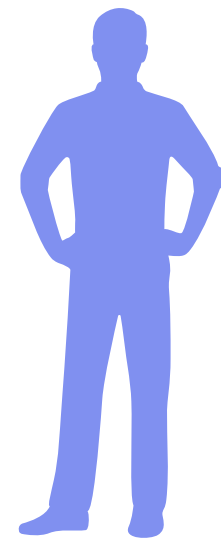


Books  
read

### Continuous



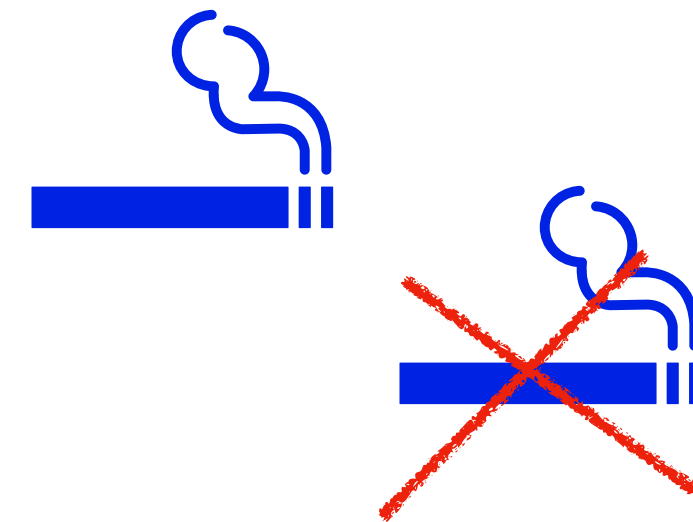
Time



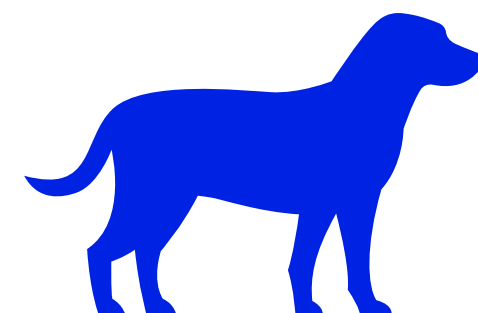
Age

## Categorical variables

### Nominal



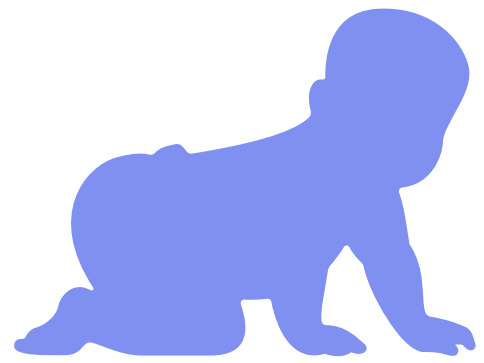
Smoker vs.  
non-smoker



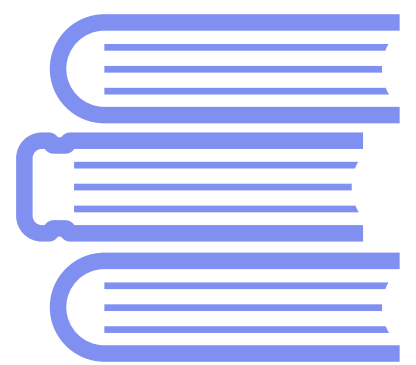
Dog  
breed

## Quantitative variables

### Discrete



Number of  
children

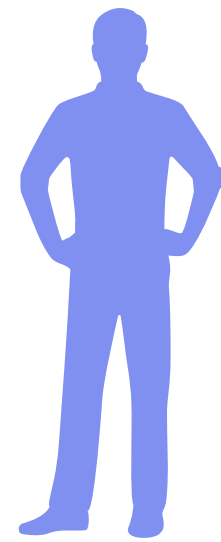


Books  
read

### Continuous



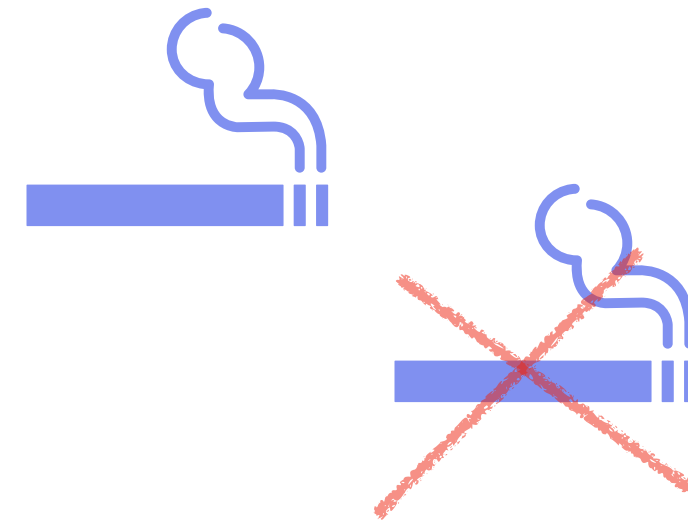
Time



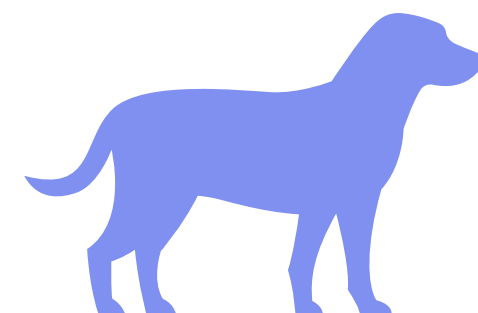
Age

## Categorical variables

### Nominal

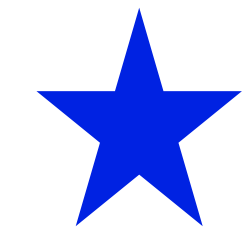


Smoker vs.  
non-smoker

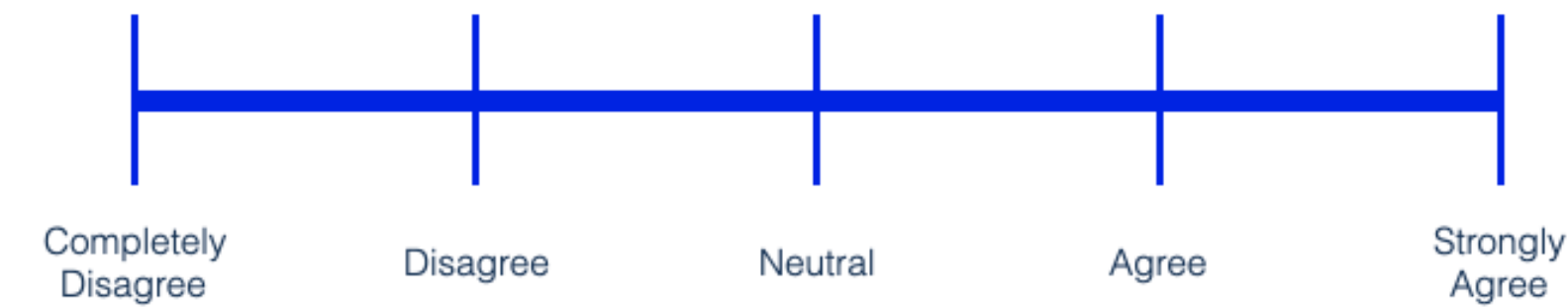


Dog  
breed

### Ordinal




Star ratings

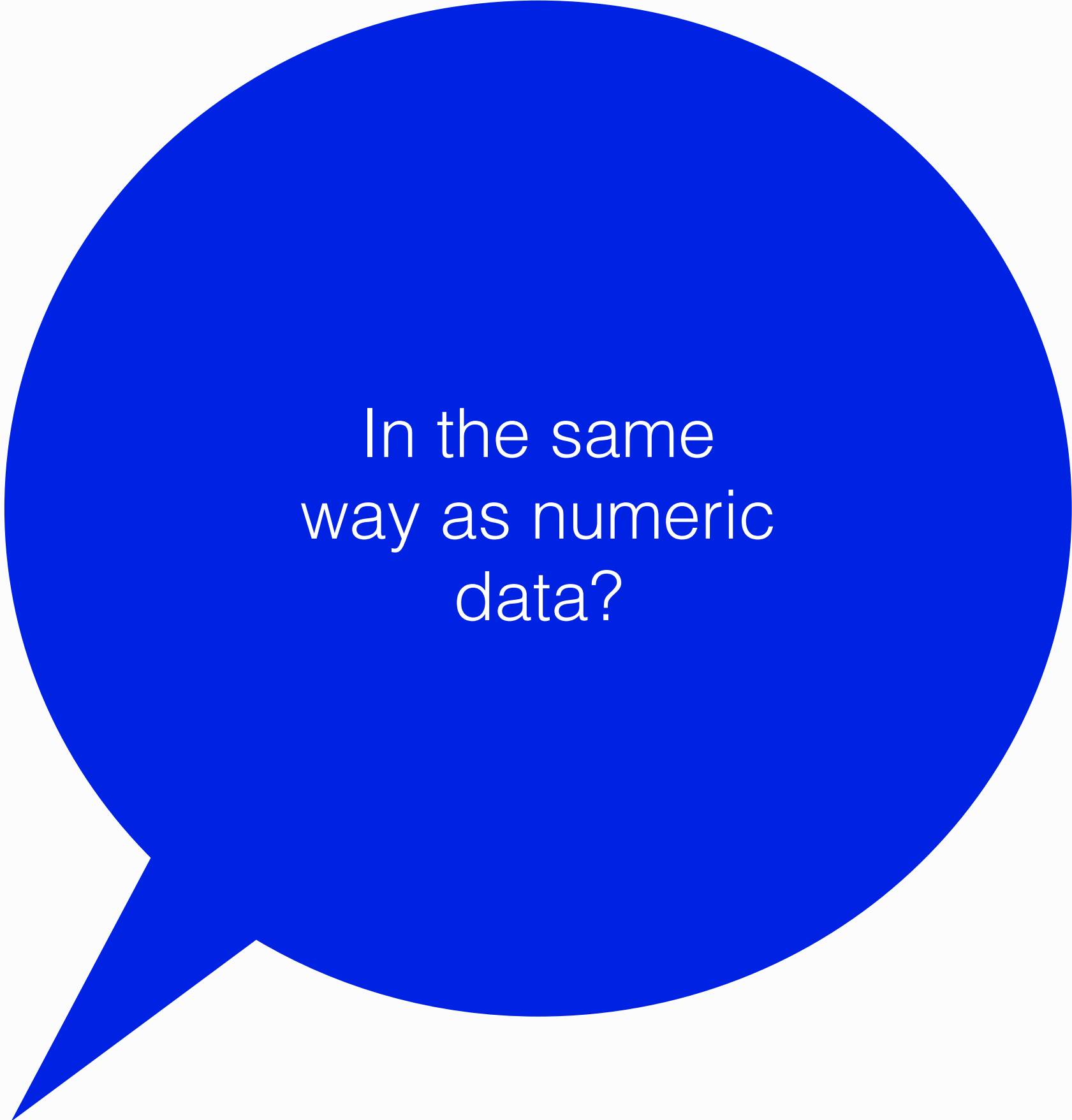


Likert scales






How should you  
analyze ordinal  
data?




In the same  
way as numeric  
data?



How should you  
analyze ordinal  
data?



In the same  
way as numeric  
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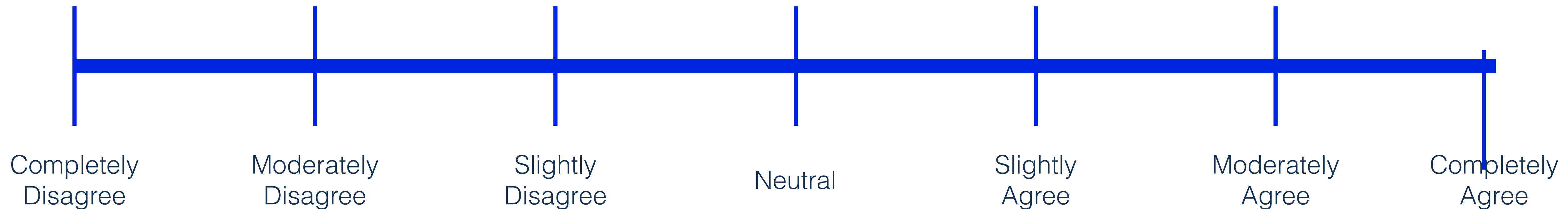
How should you  
analyze ordinal  
data?

Why can't we use the same models for ordinal and numeric data?

Let's look at three reasons!

# Why can't we use numeric models on ordinal data?

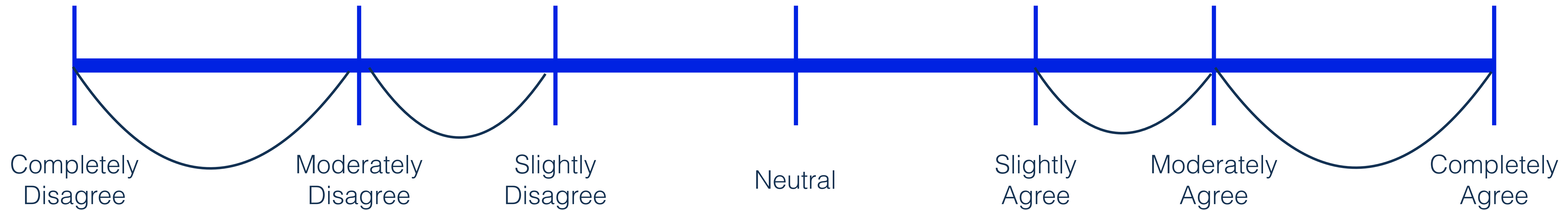
1 | Numeric models assume that the distance between adjacent responses is equidistant....



# Why can't we use numeric models on ordinal data?

1 | Numeric models assume that the distance between adjacent responses is equidistant....

But in reality, participants might perceive the distance between certain ratings to be much larger/smaller



## Why can't we use numeric models on ordinal data?

- 1 | Numeric models assume that the distance between adjacent responses is equidistant....
- 2 | They also assume that the data is normally distributed which is often not the case with ordinal data

## Why can't we use numeric models on ordinal data?

- 1 | Numeric models assume that the distance between adjacent responses is equidistant....
- 2 | They also assume that the data is normally distributed which is often not the case with ordinal data
- 3 | They treat the data as continuous instead of categorical



## What might happen if we use numeric models on ordinal data?

- a | Low rates of detecting effects
- b | Distorted effect-size estimates
- c | Inflated false alarm rates
- d | Inversion of differences between groups

In the  
way as  
data

Should we use  
specialized  
models  
instead?

How should you  
analyze ordinal  
data?

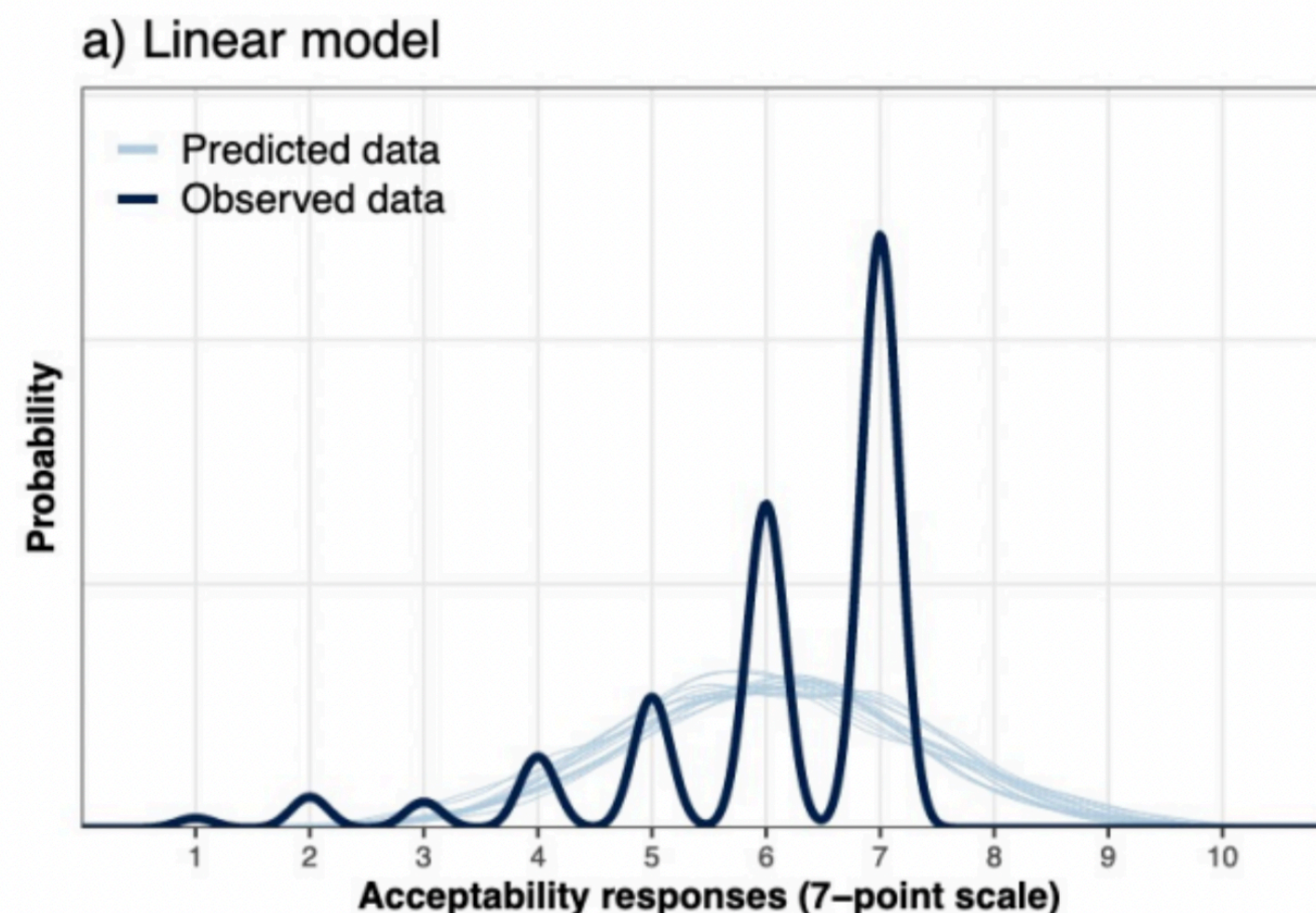


**YES! ORDINAL REGRESSION MODELS**

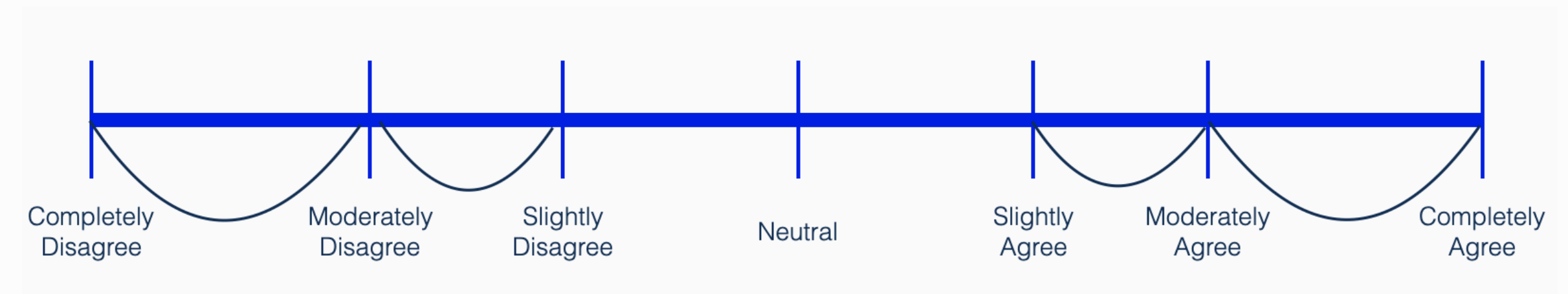
# ORDINAL REGRESSION MODELS

As one or more of the independent variables changes, there is a shift towards either end of the spectrum of the ordinal response for the DV.

They can handle non-normally distributed data



They allow for unequal distances between responses



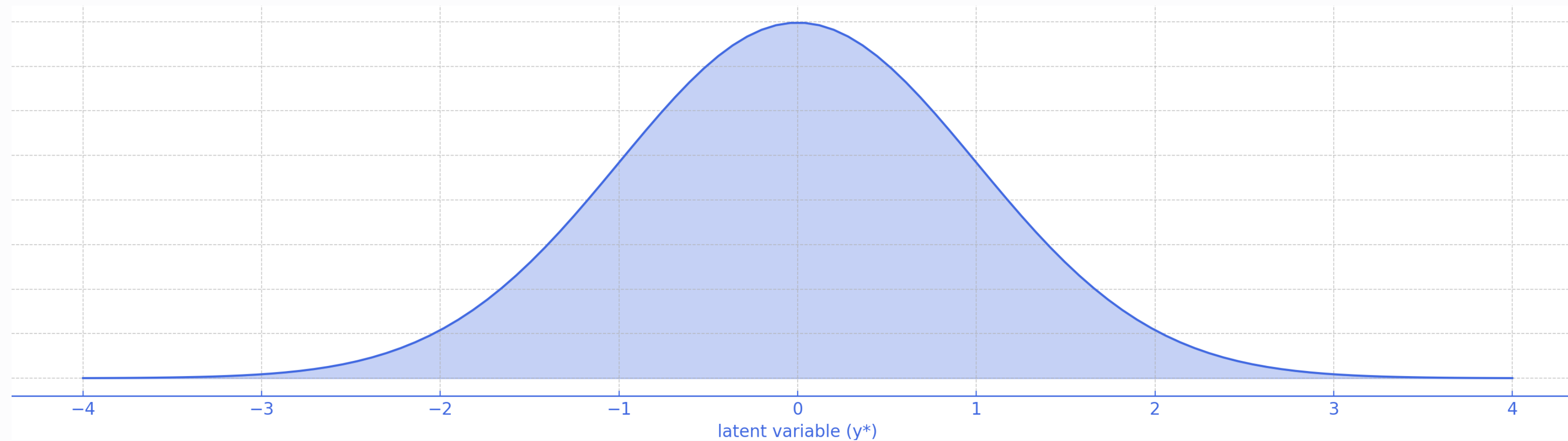
1 | CUMULATIVE MODELS

2 | SEQUENTIAL MODELS

2 | ADJACENT-CATEGORY MODELS

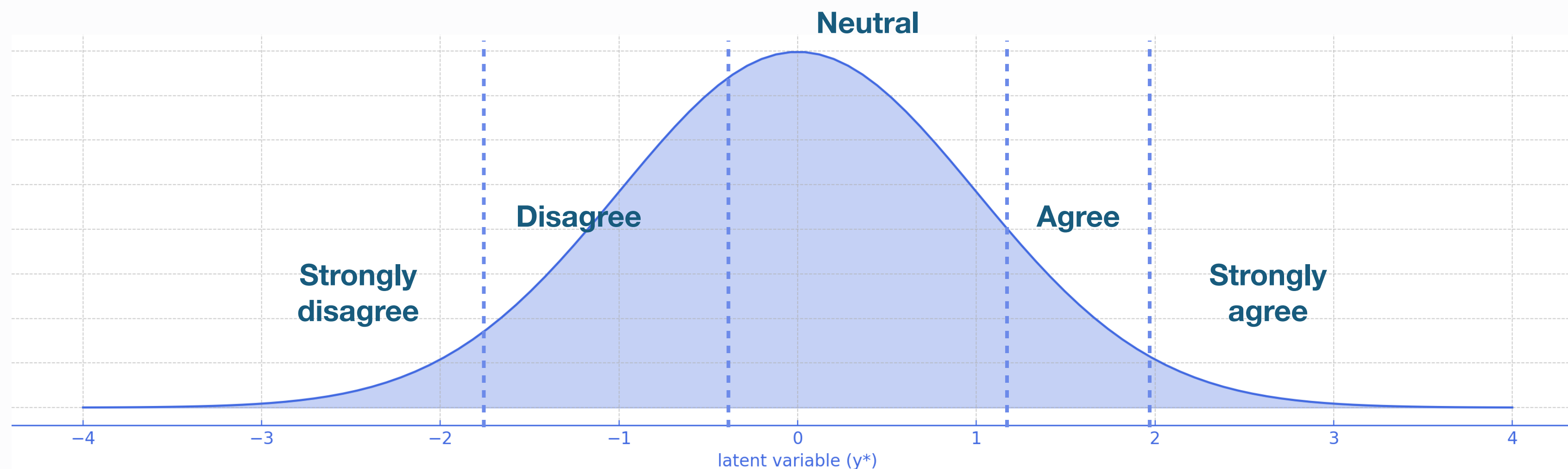
# 1 | CUMULATIVE MODELS

1 | Assume that the observed data originate from the categorization of a latent continuous variable



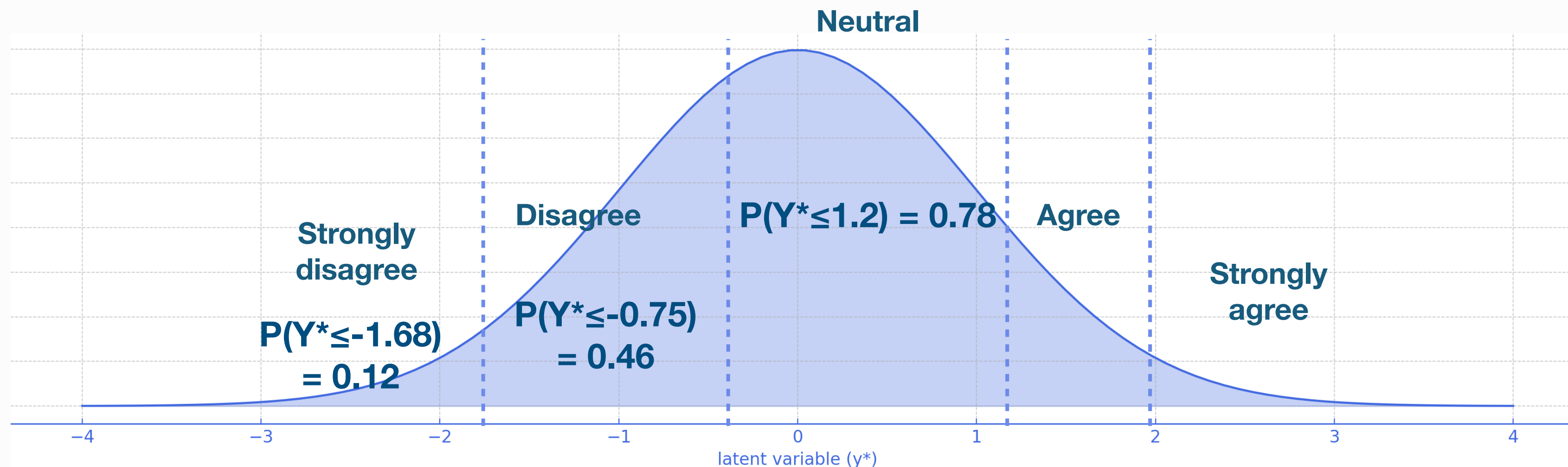
# 1 | CUMULATIVE MODELS

2 | Set thresholds: Each category has a threshold on this latent continuum. The distance between these thresholds isn't fixed and is part of what the model estimates



# 1 | CUMULATIVE MODELS

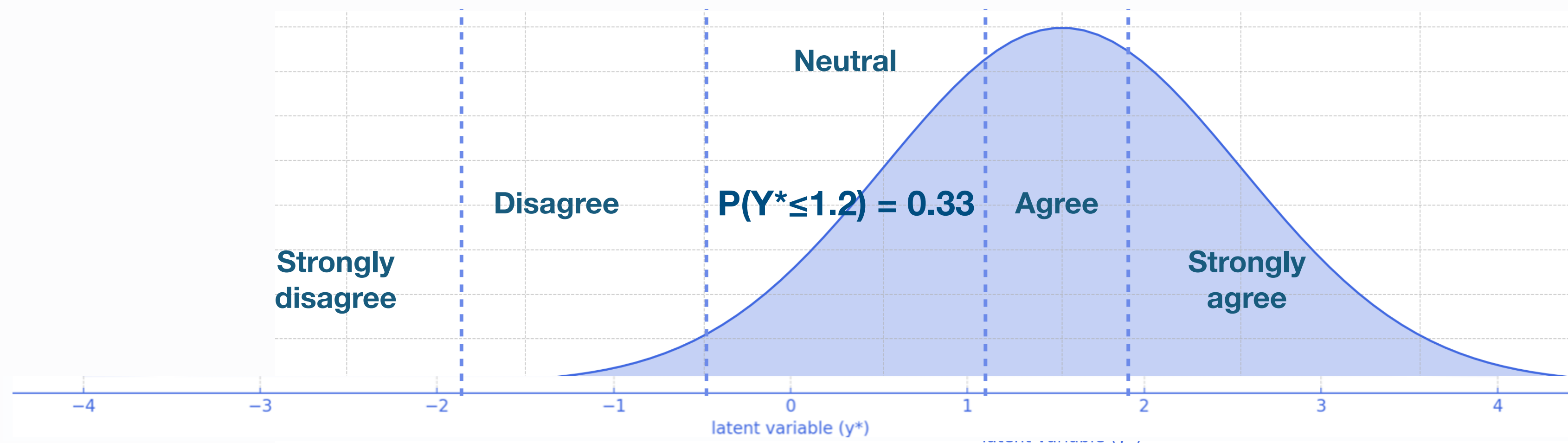
3 | Estimating **cumulative probabilities**: The model calculates the probability of the latent variable falling within or below specific categories.  **$F(Y^*) = P(Y^* \leq X)$**





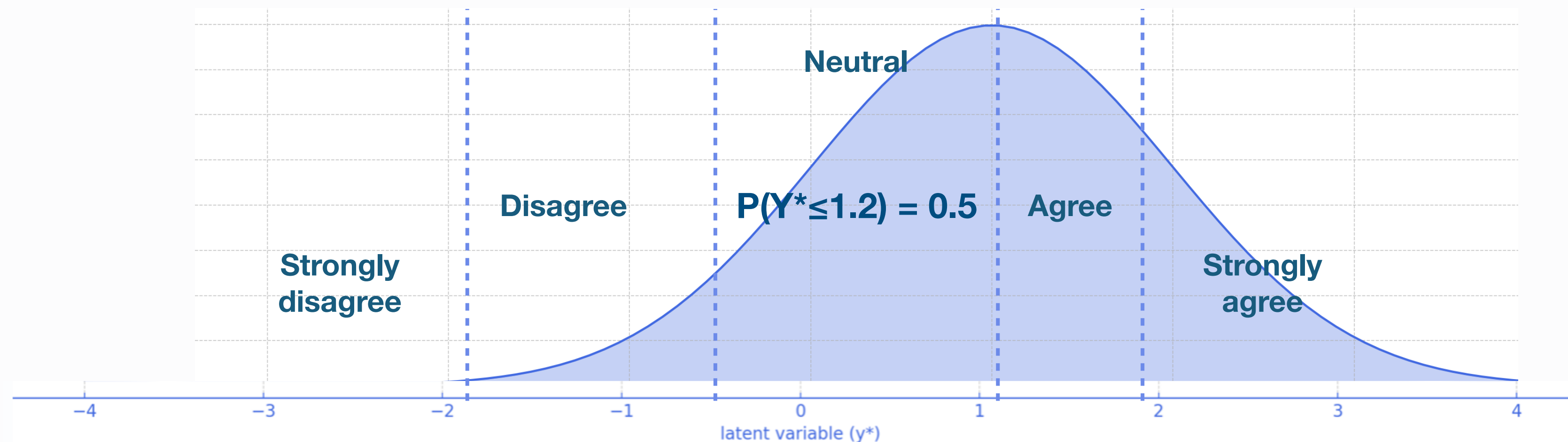
# 1 | CUMULATIVE MODELS

4 | Independent variables can shift the distribution curve to the left or to the right, thereby affecting the probability of falling within a certain category



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4 | Independent variables can shift the distribution curve to the left or to the right, thereby affecting the probability of falling within a certain category



# INTERPRETING COEFFICIENT IN AN ORDINAL MODEL

```
dat <- read.dta("https://stats.idre.ucla.edu/stat/data/ologit.dta")
head(dat)
```

##		apply	pared	public	gpa
## 1	very likely	0	0	3.26	
## 2	somewhat likely	1	0	3.21	
## 3	unlikely	1	1	3.94	
## 4	somewhat likely	0	0	2.81	
## 5	somewhat likely	0	0	2.53	
## 6	unlikely	0	1	2.59	

# INTERPRETING COEFFICIENT IN AN ORDINAL MODEL

```
## Call:
## polr(formula = apply ~ pared + public + gpa, data = dat, Hess = TRUE)
##
## Coefficients:
##           Value Std. Error t value
## pared      1.0477      0.266   3.942
## public    -0.0588      0.298  -0.197
## gpa        0.6159      0.261   2.363
##
## Intercepts:
##           Value Std. Error t value
## unlikely|somewhat likely    2.204    0.780    2.827
## somewhat likely|very likely    4.299    0.804    5.345
##
## Residual Deviance: 717.02
## AIC: 727.02
```

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## gpa      0.6159      0.261   2.363
##
```

$$Y^* = 1.0477 * \text{pared} - 0.0588 * \text{public} + 0.6159 * \text{gpa}$$

```
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```

# THE PROPORTIONAL ODDS ASSUMPTION

The relationship between each pair of outcome groups is statistically the same.

```
## Call:
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##
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**QUESTIONS?**