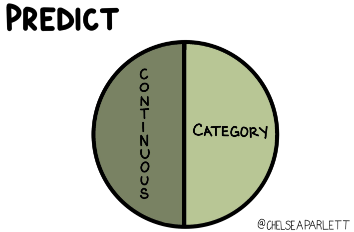
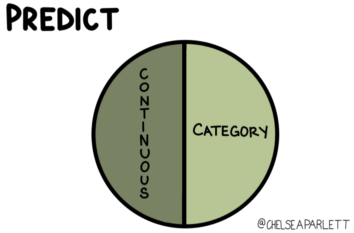


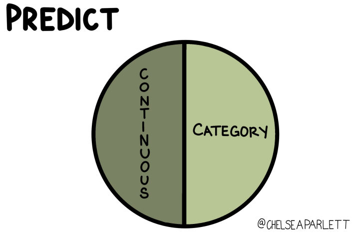
Logistic Regression

Chelsea Parlett-Pelleriti

Linear Regression in Disguise



Predictions



Linear

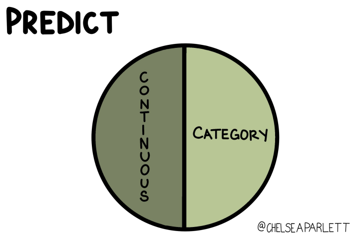
Continuous Variable (can be -∞ to ∞)

Logistic

Binary Categorical Variable (can be 0 or 1)

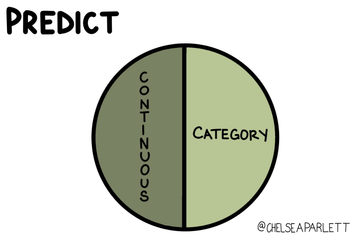
?

Getting from Binary to Continuous



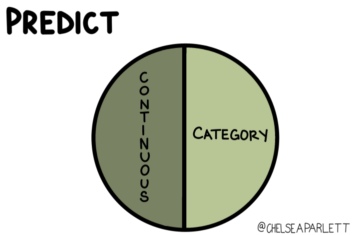
1. Predict Probabilities
2. Convert Probabilities to Odds
3. Convert Odds to Log Odds

Getting from Binary to Continuous

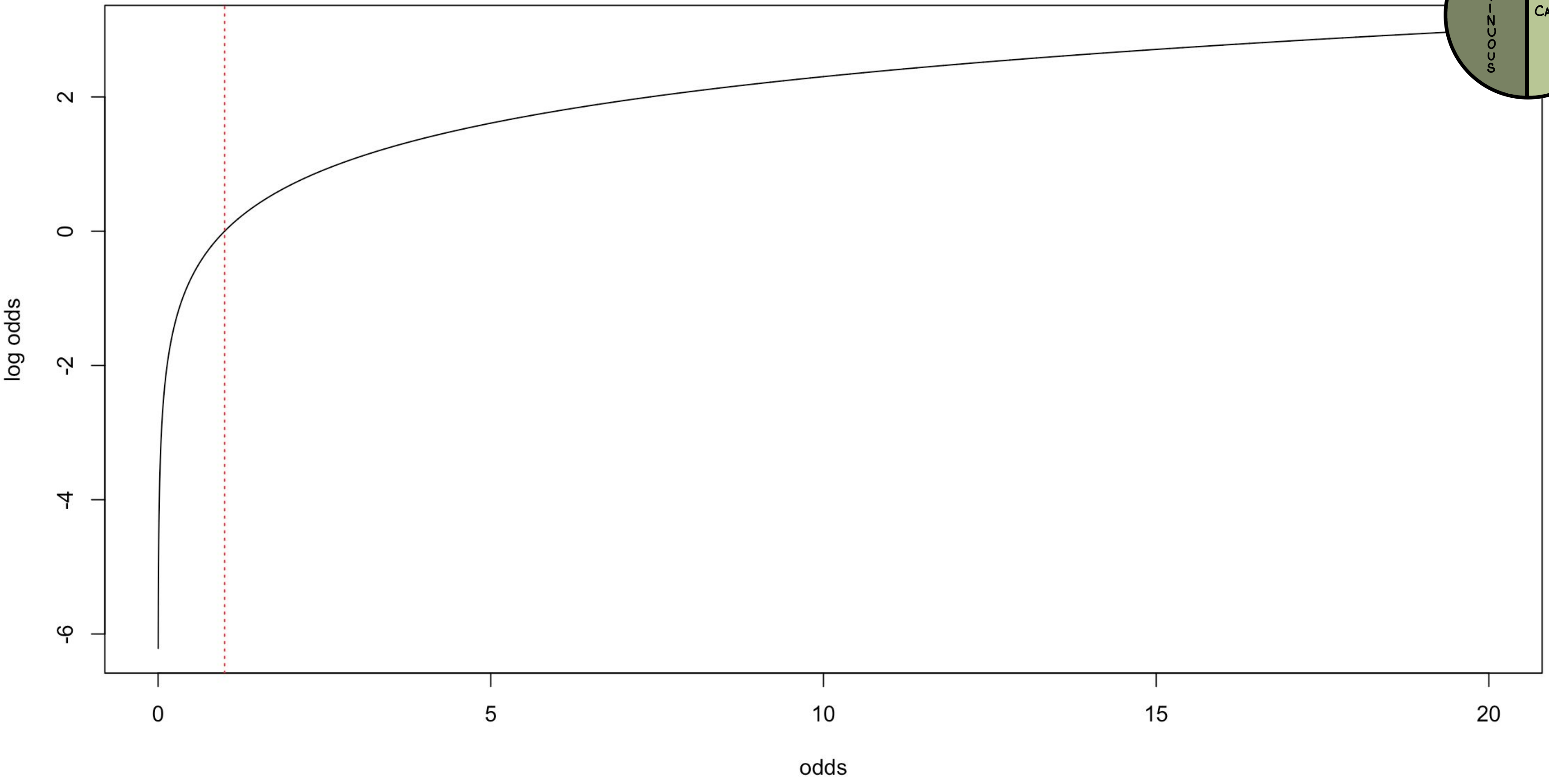


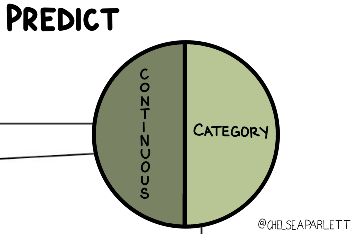
1. Predict Probabilities
2. Convert Probabilities to Odds
3. Convert Odds to Log Odds

Getting from Binary to Continuous

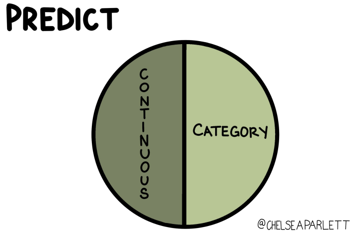


1. Predict Probabilities
2. Convert Probabilities to Odds
3. Convert Odds to Log Odds


log odds
odds
-6
-4
-2
0
2
0
5
10
15
20

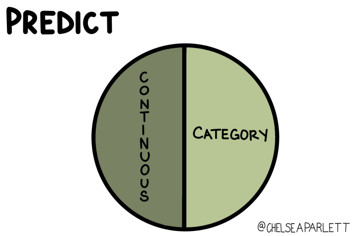

PREDICT
CONTINUOUS
CATEGORY
@CHELSEAPARLETT

Getting from Binary to Continuous

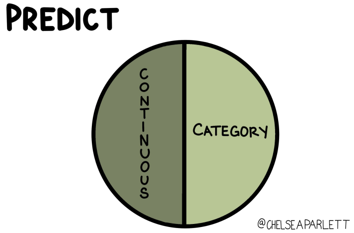


1. Predict Probabilities
2. Convert Probabilities to Odds
3. Convert Odds to Log Odds

The Final Formula



$$\log(p/1-p) = mx + b$$

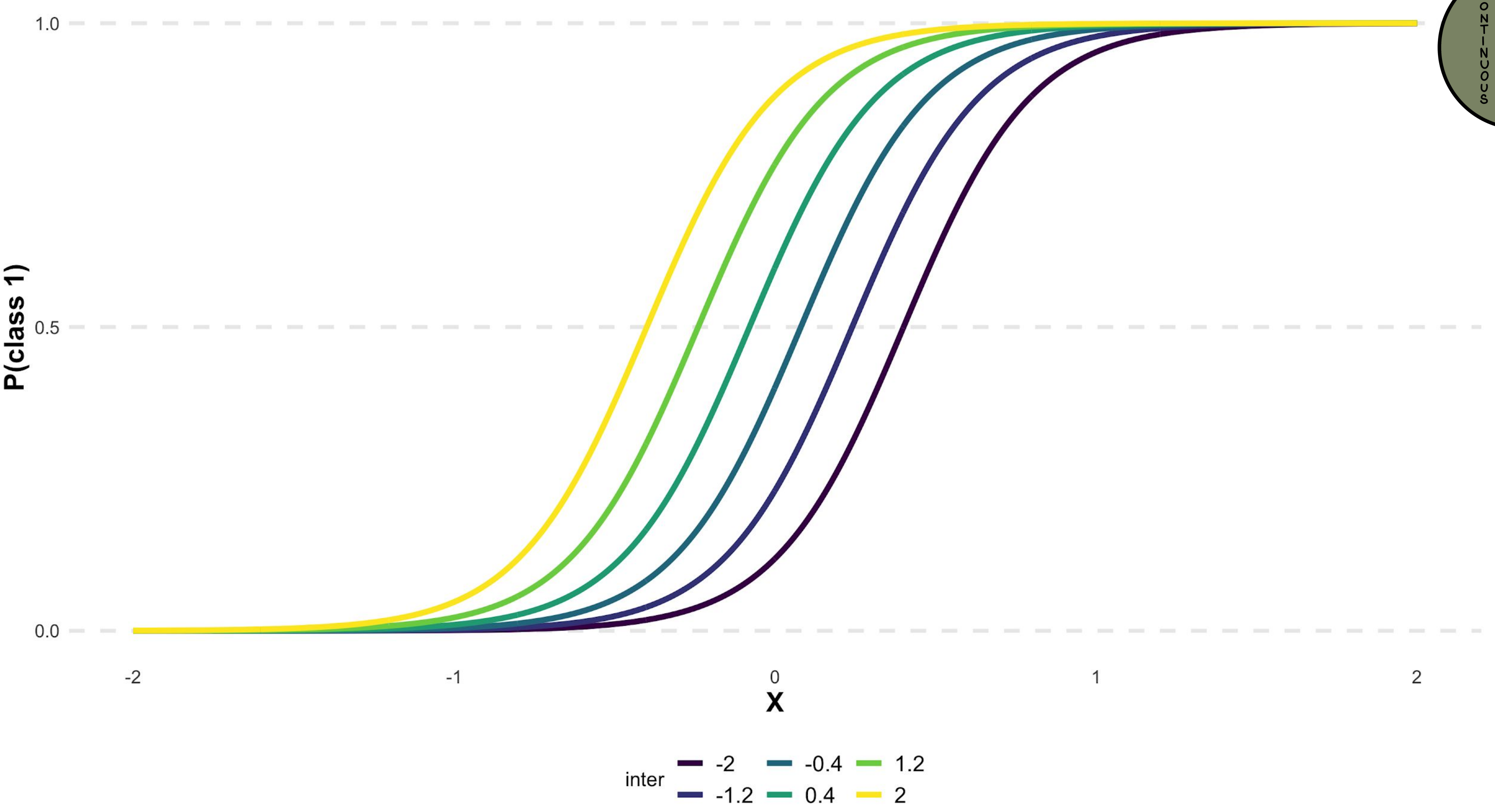


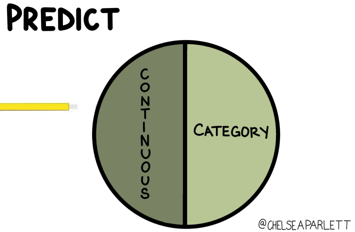
All the Steps

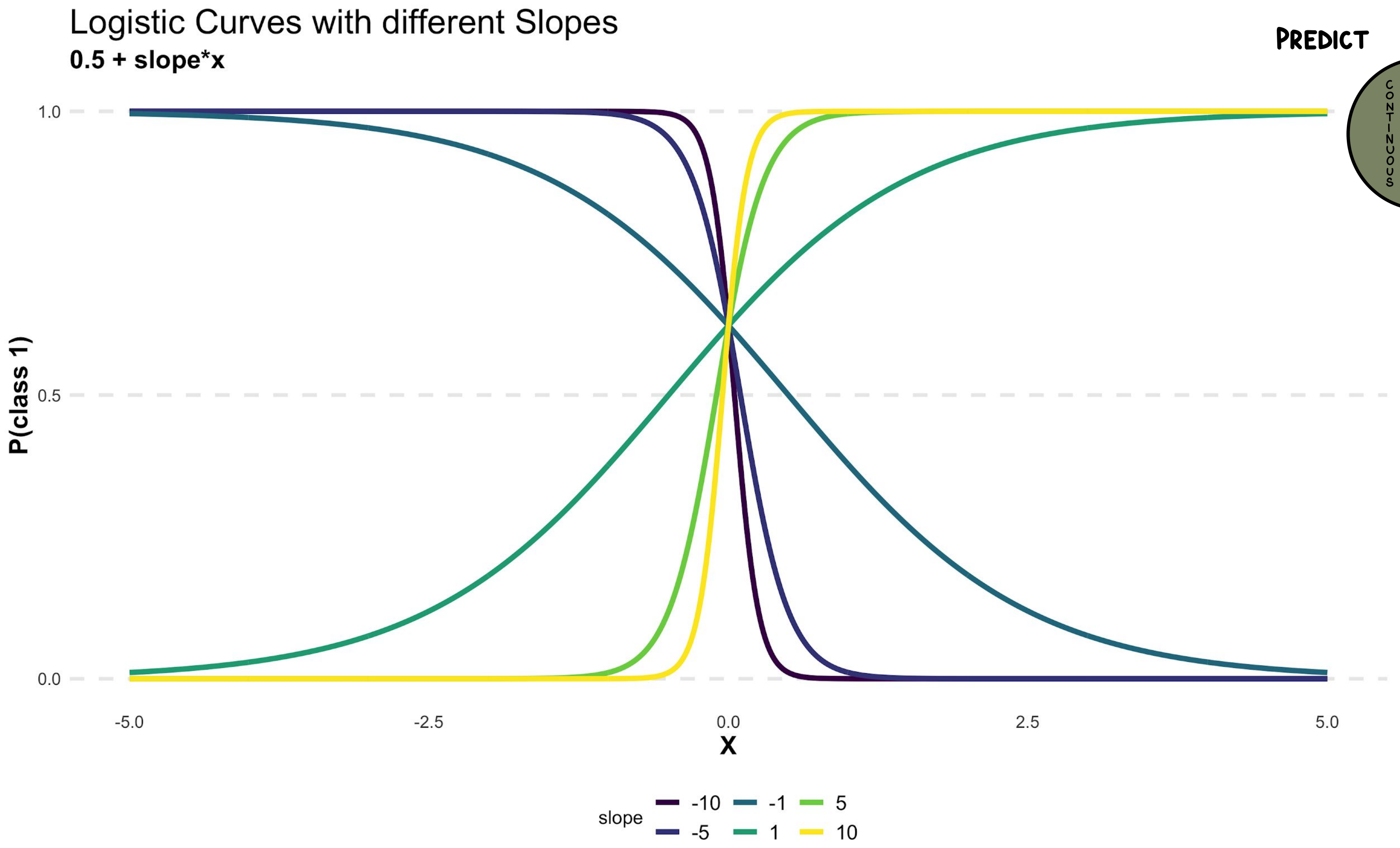
Probability p	**Odds** (p/1-p)	**Log Odds** log((p/1-p))
0.1	0.1111	-2.1972
0.5	**1**	**0**
0.9	9	2.1972

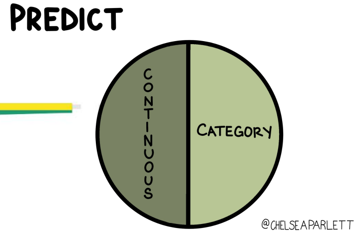
Logistic Curves with different Intercepts

inter + 5x

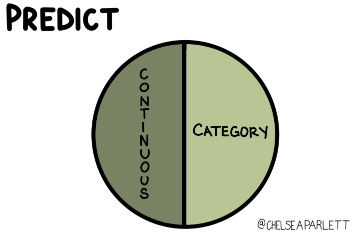





Logistic Curves with different Slopes
0.5 + slope*x
1.0
0.5
0.0
P(class 1)
-5.0
-2.5
0.0
2.5
5.0
X
slope
-10
-5
-1
1
5
10

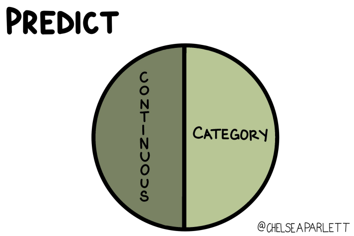

PREDICT
CONTINUOUS
CATEGORY
@CHELSEAPARLETT

Interpreting Coefficients

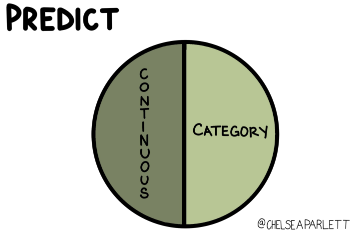


Probability p	**Odds** (p/1-p)	**Log Odds** log((p/1-p))
0.1	0.1111	-2.1972
0.5	**1**	**0**
0.9	9	2.1972

Interpreting Coefficients

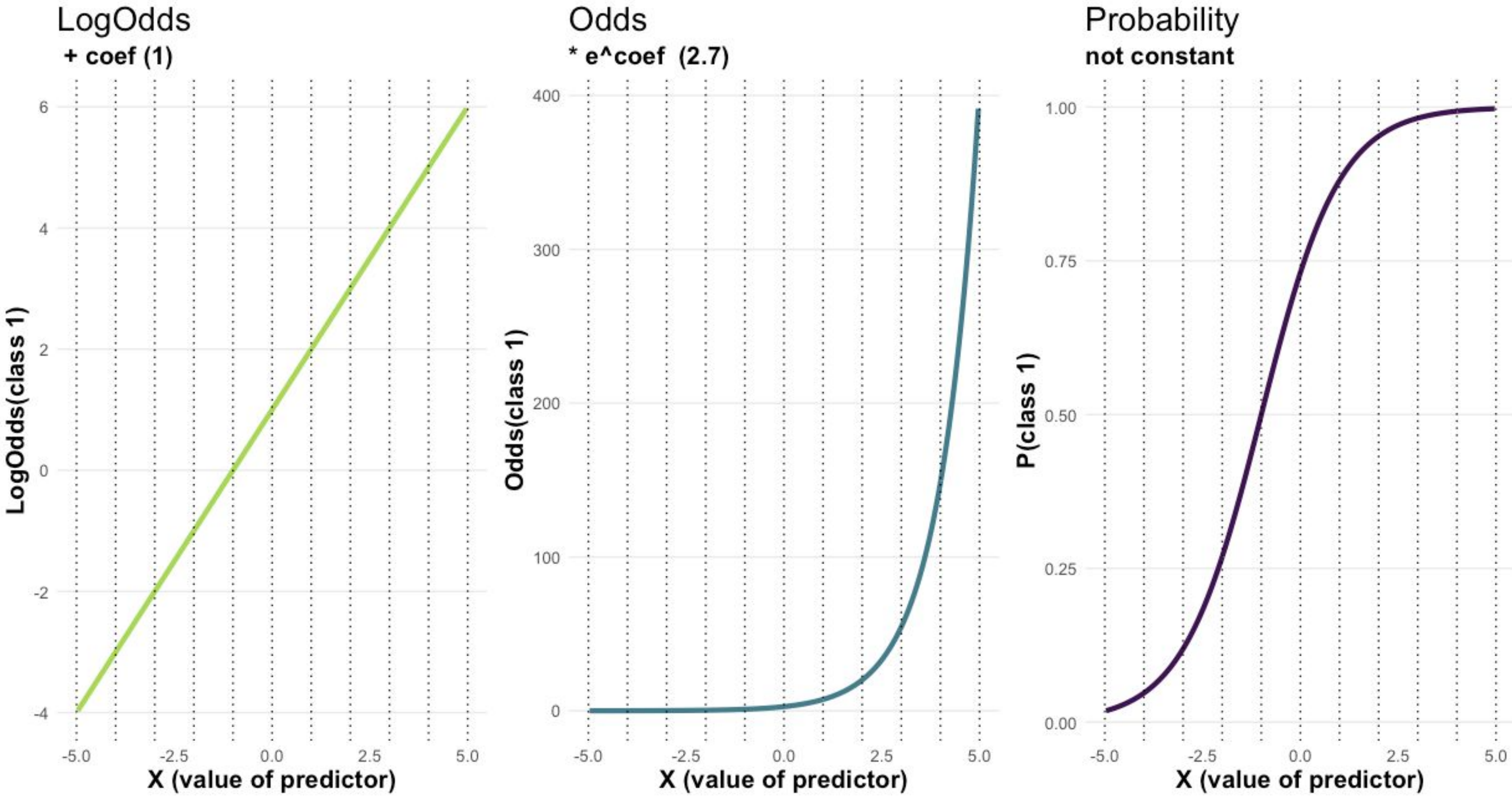


	coef
const	-2.9777
age	0.1445
income	-0.0066
months_subbed	0.0015

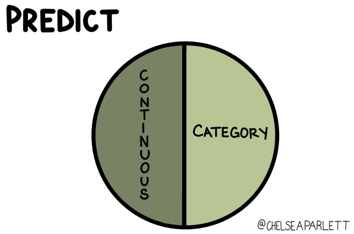


Interpreting Coefficients

	coef	e^{coef}
const	-2.9777	0.05090979
age	0.1445	1.155462
income	-0.0066	0.9934217
months_subbed	0.0015	1.001501

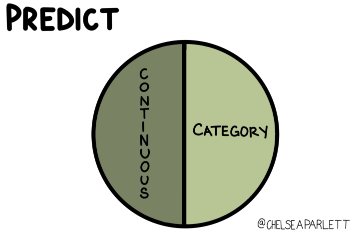

LogOdds
+ coef (1)
LogOdds(class 1)
X (value of predictor)
Odds
* e^coef (2.7)
Odds(class 1)
X (value of predictor)
Probability
not constant
P(class 1)
X (value of predictor)

Interpreting Coefficients



- ✔️ Log odds
- ✔️ Odds
- ⚠️ Probabilities*

Loss Functions



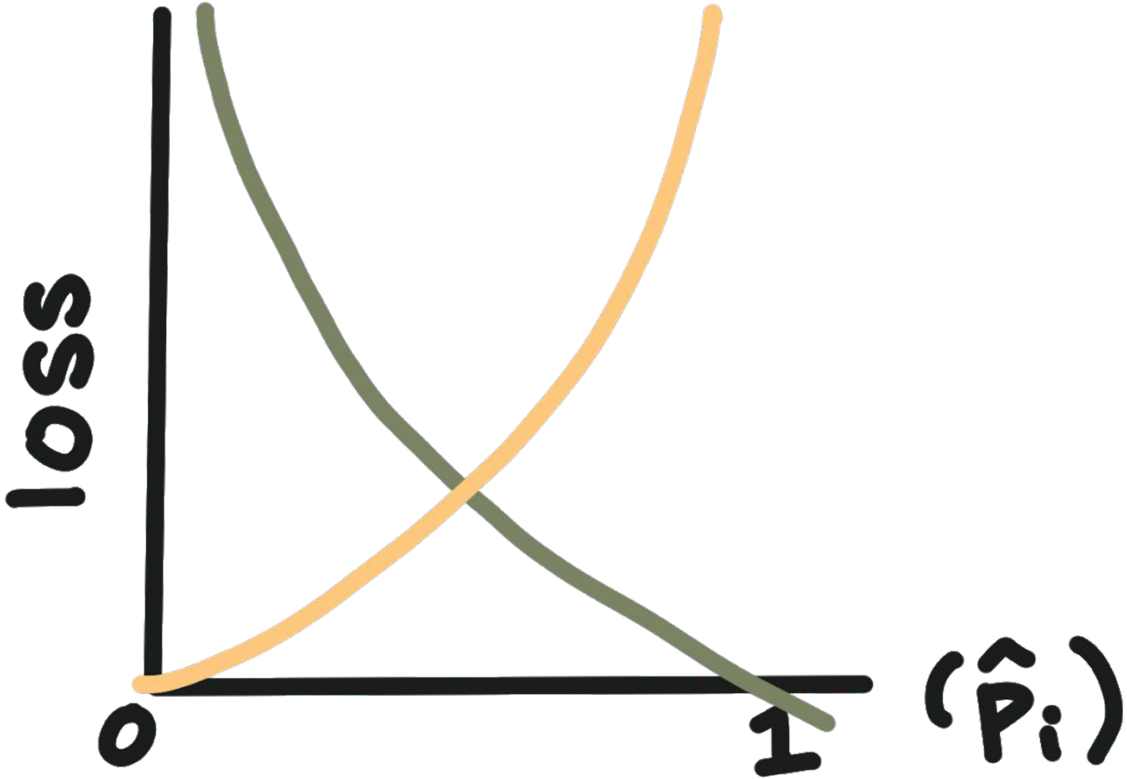
LINEAR:

$$(\hat{y}_i - y_i)^2$$

LOGISTIC:

$$\begin{cases} -\log(\hat{p}_i) & \text{if } y=1 \\ -\log(1-\hat{p}_i) & \text{if } y=0 \end{cases}$$

Loss Functions



LINEAR: $(\hat{y}_i - y_i)^2$

LOGISTIC: $\begin{cases} -\log(\hat{p}_i) & \boxed{\text{if } y=1} \\ -\log(1-\hat{p}_i) & \boxed{\text{if } y=0} \end{cases}$

Approximate Methods