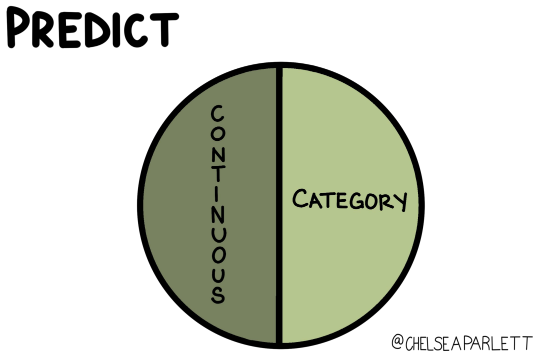


Logistic Regression II

Dr. Chelsea Parlett-Pelleriti

Outline

- Metrics
- Calibration
- Interpreting Coefficients

Metrics

Assessing Model Performance

- Did it make the correct prediction? (accuracy, sensitivity, specificity, F1 score)
- Distinguishing between classes (ROC AUC)

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

Accuracy

Correct Predictions

True Positive (**TP**) + True Negative (**TN**)

All Predictions

False Negative (**FN**) + False Positive (**FP**) +

True Positive (**TP**) + True Negative (**TN**)

"How often is the model correct?"

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative (**FN**)
Actual Negative	False Positive (**FP**)	True Negative (**TN**)

Sensitivity/Recall

Correctly Predicted Positives

True Positive (**TP**)

Actual Positives

False Negative **(FN)** + True Positive (**TP**)

"How often is the model correct for Positive Cases?"

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

Specificity

Correctly Predicted Negatives

True Negative **(TN)**

Actual Negatives

True Negative **(TN)** + False Positive **(FP)**

"How often is the model correct for Negative Cases?"

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive **(TP)**	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

Precision

Correctly Predicted Positives

True Positive (**TP**)

Actual Positives

False Positive **(FP)** + True Positive (**TP**)

"How many of the predicted Positives are correct?"

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

F1 Score

$$\frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

Combination of Precision (how often predicted positives ARE positive) and Recall (how often we correctly predict actual positives)

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

ROC AUC

Correctly Predicted Positives

True Positive (**TP**)

Actual Positives

False Negative **(FN)** + True Positive (**TP**)

	Predicted Positive	***Predicted*** Negative
Actual Positive	True Positive (**TP**)	False Negative **(FN)**
Actual Negative	False Positive **(FP)**	True Negative **(TN)**

1 -

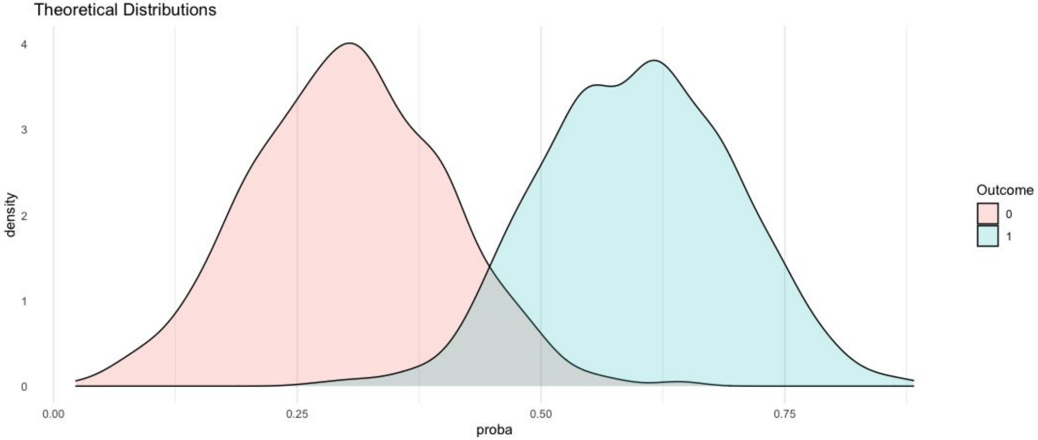
Correctly Predicted Negatives

True Negative **(TN)**

Actual Negatives

True Negative **(TN)** + False Positive **(FP)**

ROC AUC


Theoretical Distributions
density
proba
0.00
0.25
0.50
0.75
0
1
2
3
4
Outcome
0
1

Calibration

Calibration

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

Calibration

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

p(dog) = 80%

p(dog) = 51%

p(dog) = 51%

p(dog) = 51%

p(dog) = 51%

p(dog) = 51%

Calibration

p(dog) = 80% p(dog) = 80% p(dog) = 80% p(dog) = 80% p(dog) = 80%

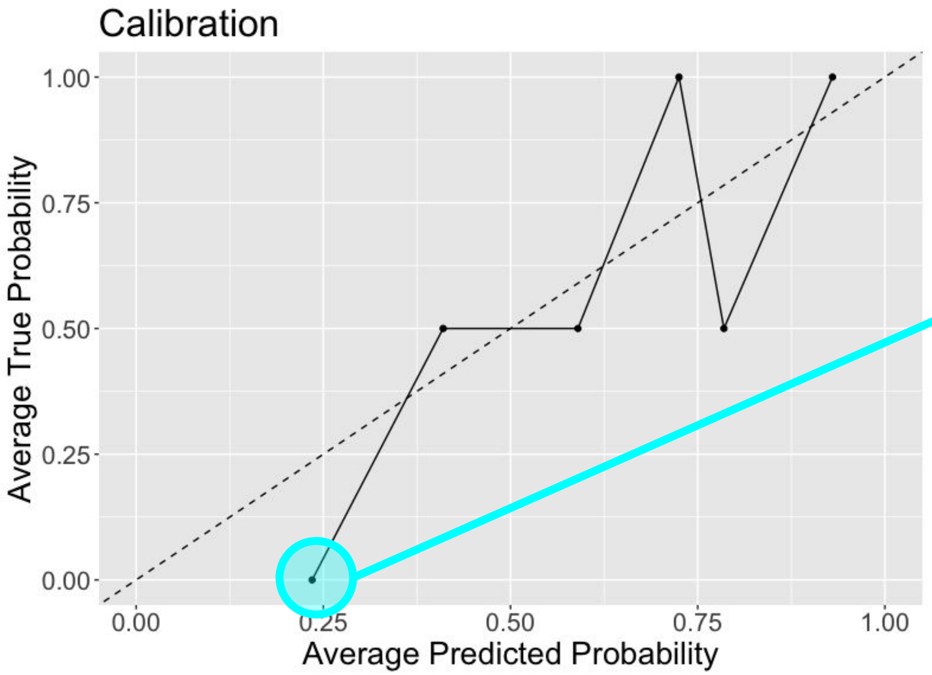
p(dog) = 51% p(dog) = 51% p(dog) = 51% p(dog) = 51% p(dog) = 51%

Actual	Predicted	Avg Predicted	Avg Actual
0	0.2		
0	0.27		
1	0.4		
0	0.42		
0	0.53		
1	0.65		
1	0.70		
1	0.75		
0	0.77		
1	0.80		
1	0.91		
1	0.95		

Actual	Predicted	Avg Predicted	Avg Actual
0	0.2		
0	0.27		
1	0.4		
0	0.42		
0	0.53		
1	0.65		
1	0.70		
1	0.75		
0	0.77		
1	0.80		
1	0.91		
1	0.95		

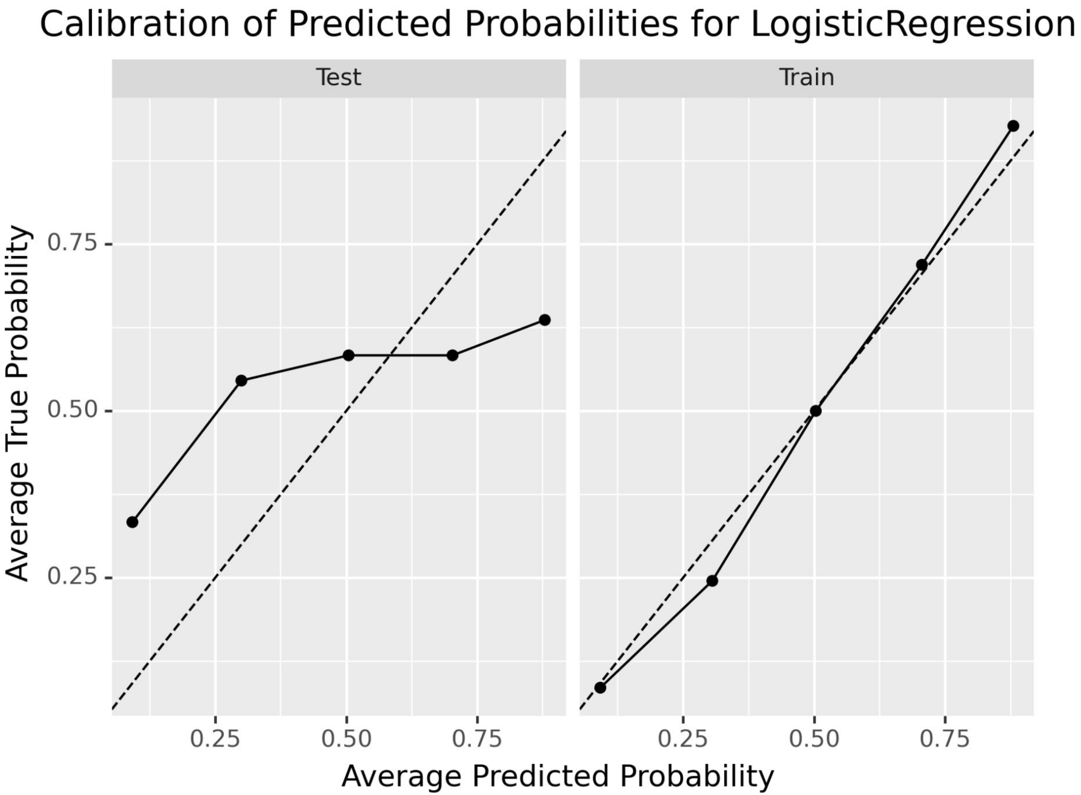
Actual	Predicted	Avg Predicted	Avg Actual
0	0.2	0.235	
0	0.27		
1	0.4	0.41	
0	0.42		
0	0.53	0.59	
1	0.65		
1	0.70	0.725	
1	0.75		
0	0.77	0.785	
1	0.80		
1	0.91	0.93	
1	0.95		

Actual	Predicted	Avg Predicted	Avg Actual
0	0.2	0.235	0
0	0.27		
1	0.4	0.41	0.5
0	0.42		
0	0.53	0.59	0.5
1	0.65		
1	0.70	0.725	1
1	0.75		
0	0.77	0.785	0.5
1	0.80		
1	0.91	0.93	1
1	0.95		

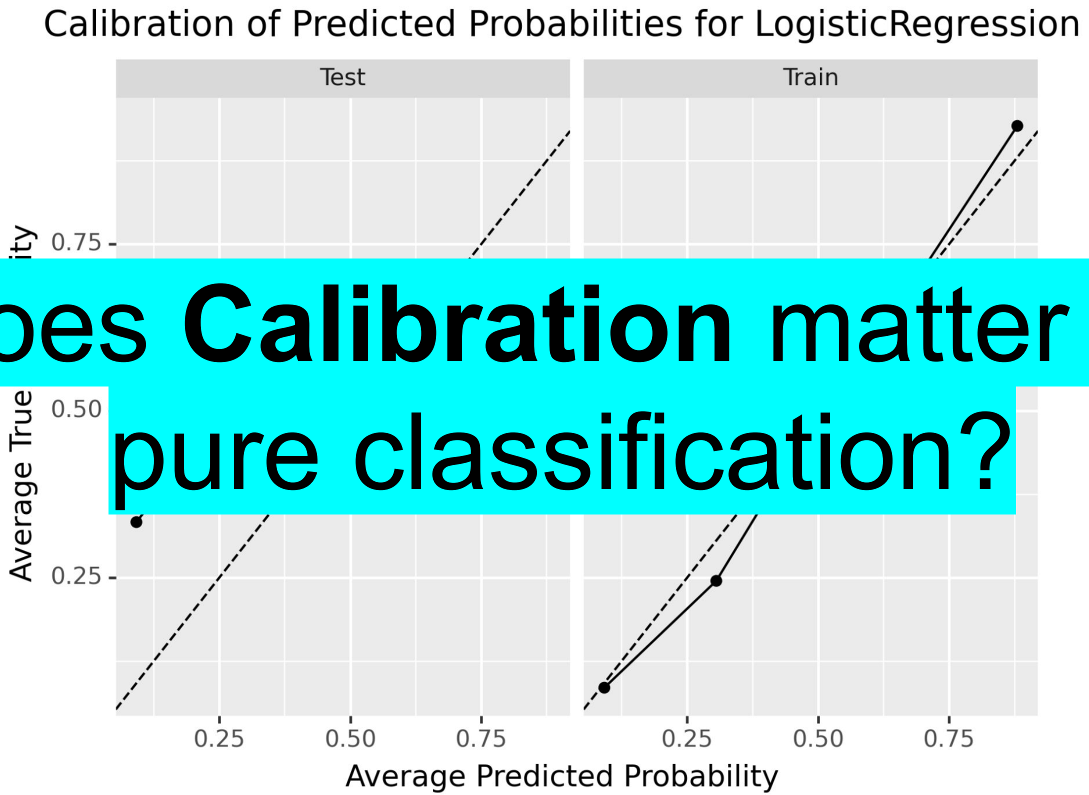


Actual	Predicted	Avg Predicted	Avg Actual
0	0.2	0.235	0
0	0.27		
1	0.4	0.41	0.5
0	0.42		
0	0.53	0.59	0.5
1	0.65		
1	0.70	0.725	1
1	0.75		
0	0.77	0.785	0.5
1	0.80		
1	0.91	0.93	1
1	0.95		

Calibration



Calibration



Does **Calibration** matter for pure classification?

Calibration

p(dog) = 80%   p(dog) = 80%   p(dog) = 80%   p(dog) = 80%   p(dog) = 80%

p(dog) = 51%   p(dog) = 51%   p(dog) = 51%   p(dog) = 51%   p(dog) = 51%

Interpreting Logistic Regression Models

Probabilities, Odds, Log Odds

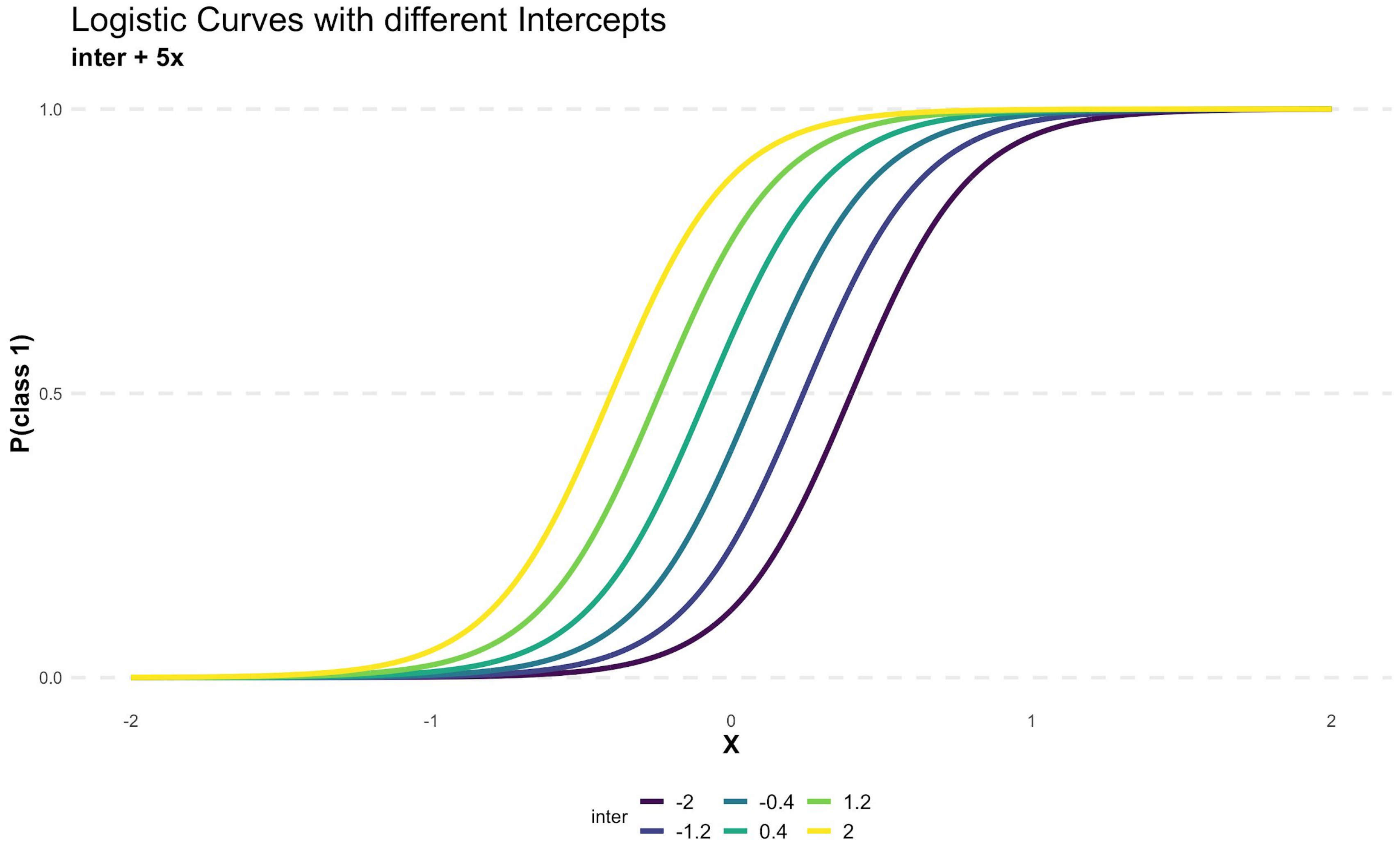
Attempt 1: probabilities

Attempt 2: odds

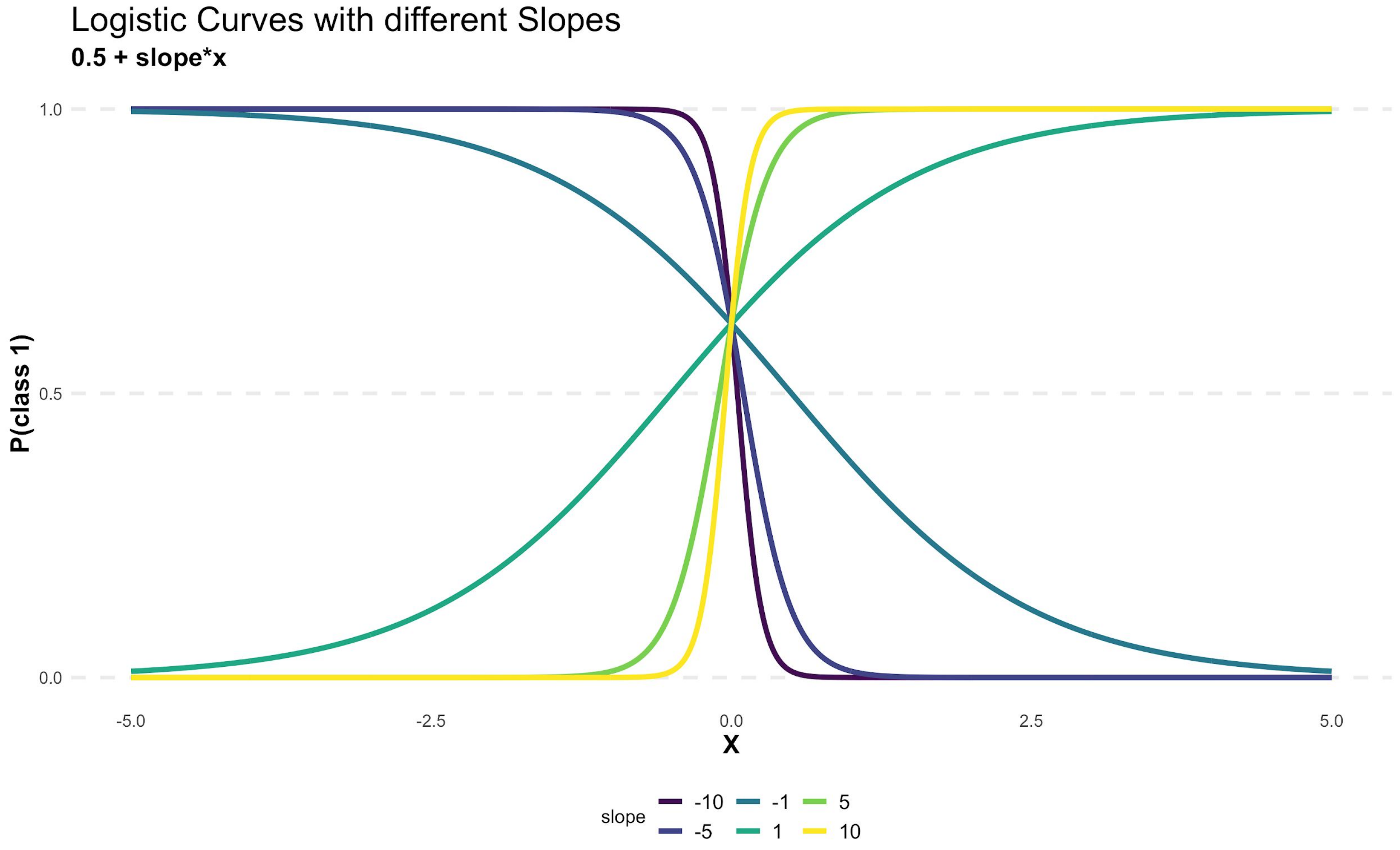
Attempt 3: log odds

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
P(class 1)
1.0
0.5
0.0
-2
-1
0
1
2
X
inter
-2
-1.2
-0.4
0.4
1.2
2


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

Interpreting Coefficients

A 1-**unit/sd** increase in ____ causes our predicted *log odds* to (**increase/decrease**) by _____

	coef
const	-2.9777
age	0.1445
income	-0.0066
months_subbed	0.0015

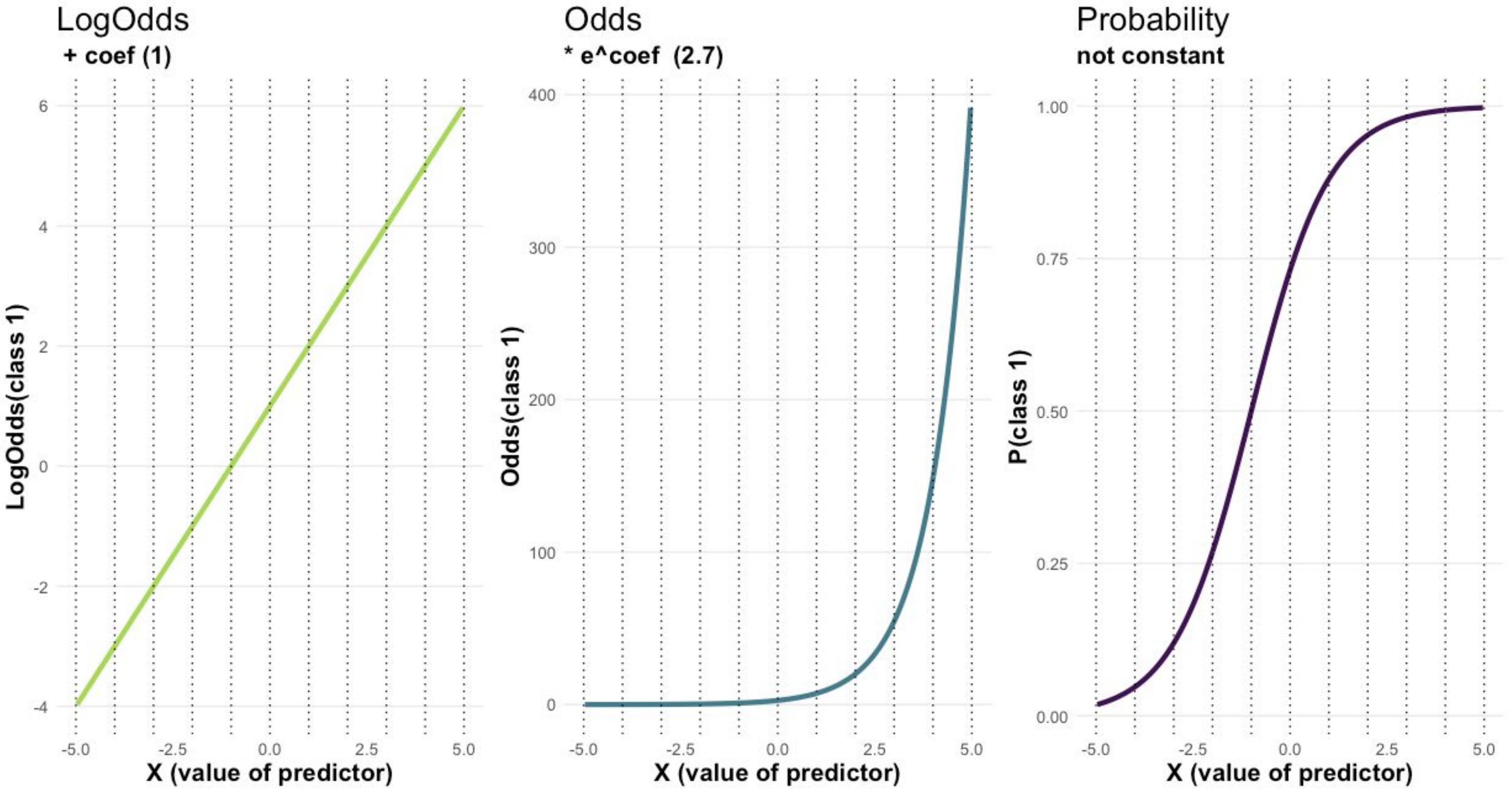
Interpreting Coefficients

A 1-**unit/sd** increase in ____ causes our predicted *odds* to **be multiplied** by _____

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

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



LogOdds
+ coef (1)
LogOdds(class 1)
6
4
2
0
-2
-4
-5.0
-2.5
0.0
2.5
5.0
X (value of predictor)
Odds
* e^coef (2.7)
Odds(class 1)
400
300
200
100
0
-5.0
-2.5
0.0
2.5
5.0
X (value of predictor)
Probability
not constant
P(class 1)
1.00
0.75
0.50
0.25
0.00
-5.0
-2.5
0.0
2.5
5.0
X (value of predictor)

Interpreting Coefficients

✅ Log odds

✅ Odds

⚠️ Probabilities*