Predictive Analytics – Session 1

The Predictive Mindset
Predicting with Regression

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What is your perception of

PREDICTIVE ANALYTICS?

History $\rightarrow$ future,

"Likelihood" $\Rightarrow$ error

The Predictive Mindset

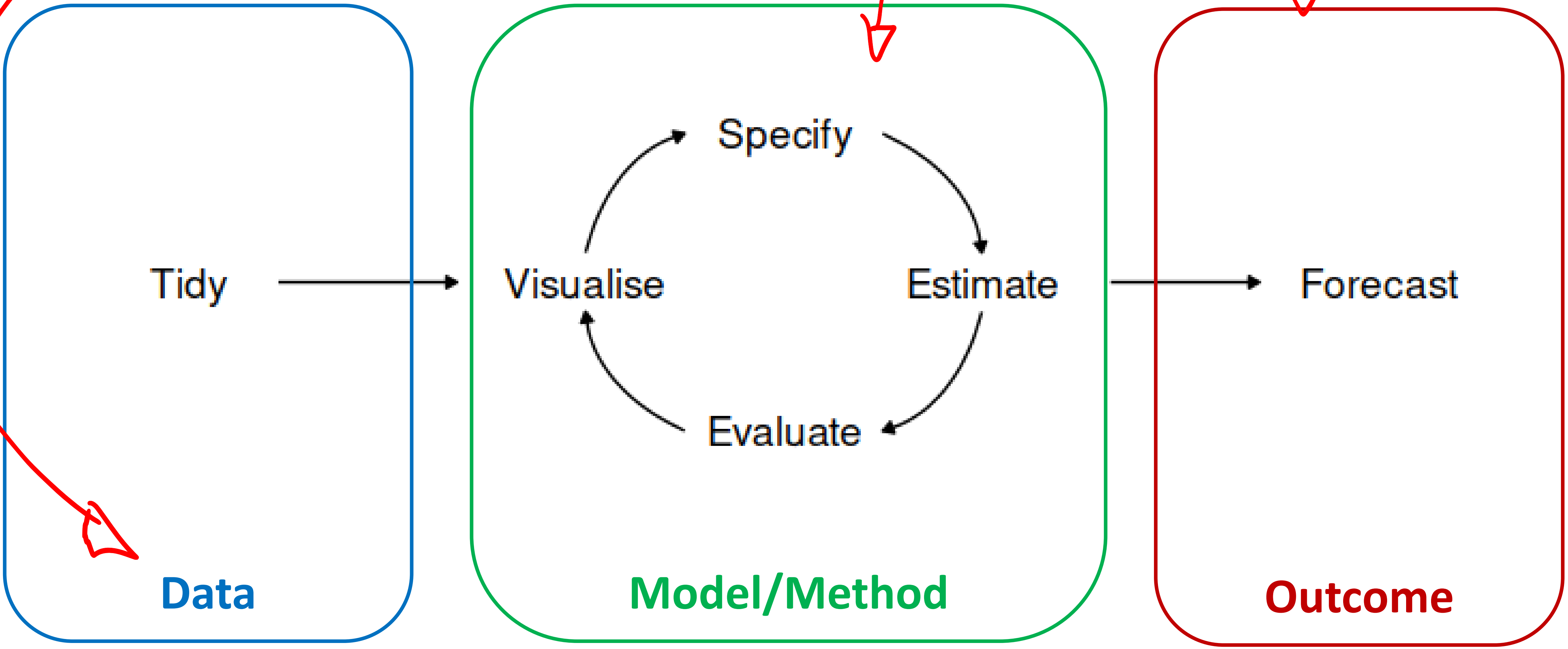
Predictive Analytics:

- Focus on the future – “Predictive”
- … by learning from the past – “Analytics”
- **For your business context**

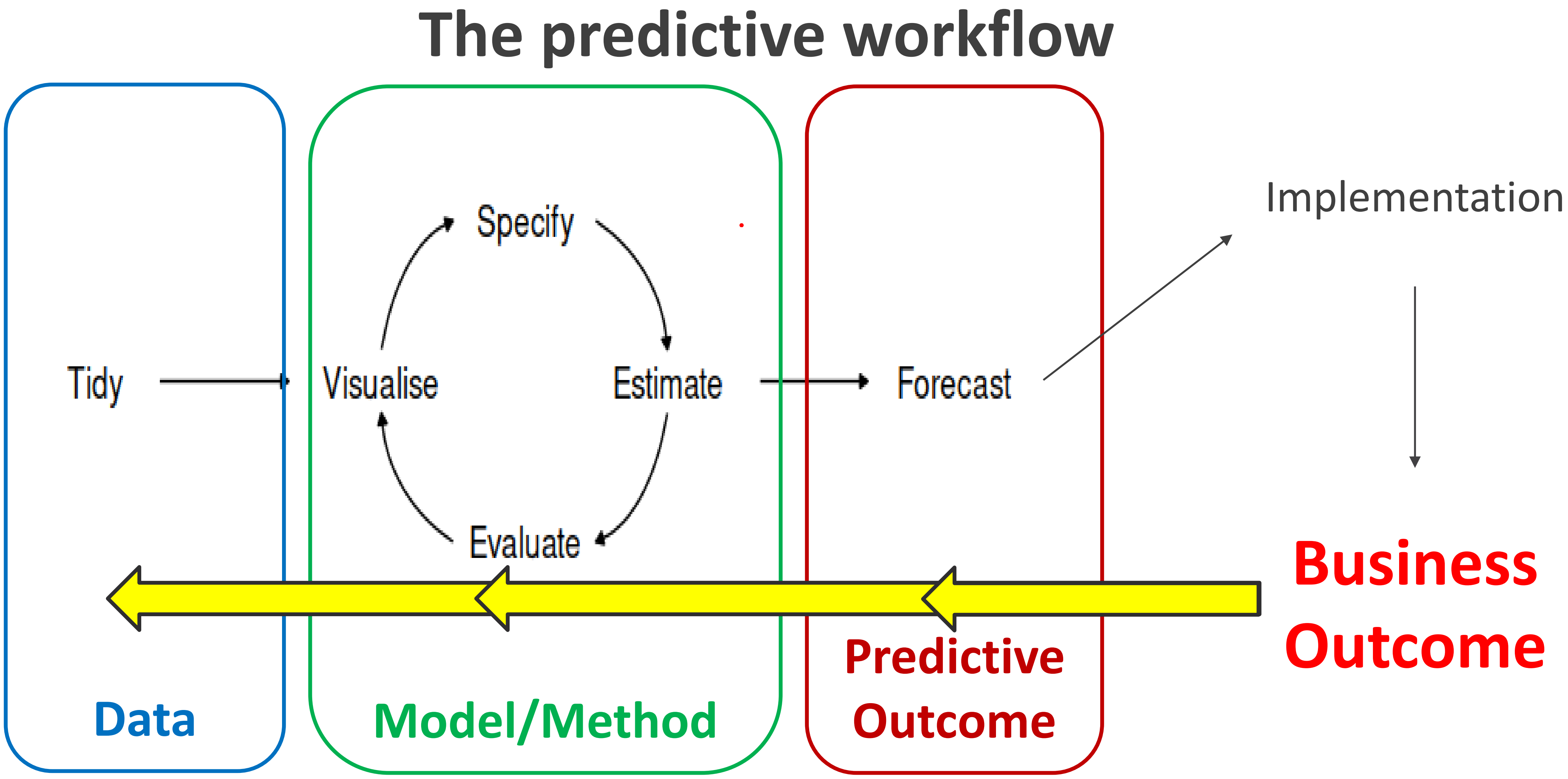
The Predictive Mindset

Well-defined problem

The predictive workflow



The Predictive Mindset



The Predictive Mindset

Example: What do loan lenders want?

		Actual Observation	
		Good loan	Bad loan
Predicted Outcome	Good loan	True Positive	False Positive
	Bad loan	False Negative	True Negative

The Predictive Mindset

Example: What do loan lenders want?

		Actual Observation	
		Good loan	Bad loan
Predicted Outcome	Good loan	True Positive	False Positive
	Bad loan	False Negative	True Negative

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total}$$

The Predictive Mindset

Example: What do loan lenders want?

- Who do they see?

		Actual Observation	
		Good loan	Bad loan
Predicted Outcome	Good loan	True Positive	False Positive
	Bad loan	False Negative	True Negative

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

The Predictive Mindset

Example: What about fraud detection?

		Actual Observation	
		Fraud	Not Fraud
Predicted Outcome	Fraud	True Positive	False Positive
	Not Fraud	False Negative	True Negative

The Predictive Mindset

Example: What about fraud detection?

- False negative more devastating

		Actual Observation	
		Fraud	Not Fraud
Predicted Outcome	Fraud	True Positive	False Positive
	Not Fraud	False Negative	True Negative

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

The Predictive Mindset

Key takeaway:

Assessment of predictions are context specific.

Make sure you use the measure of accuracy that is appropriate to your context!

The Predictive Mindset

Discussions:

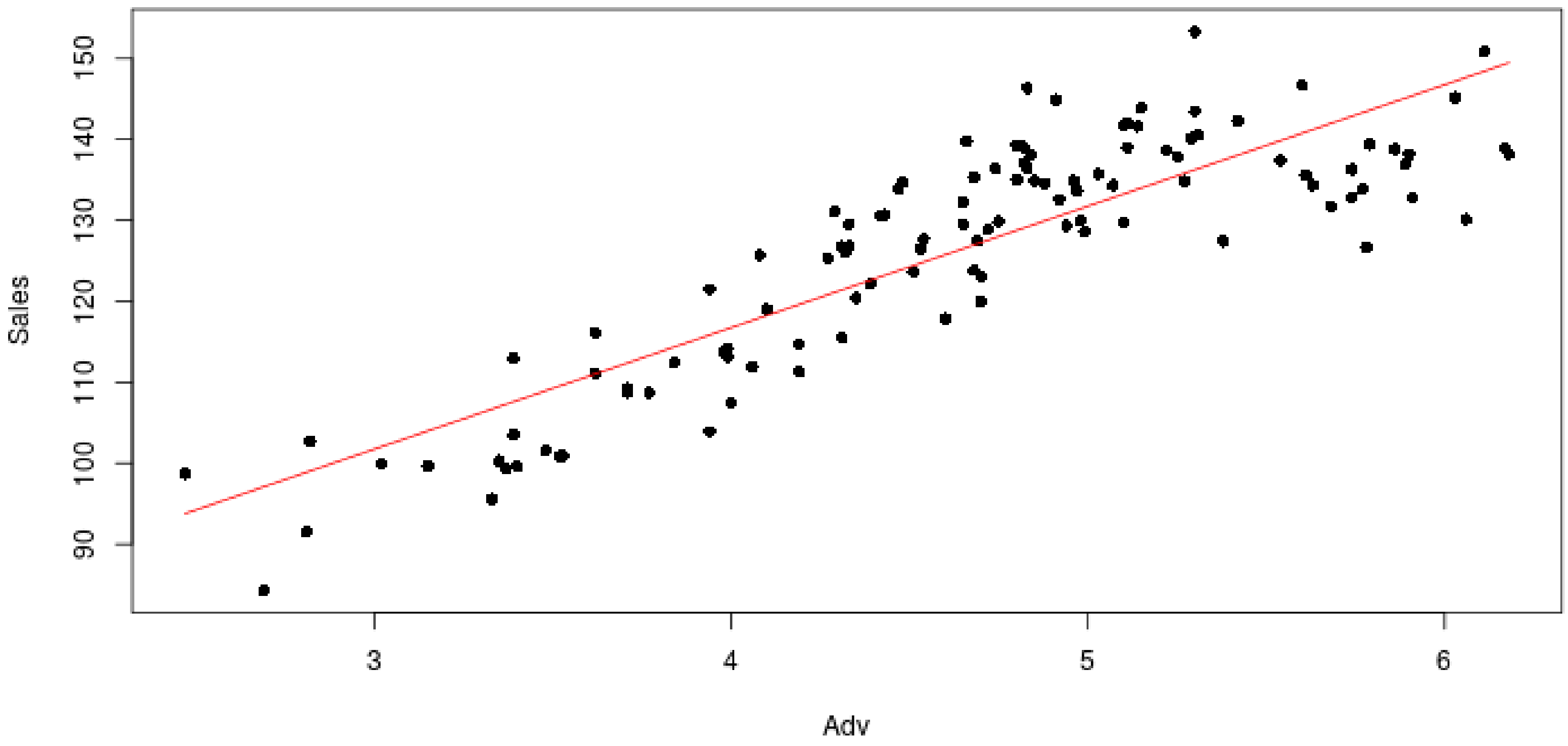
- Does “good fit” imply “good prediction”?

- Is Prediction = Truth?

The Predictive Mindset

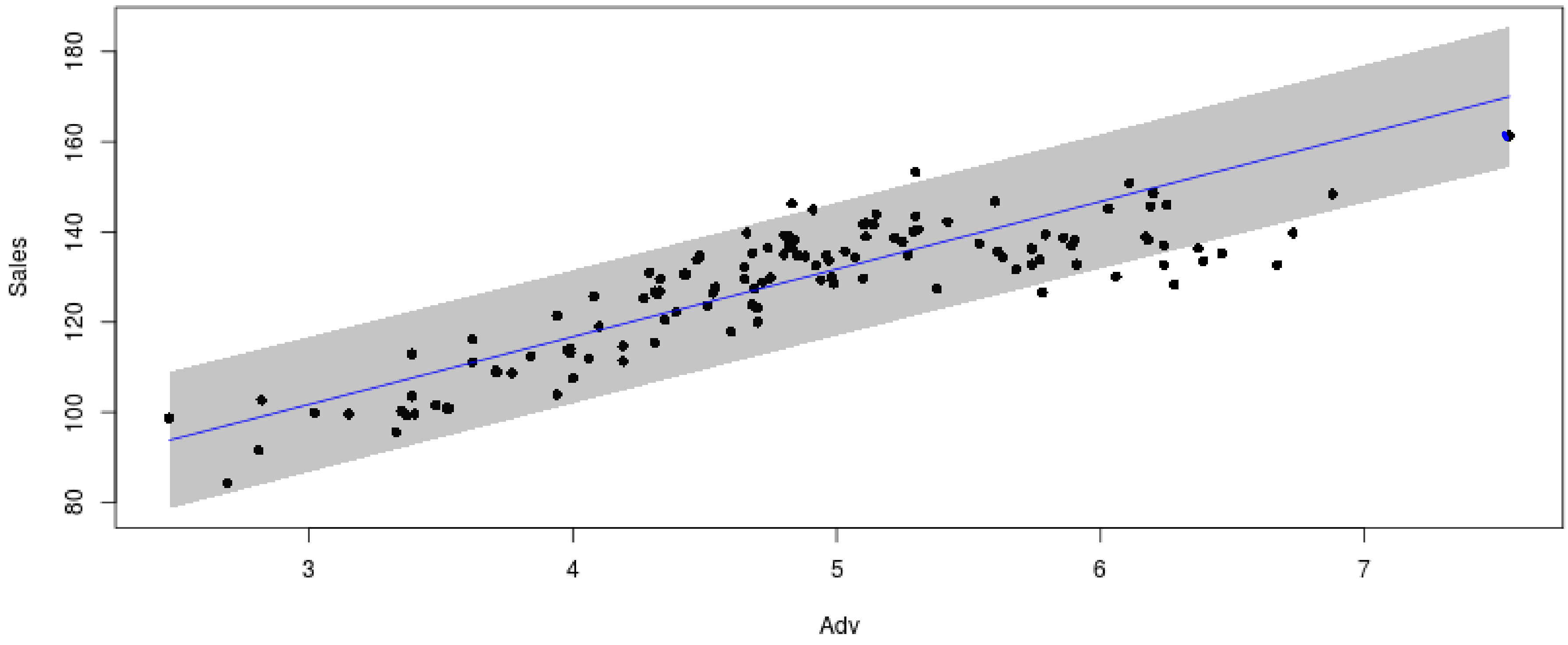
Good fit?

R-Square = 75%



The Predictive Mindset

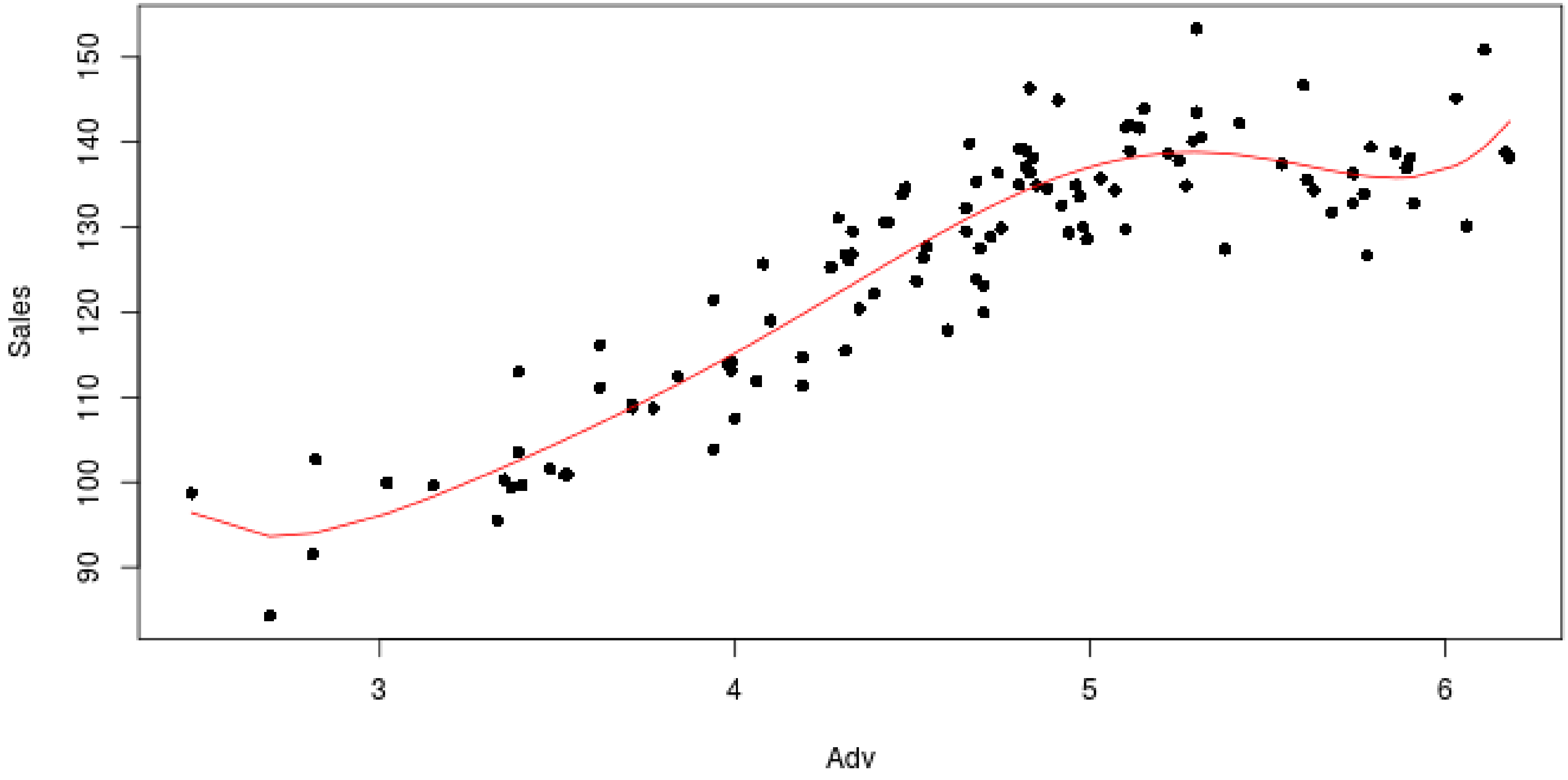
Good prediction?



The Predictive Mindset

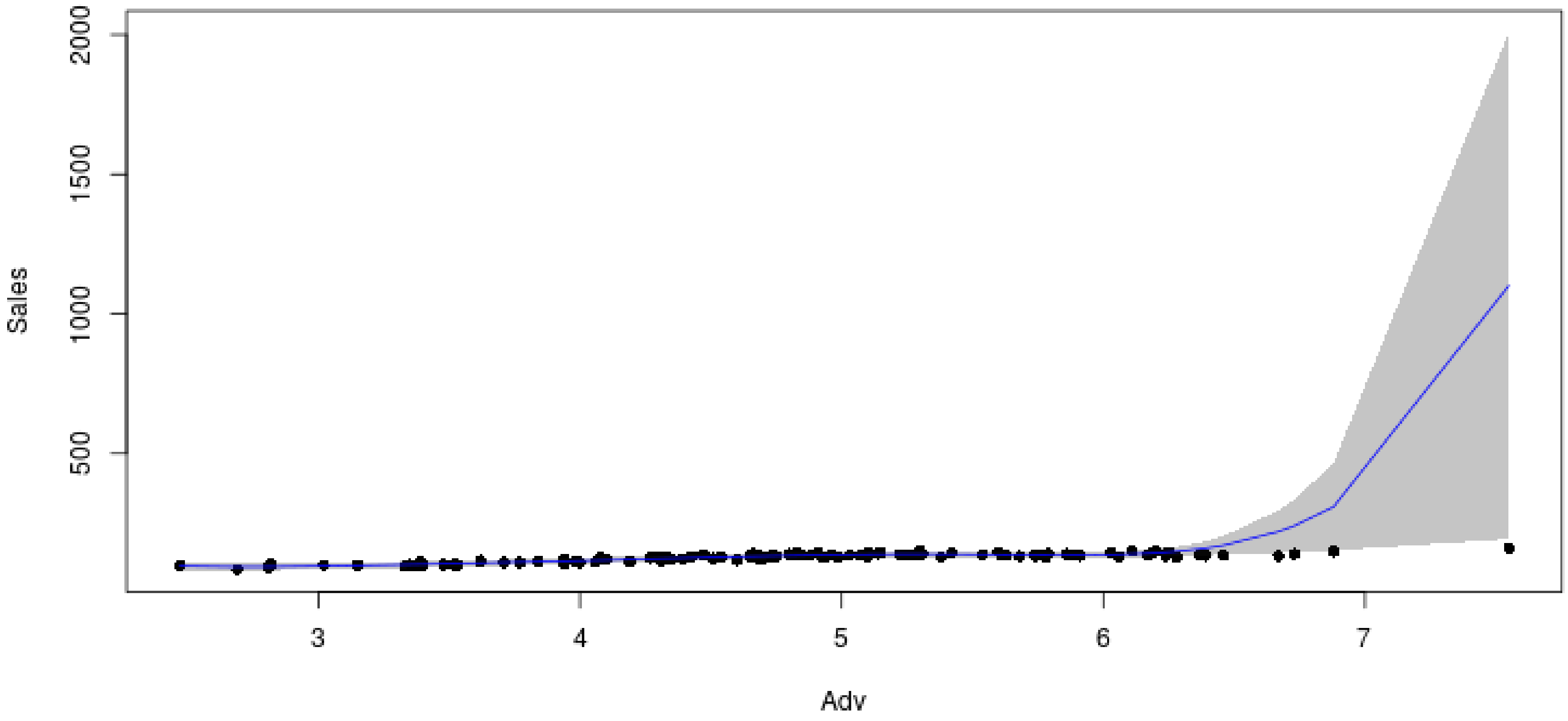
Better fit?

R-Square = 87%



The Predictive Mindset

Better prediction?



The Predictive Mindset

“All models are wrong…

but some are useful…”

George Box (1987)

The Predictive Mindset

Key takeaway:

Use of analytics outcome dictates the analytics process

The Predictive Mindset

Driver of Predictive Analytics

Good fit $\neq$ Good prediction

Prediction $\neq$ Truth

Business loss $\neq$ Statistical loss

The Predictive Mindset

Key Questions

- How large is the potential error from predictions?
- How does prediction error impact our business?
- Are there other methods that returns smaller error? How do we compare them?

Predictive Assessments

Quantifying potential error

- We know from the outset that **Prediction $\neq$ Truth**

- How large is this potential error?

PREDICTION INTERVAL

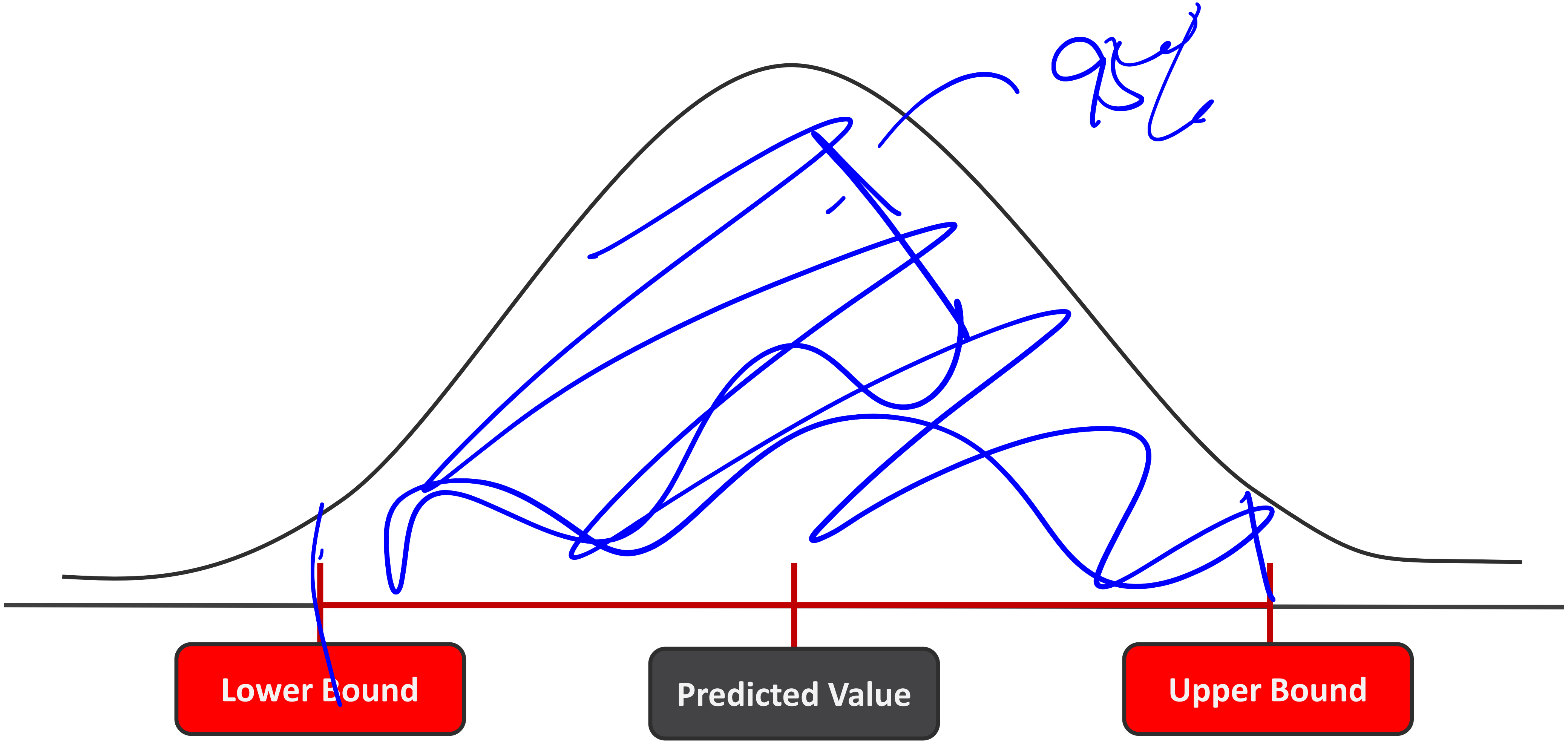
Predictive Assessments

Quantifying <u>potential</u> error

- The **prediction interval**: a range that we expect cover the truth with a given probability
- E.g. 95% prediction interval: we expect that the truth will be within this interval with 95% probability

Predictive Assessments

Quantifying potential error



Predictive Assessments

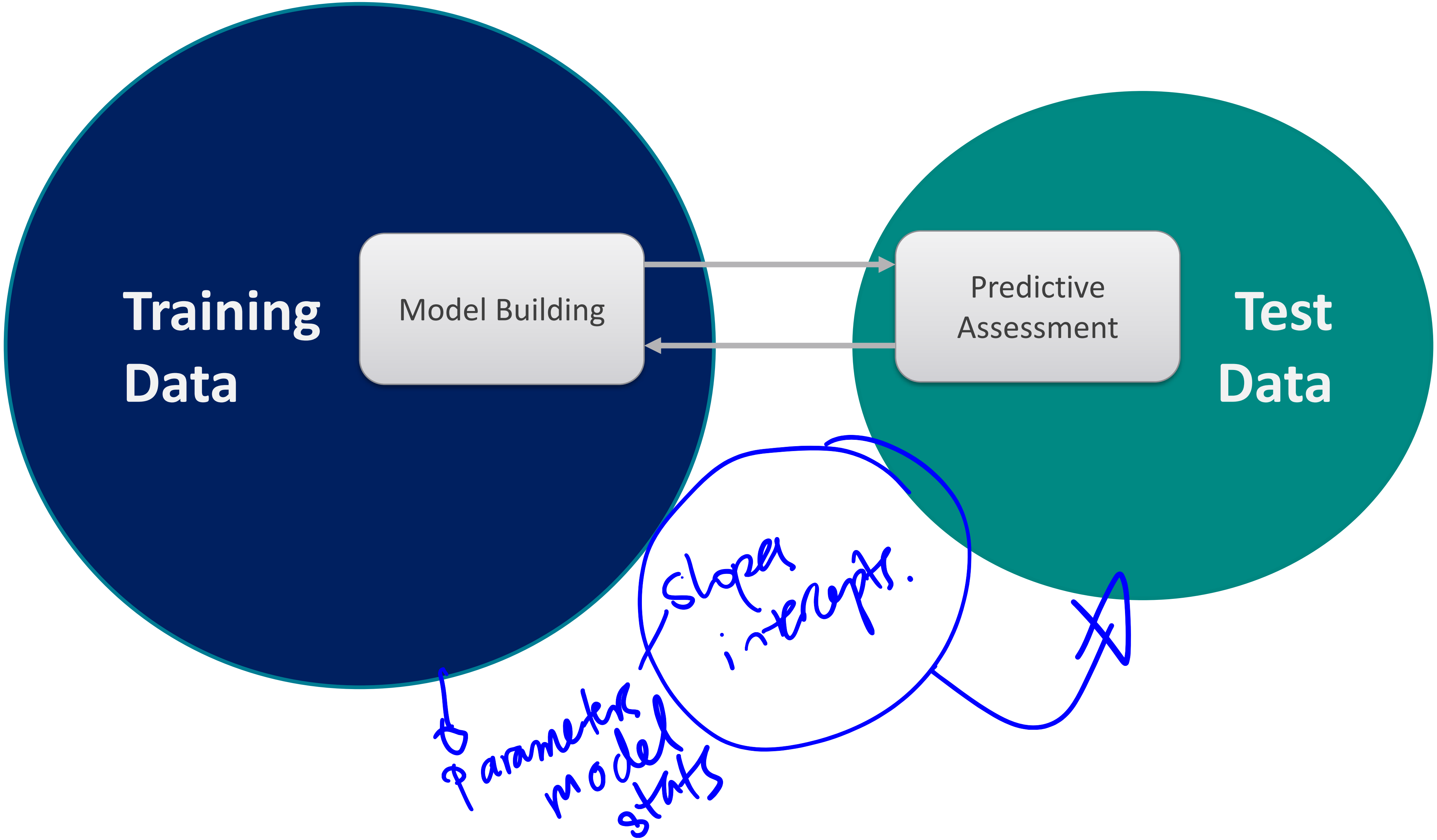
Quantifying potential error

- Small model error → small potential error
- The further away the input is from its centre → larger potential error
- Smaller sample size → larger potential error
- **Narrower** interval for a given probability level is **preferred**

Predictive Assessments

But how do we know if the model/method generate accurate prediction?

Predictive Assessments



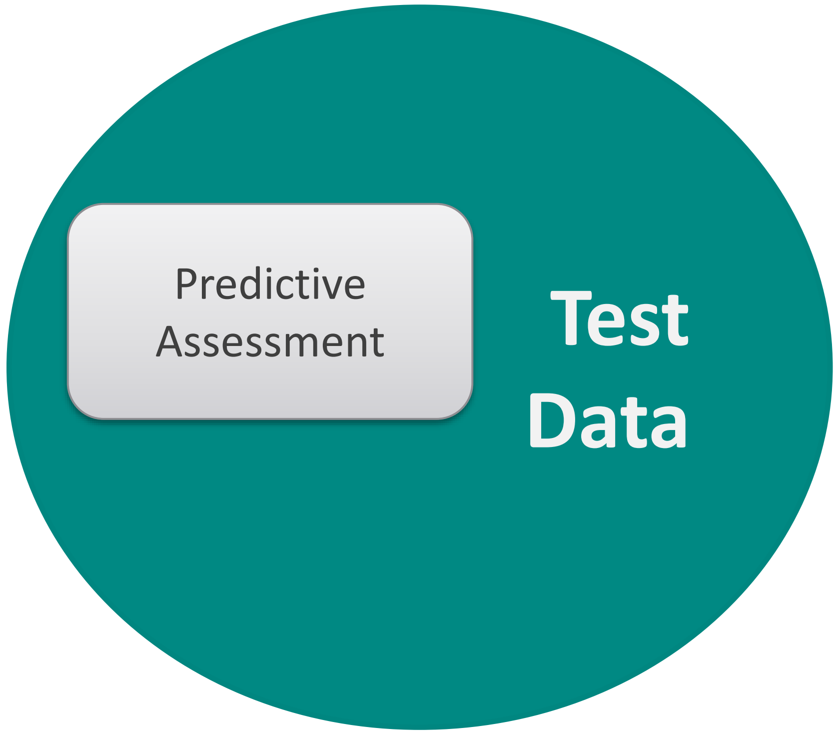
Predictive Assessments

- Split the data into training & test sets
- Both should have **similar characteristics** and **representative** of the population
- Training data – use to build models
- Typically larger in size than the test data

80/20

Predictive Assessments

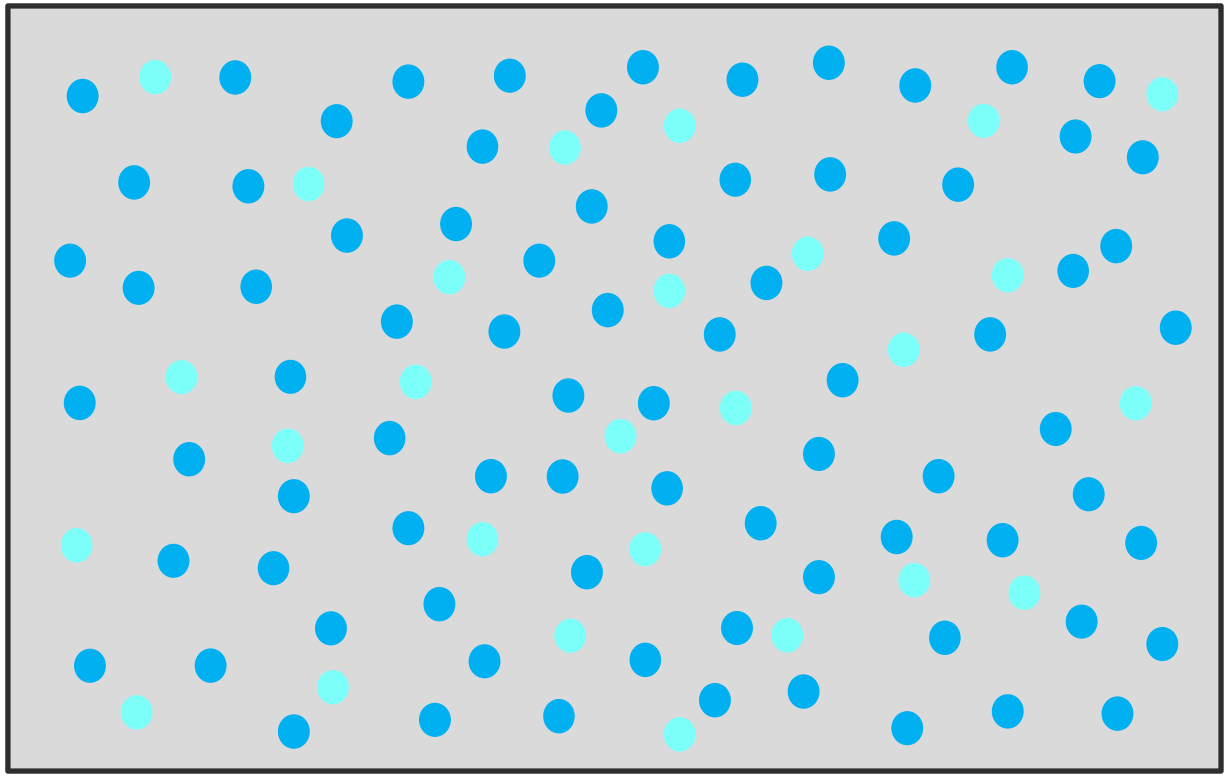
- Use the model to construct from the training data
- Predict the observations using test set characteristics
- Compare the predictions to the actual realizations
- **Error = Actual – Prediction**



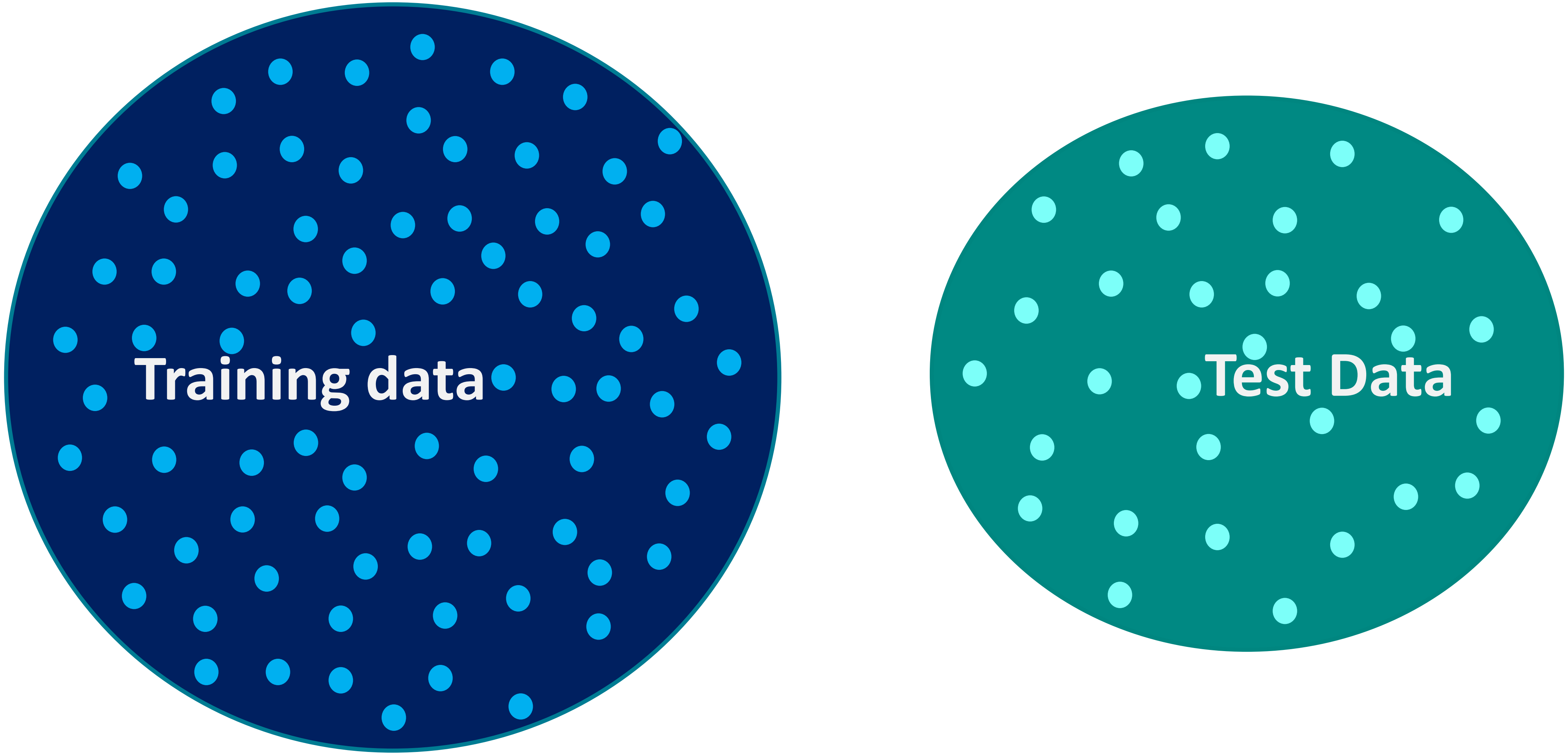
Predictive Assessments

Training vs test split

- For cross-sectional data, we need to make sure that the two samples are representative of population



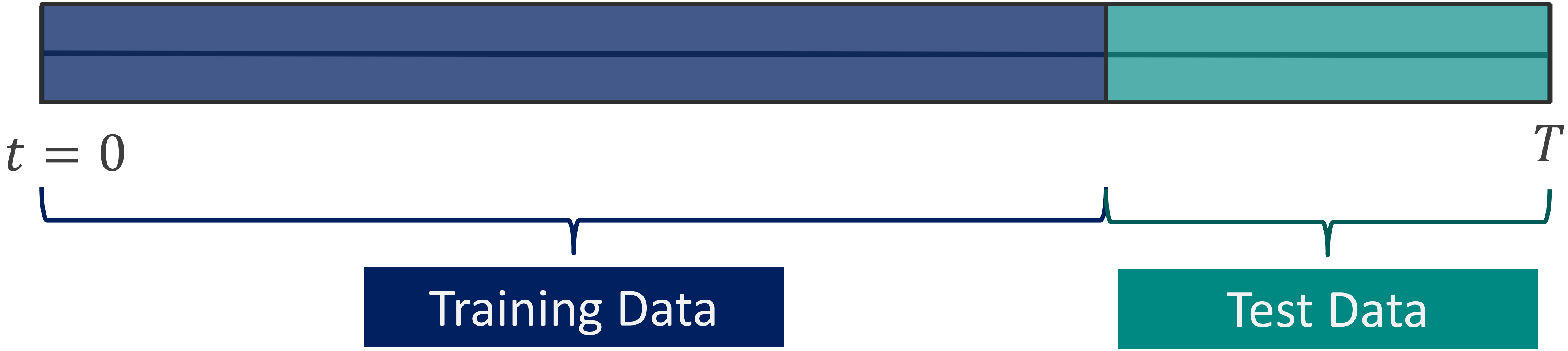
Predictive Assessments



Predictive Assessments

Training vs test split

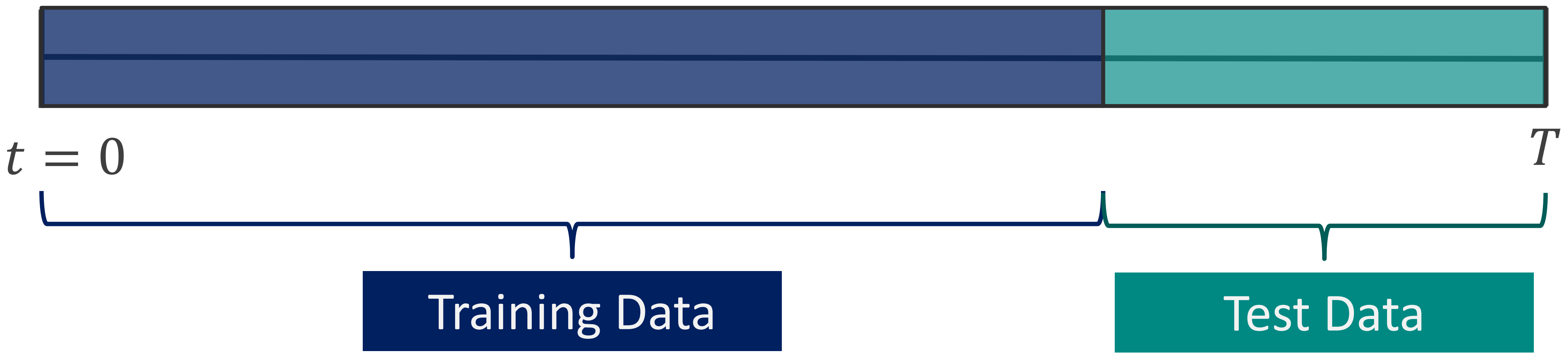
- For time series data, there is a natural sequence
- Data split by time



Predictive Assessments

Time series predictions

- **Long-horizon** prediction
- Short-horizon **real time** prediction



Predictive Assessments

Key takeaway:

The predictive assessment process should mimic the intended use as much as possible.

Predictive Assessments

Evaluating predictive accuracy

- Various statistics available to measure predictive accuracy
- Computed over the **test data**
- **E.g. Mean squared error**

$$MSE = average(error^2)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2$$

Where $e_i = Actual_i - Predicted_i$

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Root mean square error (RMSE)
- Mean absolute error (MAE)
- Mean absolute percentage error (MAPE)
- Mean absolute scaled error (MASE)

Smaller values are preferred!

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Root mean square error (RMSE)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(e_i)^2}$$

- In the same unit as the data
- Akin to the out-of-sample standard error of the regression
- **Commonly used** and reported metric
- Highly **influenced by extreme values** due to the power function

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_i|$$

- In the same unit as the data
- **Overcome the issue of extreme value** domination in the MSE and RMSE

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Mean absolute percentage error (MAPE)

$$MAPE = 100 \times \frac{1}{N} \sum_{i=1}^{N} \left| \frac{e_i}{Actual_i} \right|$$

- In percentage unit – unit insensitive
- Measures how large the predictive error is **relative** to actual value
- Con: Undefined if "Actual" is zero, and gets "explosive" when "Actual" is close to zero
- **Do not use if the data can the value of zero!**

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Mean absolute scaled error (MASE)

$$MASE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{e_i}{BE}\right|$$

where $BE = \frac{1}{N}\sum_{i=1}^{N}|Actual_i - Naive|$

- Measures how well a method predicts **relative to the naïve** prediction
- For cross sectional data, the naïve method is the sample mean

Predictive Assessments

Commonly reported measures of predictive accuracy:

- Mean absolute scaled error (MASE)

$$MASE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{e_i}{BE}\right|$$

- Benchmark value for MASE is 1.
- **MASE = 1:** your method is doing as good as the naïve
- **MASE > 1:** your method is doing worse than the naïve
- **MASE < 1:** your method is doing better than the naïve ← **PREFERRED!**

Predictive Assessments

Evaluating predictive accuracy

- Note that these are **statistical** metrics
- That is, they are simply measure of **distances** (or relative distances)
- In many cases, there will be **conflicts** across these measures
- The impact of prediction errors on the **business** may not be captured accurately
- Consider defining **user-specific loss** functions of prediction errors

Predictive Assessments

Evaluating predictive accuracy

- Example: predicting demand impacts has certain implications on inventory management.
- Would overpredicting have the same consequence as underpredicting demand?

Costs

Overprediction
- handling / storage
- credits

Larger consequence

Under

Sales cost / loss of profit

Customer exp / goodwill.

Predictive Assessments

Evaluating predictive accuracy

- Example: predicting real estate prices.
- What would be the consequence of errors for a banker using the predicted price to assess loan collateral?
- What would be the consequence of errors for a real estate agent using the predicted price to propose an advertise price?

Predictive Assessments

Key takeaway:

Ultimately, we pick methods that minimizes collective error/user-specific loss over the test data

Predicting with Regression

- The **multiple linear regression – how do we predict?**

$$Y = c + b_1X_1 + b_2X_2 + \cdots + b_kX_k + error$$

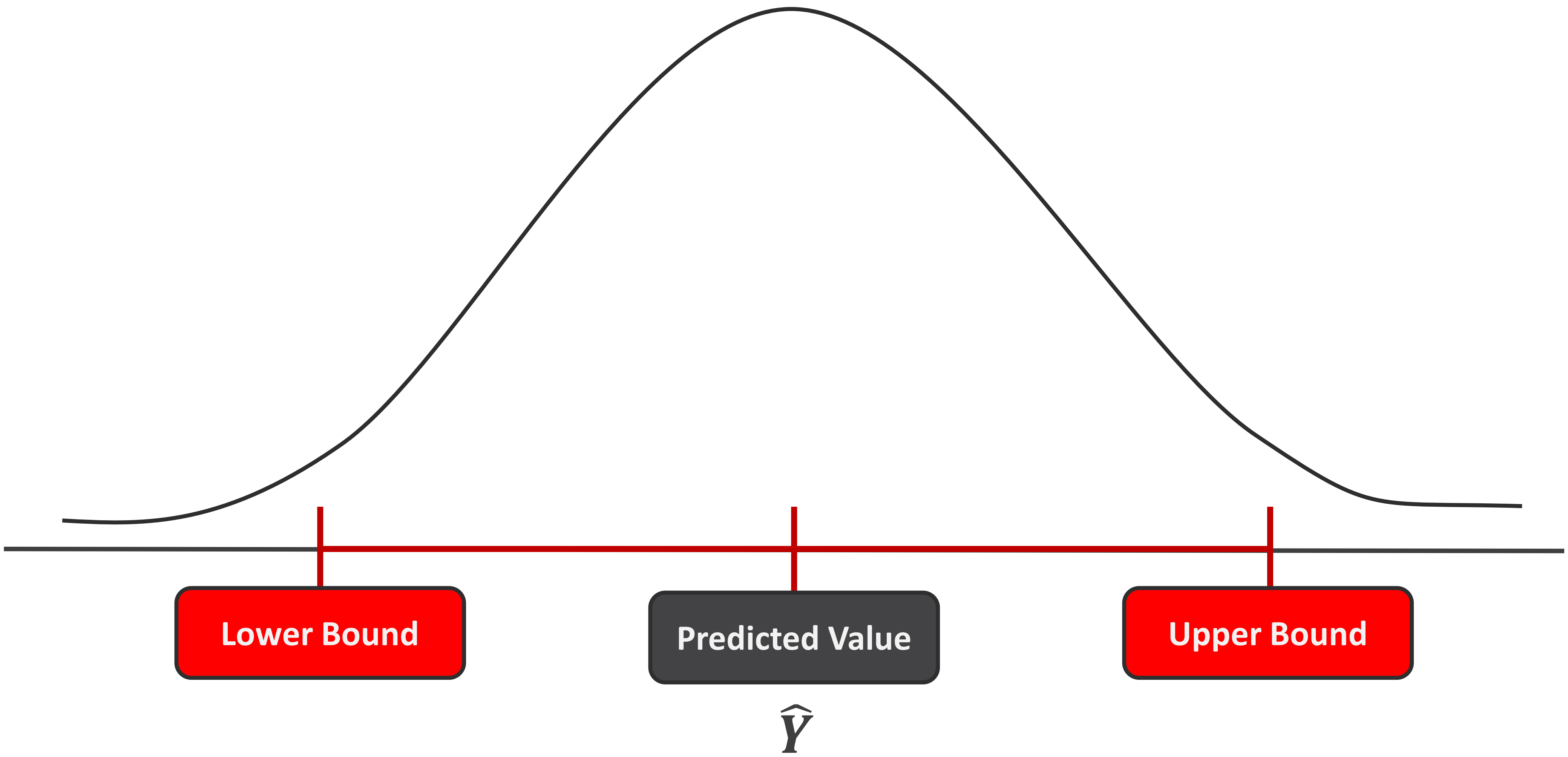
- **Form an expectation!**

$$\hat{Y} = E(Y|X_1, X_2, \ldots, X_k) = c + b_1X_1 + b_2X_2 + \cdots + b_kX_k$$

- Because the error is always present, $actual \neq prediction$

Predicting with Regression

Quantifying potential error



Predicting with Regression

- The **multiple linear regression – the prediction**

$$\hat{Y} = E(Y|X_1, X_2, \ldots, X_k) = c + b_1X_1 + b_2X_2 + \cdots + b_kX_k$$

- **Quantifying the uncertainty** – the 95% prediction interval

$$LowerBound = \hat{Y} - 1.96(Prediction\ Error)$$

$$UpperBound = \hat{Y} + 1.96(Prediction\ Error)$$

- The model indicates that there is a 95% **probability** that the actual value will be between the lower bound and the upper bound

Predictive Assessments Work Through

Regression example

- Goal: Construct a **predictive model** for property prices (Real Estate data)
- Let's compare
  - Multiple linear regression model
  - Stepwise regression
  - Nonlinear regression with quadratic and interactions
- **Real Estate Prices with Regression page**

Predictive Assessments Work Through

Regression example

- Goal: Construct a predictive model for property prices (Real Estate data)
- What do the statistical metrics say?

	RMSE	MAE	MAPE	MASE
Linear	296.337	185.768	13.885	0.592
Stepwise	295.628	186.304	13.940	0.593
Nonlinear	**280.542**	**175.747**	**13.387**	**0.560**

Green is best

Red is worst

Predictive Assessments Work Through

Regression example

- What if you are a banker? How do the models compare if we value a conservative prediction more than an overestimate? (as lenders!)
- →Give double the weight to errors from overestimation

	Banker
Linear	259.730
Stepwise	260.297
Nonlinear	**245.350**

Green is best

Red is worst

Predictive Assessments Work Through

Regression example

- What if you are a real estate agent?
  - Low: error is within 10% of actual price.
  - Medium: error is within between 10% and 30% of actual price.
  - High: error is greater than 30% of actual price.
- The medium level errors are penalized 5 times greater than the low level error.
- The high level errors are penalized 10 times greater.

Predictive Assessments Work Through

Regression example

- What if you are a real estate agent?
- Loss function a bit more complex…

	RE Agent
Linear	**75.437**
Stepwise	77.586
Nonlinear	80.461

Green is best

Red is worst

Predictive Assessments Work Through

Regression example

- Goal: Construct a predictive model for property prices (Real Estate data)
- Collating all statistics

	RMSE	MAE	MAPE	MASE	Banker	RE Agent
Linear	296.337	185.768	13.885	0.592	259.730	**75.437**
Stepwise	295.628	186.304	13.940	0.593	260.297	77.586
Nonlinear	**280.542**	**175.747**	**13.387**	**0.560**	**245.350**	80.461

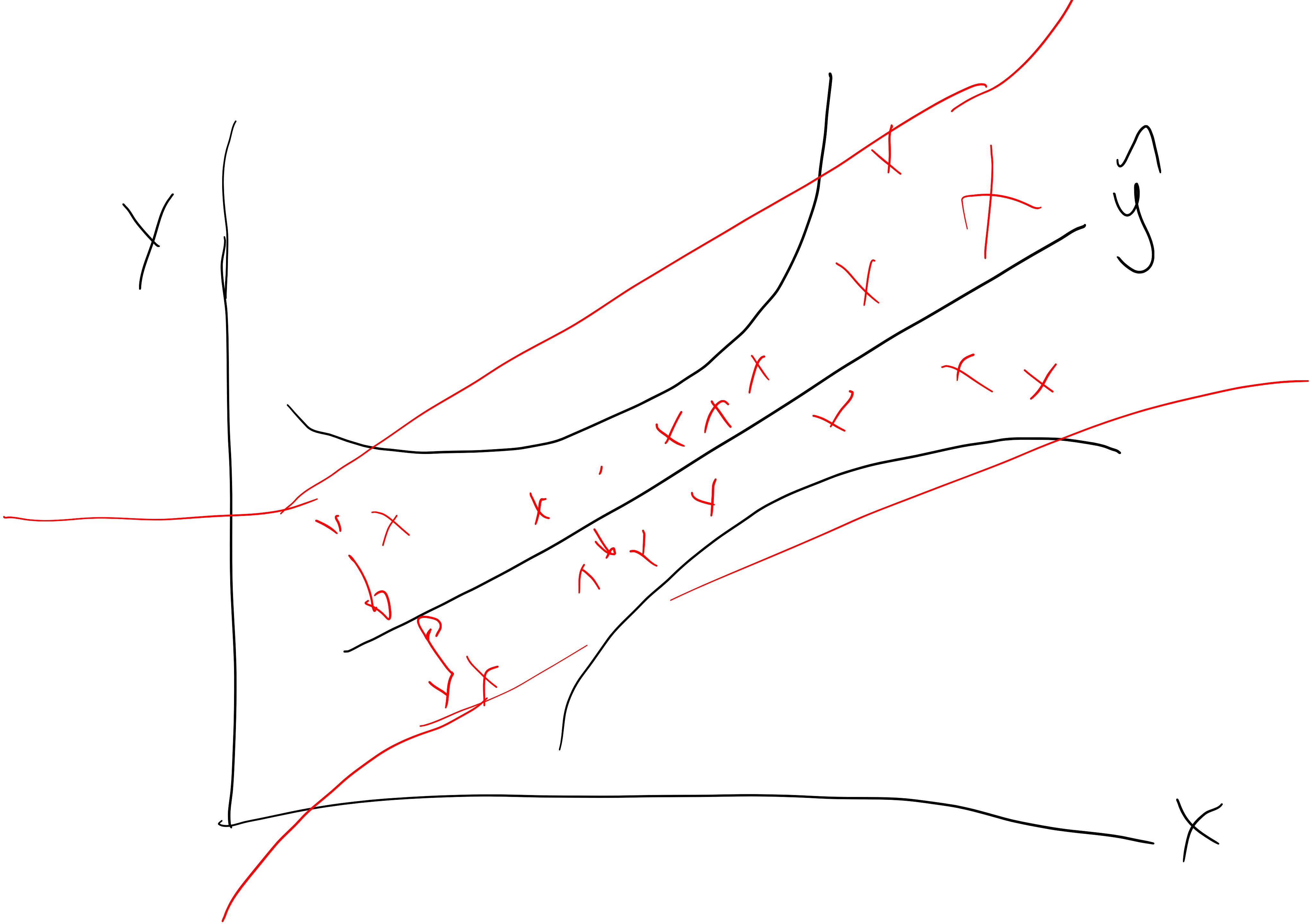
Green is best

Red is worst

Predictive Analytics Session 1

Key takeaway:

Predictive assessments are useful only when the analytics address the context of the predictive outcome.



Y
$\hat{y}$
X