



# Regularization Cross Validation

# Regularization – Cross Validation

- Cross validation is a more advanced set of methods for splitting data into training and testing sets.
- Cross Validation Relevant Reading:
  - Section 5.1 of ISLR

# Regularization – Cross Validation

- We understand the intuition behind performing a train test split, we want to fairly evaluate our model's performance on unseen data.
- Unfortunately this means we are not able to tune hyperparameters to the **entire** dataset.

# Regularization – Cross Validation

- Is there a way we can achieve the following:
  - Train on all the data
  - Evaluate on all the data
- While it sounds impossible, we can achieve this with cross validation!
- Let's have an overview of the concept...

# Regularization – Cross Validation

- Imagine our data set:

<b>X</b>			<b>y</b>
<b>Area m<sup>2</sup></b>	<b>Bedrooms</b>	<b>Bathrooms</b>	<b>Price</b>
200	3	2	\$500,000
190	2	1	\$450,000
230	3	3	\$650,000
180	1	1	\$400,000
210	2	2	\$550,000

# Regularization – Cross Validation

- Let's convert this data into colored blocks for cross-validation

X			y
Area m <sup>2</sup>	Bedrooms	Bathrooms	Price
200	3	2	\$500,000
190	2	1	\$450,000
230	3	3	\$650,000
180	1	1	\$400,000
210	2	2	\$550,000

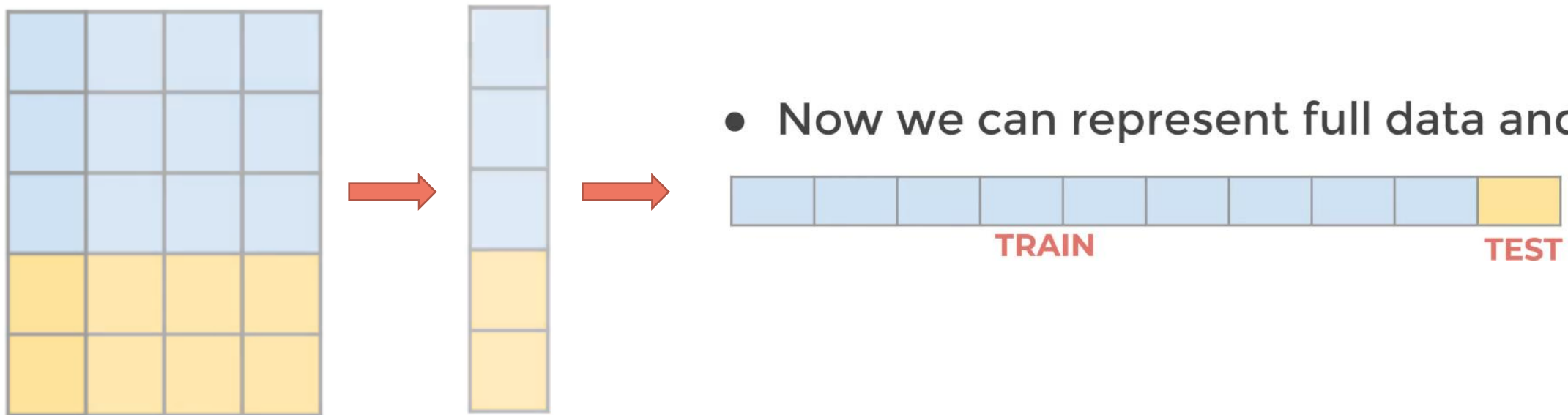
# Regularization – Cross Validation

- Color based off train vs. test set.

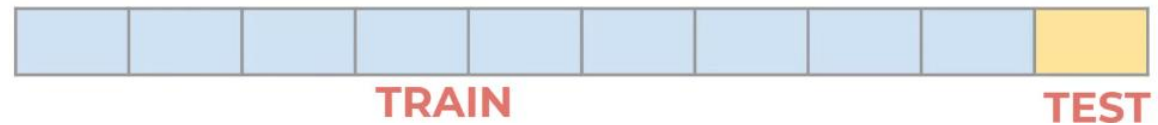
				<b>X</b>			<b>y</b>
				<b>x<sub>1</sub></b>	<b>x<sub>2</sub></b>	<b>x<sub>3</sub></b>	<b>y</b>
<b>TRAIN</b>		$x_1^1$	$x_1^1$	$x_1^1$	$x_1^1$	$x_1^1$	$y_1$
		$x_1^2$	$x_1^2$	$x_1^2$	$x_1^2$	$x_1^2$	$y_2$
		$x_1^3$	$x_1^3$	$x_1^3$	$x_1^3$	$x_1^3$	$y_3$
<b>TEST</b>		$x_1^4$	$x_1^4$	$x_1^4$	$x_1^4$	$x_1^4$	$y_4$
		$x_1^5$	$x_1^5$	$x_1^5$	$x_1^5$	$x_1^5$	$y_5$

# Regularization – Cross Validation

- Rotate and resize:



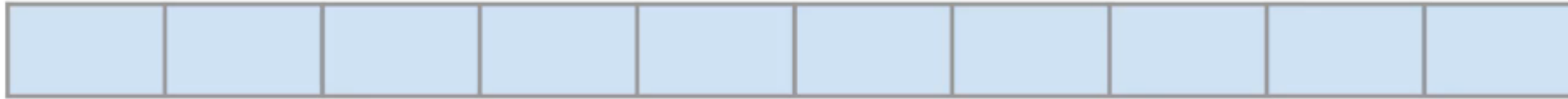
- Now we can represent full data and splits:



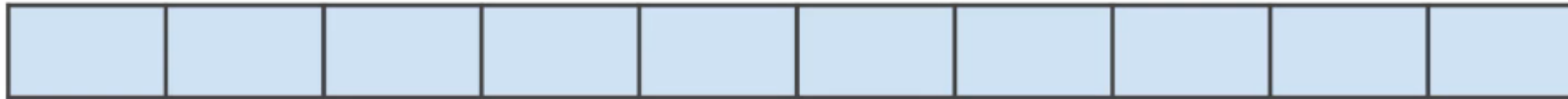


# Regularization – Cross Validation

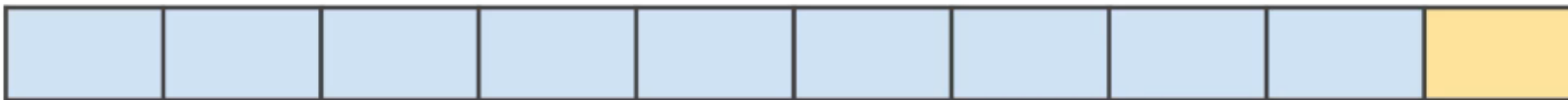
- How does cross validation work?



- Split data into  $K$  equal parts:

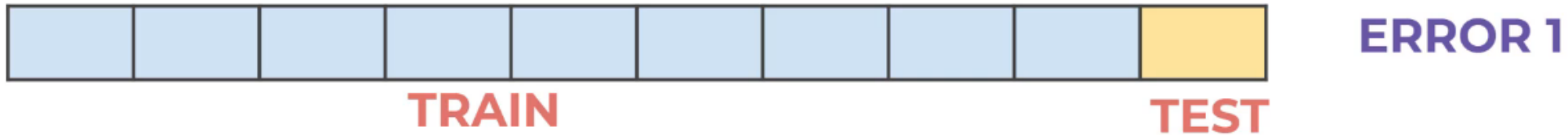


- $1/K$  left as test set

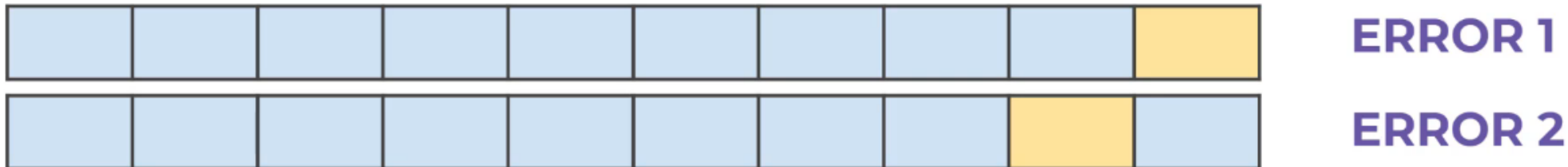


# Regularization – Cross Validation

- Train model and get error metric for split:

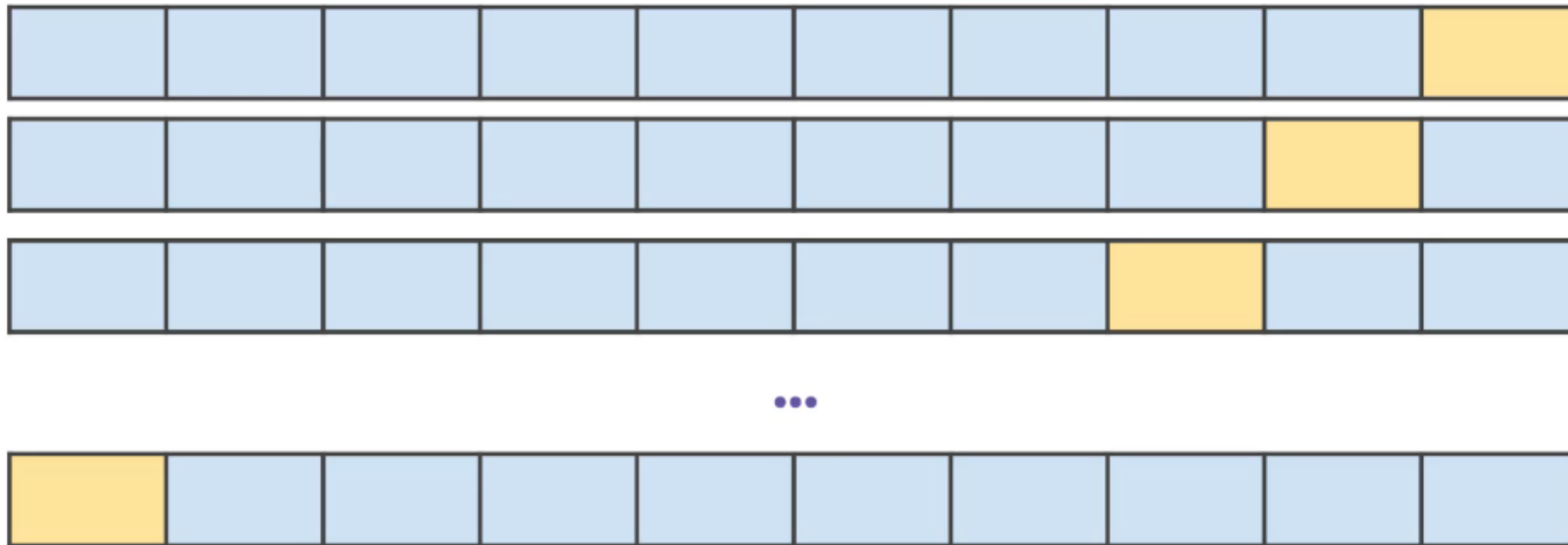


- Repeat for another 1/K split



# Regularization – Cross Validation

- Keep repeating for all possible splits



**ERROR 1**

**ERROR 2**

**ERROR 3**

...

**ERROR K**

**MEAN  
ERROR**

# Regularization – Cross Validation

- We were able to train on all data **and** evaluate on all data!
- We get a better sense of true performance across multiple potential splits.
- What is the cost of this?
  - We have to repeat computations  $K$  number of times!

# Regularization – Cross Validation

- This is known as K-fold cross-validation.
- Common choice for K is 10 so each test set is 10% of your total data.
- Largest K possible would be K equal to the number of number of rows.
  - This is known as **leave one out cross validation**.
  - **Computationally expensive!**

# Regularization – Cross Validation

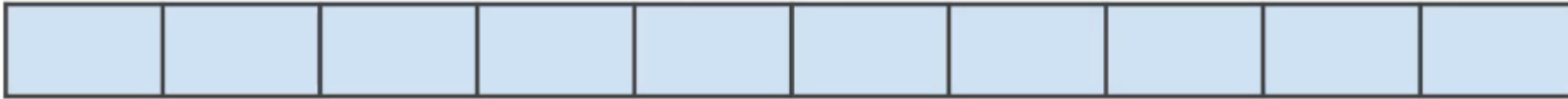
- One consideration to note with K-fold cross validation and a standard train test split is fairly tuning hyperparameters.
- If we tune hyperparameters to test data performance, are we ever fairly getting performance metrics?

# Regularization – Cross Validation

- How can we understand how the model behaves for data that it has not seen **and** not been influenced by for hyperparameter tuning?
- For this we can use a **hold out** test set.
- Let's explore what this looks like...

# Regularization – Cross Validation- hold out Test Set

- Start with entire data set:



- Remove a hold out test set



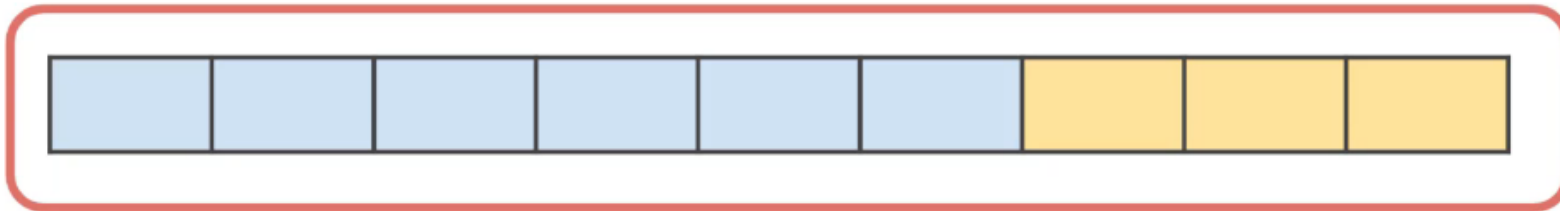


# Regularization – Cross Validation- hold out Test Set

- Perform “classic” train test split:

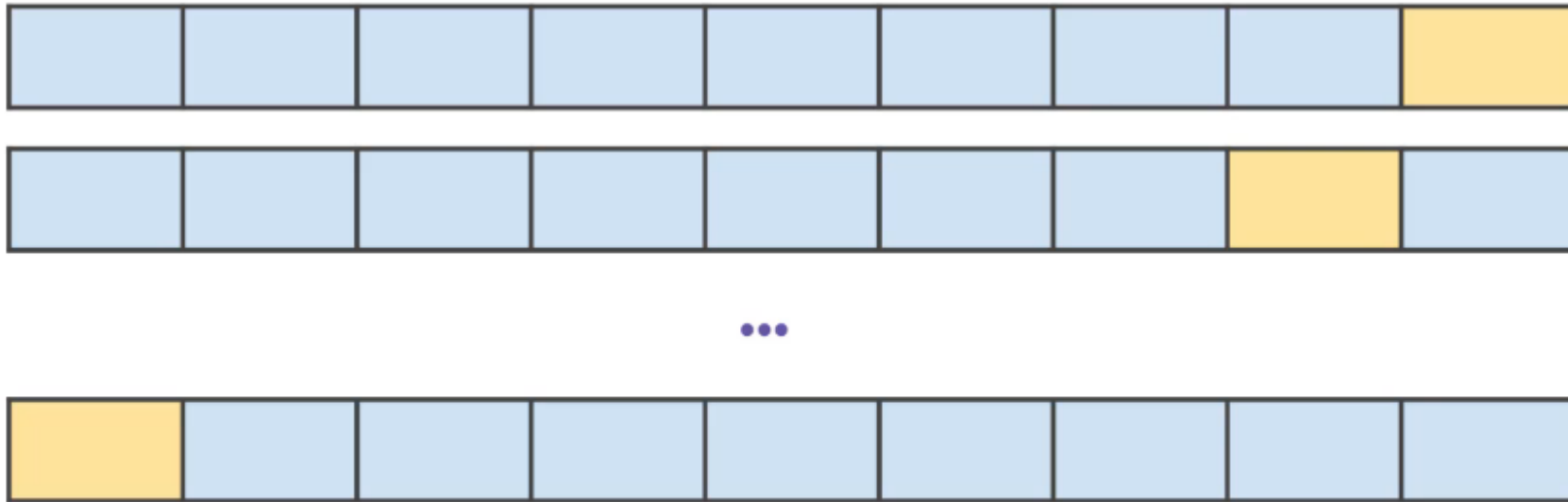


- Train and tune on this data:



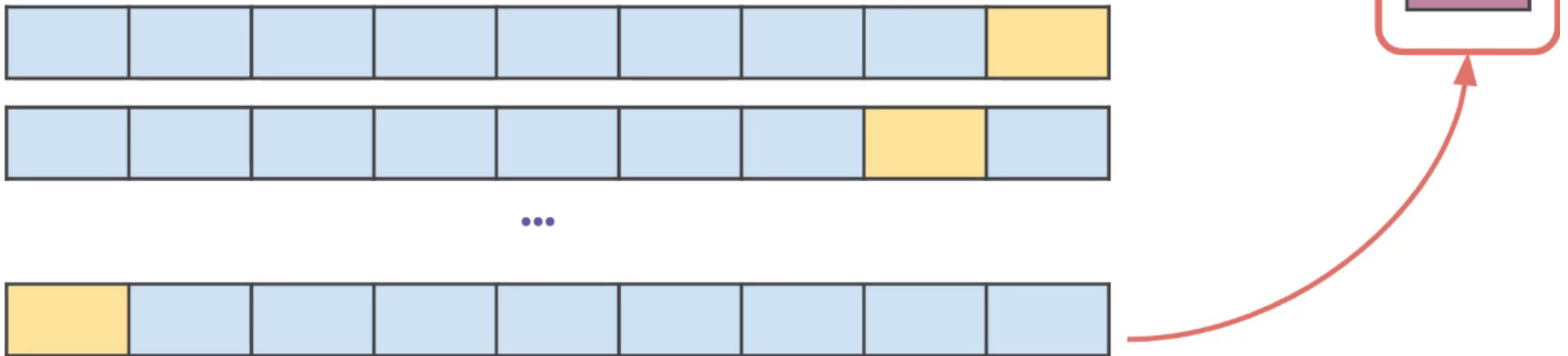
# Regularization – Cross Validation- hold out Test Set

- Or K-Fold cross validation



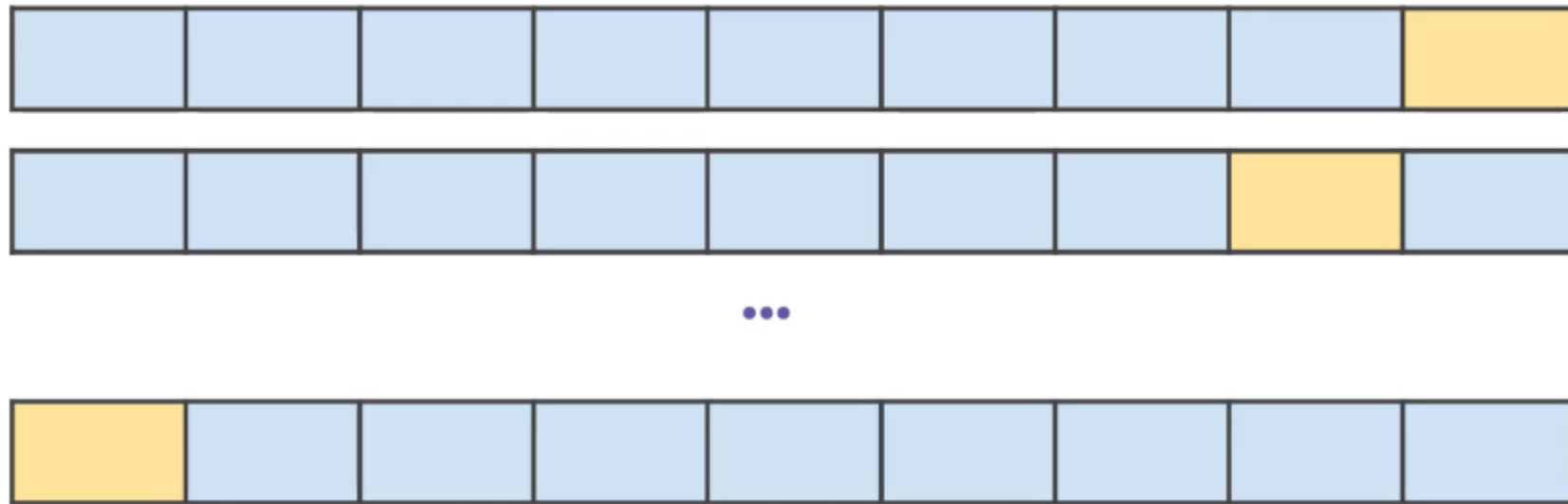
# Regularization – Cross Validation- hold out Test Set

- **After training and tuning perform final evaluation hold out test set.**



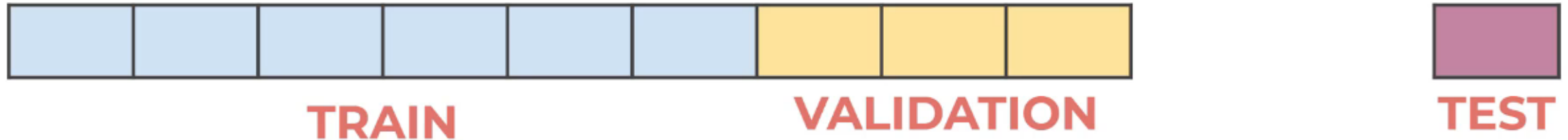
# Regularization – Cross Validation- hold out Test Set

- Can **not** tune after this **final** test evaluation!



# Regularization – Cross Validation- hold out Test Set

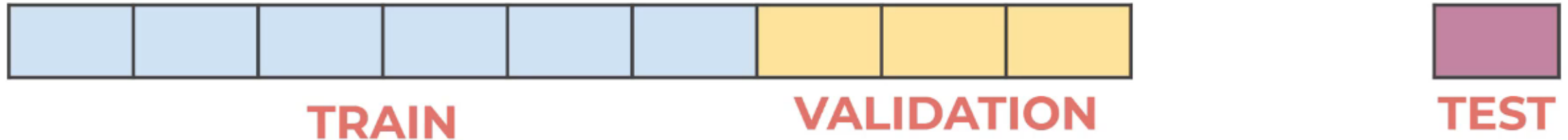
- Train | Validation | Test Split



- Allows us to get a true final performance metric to report.
- No editing model after this!

# Regularization – Cross Validation- hold out Test Set

- Train | Validation | Test Split



- Allows us to get a true final performance metric to report.
- No editing model after this!

# Regularization – Cross Validation- hold out Test Set

- All these approaches are valid, each situation is unique!
- Keep in mind:
  - Previous modeling work
  - Reporting requirements
  - Fairness of evaluation
  - Context of data and model