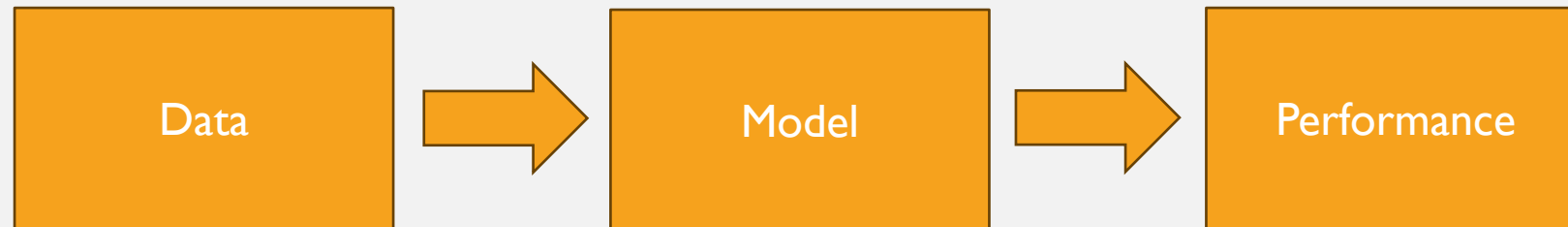


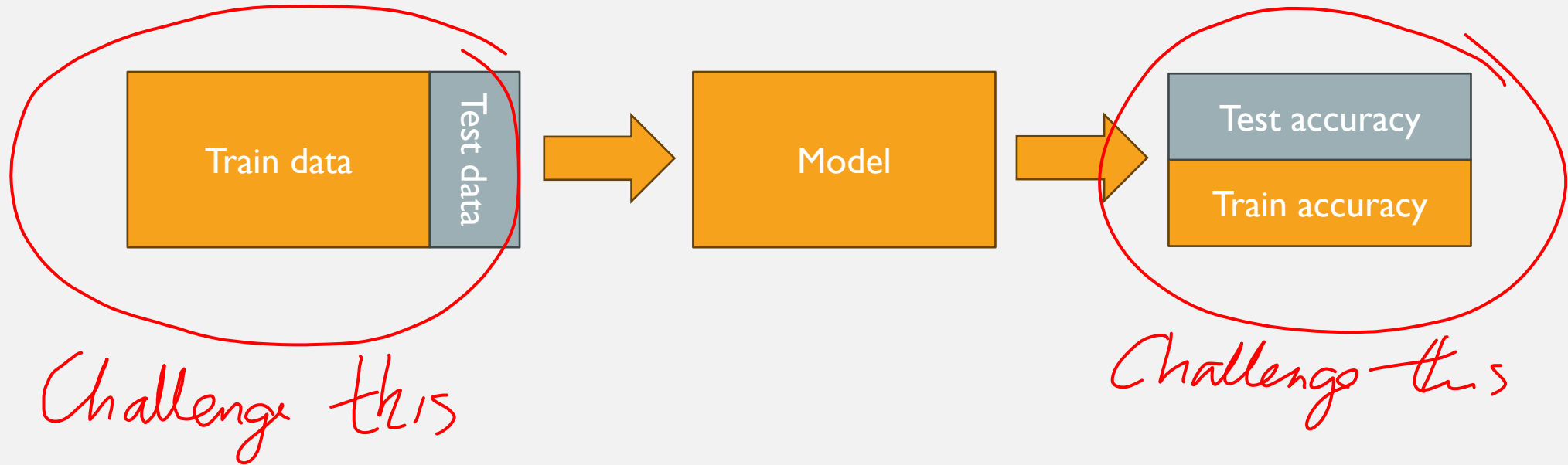
# VALIDATION METHODS & PERFORMANCE METRICS

Lecture 6  
MALI, 2024

# THE BIG PICTURE

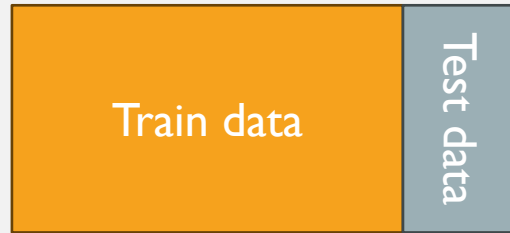


# THE BIG PICTURE



# VALIDATION METHODS

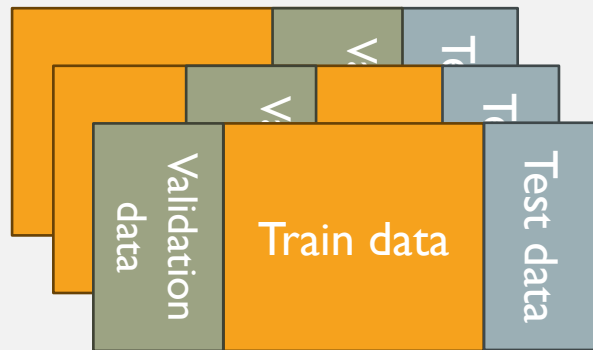
# VALIDATION METHODS



Train-test methodology



Train-val-test methodology



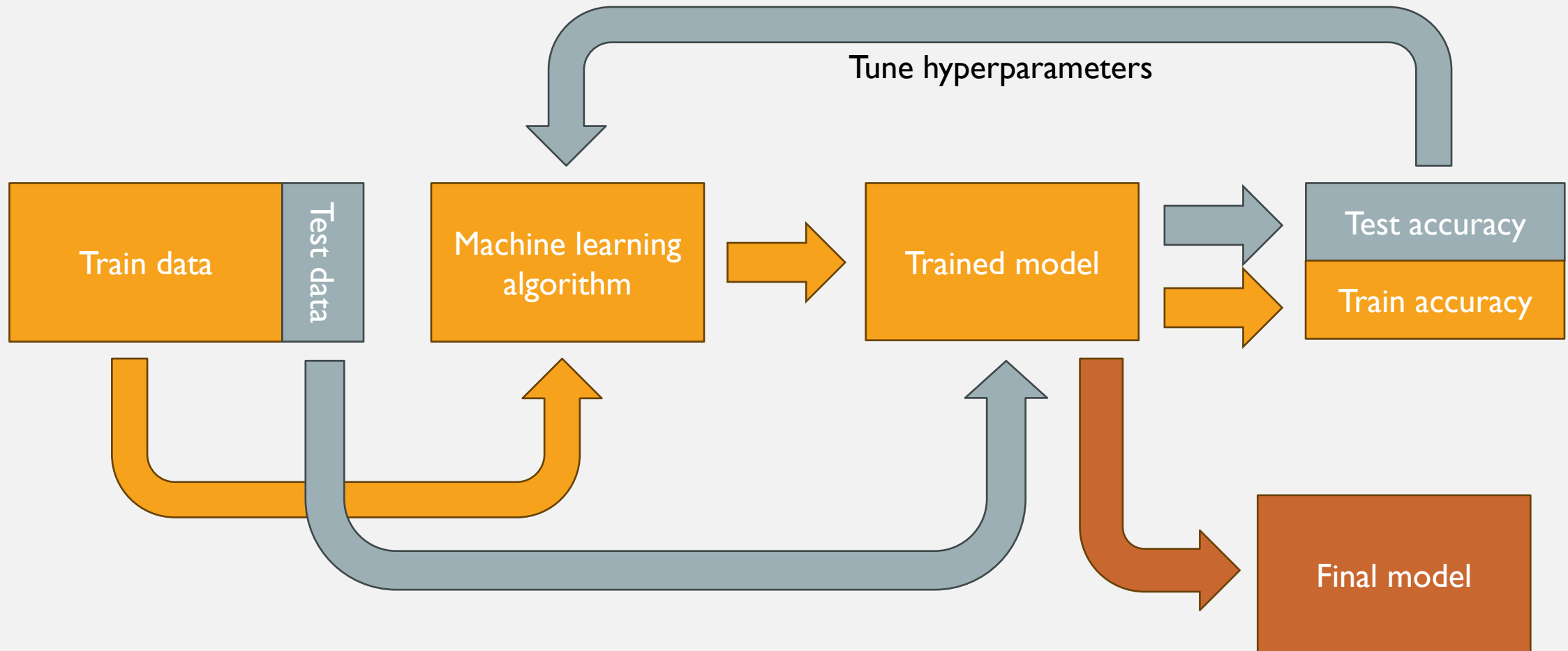
Cross-validation methodology



Leave-1-out cross validation methodology

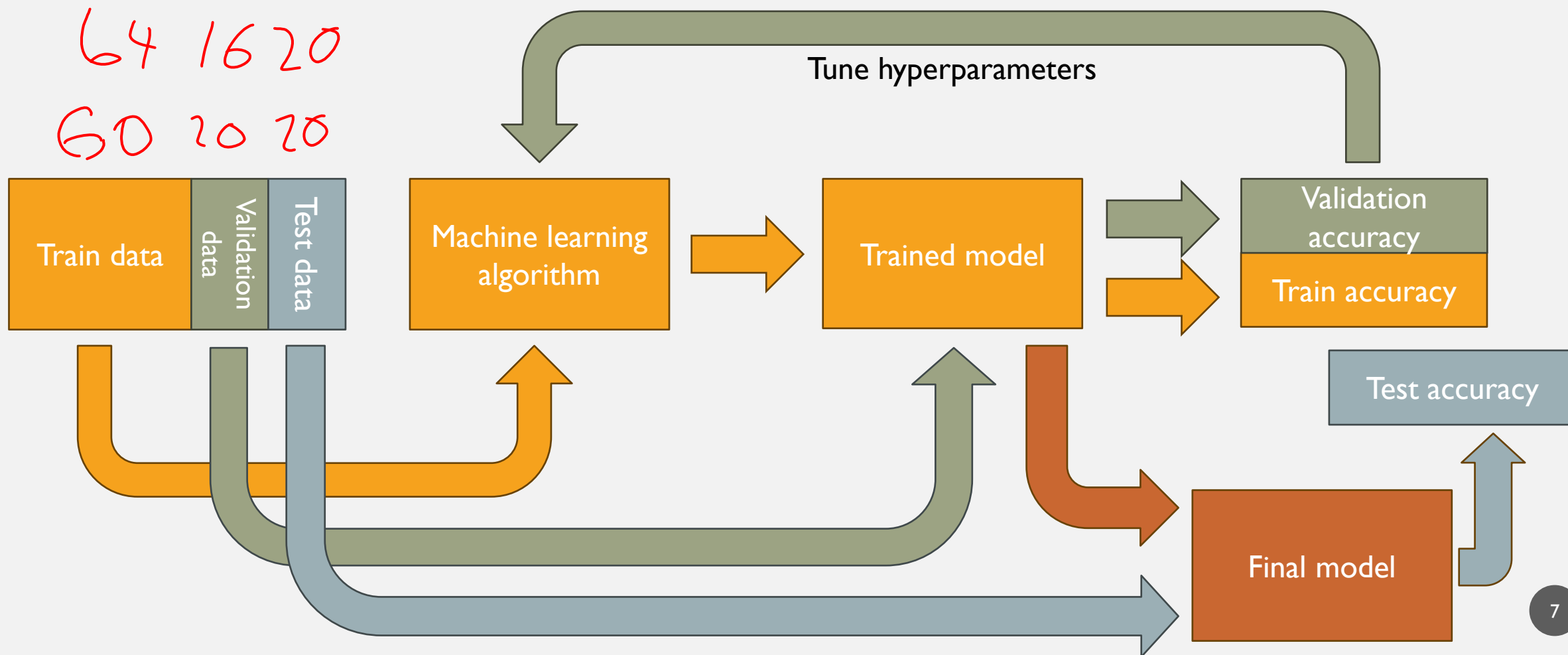
# TRAIN-TEST METHODOLOGY

*Model indirectly sees test data*

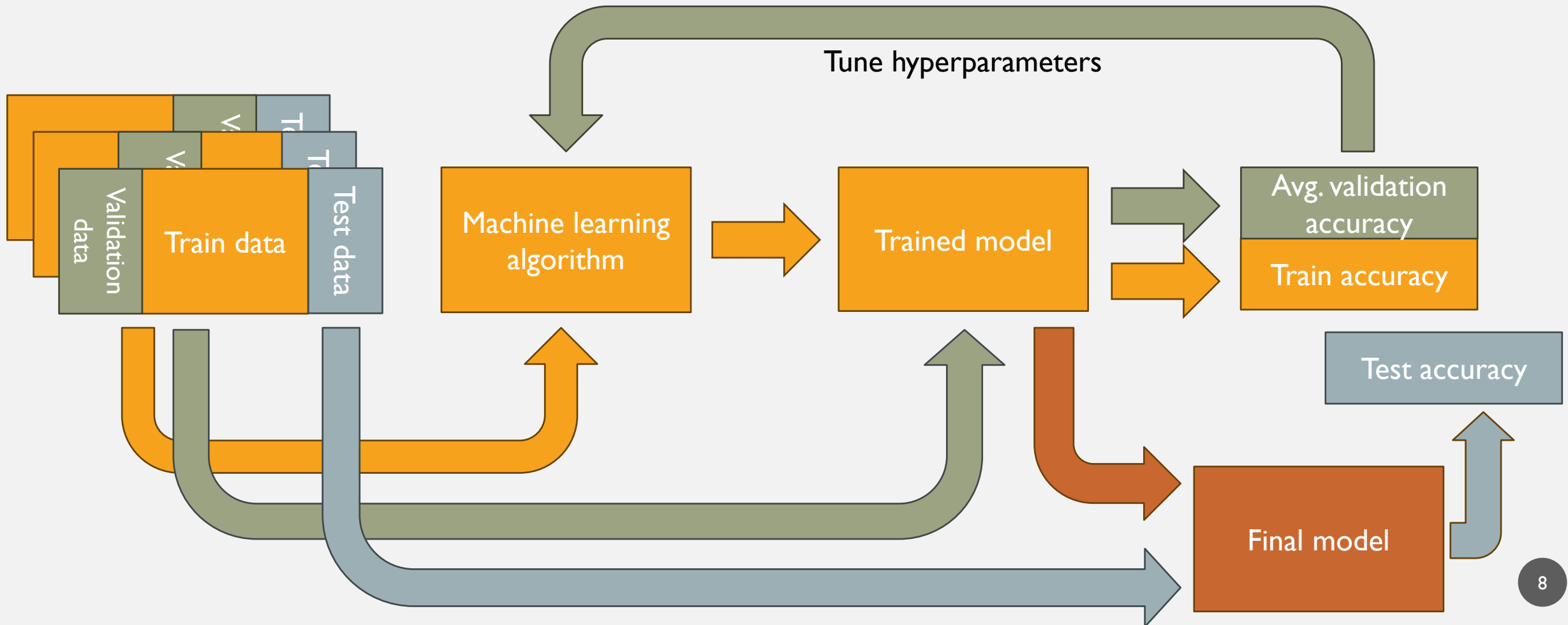


# TRAIN-VAL-TEST METHODOLOGY

Algorithm  
does not see  
test data

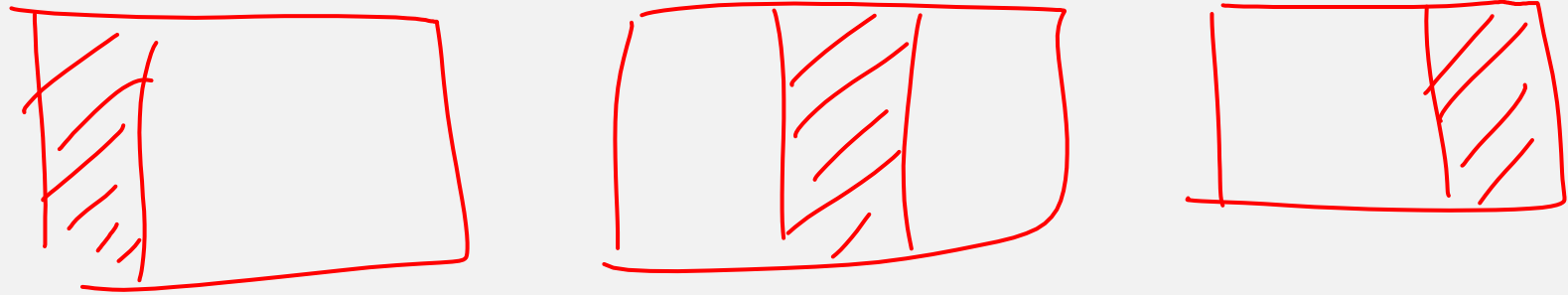


# CROSS-VALIDATION METHODOLOGY





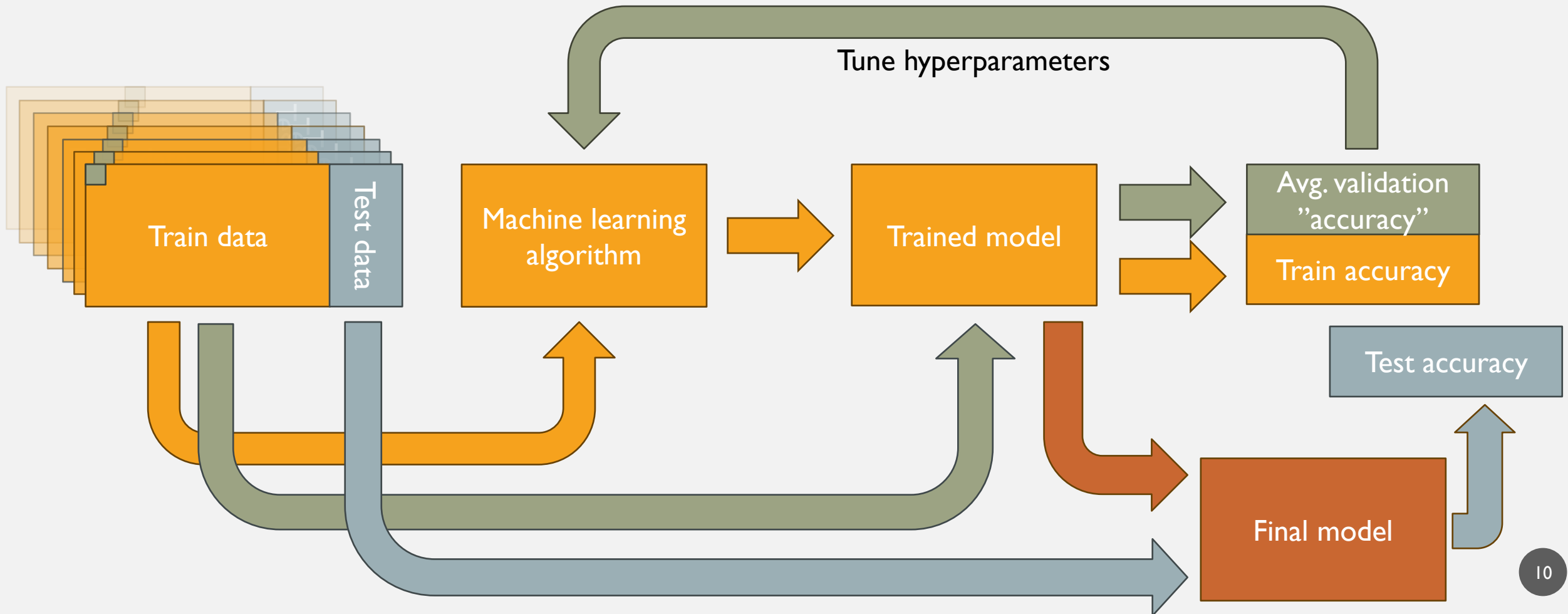
## CROSS-VALIDATION METHODOLOGY



- \* Split data into folds (here 3, could be 5, 10)
- \* Train on larger set, validate on smaller
- \* Accuracy = average all models

# LEAVE-1-OUT CROSS-VALIDATION METHODOLOGY

Special case  
of CV with  
folds of size  
1



## CODE EXAMPLE



*Jupyter Notebook* **Validation methods**

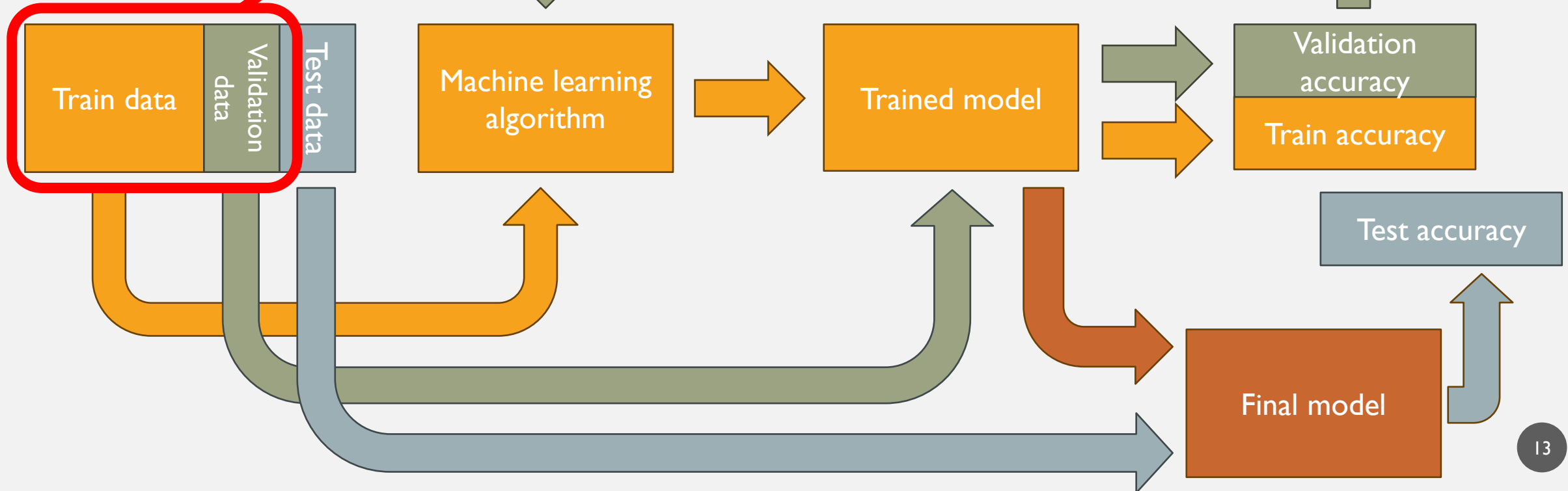
## A NOTE ON PREPROCESSING

- Deal with outliers
- Deal with missing values
- Normalize/scale data
- One-hot encoding
- Representing text data
- ...

but when should  
you do this?

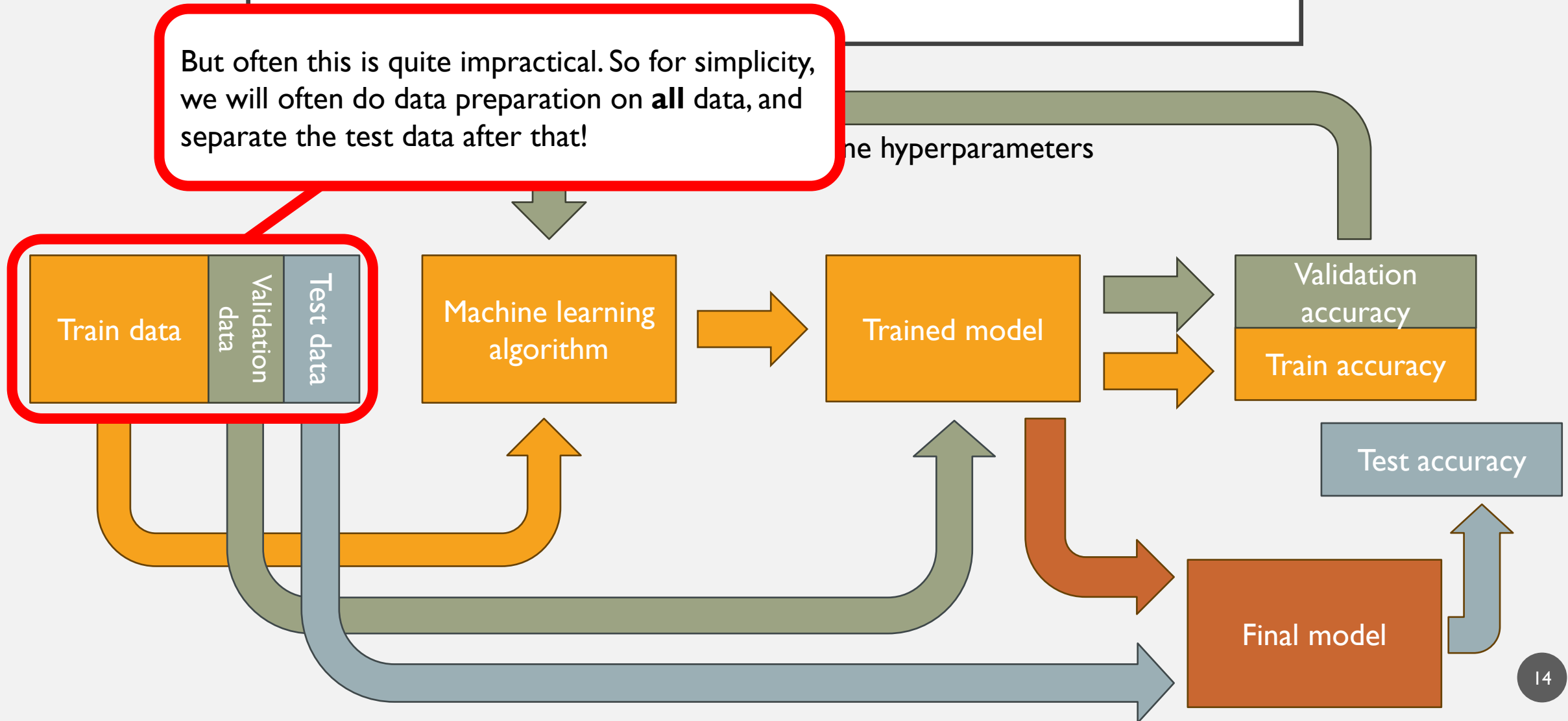
# A NOTE ON PREPROCESSING

Ideally you should isolate your testing data **before** you do anything else! That means only doing data cleaning and feature engineering on training and validation data.



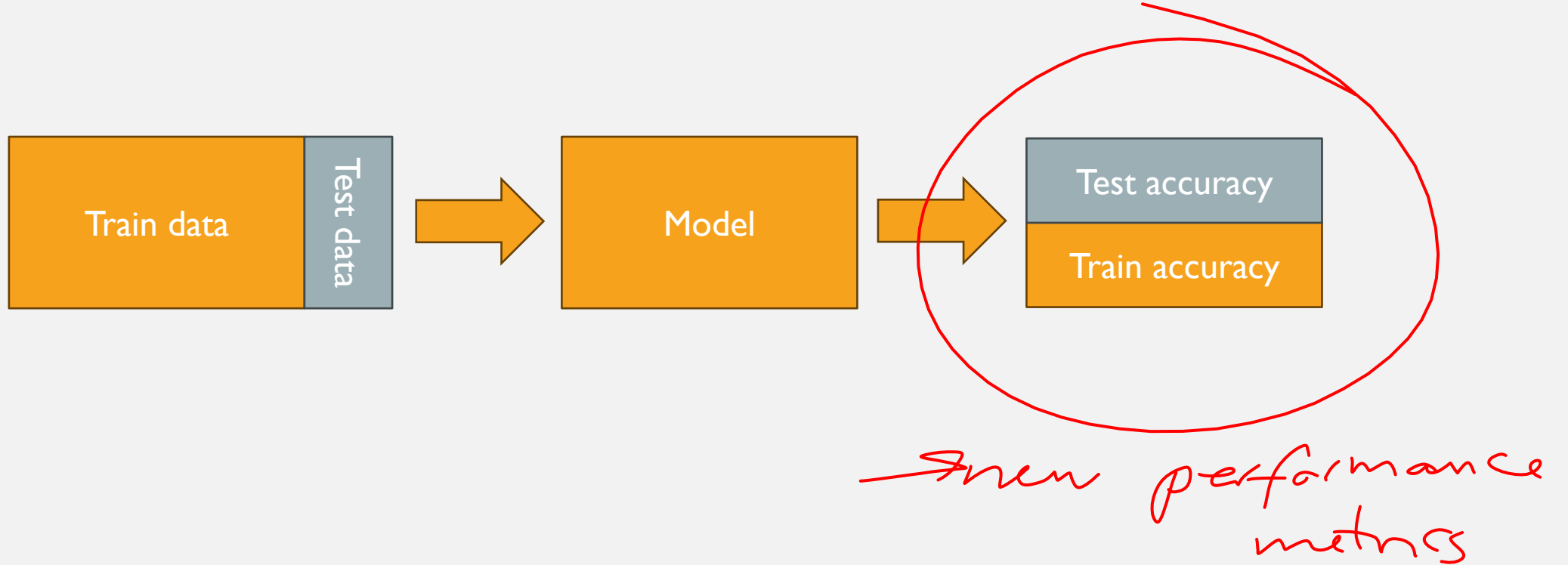
# A NOTE ON PREPROCESSING

But often this is quite impractical. So for simplicity, we will often do data preparation on **all** data, and separate the test data after that!



# PERFORMANCE METRICS

# THE BIG PICTURE





## TYPES OF ERRORS

predict  
orangutan



"This is an orangutan"

is not orangutan



"This is an orangutan"

predict  
not orangutan







"This is not an orangutan"



"This is not an orangutan"

# TYPES OF ERRORS

		true class	
		positive	negative
predicted class	positive	 <p>TRUE POSITIVE</p> <p>"This is an orangutan"</p>	 <p>FALSE POSITIVE</p> <p>"This is an orangutan"</p>
	negative	 <p>FALSE NEGATIVE</p> <p>"This is not an orangutan"</p>	 <p>TRUE NEGATIVE</p> <p>"This is not an orangutan"</p>

# TYPES OF ERRORS



"orangutan"



"not orangutan"



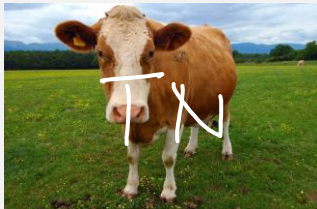
"orangutan"



"not orangutan"



"orangutan"



"not orangutan"



"orangutan"



"orangutan"



"orangutan"



"not orangutan"



"not orangutan"



"orangutan"

		true class	
		positive	negative
predicted class	positive	TRUE POSITIVE	FALSE POSITIVE
	negative	FALSE NEGATIVE	TRUE NEGATIVE



# TYPES OF ERRORS



"orangutan"



"not orangutan"



"orangutan"



"not orangutan"



"orangutan"



"not orangutan"



"orangutan"



"orangutan"



"orangutan"



"not orangutan"



"not orangutan"



"orangutan"

confusion matrix

		true class	
		positive	negative
predicted class	positive	TP = 5	FP = 2
	negative	FN = 1	TN = 4

# ACCURACY

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$
$$= \frac{5 + 4}{5 + 4 + 2 + 1} = 0.75$$

"How often do we get the right answer?"

predicted class  
negative positive

true class	
positive	negative
TP = 5	FP = 2
FN = 1	TN = 4

# WHY ACCURACY IS NOT GOOD ENOUGH

A model to predict whether or not someone is a terrorist:

*Everyone is **not** a terrorist.*

$$\text{accuracy} = \frac{0 + 9999}{0 + 9999 + 0 + 1} = 0.9999$$

but the model is useless  
particularly bad for skewed dataset

		true class	
		positive	negative
predicted class	positive	TP = 0	FP = 0
	negative	FN = 1	TN = 9999

## PERFORMANCE METRICS

- $\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{\text{correct predictions}}{\text{all predictions}}$

- $\text{precision} = \frac{TP}{TP+FP} = \frac{\text{correct positive predictions}}{\text{all positive predictions}}$

"how often is a positive answer correct?"

- $\text{recall} = \frac{TP}{TP+FN} = \frac{\text{correct positive predictions}}{\text{all positive instances}}$

"how often is a positive instance correctly identified?"

## USING RECALL INSTEAD

A model to predict whether or not someone is a terrorist:

*Everyone is **not** a terrorist.*

$$\text{recall} = \frac{TP}{TP + FN} = \frac{0}{0 + 1} = 0$$

*terrible model  
with accuracy = 99,99%*

predicted class  
positive  
negative

true class	
positive	negative
TP = 0	FP = 0
FN = 1	TN = 9999



## SOME EXAMPLES

- Determine whether someone is a terrorist
  - *avoid false negatives – use recall!*
- Determine whether you have COVID-19 during the pandemic
  - *avoid false negatives – use recall!*
- Determine whether a video is suitable for children to watch
  - *avoid false positives – use precision!*
- Determine whether someone should be sentenced to life in prison
  - *"Innocent until proven guilty" means avoid false positives – use precision!*

To optimize hyperparameters on a particular metric:

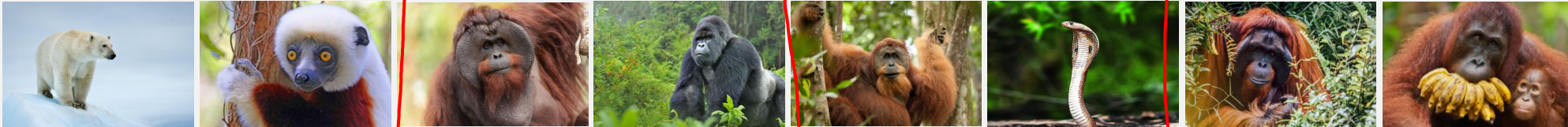
```
GridSearchCV(clf, parameters, scoring="recall")
```

```
GridSearchCV(clf, parameters, scoring="precision")
```

# THE PRECISION/RECALL TRADE-OFF

High recall usually means low precision – and vice versa

decision thresholds →



propability of  
orangutan

Precision  $\frac{4}{4+2} = 0.67$

$\frac{3}{3+1} = 0.75$

$\frac{2}{2+0} = 1.0$

Recall  $\frac{4}{4+0} = 1.0$

$\frac{3}{3+1} = 0.75$

$\frac{2}{2+2} = 0.5$

precision =  $\frac{TP}{TP+FP}$

recall =  $\frac{TP}{TP+FN}$

# THE PRECISION/RECALL TRADE-OFF

High recall usually means low precision – and vice versa

$$\text{precision} = \frac{TP}{TP+FP}$$

high prec  
⇒ avoid FP

$$\text{recall} = \frac{TP}{TP+FN}$$

high recall  
⇒ avoid FN

$$F_1\text{-score} = \frac{TP}{TP + \frac{FP+FN}{2}}$$

try to avoid both

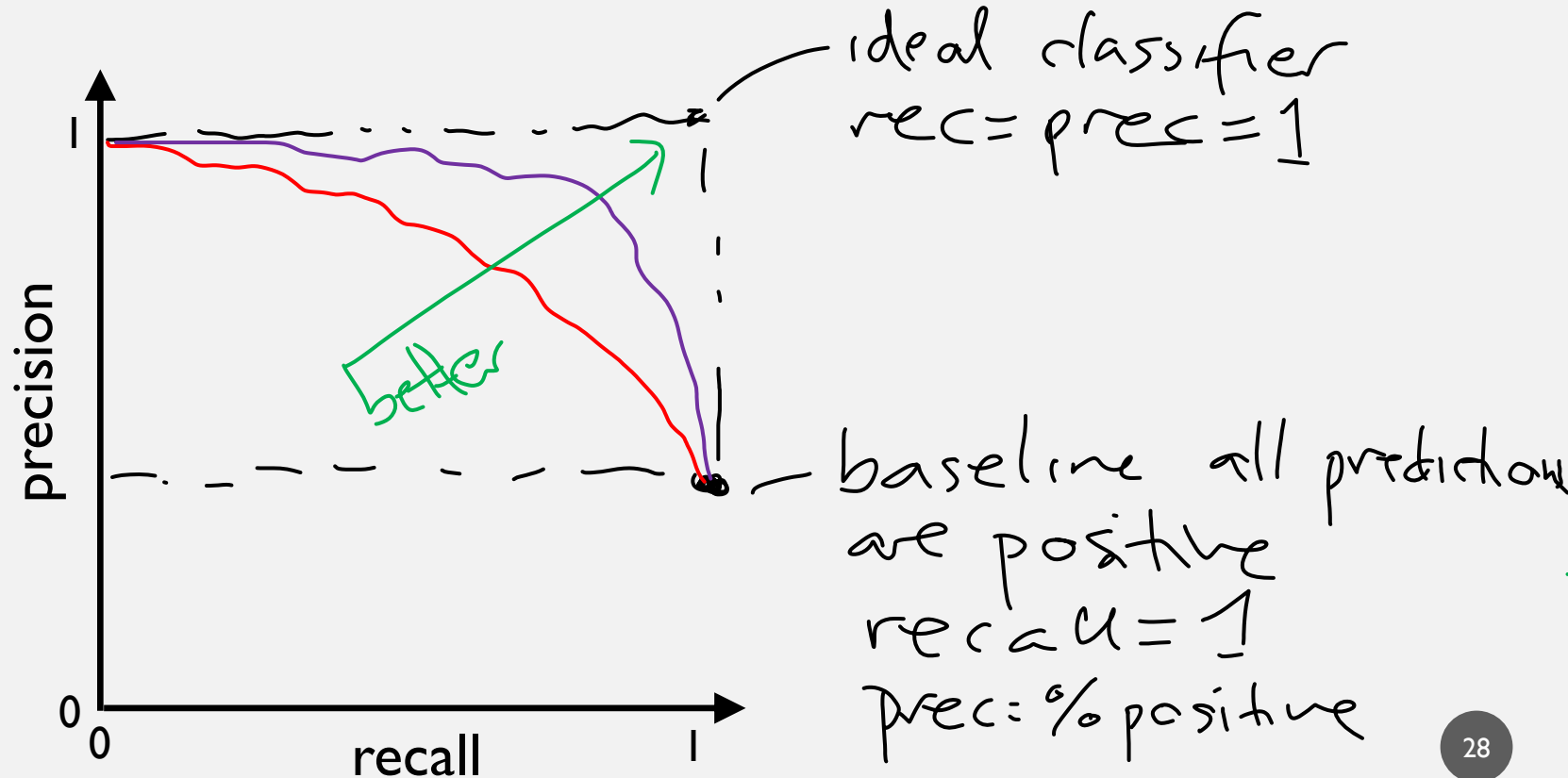
# THE PRECISION-RECALL CURVE

$$\text{precision} = \frac{TP}{TP+FP}$$

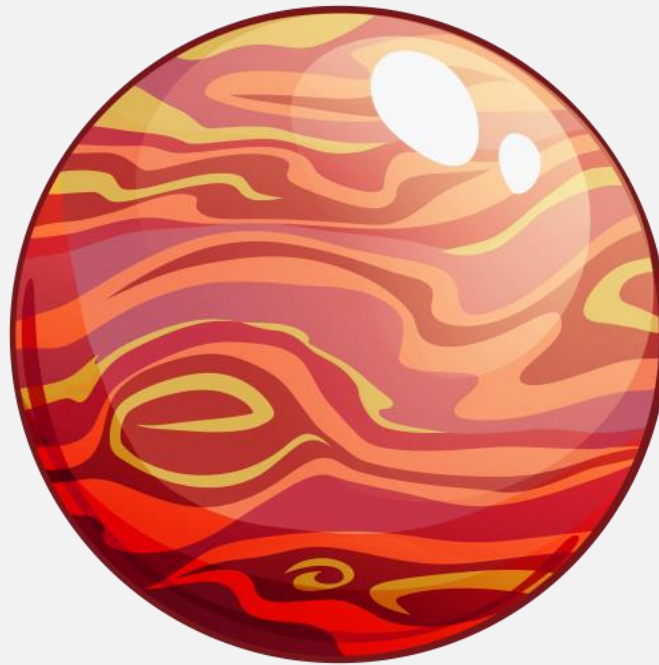
$$\text{recall} = \frac{TP}{TP+FN}$$

AUC = area  
under curve

max 1



## CODE EXAMPLE



*Jupyter Notebook* **Performance metrics**

# METRICS IN MULTICLASS PROBLEMS

Confusion matrix

True label	dog	snake	horse	elephant	bear	cat	orangutan	tiger	sloth
	544	26	2	0	24	0	18	31	5
	37	92	0	0	8	0	1	6	6
	3	3	69	34	0	7	9	25	0
	0	0	11	76	0	3	2	8	0
	34	13	0	0	111	0	0	1	41
	0	0	4	1	0	93	0	27	0
	17	3	6	1	0	0	80	18	0
	35	5	26	5	0	34	17	253	0
	5	14	0	0	22	0	1	0	158
Predicted label									

You can calculate all metrics for all classes, but

*the confusion matrix gives you all the information you need*

