# Classifier Evaluation

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# Why Evaluate?

You are here

Plan ➔ Acquire ➔ Prepare ➔ Explore ➔ Model ➔ Deliver

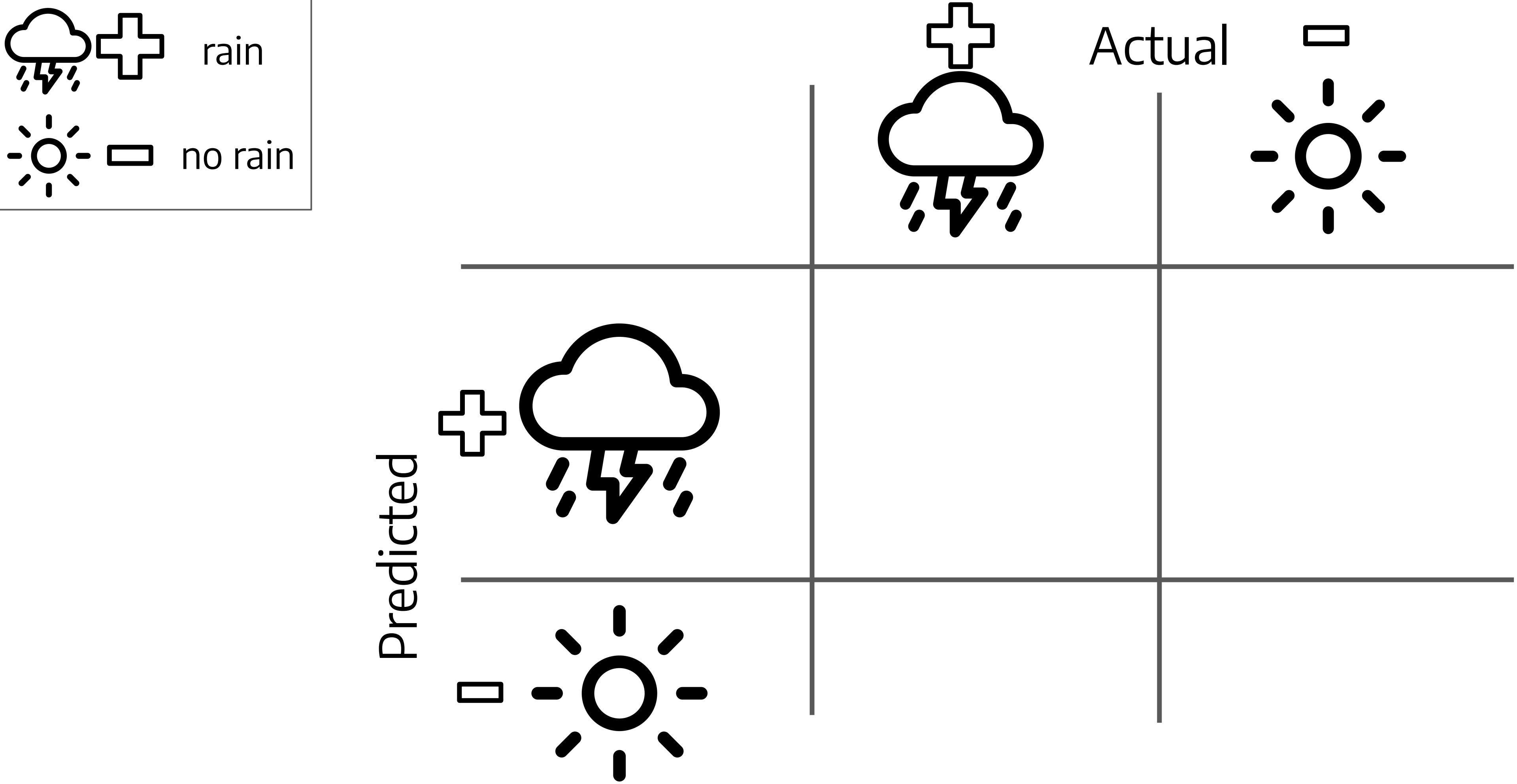
- Quantifying model performance allows to compare models (ML or otherwise!)
- How we quantify performance is key
- Many different ways to quantify depending on what we want to optimize for

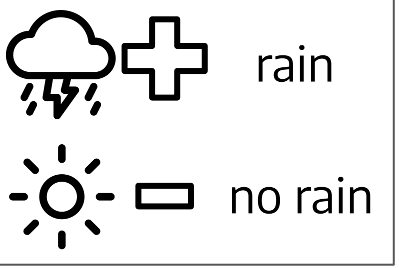
# Vocab

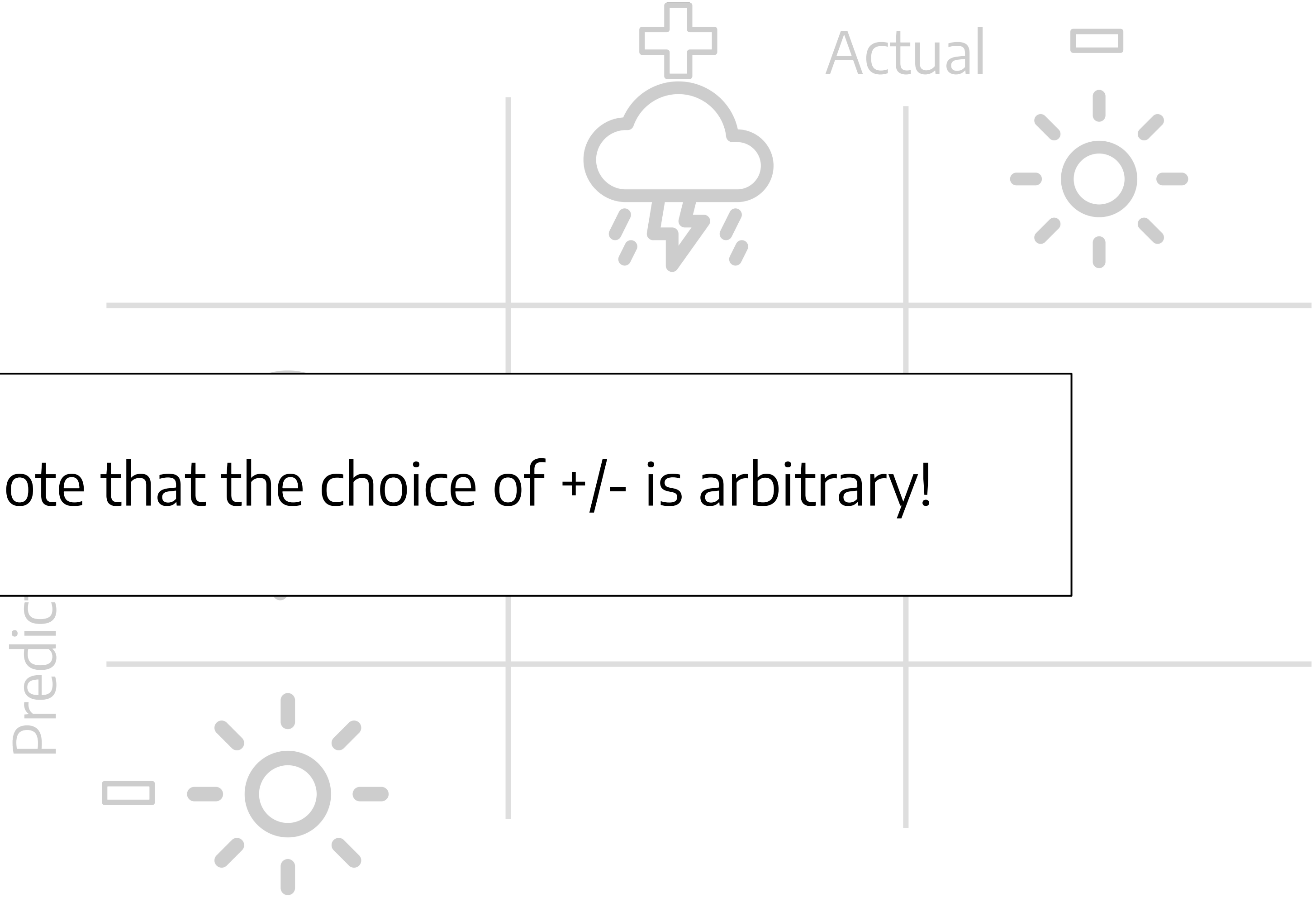
- Classifier
  - Binary
  - Multi-Class
- Evaluation Metric
- Label / target / outcome
- Actual and Predicted Values

Classification Outcomes

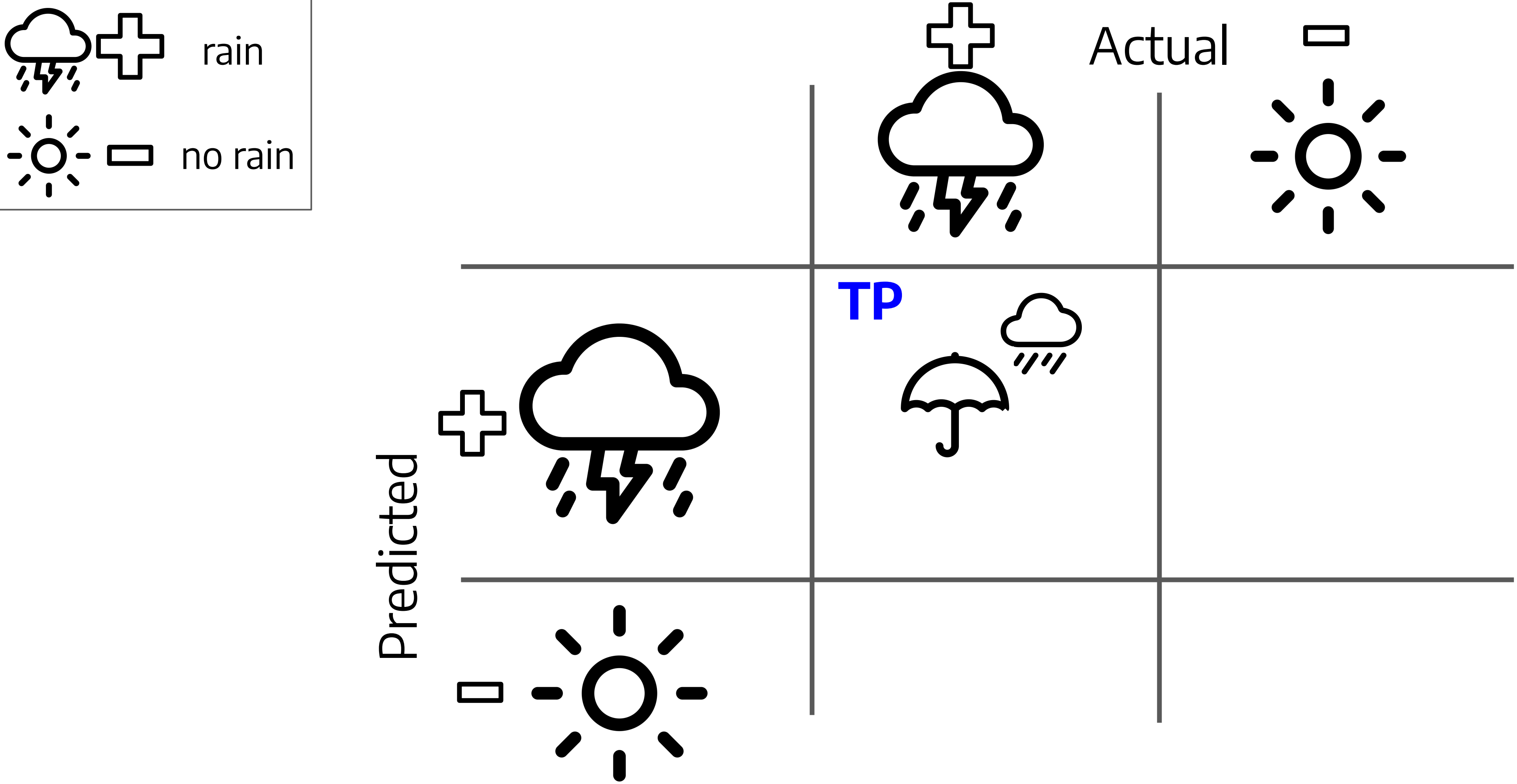
- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

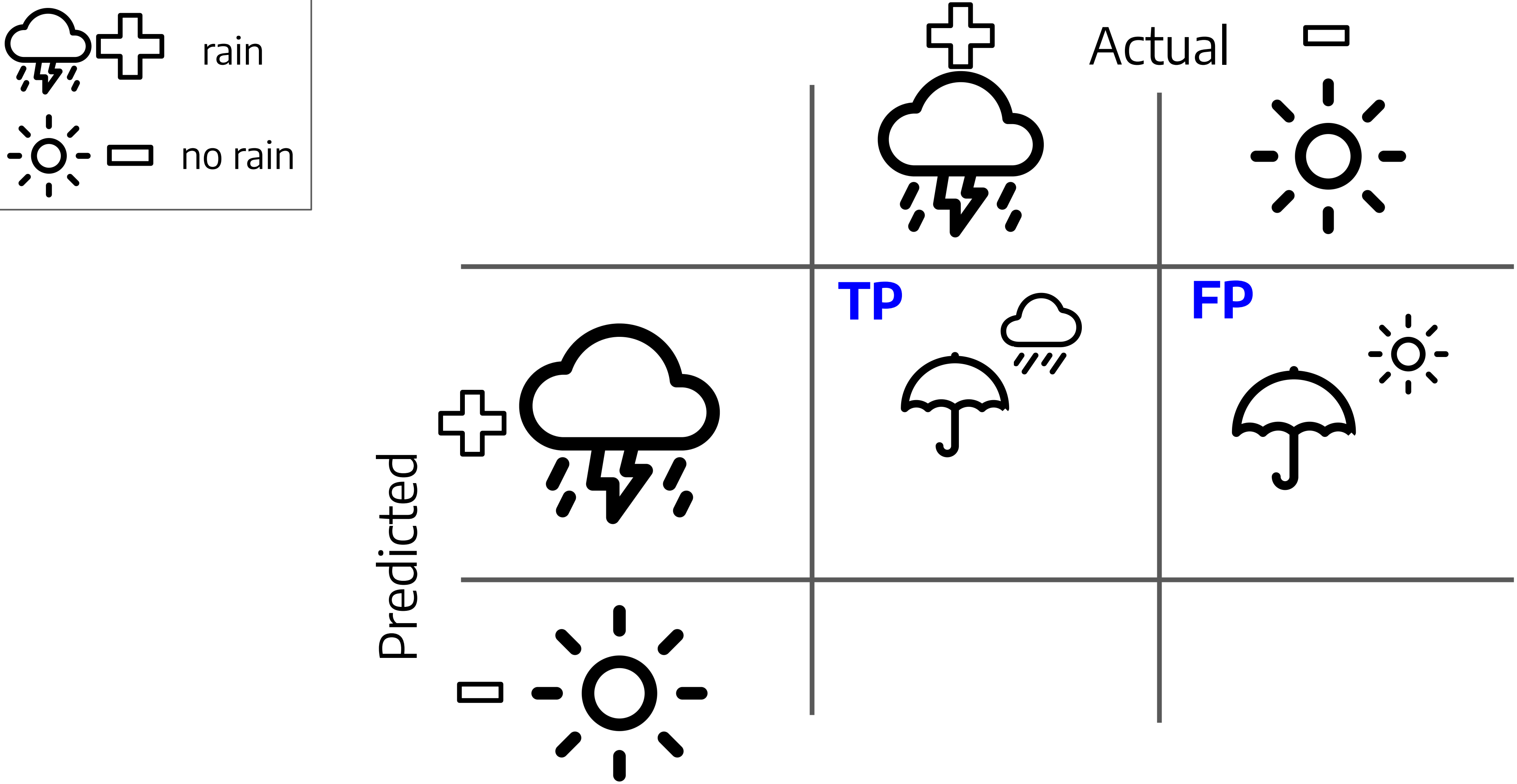

rain
no rain
Actual
Predicted



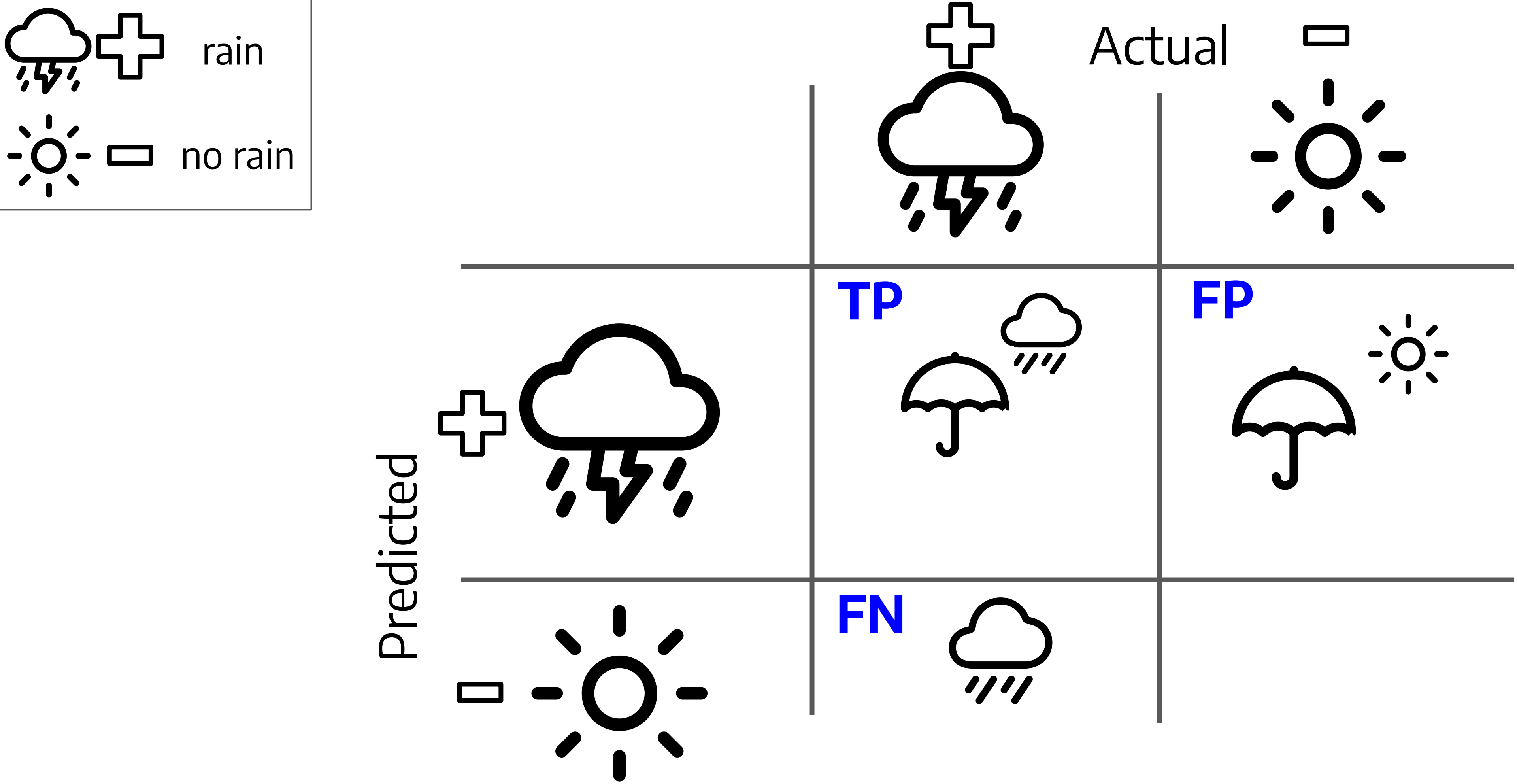




Note that the choice of +/- is arbitrary!

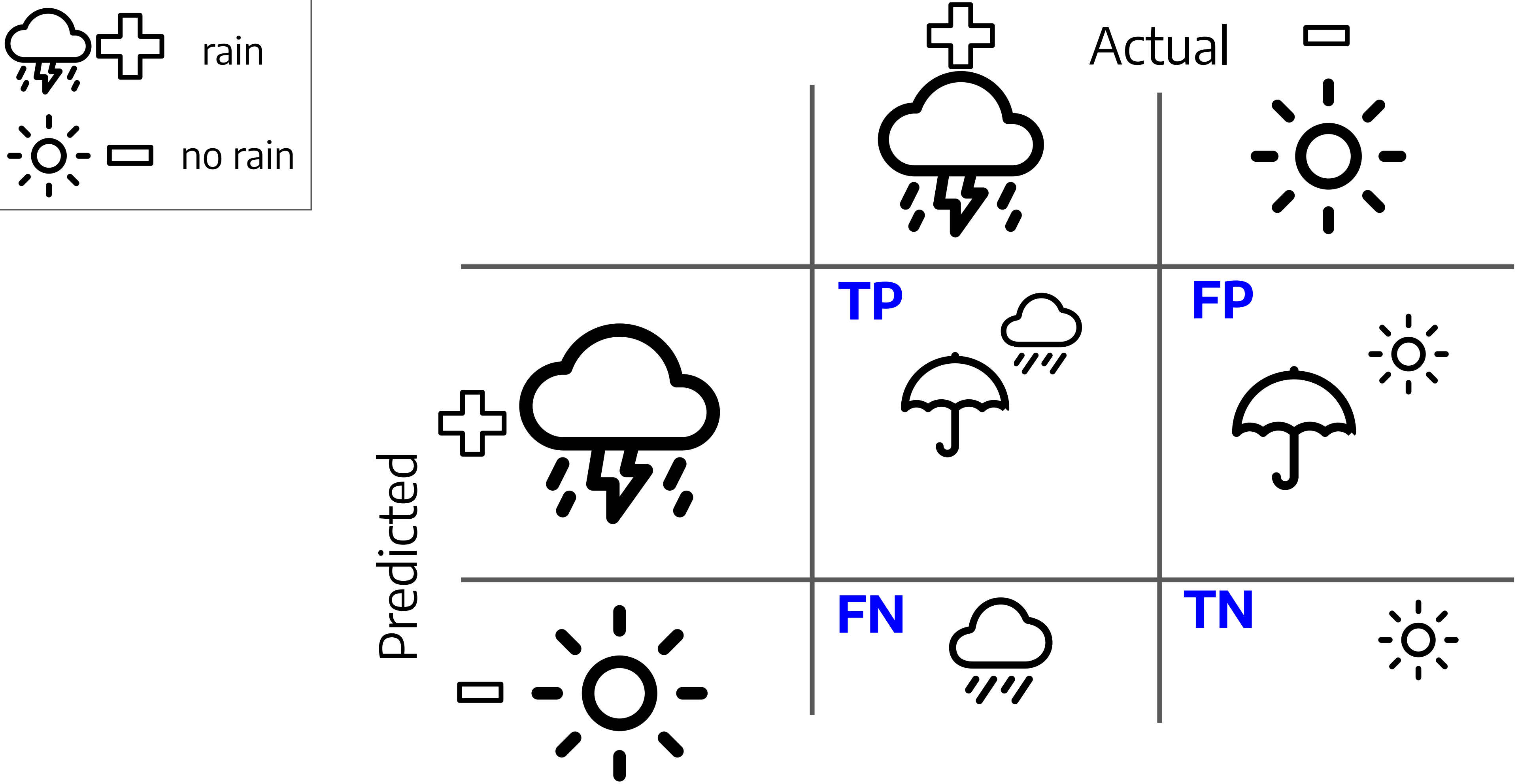

rain
no rain
Actual
Predicted
TP



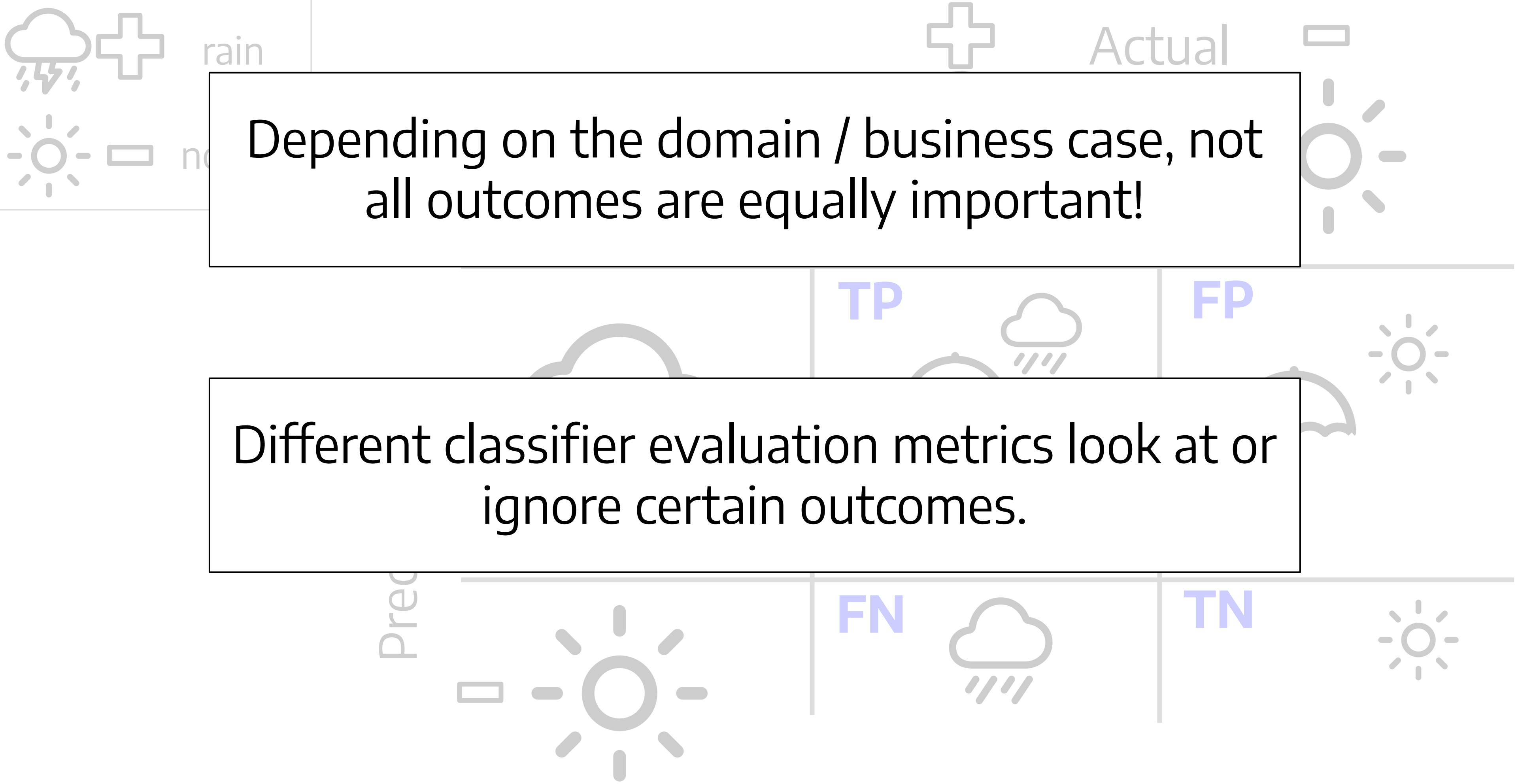
rain
no rain
Actual
Predicted
TP
FP



rain
no rain
Actual
Predicted
TP
FP
FN

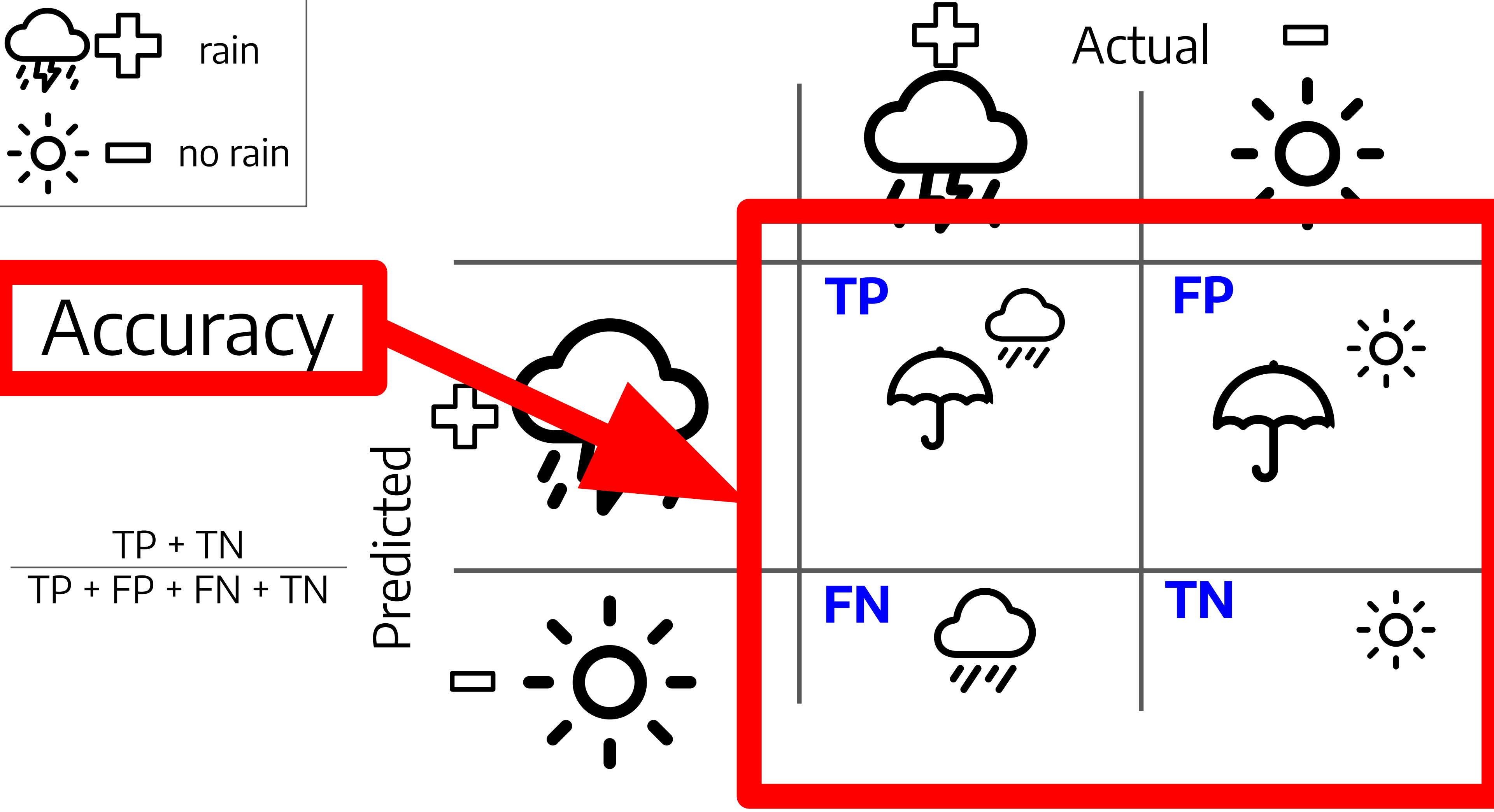


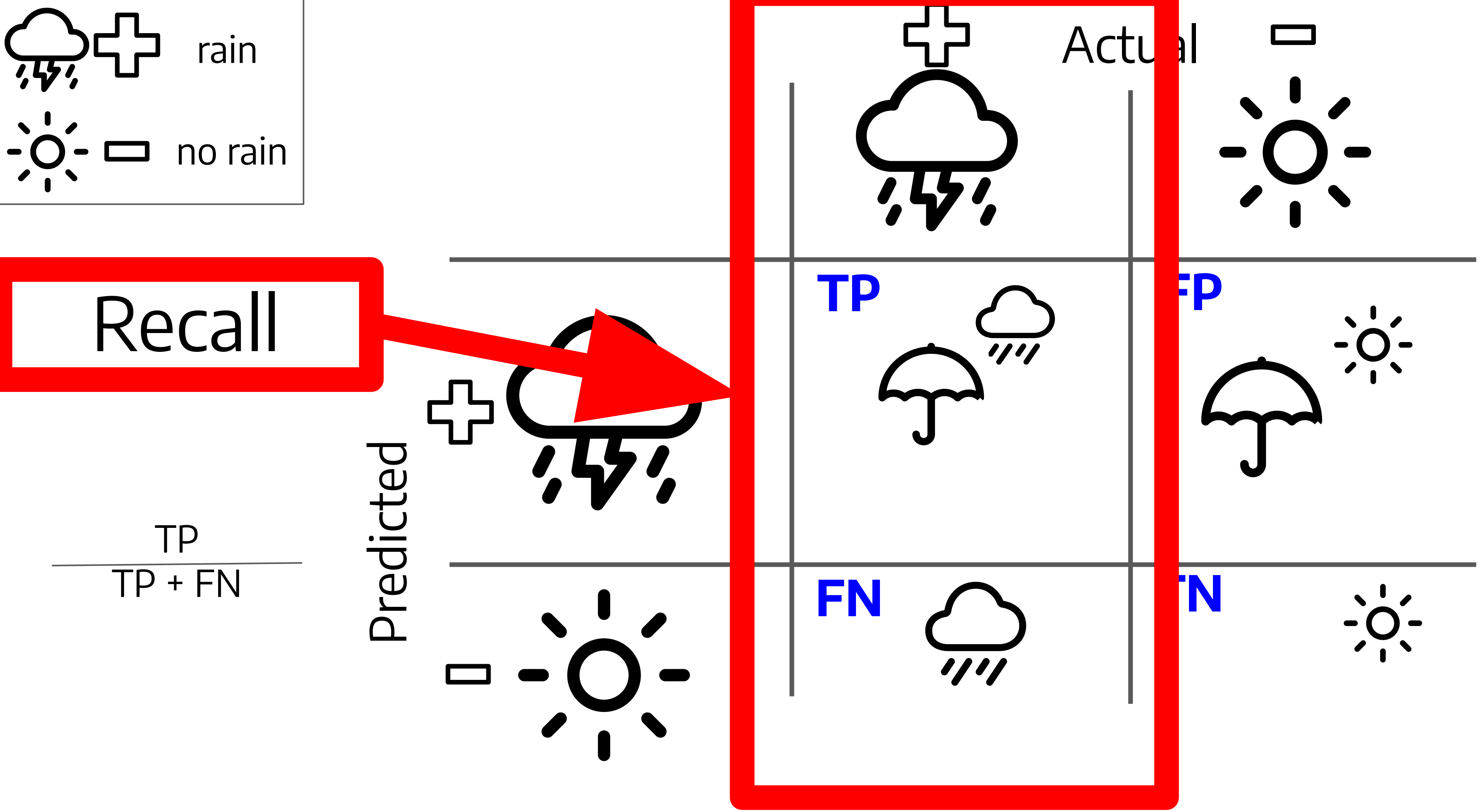
rain
no rain
Actual
Predicted
TP
FP
FN
TN



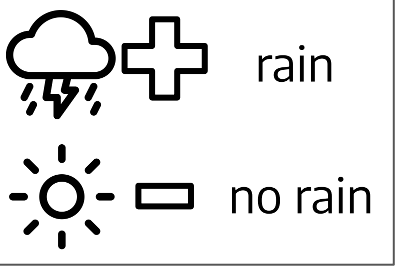

Depending on the domain / business case, not all outcomes are equally important!

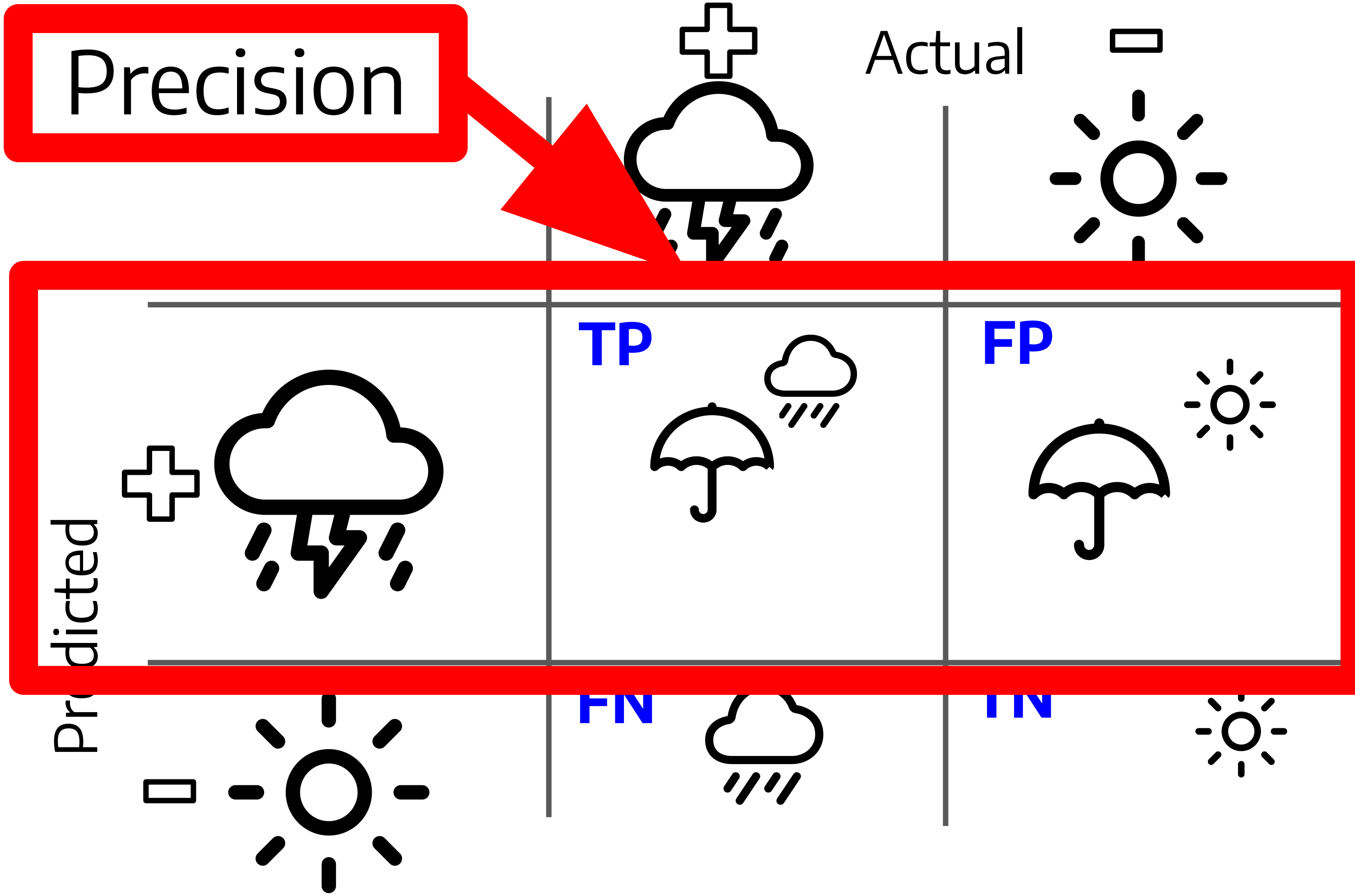
Different classifier evaluation metrics look at or ignore certain outcomes.


rain
no rain
Actual
Predicted
Accuracy
TP + TN
TP + FP + FN + TN
TP
FP
FN
TN



rain
no rain
Actual
Recall
Predicted
TP
FP
FN
TN
TP
TP + FN

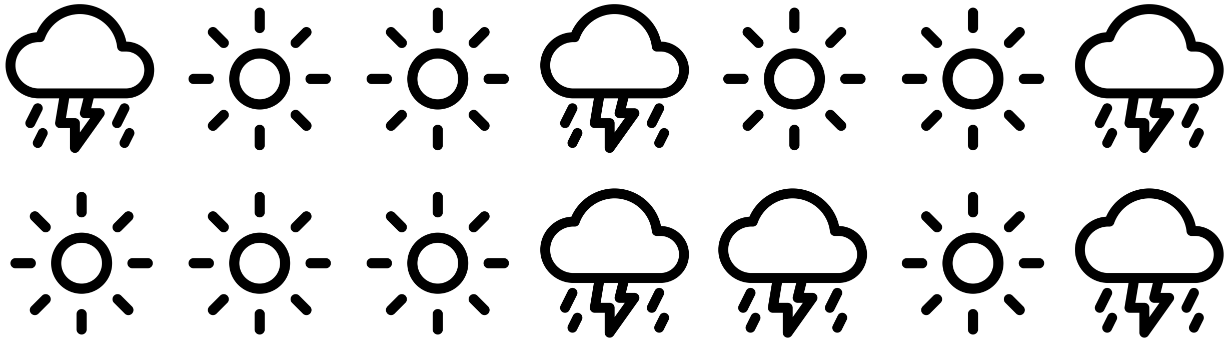



$$\frac{TP}{TP + FP}$$

Actual

Predicted



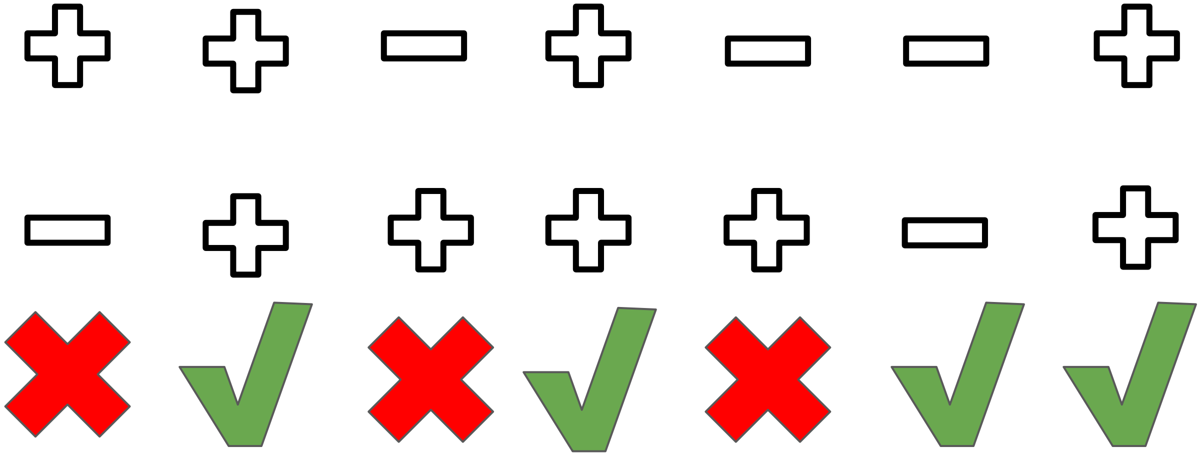
Let's look at an example...

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | − | + | + | + | + | − | + |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | − | + | + | + | + | − | + |
| | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ |

Actual

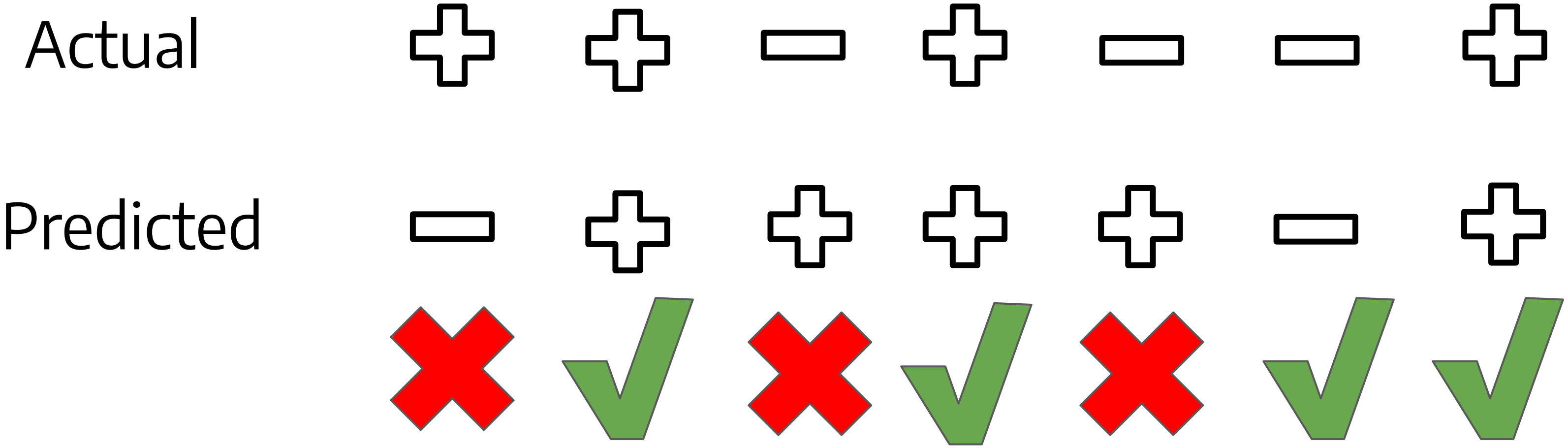
Predicted



# Accuracy

\# correct / total

$= 4 / 7 \approx 57\%$

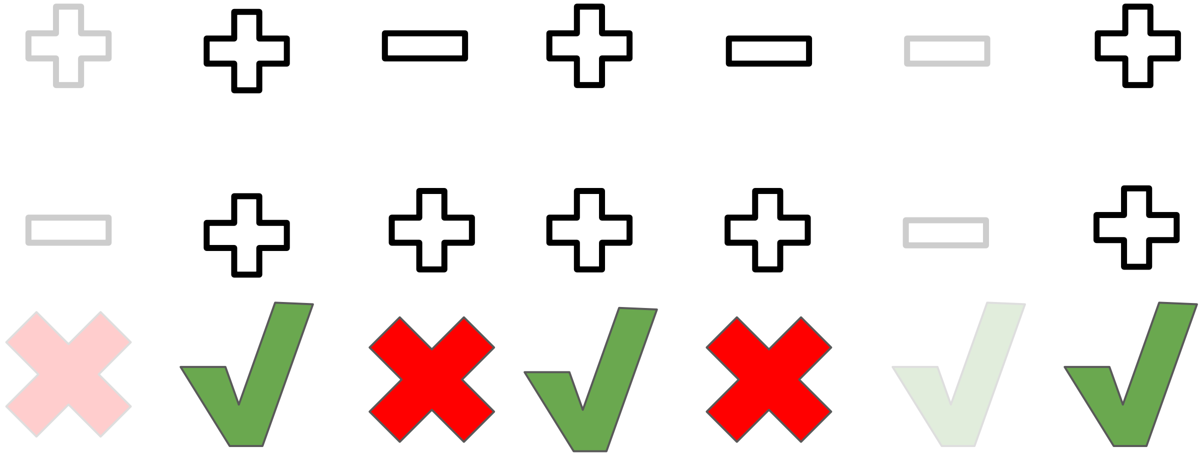



# Precision

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

Actual

Predicted



# Precision

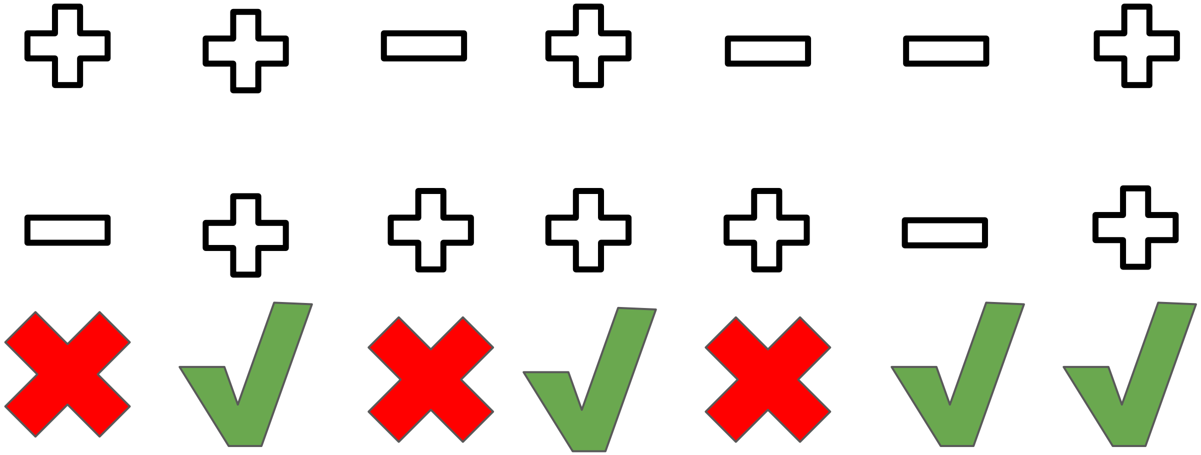
$$\frac{TP}{TP + FP}$$

$= 3 / 5 = 60\%$

How good are our positive predictions?

Actual

Predicted

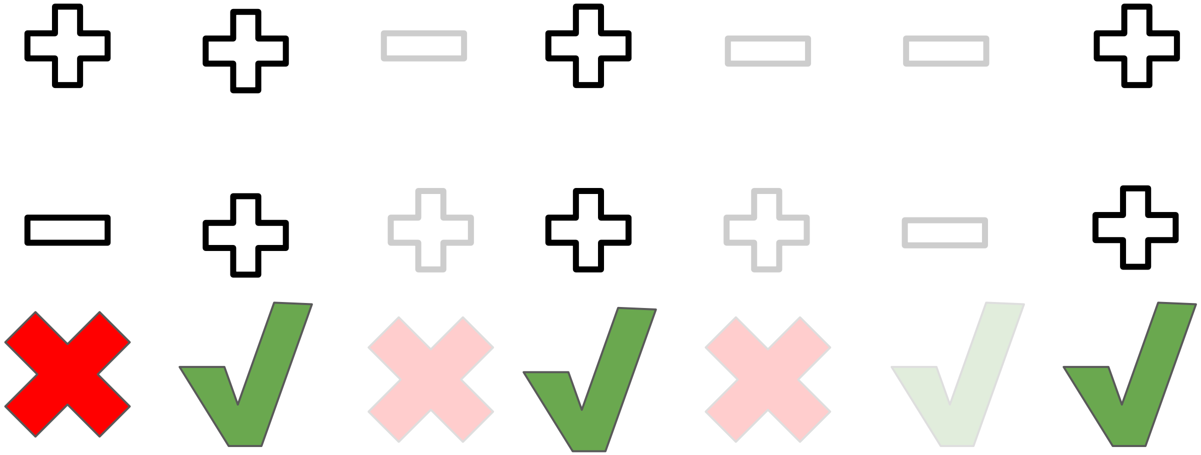


# Recall

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

Actual

Predicted



# Recall

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

$$= 3 / 4 = 75\%$$

How many of the actually positive cases do we catch?

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | + | + | + | + | + | + | + |

Consider a classifier that always predicts positive…

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | + | + | + | + | + | + | + |

Accuracy = 4 / 7 = 57%

Recall = 4 / 4 = 100%

Precision = 4 / 7 = 47%

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | − | − | − | − | − | − | − |

What if we always predict negative?

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Actual | + | + | − | + | − | − | + |
| Predicted | − | − | − | − | − | − | − |

Accuracy = 3 / 7 = 43%

Recall = 0 / 4 = 0%

Precision = 0 / 0 = undef

# Classifier Evaluation Metrics

Recap

- Accuracy: Overall Performance
- Recall: When we don't want to "miss out" on an actually positive case
- Precision: When a positive prediction is expensive

Other Metrics

- Sensitivity: aka recall
- Specificity: recall for the negative class
- F1 score: harmonic mean of precision and recall
- ROC / AUC