



AIBridge

Lecture 5

Let's talk about the last lab!

Let's talk about the last lab!

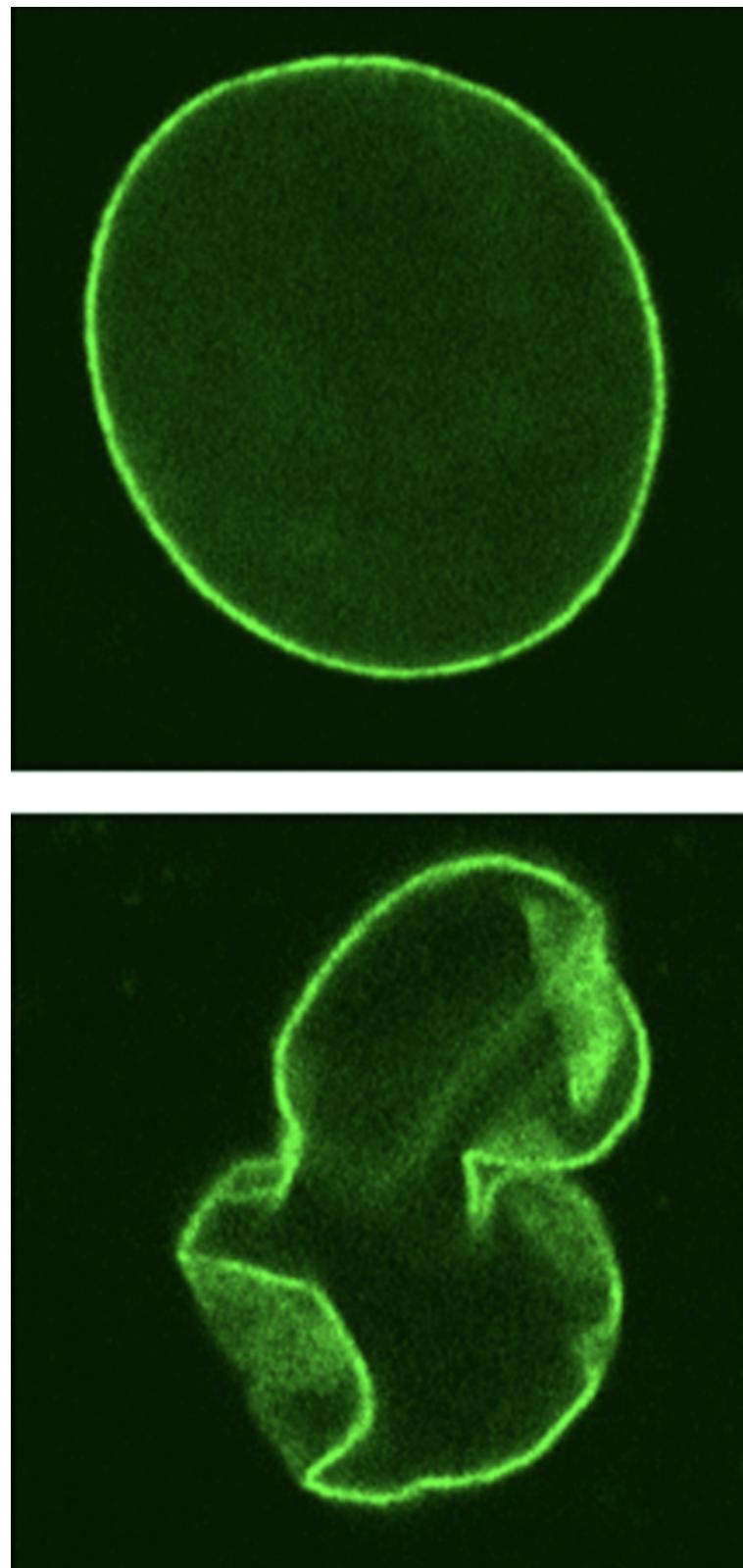
**What circumstances made the model fit better?
worse?**

what does this even mean?



Accuracy

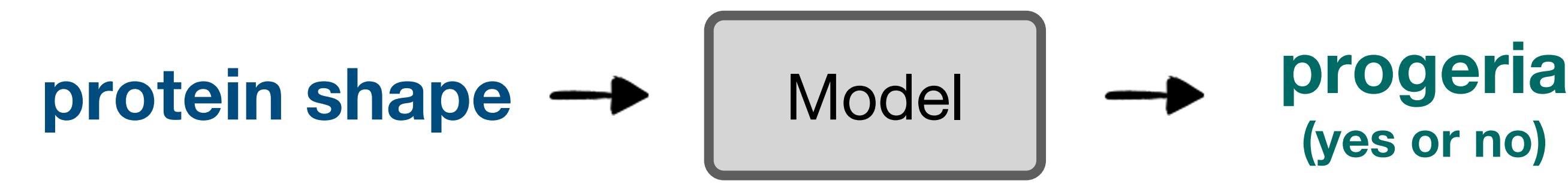
“Why is it not enough?”



Progeria affects ~159 patients in the US

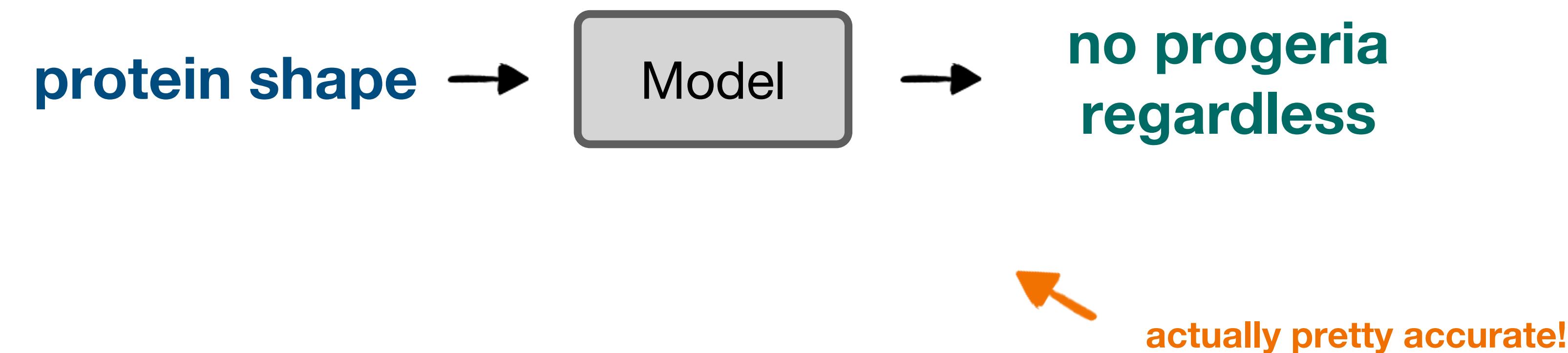
we have a dataset of all American pediatric patients

Q: If my model predicts with 99.99% accuracy, is it good enough?



Progeria affects ~159 patients in the US
we have a dataset of all American pediatric patients

a proposed model:



Progeria affects ~159 patients in the US
we have a dataset of all American pediatric patients

Accuracy , Precision, and Recall



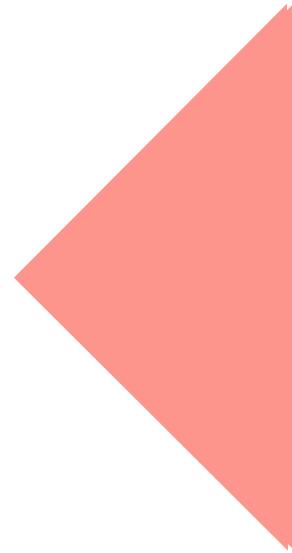
“Selection space”



“Selection space”

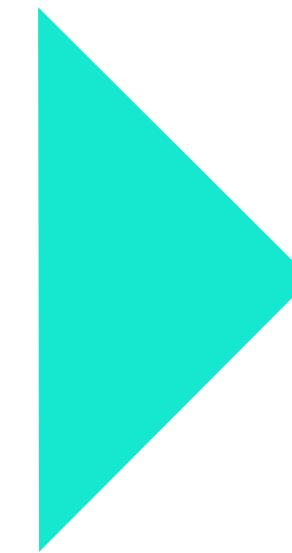
TRUE POSITIVE

TP: Model selects **positive** and patient is **positive**



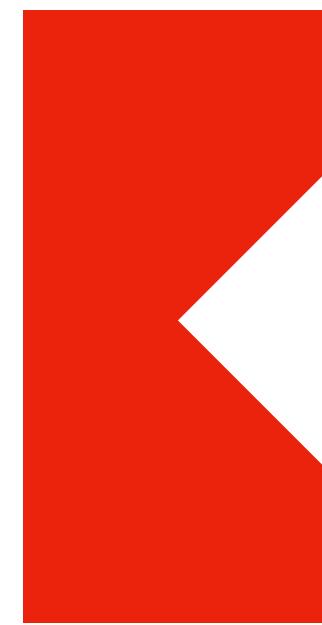
FALSE POSITIVE

FP: Model selects **positive** and patient is **negative**



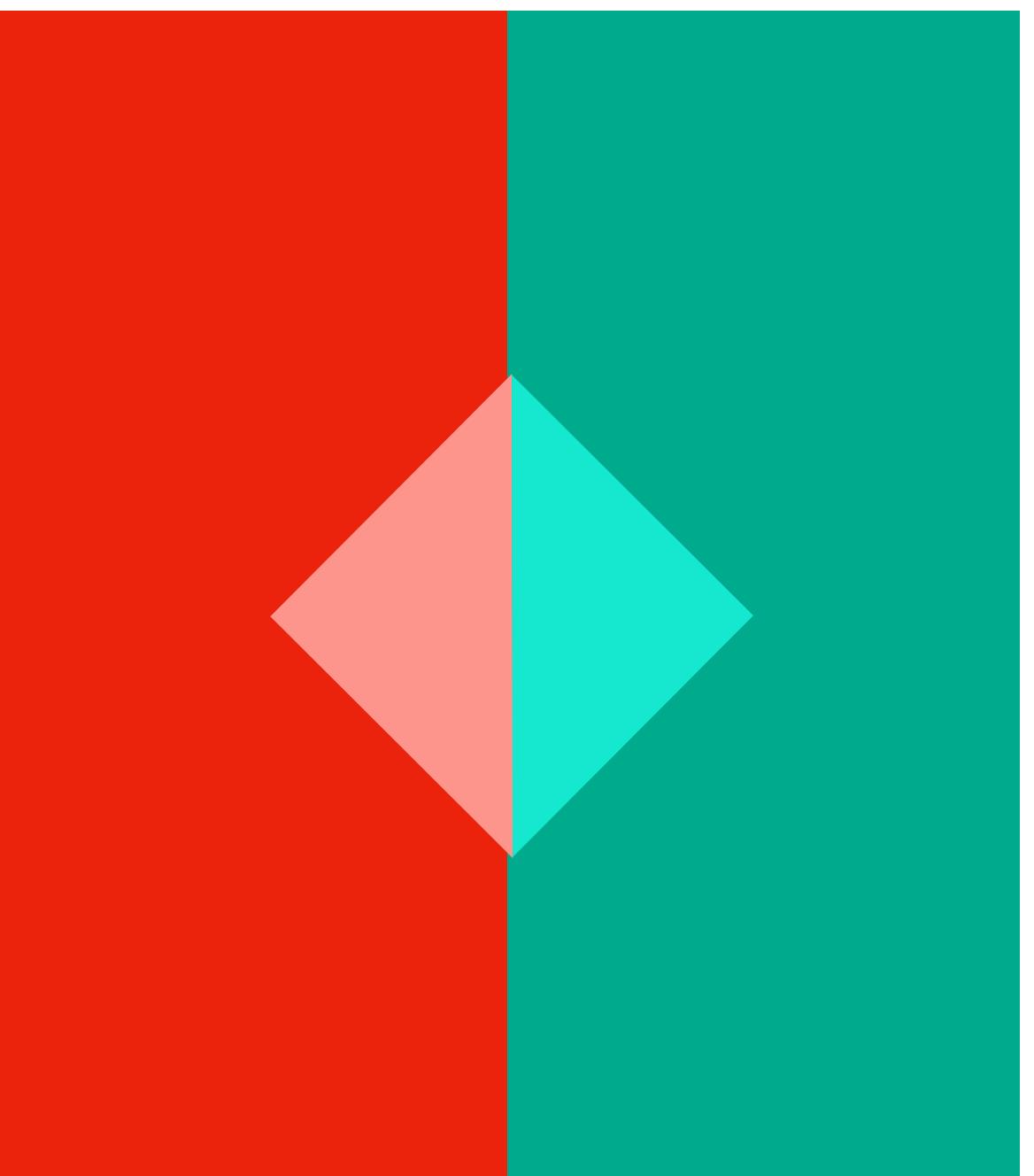
FALSE NEGATIVE

FN: Model selects **negative** and patient is **positive**



TRUE NEGATIVE

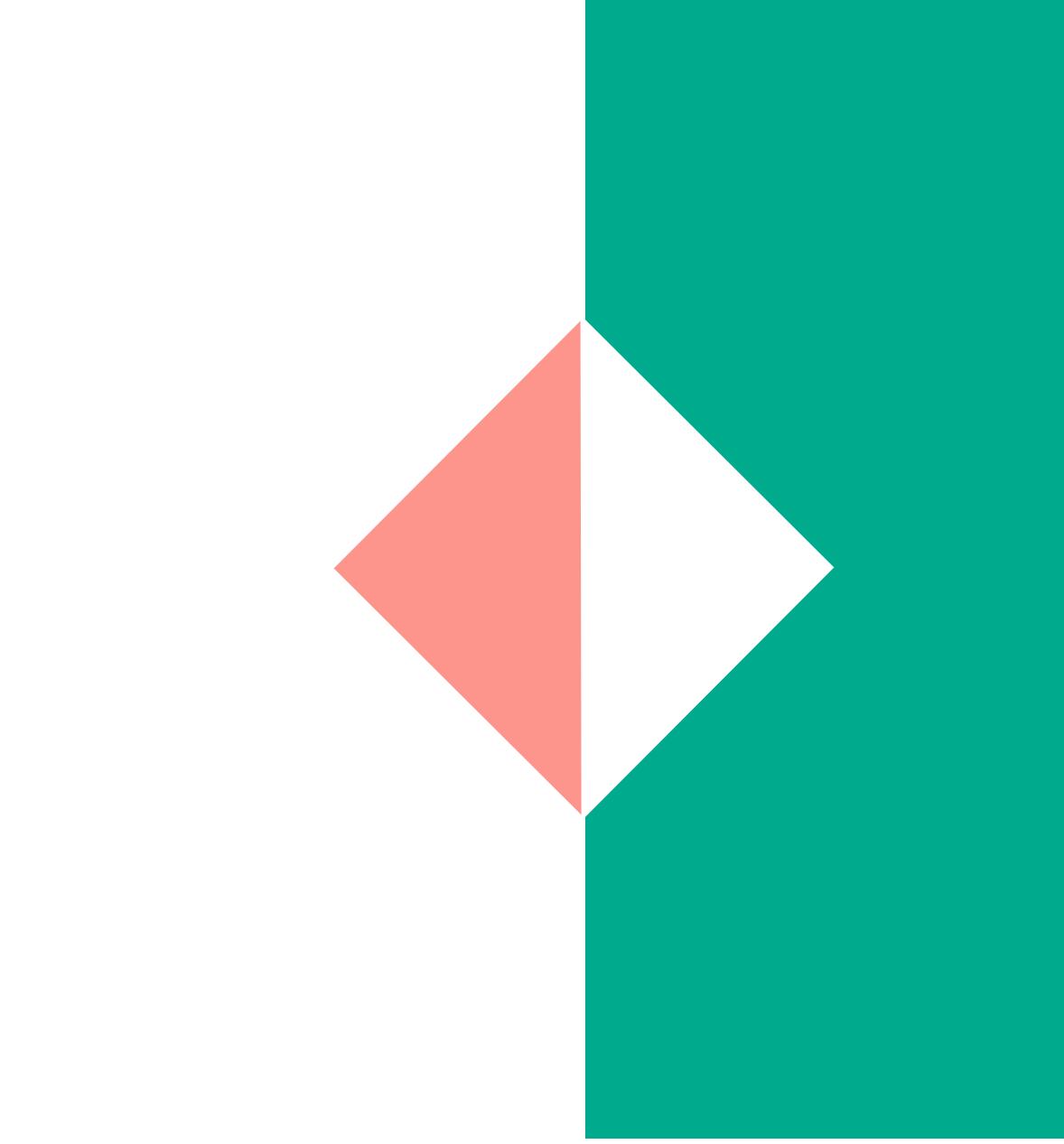
TN: Model selects **negative** and patient is **negative**



“Selection space”

Accuracy

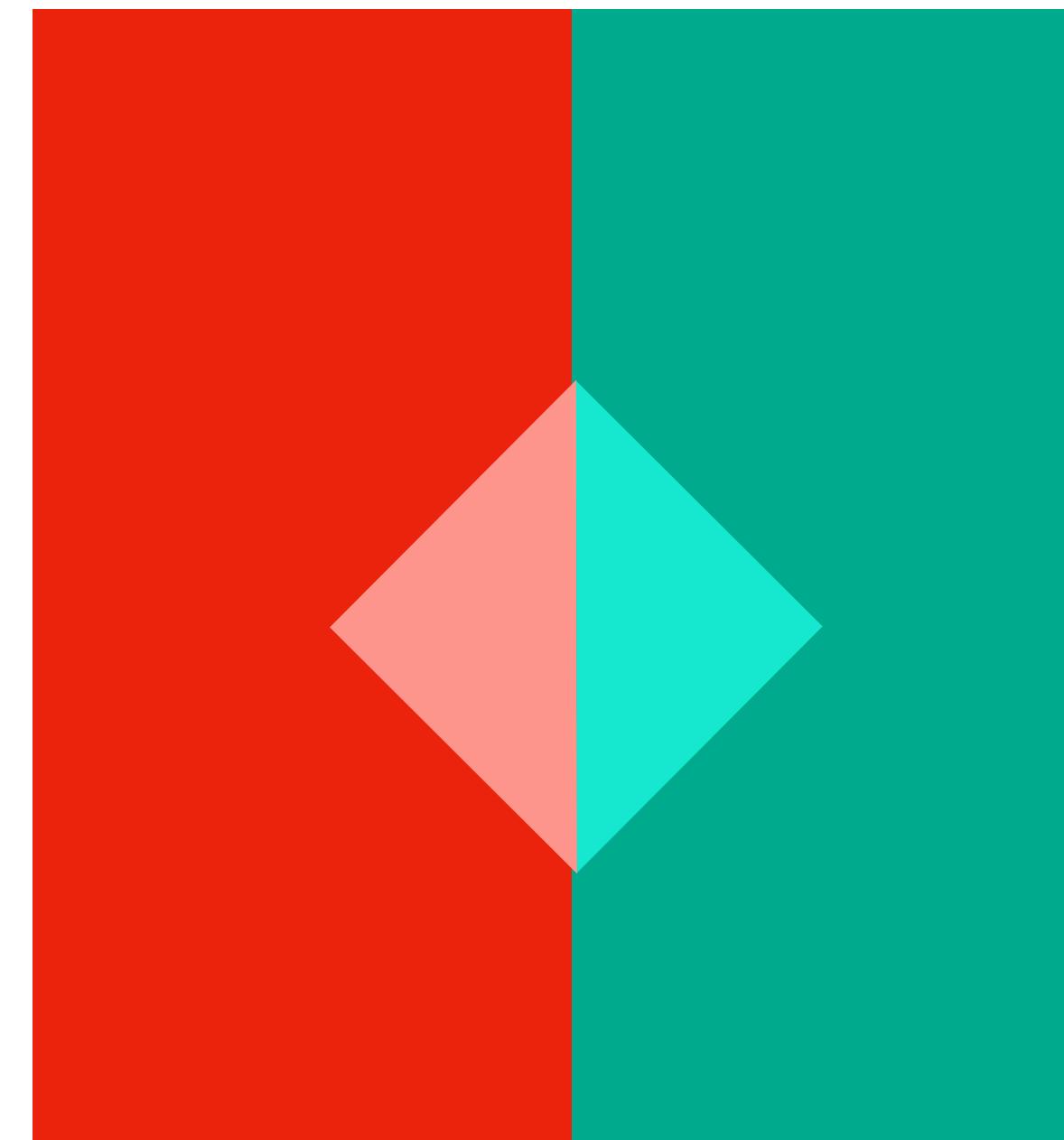
Overall ability of model



“Number of cases where we chose **positive** when patient is **positive**

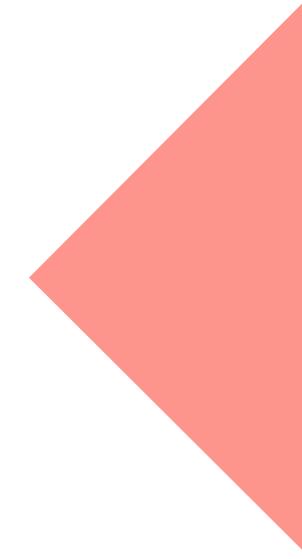
and

Number of cases where we chose **negative** when patient is **negative**”

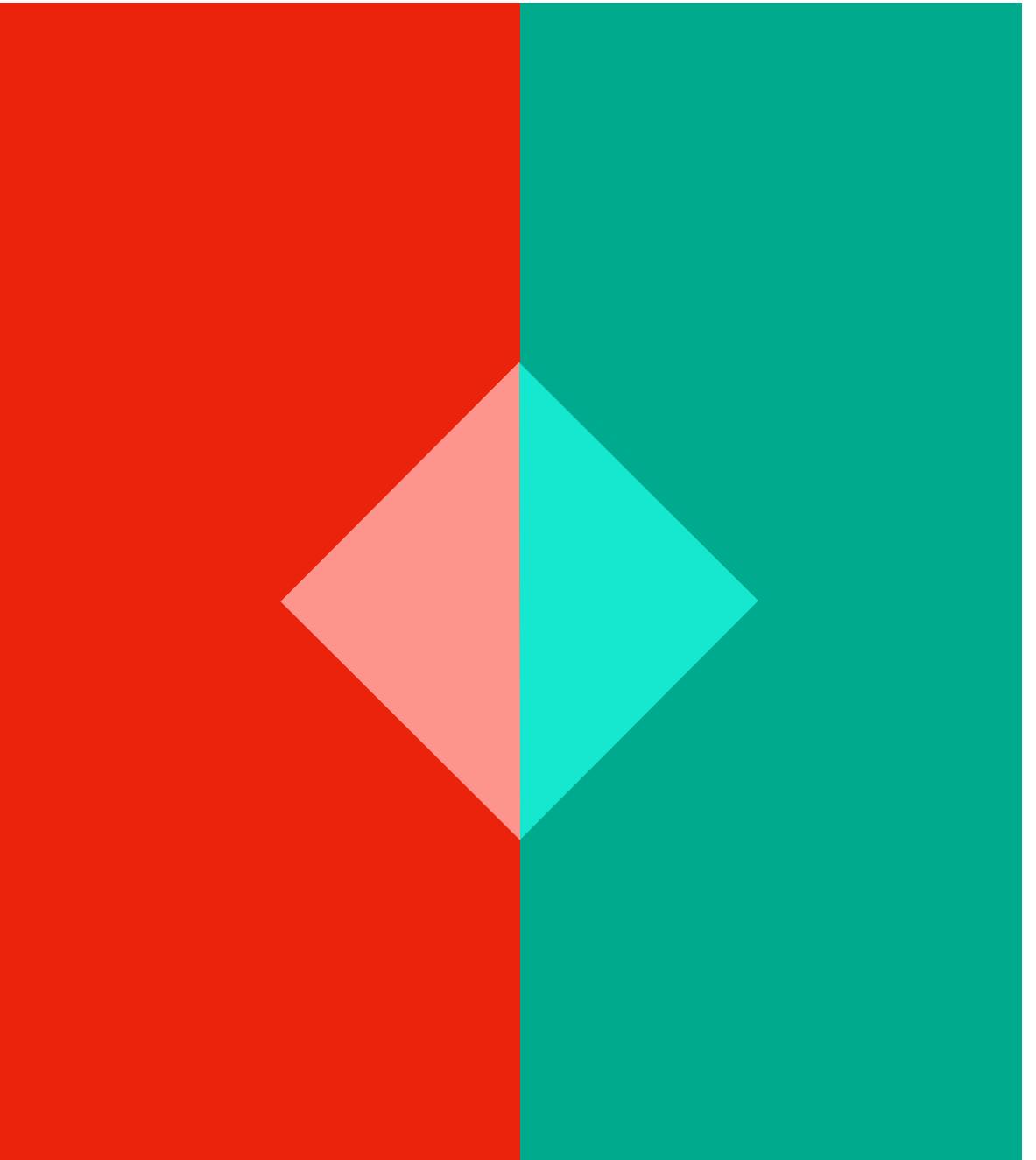
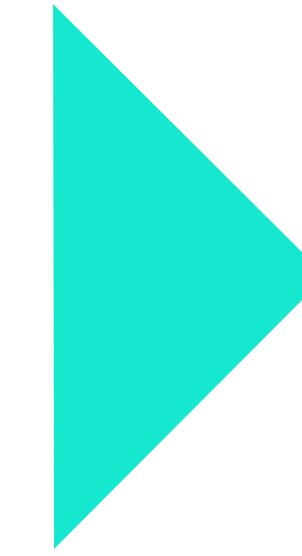


“Everything”

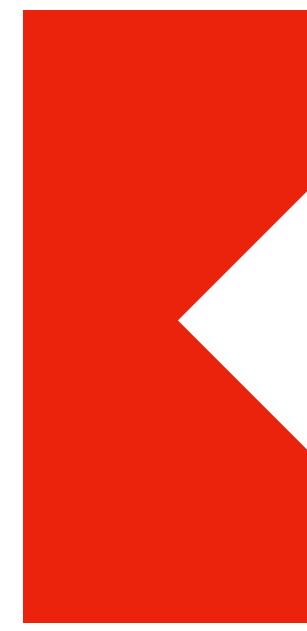
TP: Model selects **positive** and patient is **positive**



FP: Model selects **positive** and patient is **negative**



“Selection space”



FN: Model selects **negative** and patient is **positive**



TN: Model selects **negative** and patient is **negative**

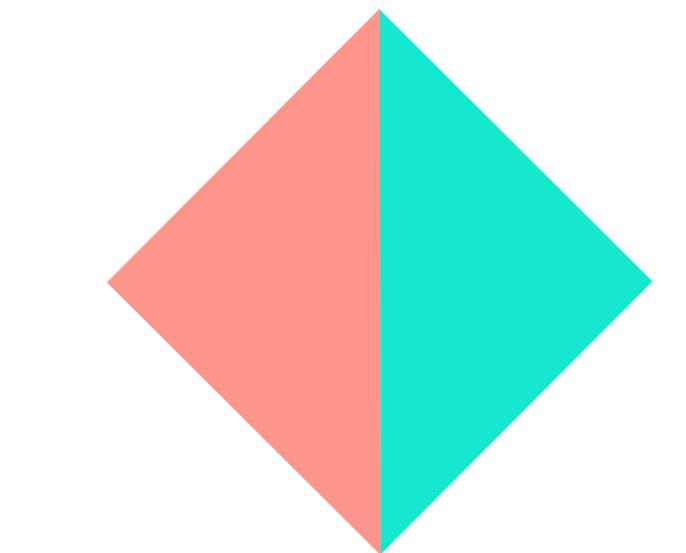
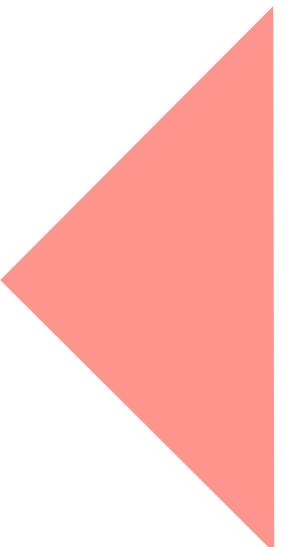
Accuracy

Overall ability of model

Precision

Accuracy of what we selected.

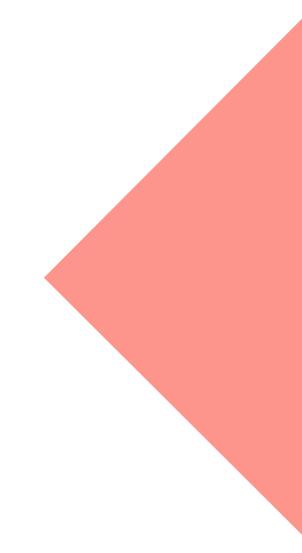
Or amount of selection that's actually correct.



“Number of cases where we chose **positive** when patient is **positive**”

“All selected **positive** by the model”

TP: Model selects **positive** and patient is **positive**

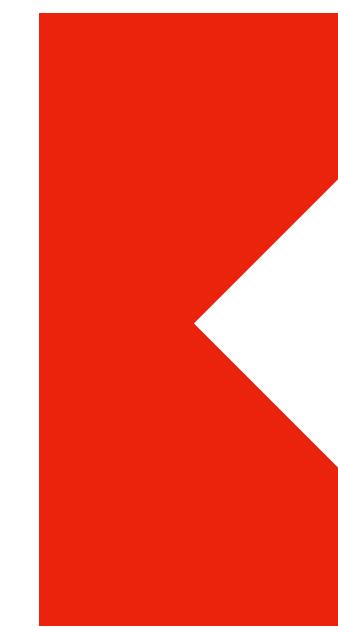
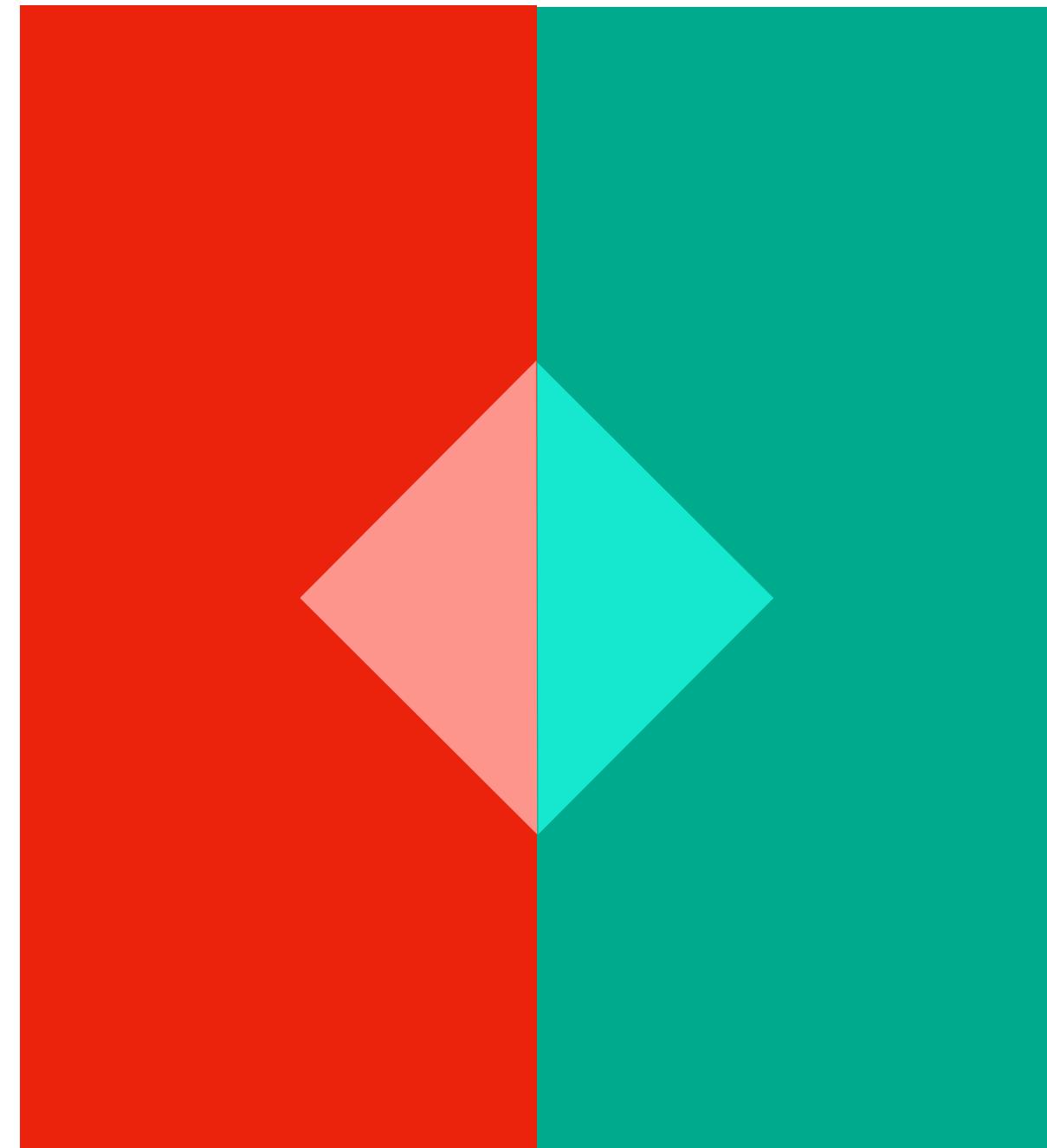


FP: Model selects **positive** and patient is **negative**



Accuracy

Overall ability of model



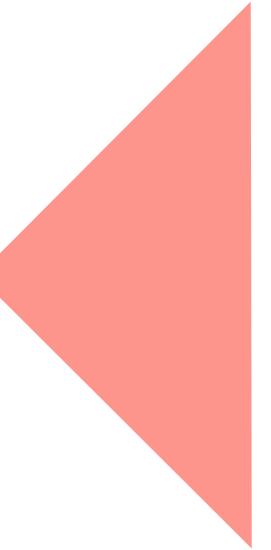
FN: Model selects **negative** and patient is **positive**



TN: Model selects **negative** and patient is **negative**

Precision

Amount of selection that's actually correct.

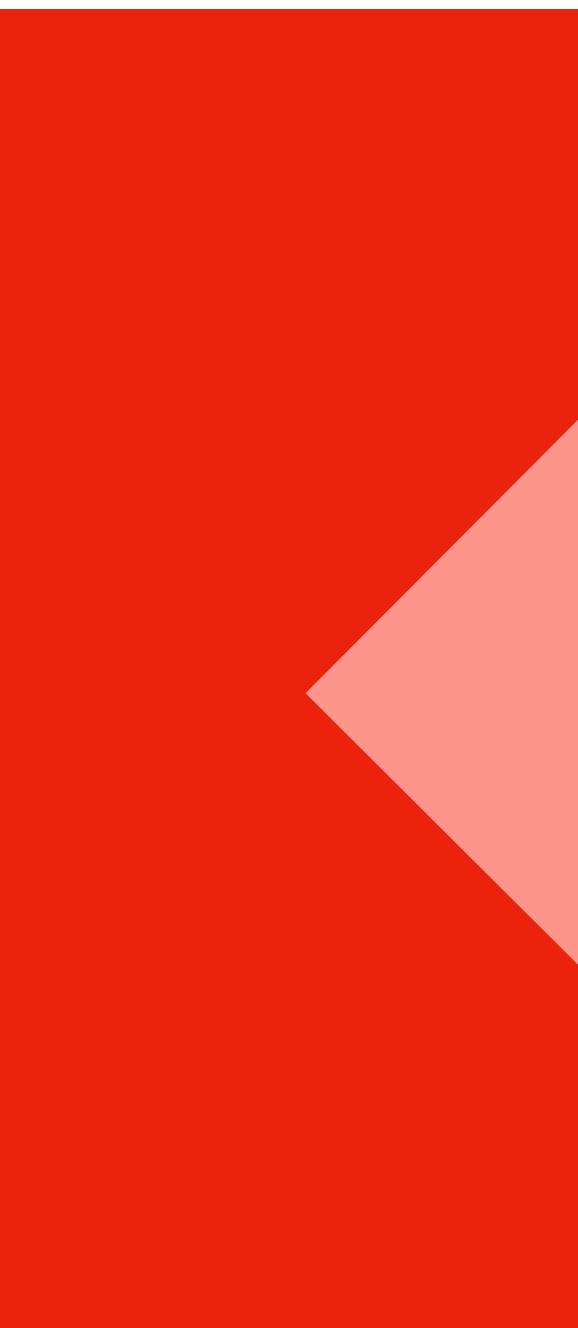


“Number of cases where we chose **positive** when patient is **positive**”

Recall

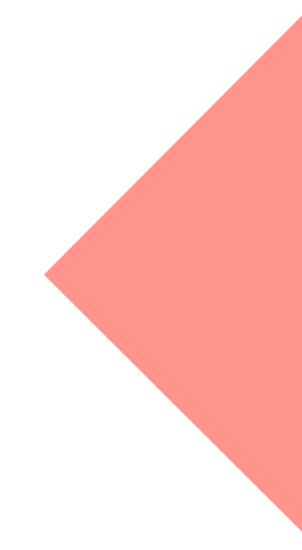
Accuracy of what we should select.

Or amount of what needs to be selected that is selected



“All cases that the patients are **positive**”

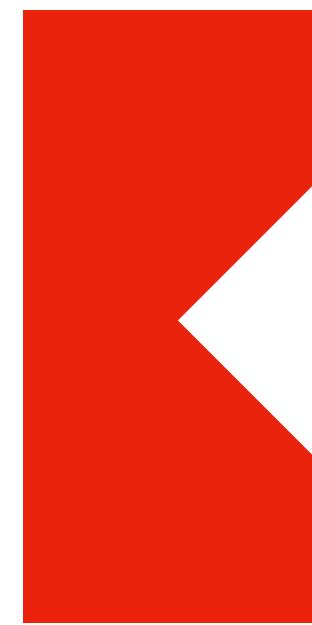
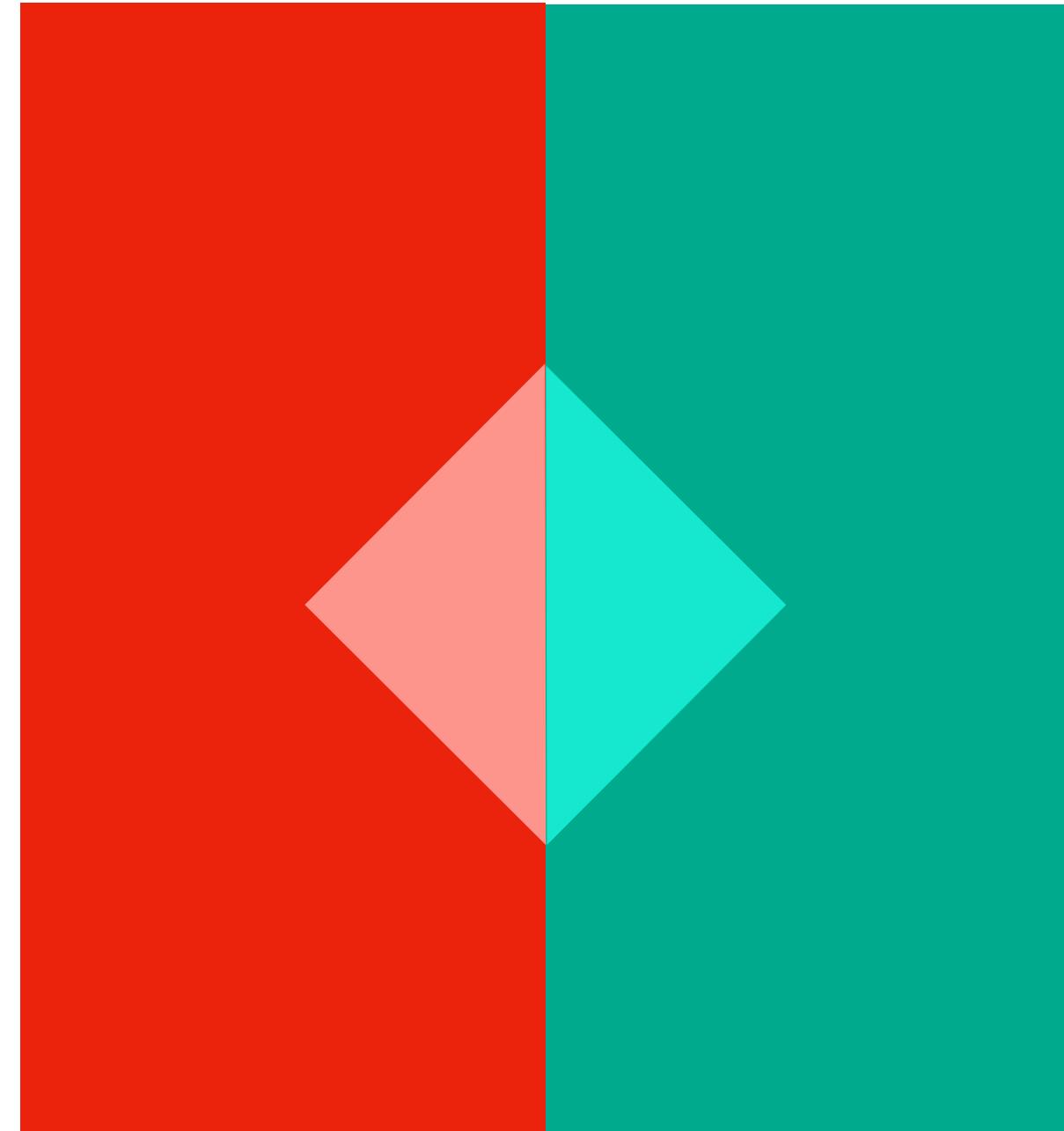
TP: Model selects **positive** and patient is **positive**



FP: Model selects **positive** and patient is **negative**



Accuracy
Overall ability of model



FN: Model selects **negative** and patient is **positive**

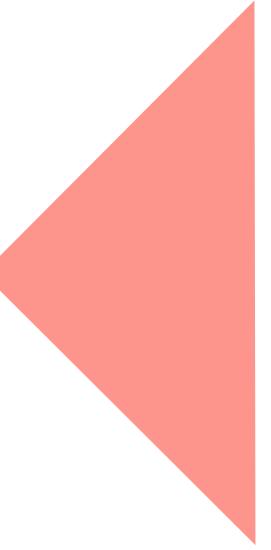


TN: Model selects **negative** and patient is **negative**

Precision
Amount of selection that's actually correct.

Recall
Amount of what needs to be selected that is selected

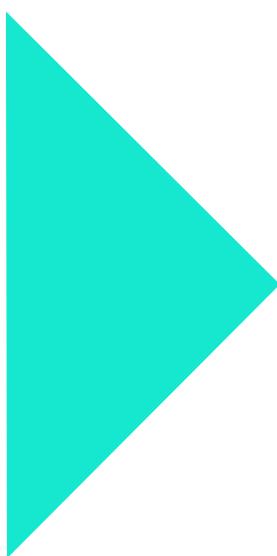
TRUE POSITIVE



FALSE NEGATIVE



FALSE POSITIVE



TRUE NEGATIVE



Accuracy

Overall ability of model

Precision

Amount of selection
that's actually correct.

Recall

Amount of what needs to
be selected that is selected

Sources: [6][7][8][9][10][11][12][13][14] [view](#) · [talk](#) · [edit](#)

		Predicted condition		
		Total population $= P + N$		
		Positive (PP)	Negative (PN)	Informedness, bookmaker informedness (BM) $= TPR + TNR - 1$
Actual condition	Positive (P)	True positive (TP), hit	False negative (FN), type II error, miss, underestimation	True positive rate (TPR), recall, sensitivity (SEN), probability of detection, hit rate, power $= \frac{TP}{P} = 1 - FNR$
	Negative (N)	False positive (FP), type I error, false alarm, overestimation	True negative (TN), correct rejection	False negative rate (FNR), miss rate $= \frac{FN}{P} = 1 - TPR$
Prevalence $= \frac{P}{P + N}$	Positive predictive value (PPV), precision $= \frac{TP}{PP} = 1 - FDR$	False omission rate (FOR) $= \frac{FN}{PN} = 1 - NPV$	Positive likelihood ratio (LR+) $= \frac{TPR}{FPR}$	Negative likelihood ratio (LR-) $= \frac{FNR}{TNR}$
Accuracy (ACC) $= \frac{TP + TN}{P + N}$	False discovery rate (FDR) $= \frac{FP}{PP} = 1 - PPV$	Negative predictive value (NPV) $= \frac{TN}{PN} = 1 - FOR$	Markedness (MK), deltaP (Δp) $= PPV + NPV - 1$	Diagnostic odds ratio (DOR) $= \frac{LR+}{LR-}$
Balanced accuracy (BA) $= \frac{TPR + TNR}{2}$	F ₁ score $= \frac{2PPV \times TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN}$	Fowlkes–Mallows index (FM) $= \sqrt{PPV \times TPR}$	Matthews correlation coefficient (MCC) $= \sqrt{TPR \times TNR \times PPV \times NPV} - \sqrt{FNR \times FPR \times FOR \times FDR}$	Threat score (TS), critical success index (CSI), Jaccard index $= \frac{TP}{TP + FN + FP}$

Accuracy

Overall ability of model

$$\frac{TP + TN}{Total}$$

exactly zero

Precision

Amount of selection that's actually correct.

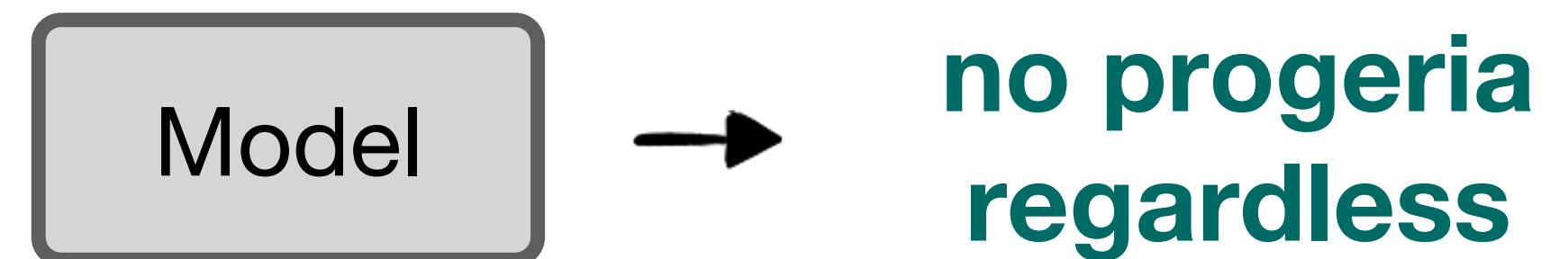
$$\frac{TP}{TP + FP}$$

Recall

Amount of what needs to be selected that is selected

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

← scaled properly!



Progeria affects ~159 patients in the US

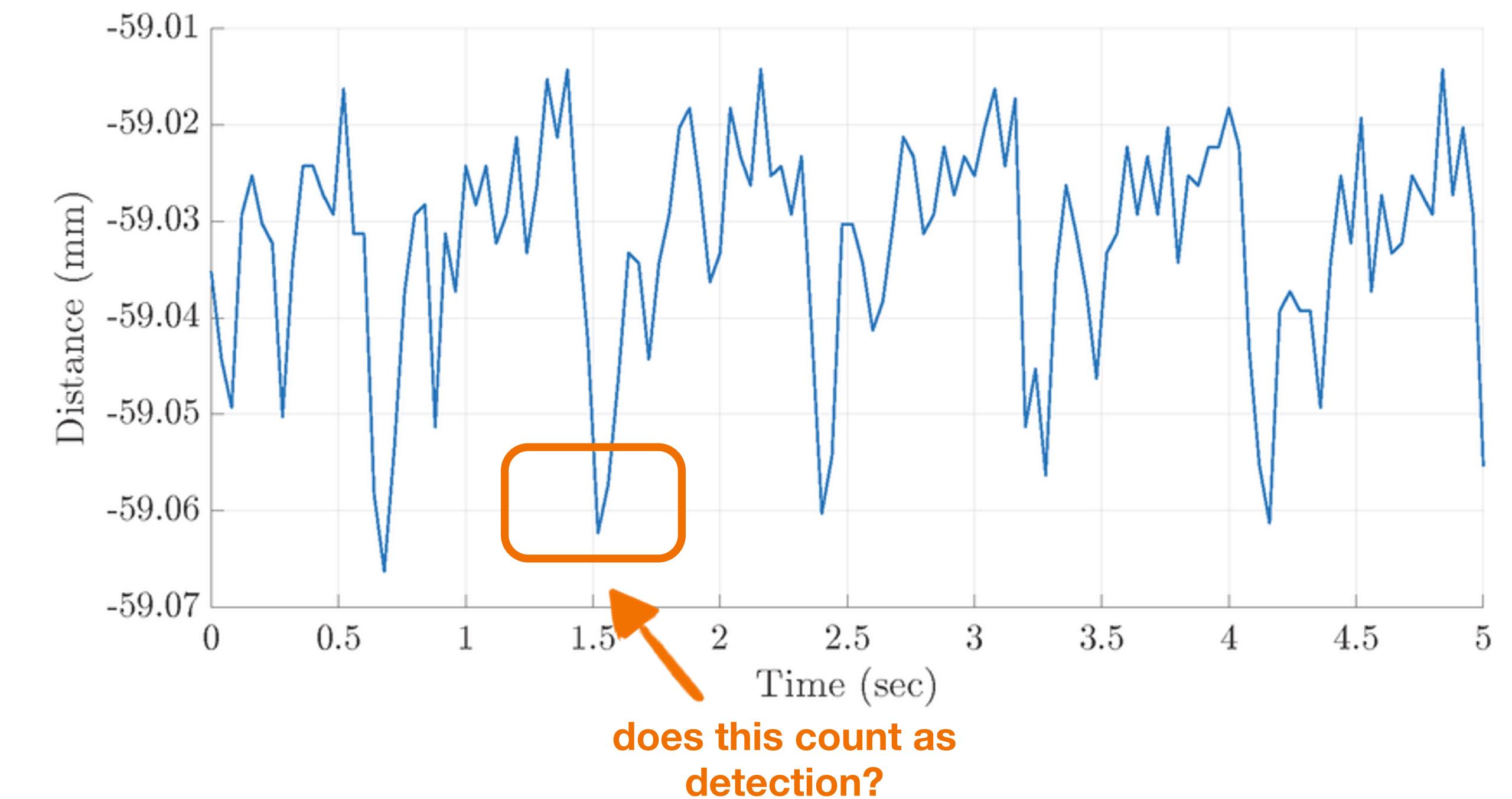
we have a dataset of all American pediatric patients

storytime!

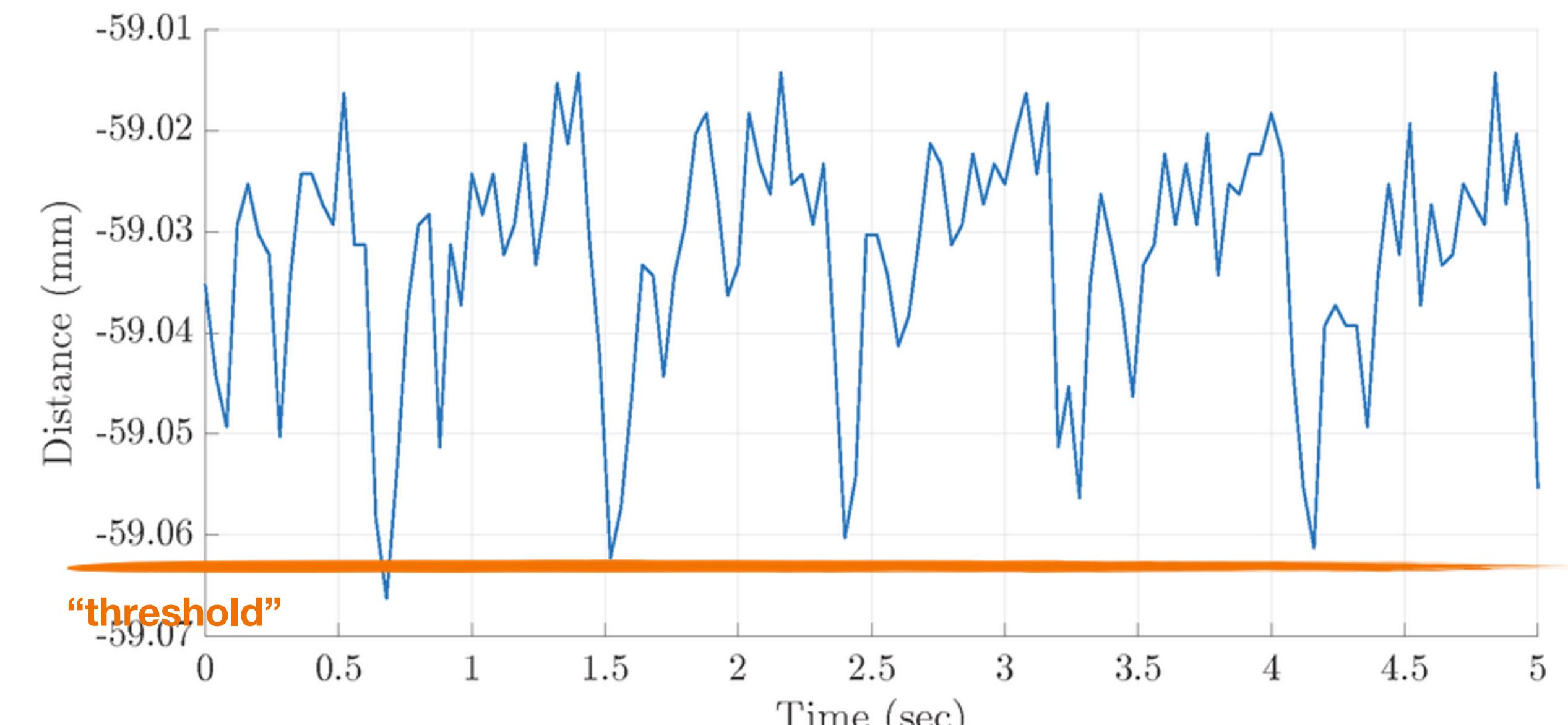
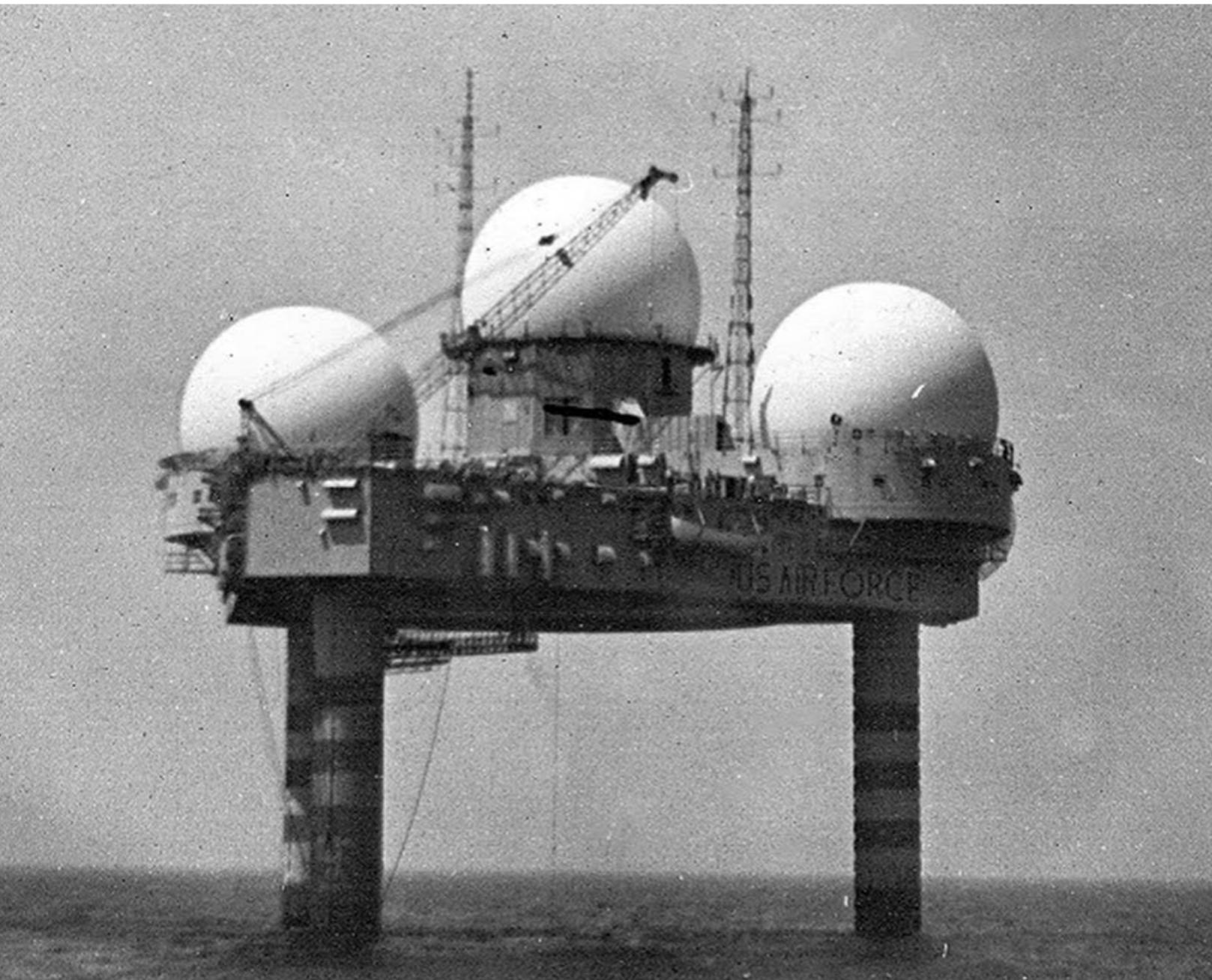
storytime!



storytime!

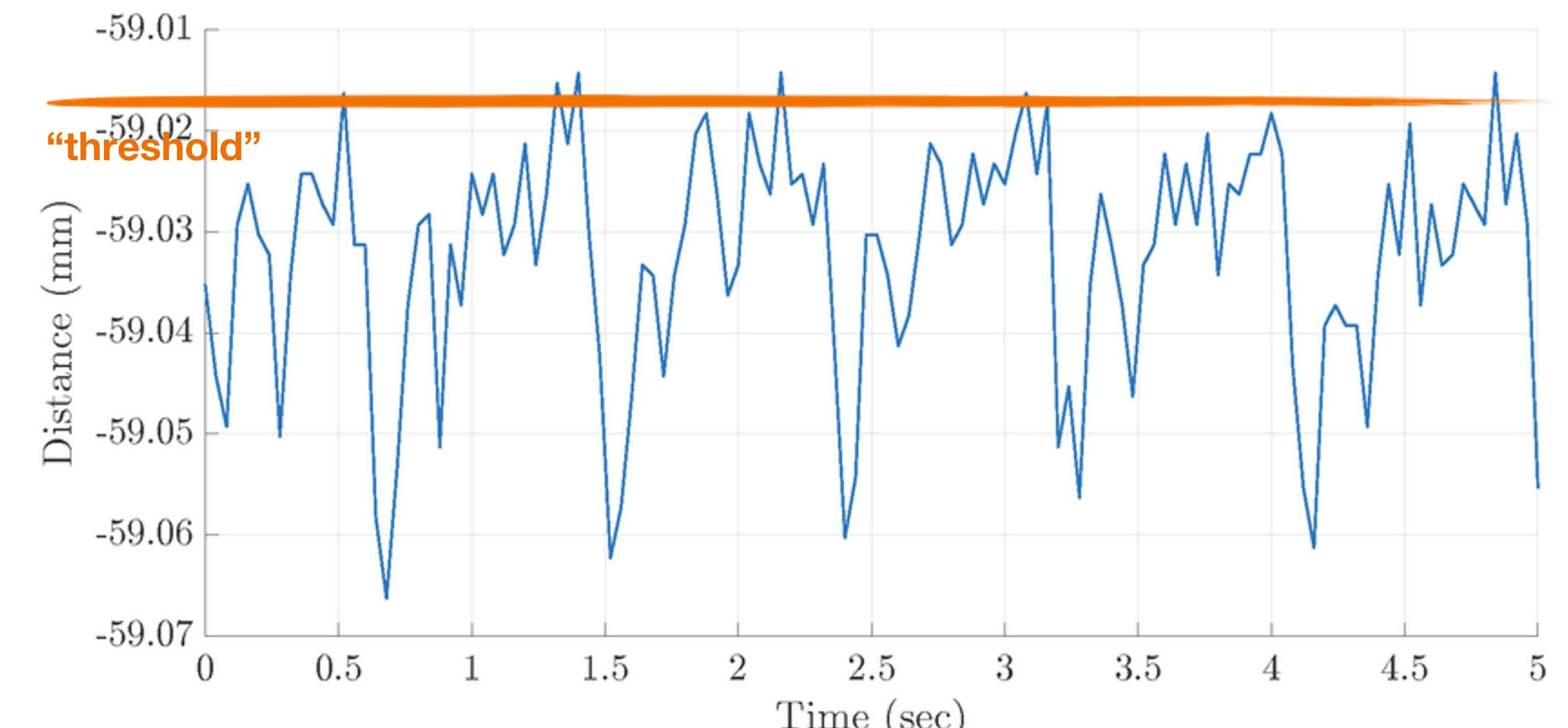
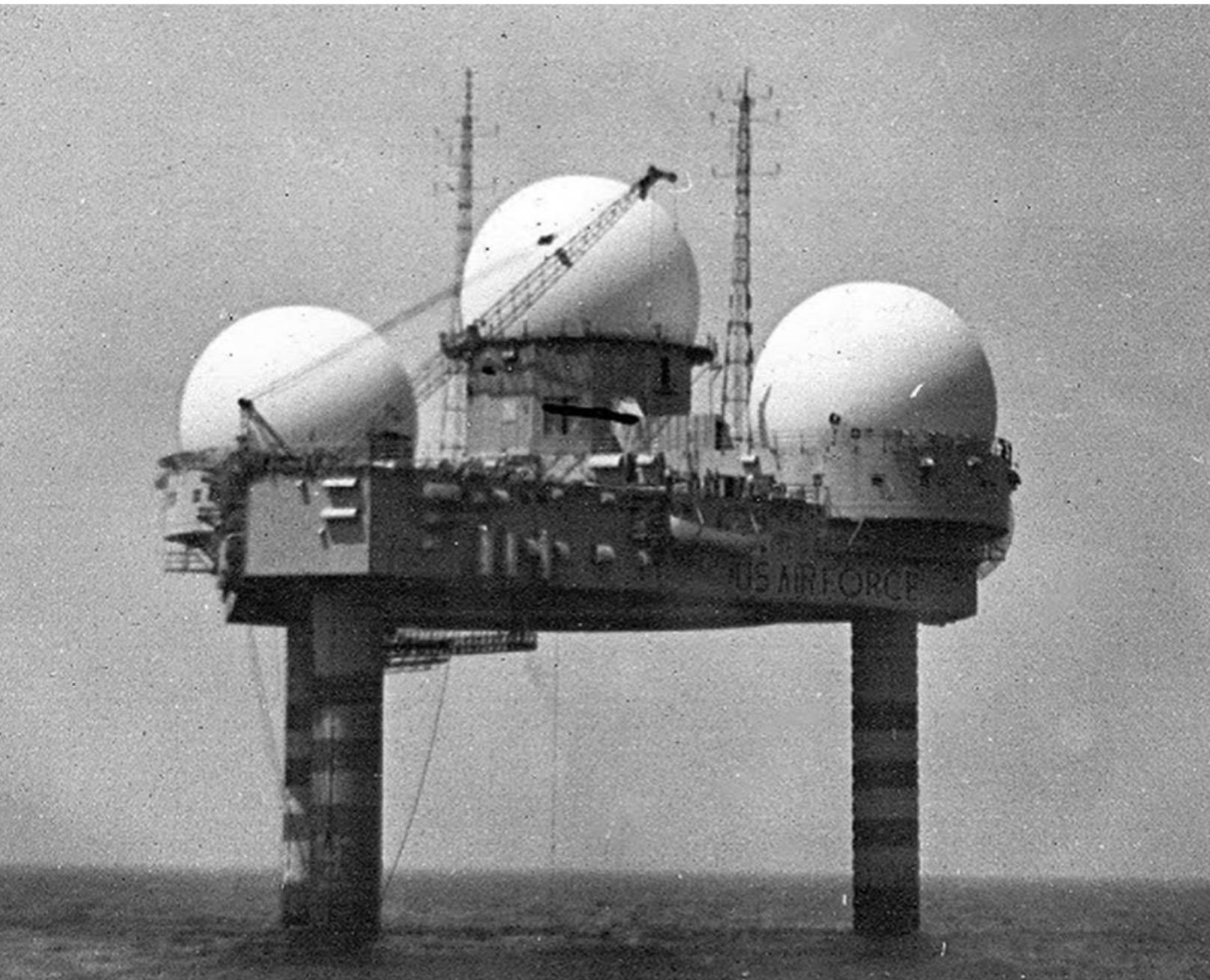


storytime!



**high recall, low
precision**

storytime!

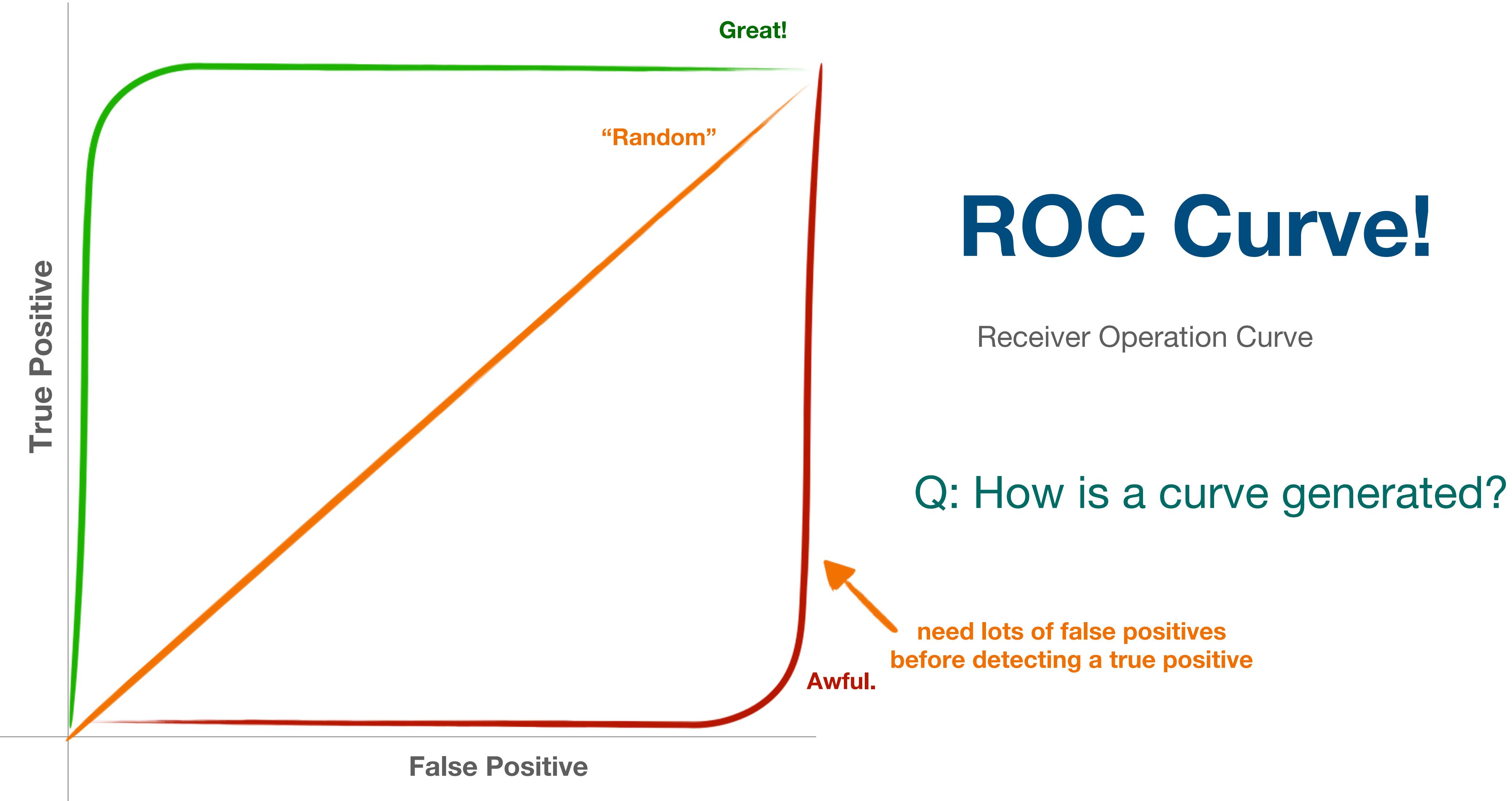


high precision, low
recall

quantifying “threshold”

**quantifying
“threshold”**

ROC Curve!

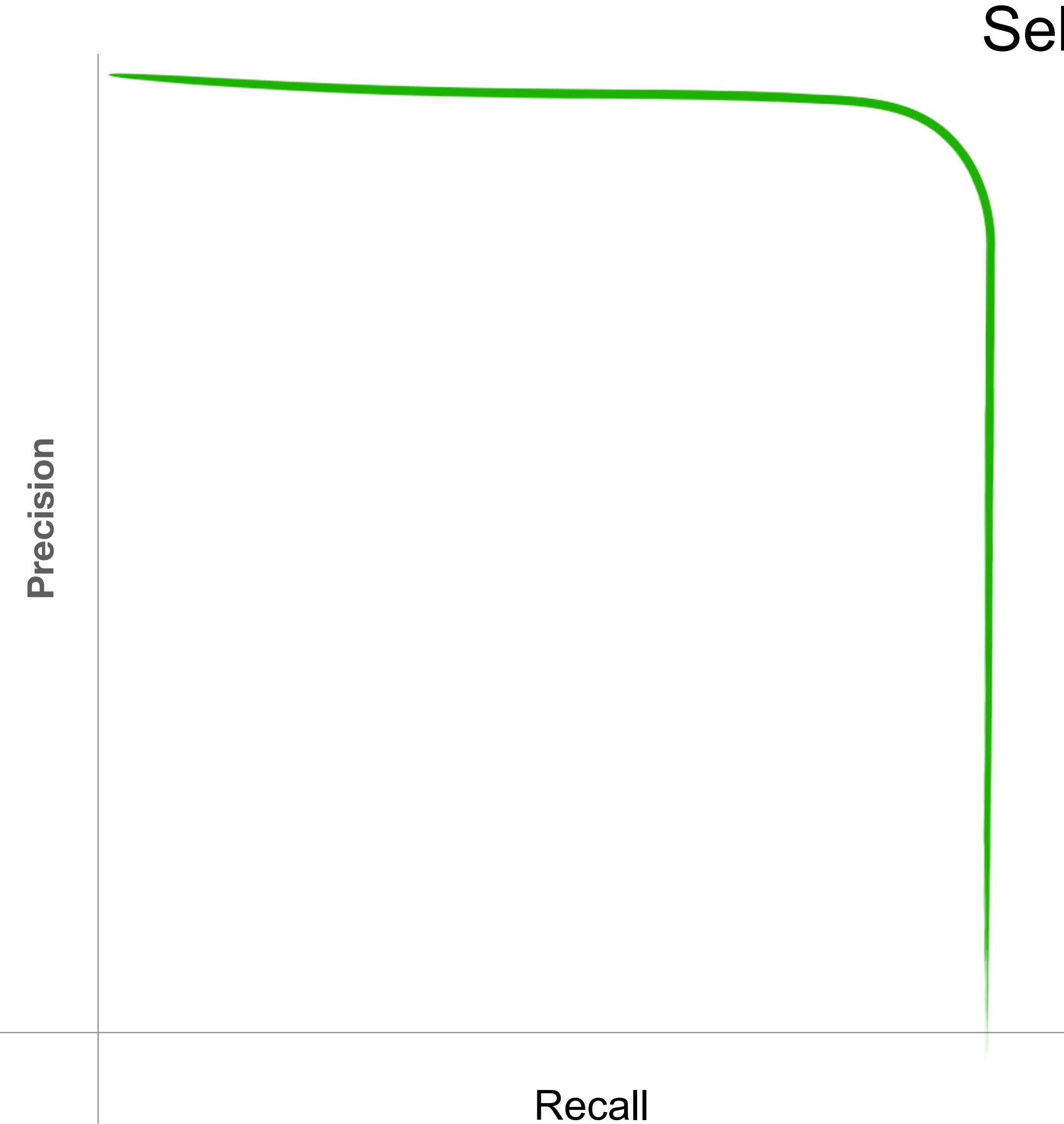


- **ROC Curve** quantify the amount of “error”/noise that is necessary for a classifier to make a good prediction



AUC
area under [the ROC] curve

Q: how do you compare these points



Self-test

Precision-recall AUC

Q: When do we really need it?
Q: what would it look like?

Especially for unbalanced datasets

what makes models fit better

more data

balanced data

normalized data

quality data

more data

balanced data

normalized data

quality data

more data

balanced data

normalized data

quality data

more data

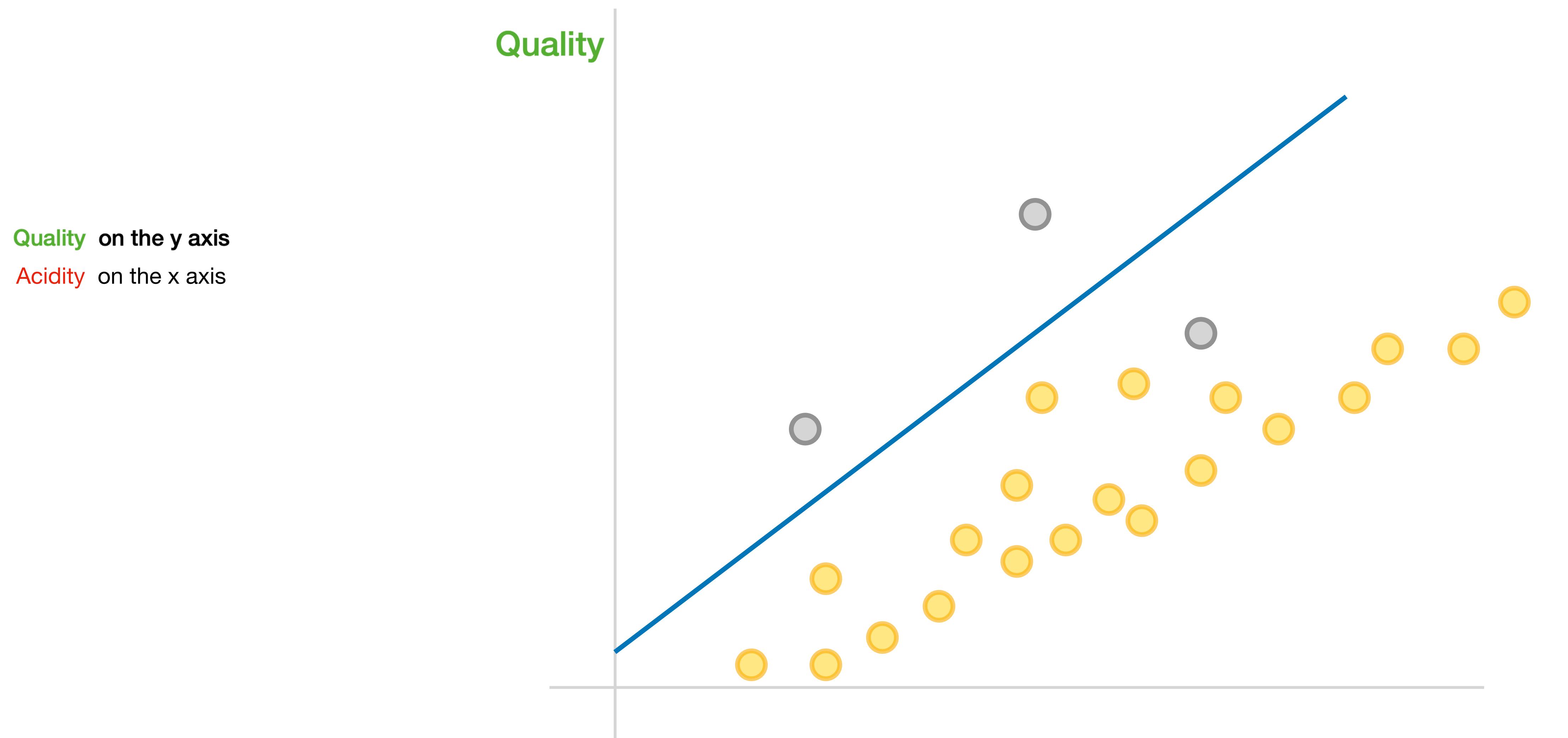
let's say we have a simpler wine dataset

Quality on the y axis

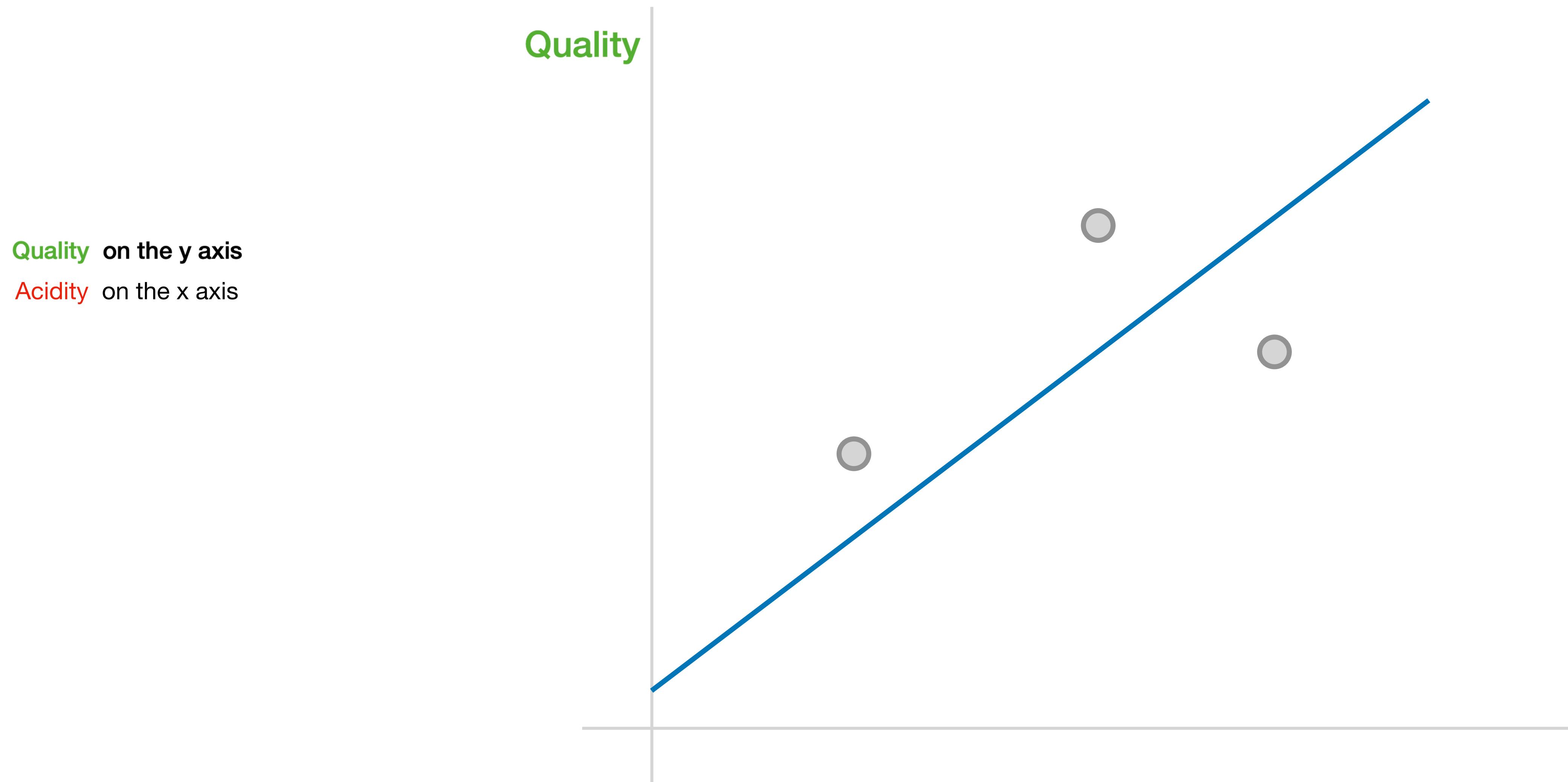
Acidity on the x axis



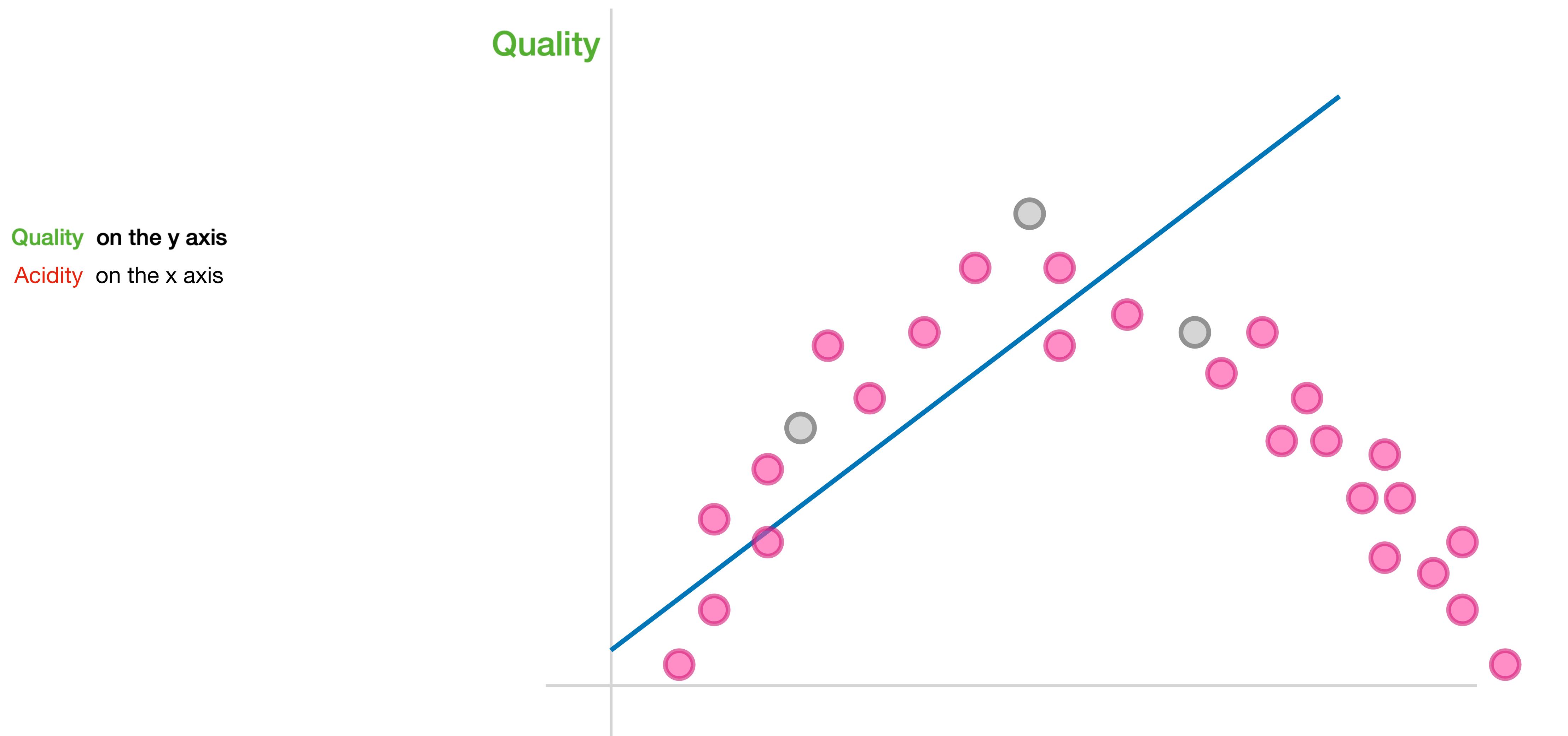
more data



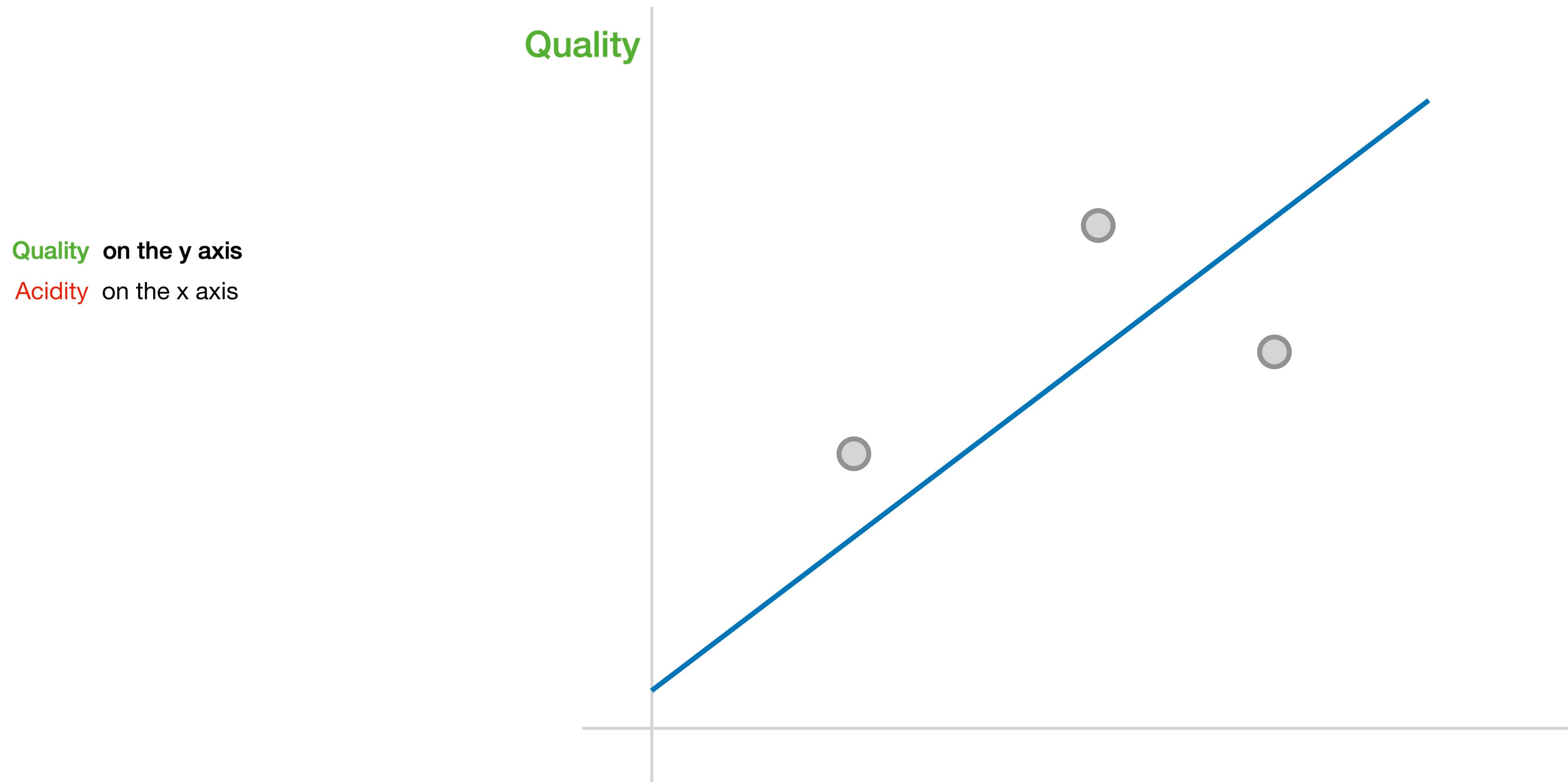
more data



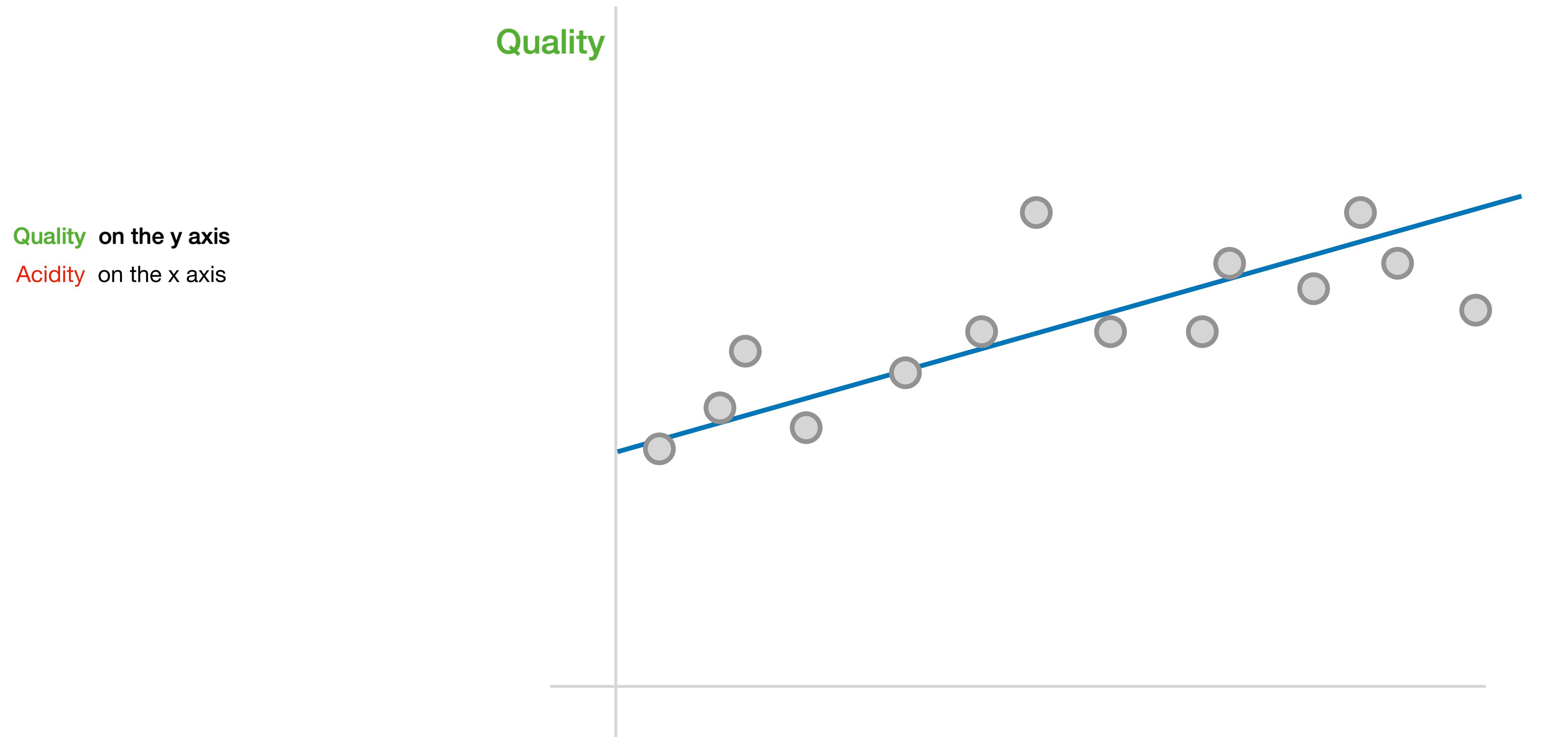
more data



more data



more data



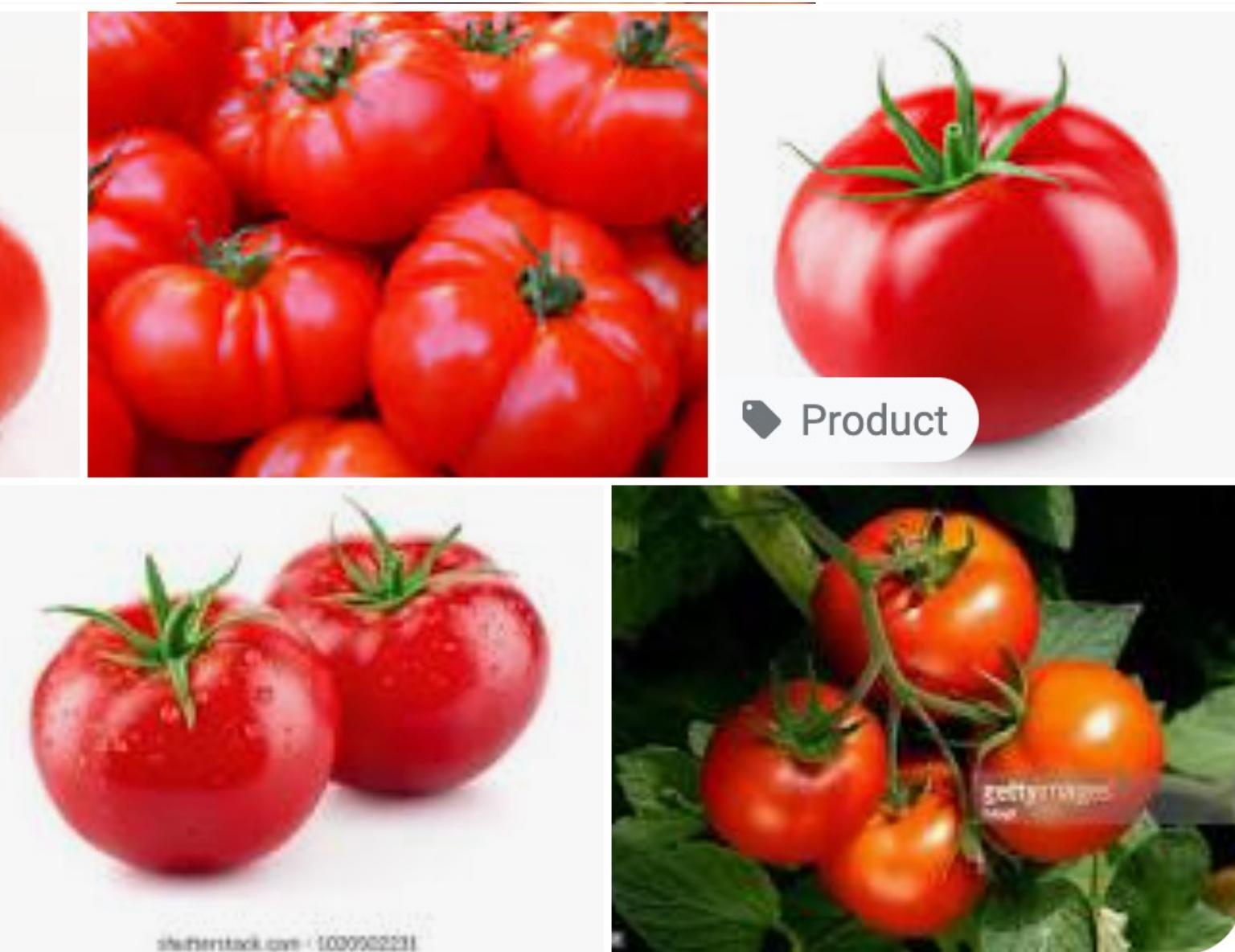
■ use more data, get more accurate results

more data

balanced data

normalized data

quality data





more data

balanced data

normalized data

quality data

more data

balanced data

normalized data

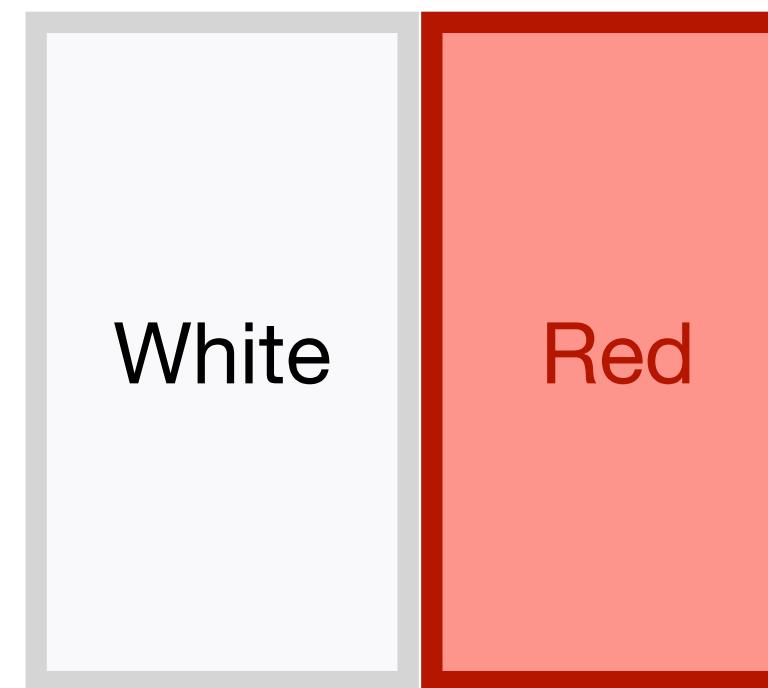
quality data

balanced data

Let's think about logistic functions!

balanced data

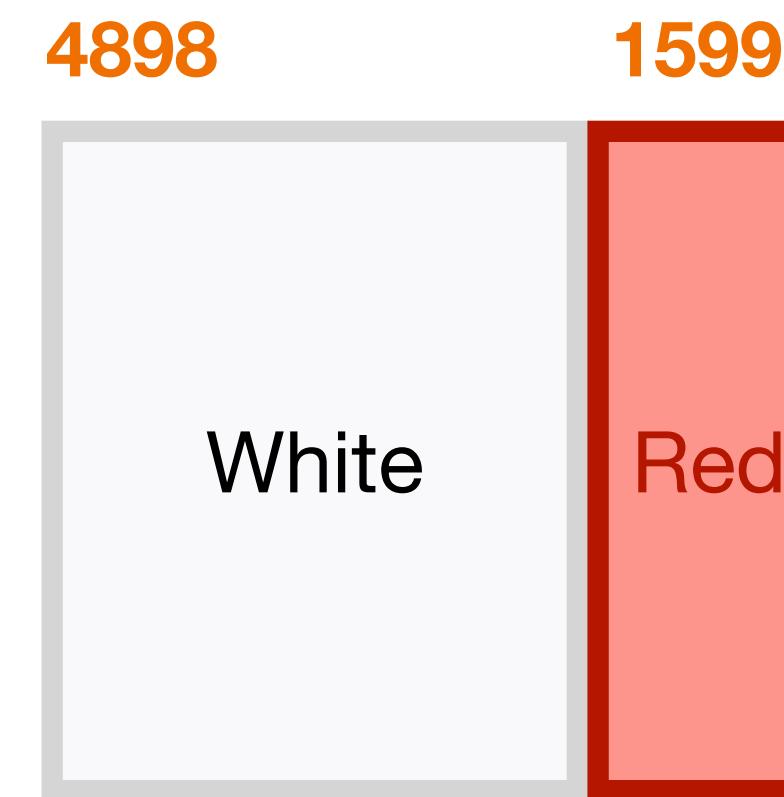
Let's think about logistic functions!



in an ideal world
...but no

balanced data

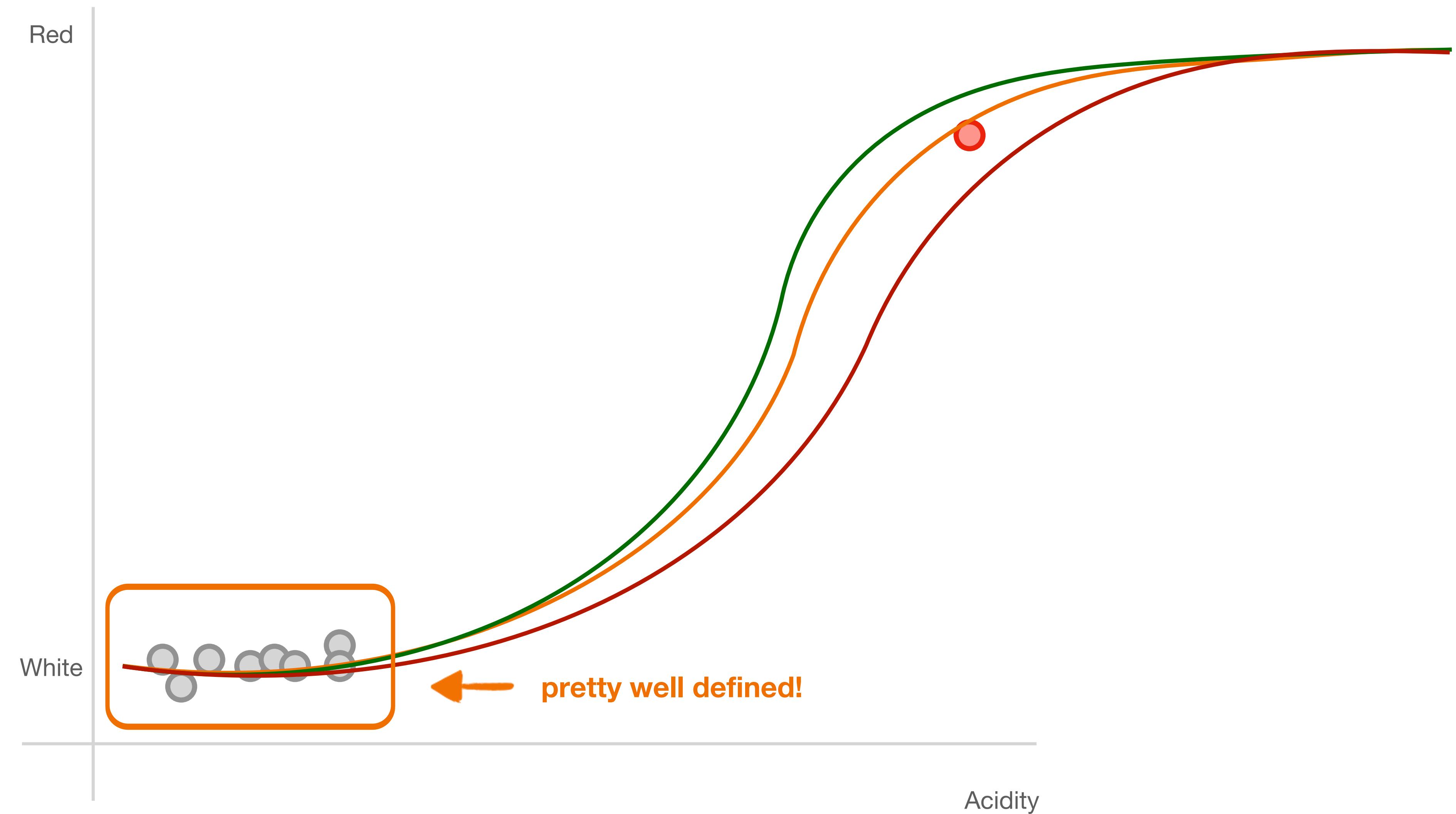
Let's think about logistic functions!



What happens when we fit this dataset entirely?

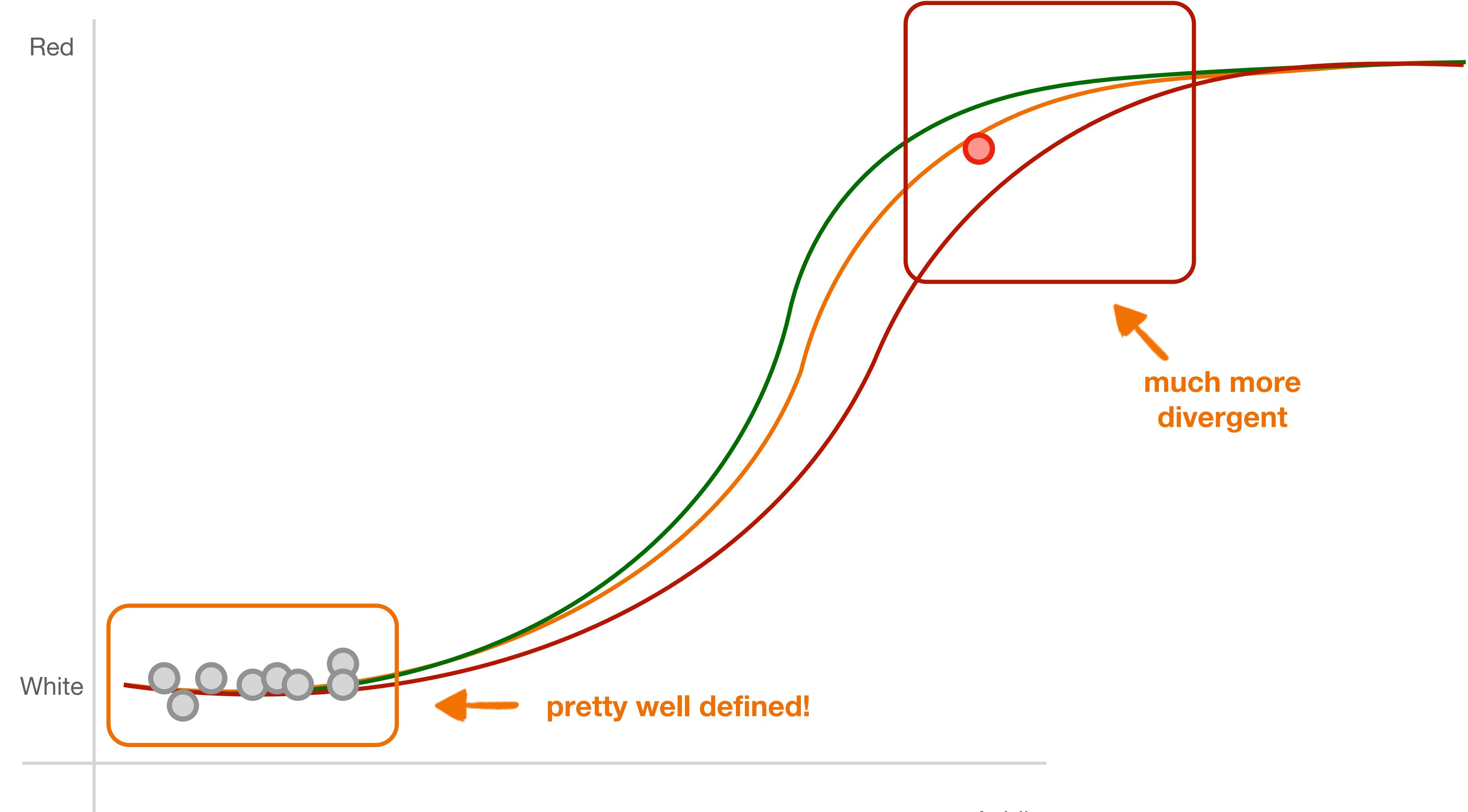
balanced data

Let's think about logistic functions!



balanced data

Let's think about logistic functions!



more data

balanced data

normalized data

quality data

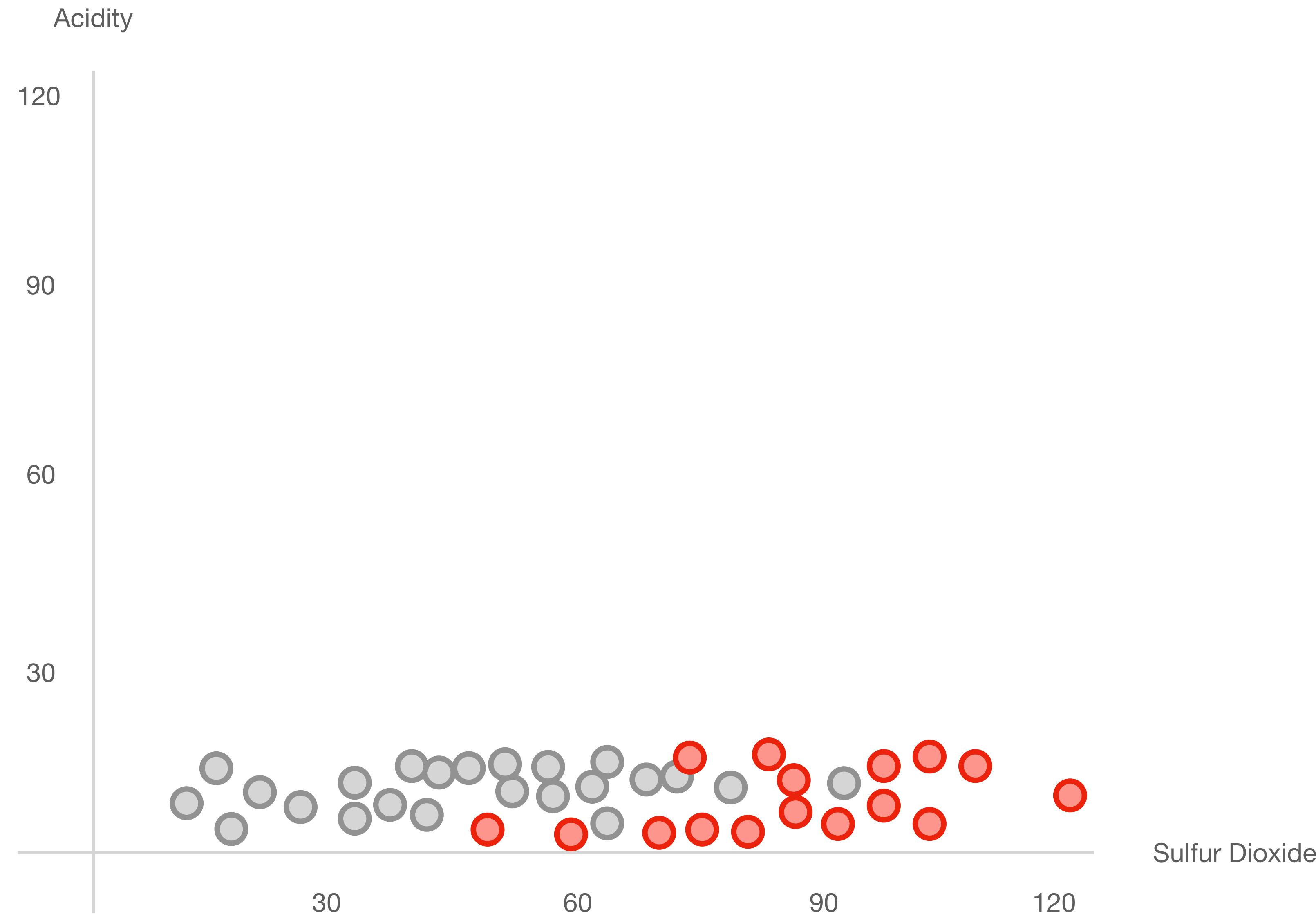
more data

balanced data

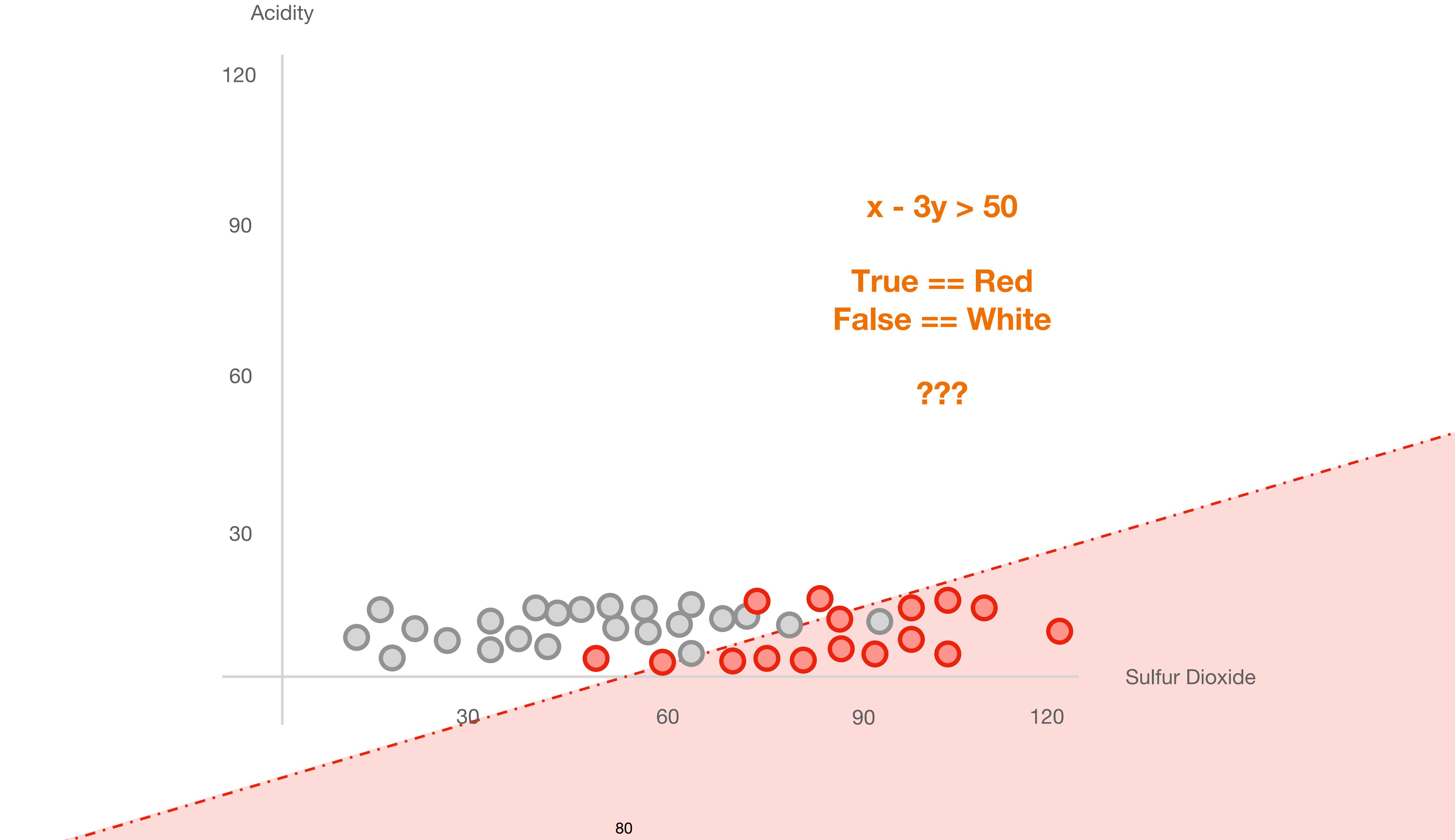
normalized data

quality data

normalized data



normalized data



normalized data



more data

balanced data

normalized data

quality data

more data

balanced data

normalized data

quality data

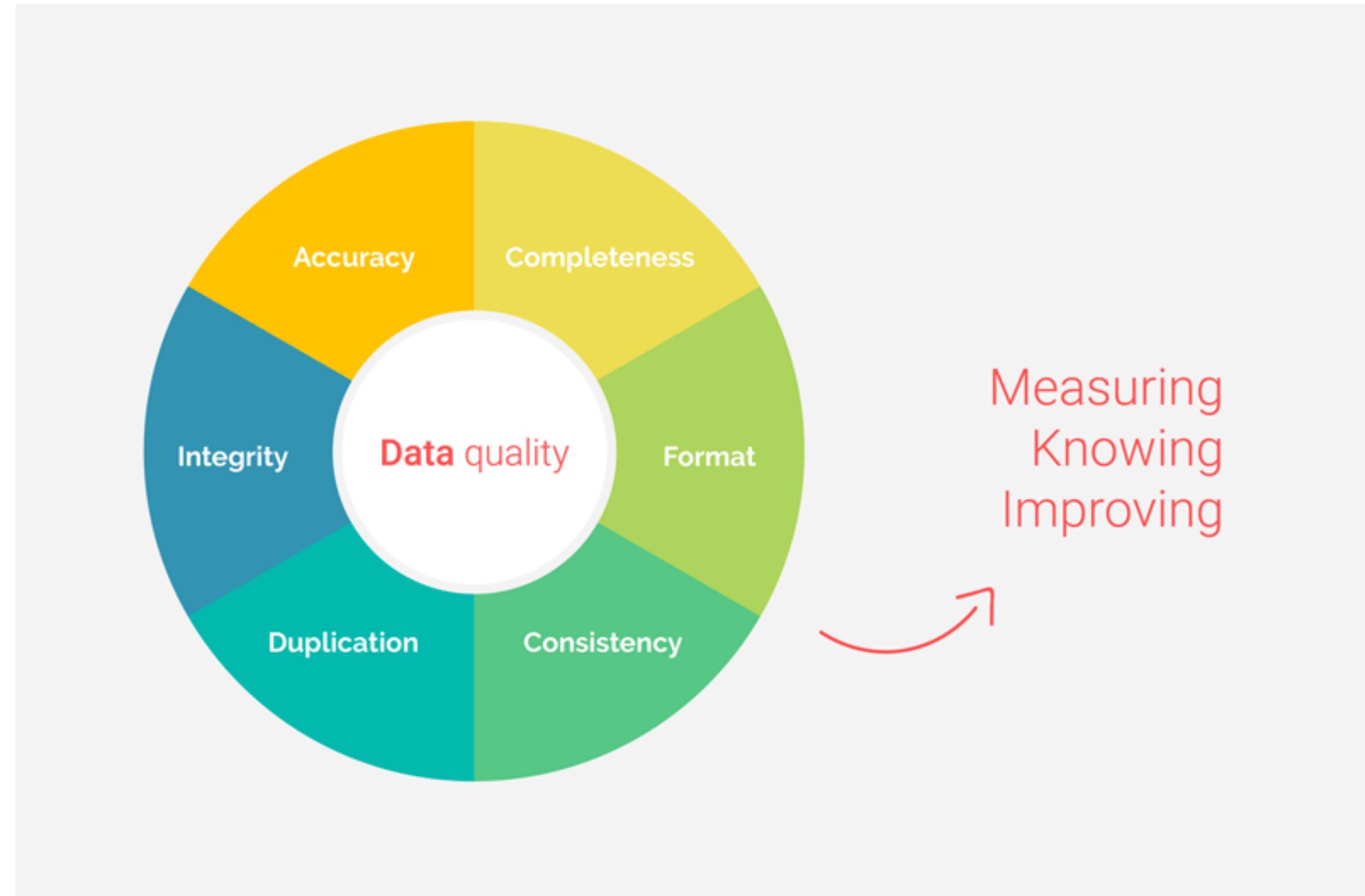


Image credit: Passionned Group

more data

balanced data

normalized data

quality data

Missing Data

Missing Data

Missing completely at random

Missing at random

Missing not at random

Missing Data

remove

Use mean/most often
regression