



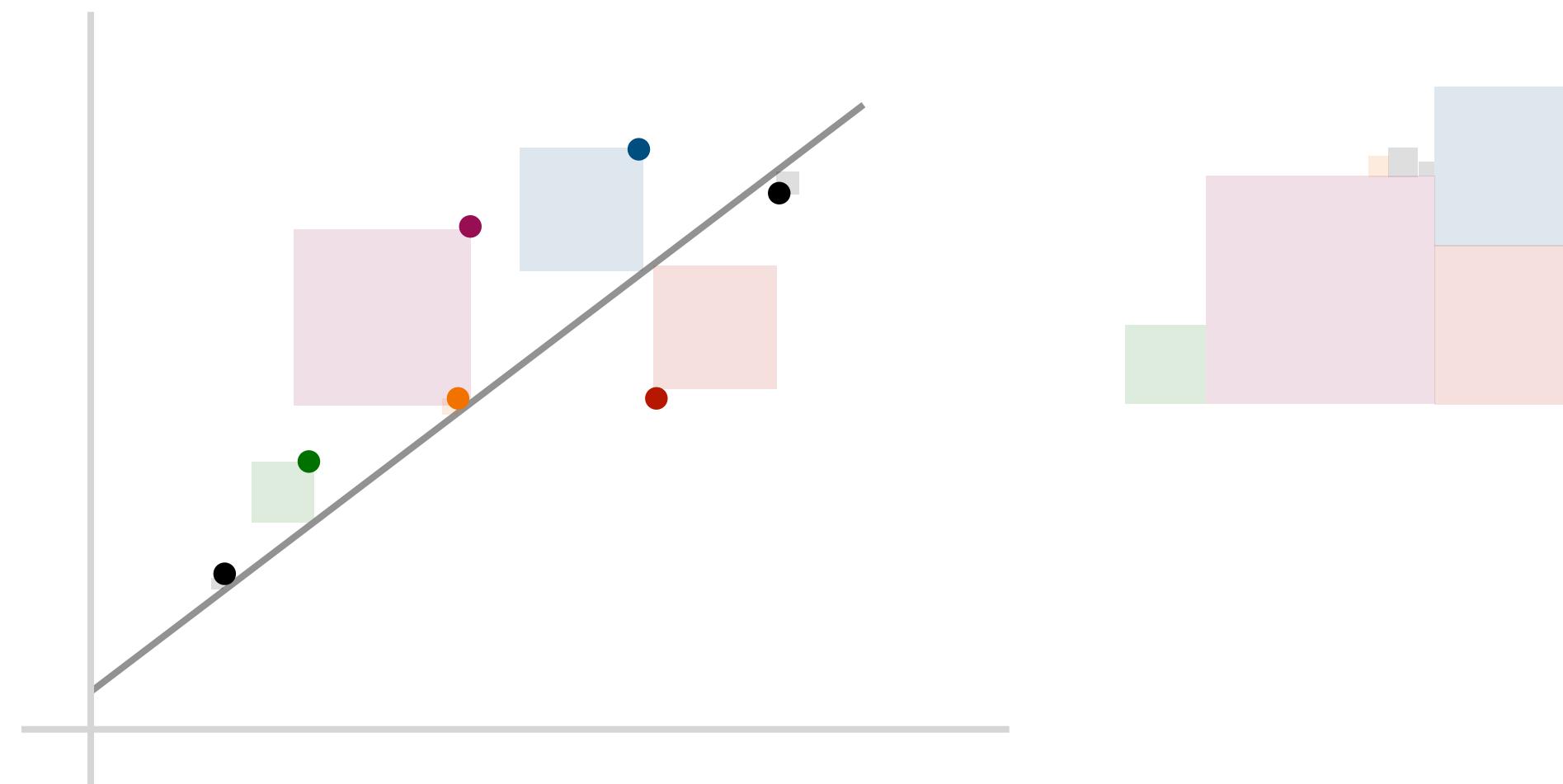
# AIBridge

## Lecture 5

**Let's talk about last week's lab!**

# Let's talk about last week's lab!

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



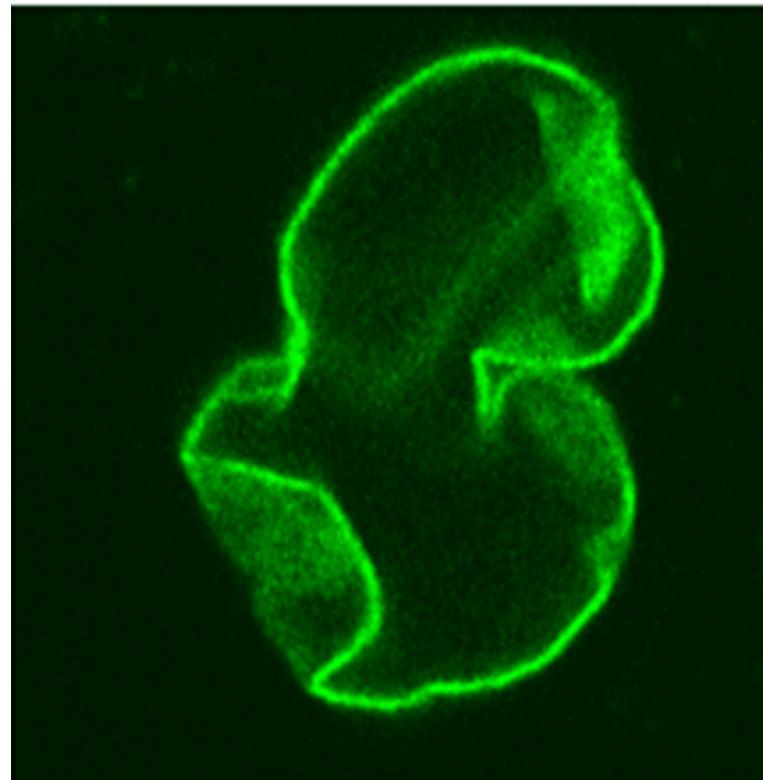
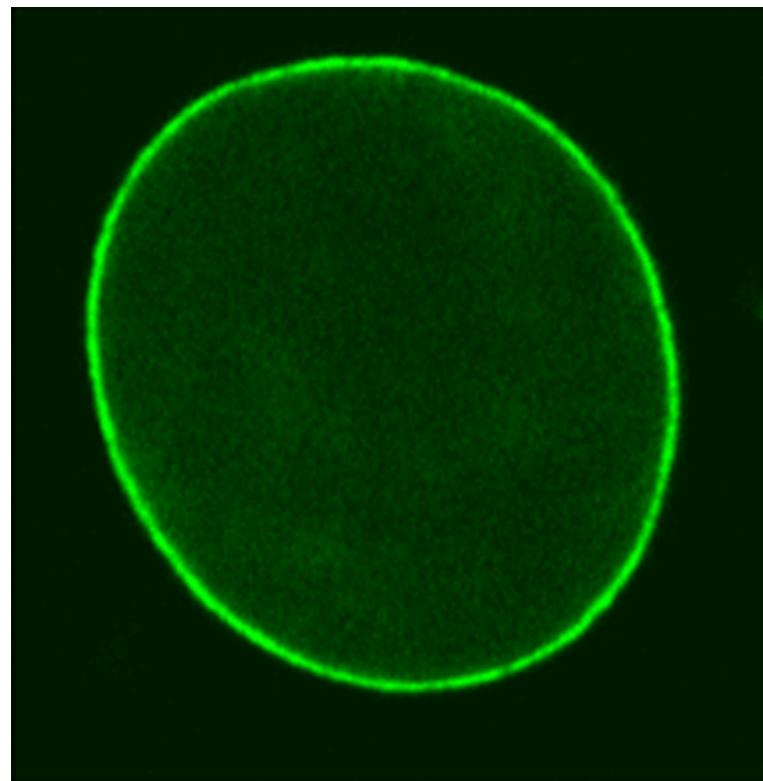
what does this even mean?



worse?

# Accuracy

“Why is it not enough?”



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

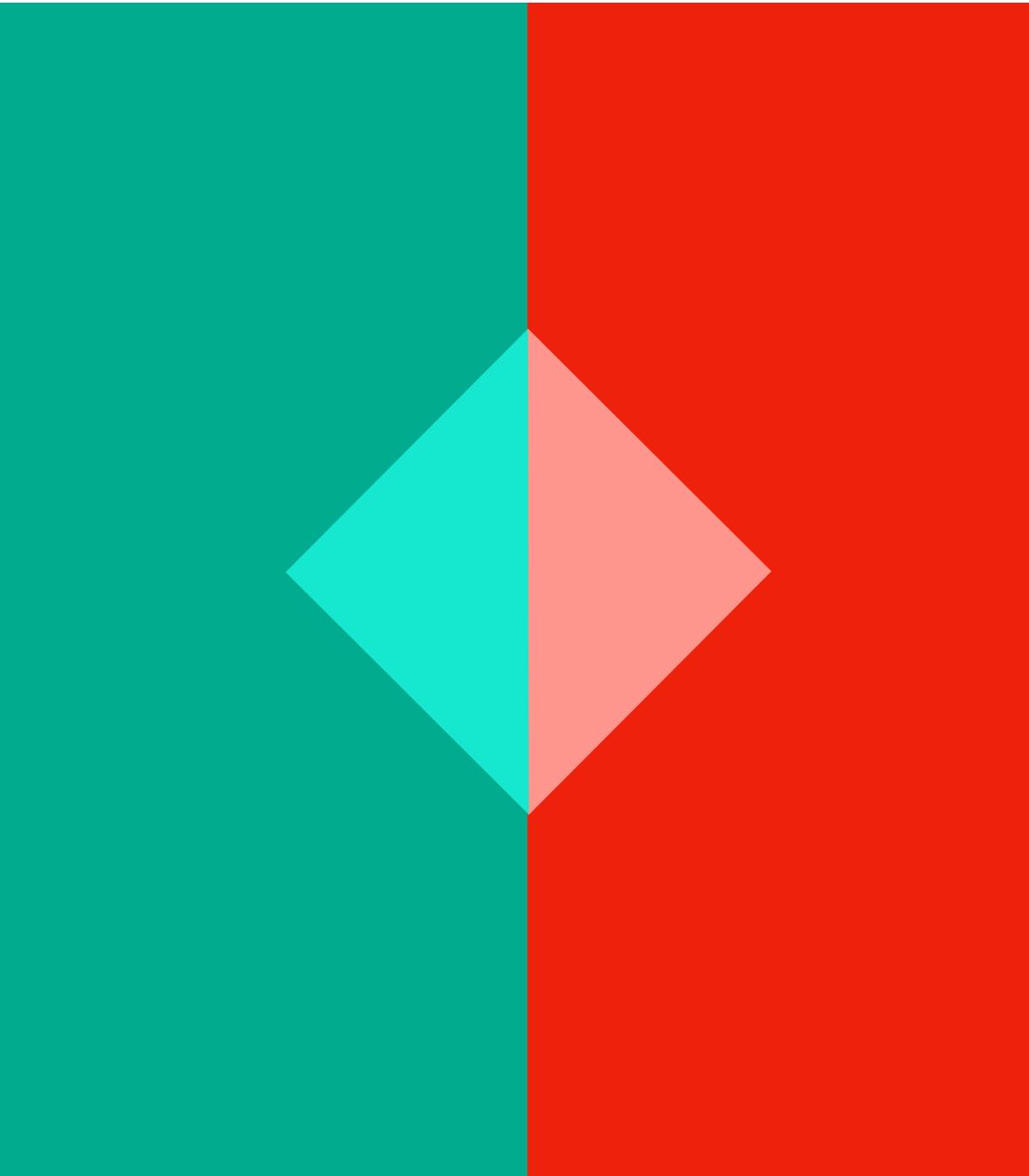
**Progeria affects ~159 patients in the US**

we have a dataset of all American pediatric patients



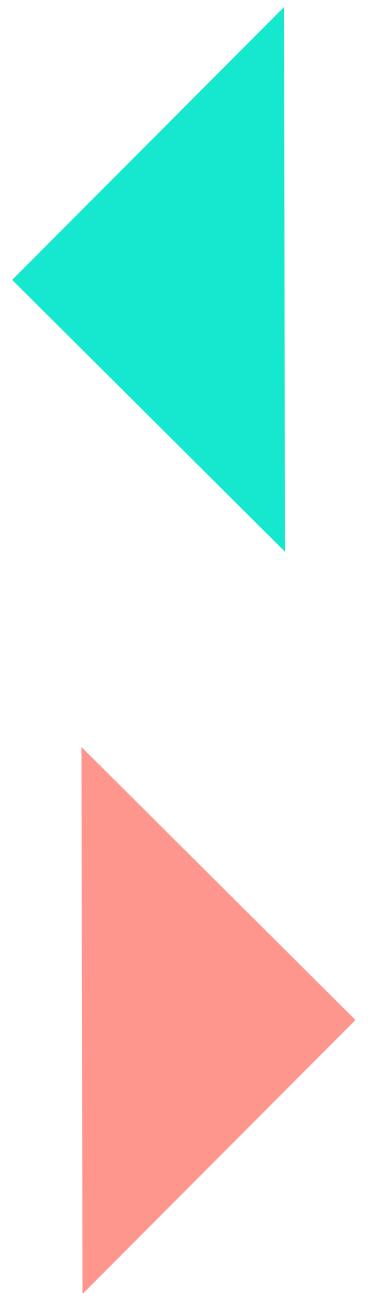
Q: If my model predicts with 99.99% accuracy, is it good enough?

# Accuracy, Precision, and Recall

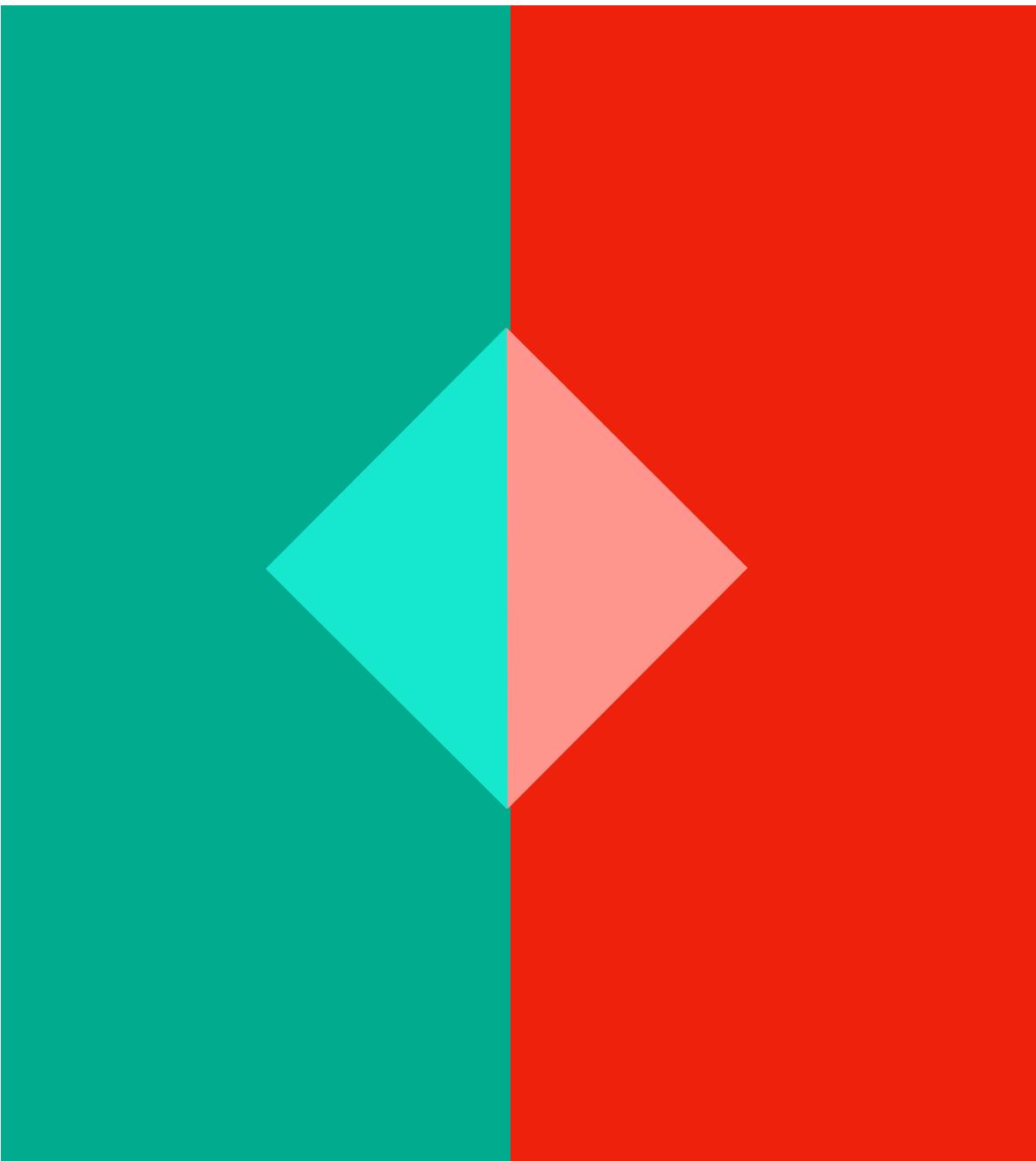


“Selection space”

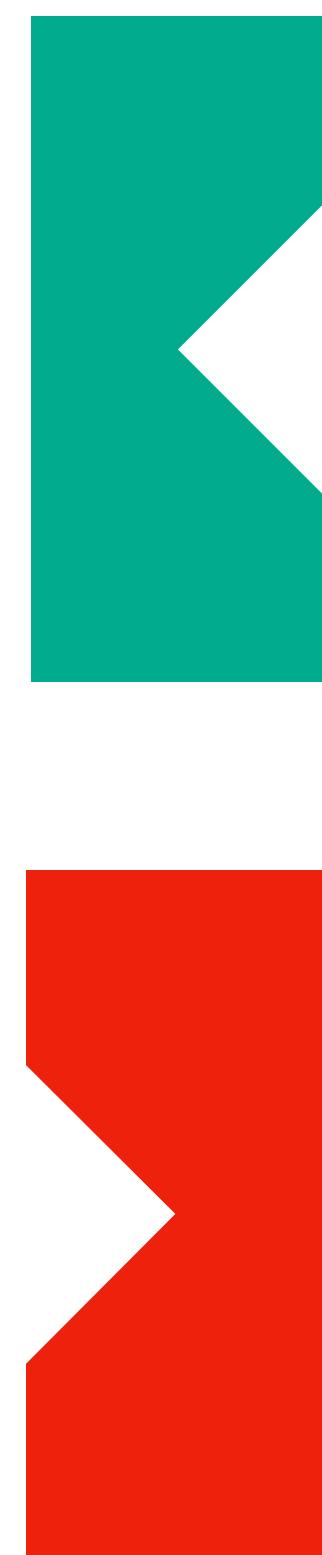
TP: Model selects **positive** and patient is **positive**



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

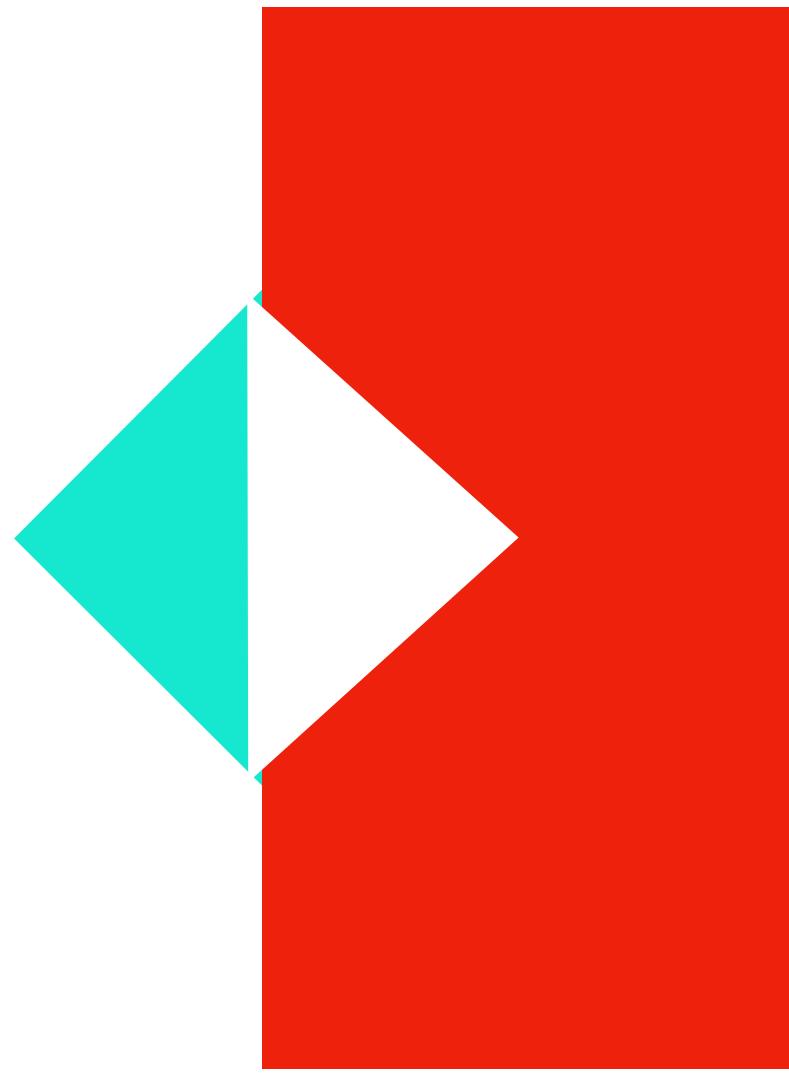


“Selection space”



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

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



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

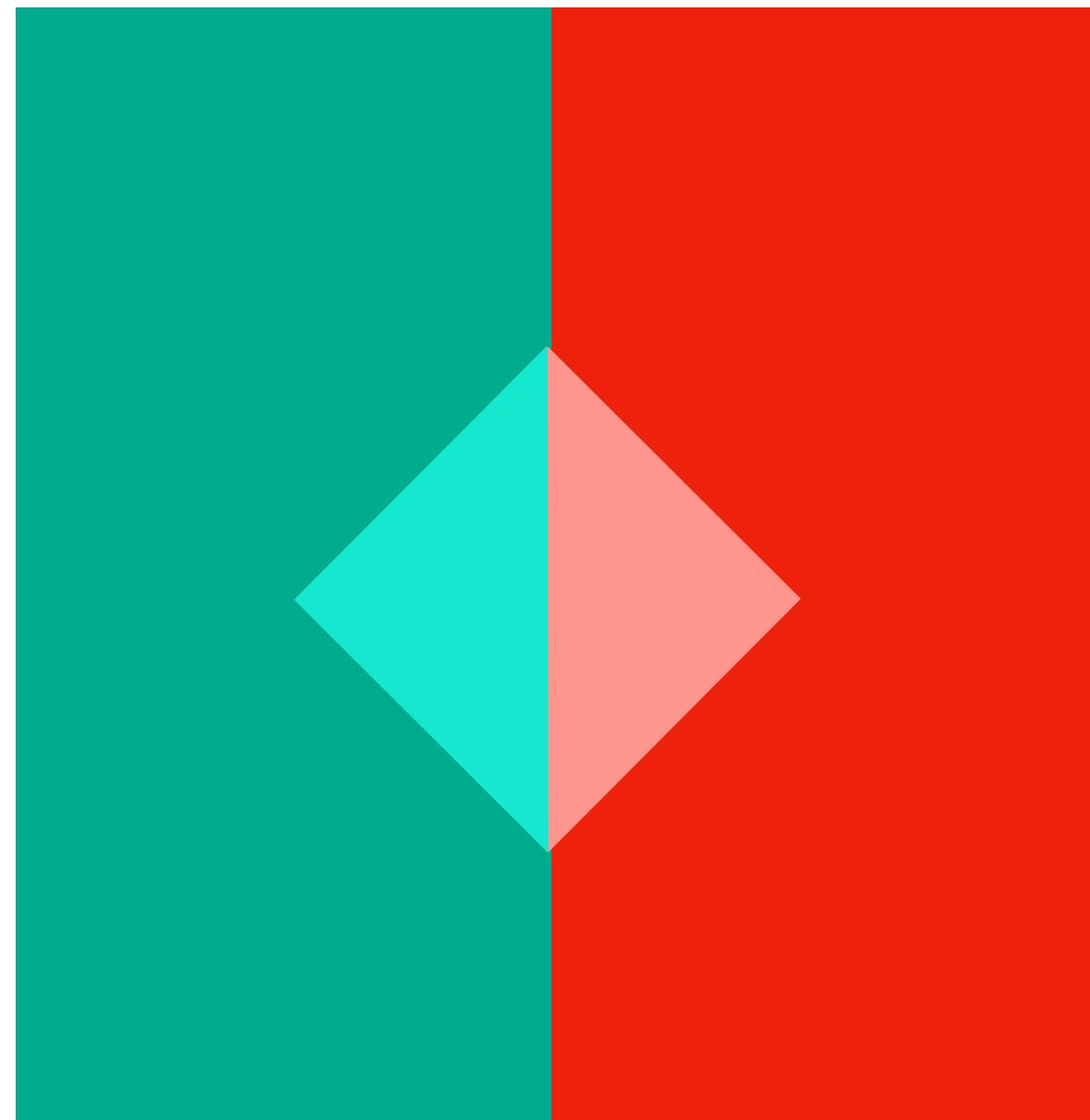
*and*

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

## Accuracy

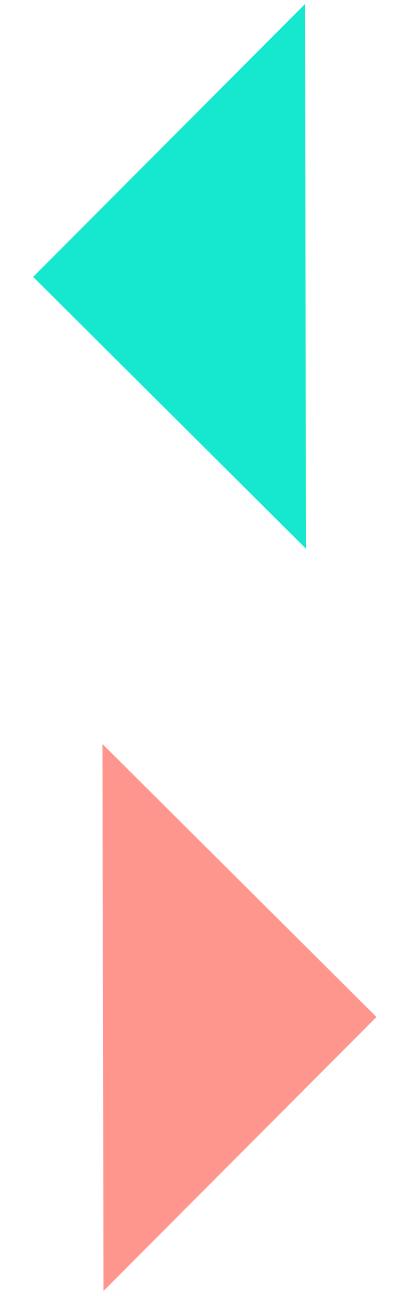
Overall ability of model

---

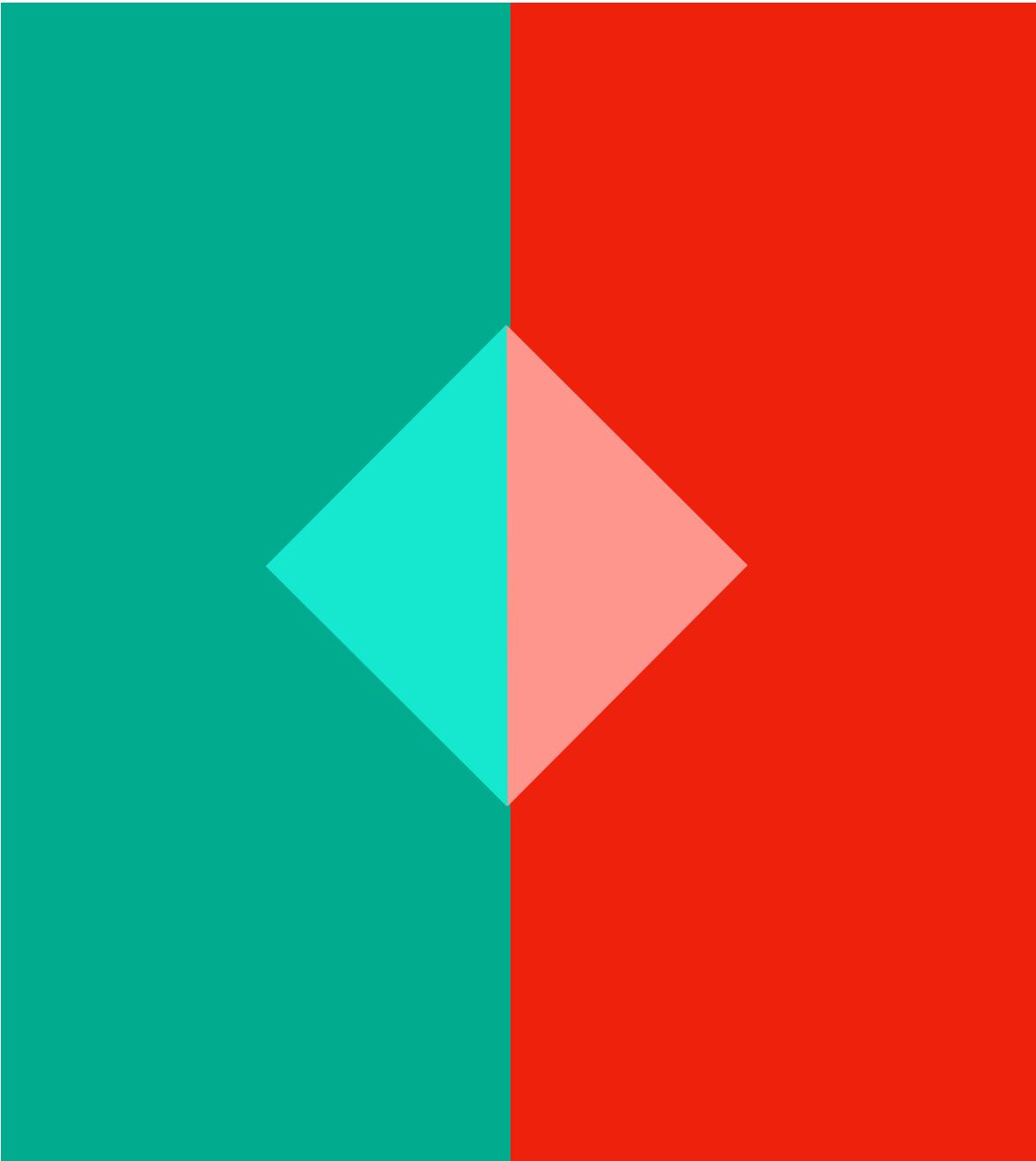


“Everything”

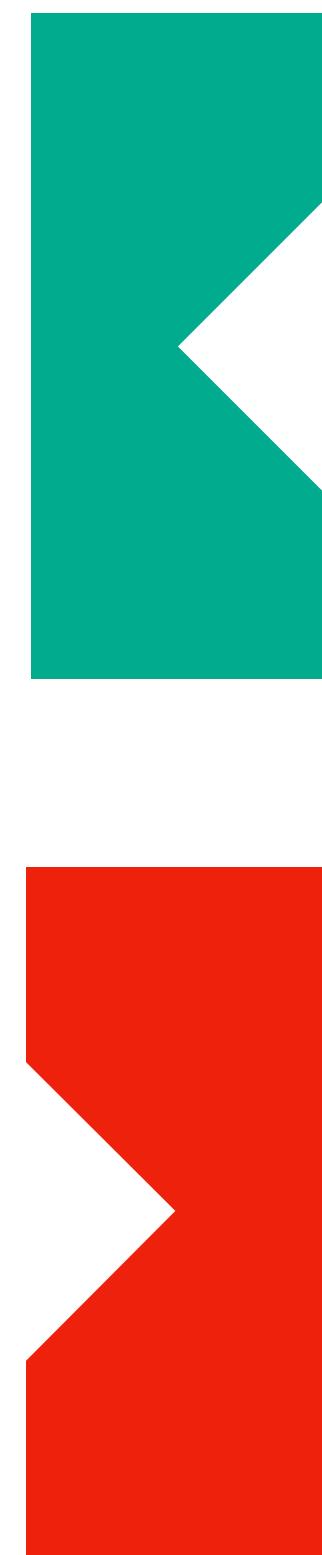
TP: Model selects **positive** and patient is **positive**



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



“Selection space”



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

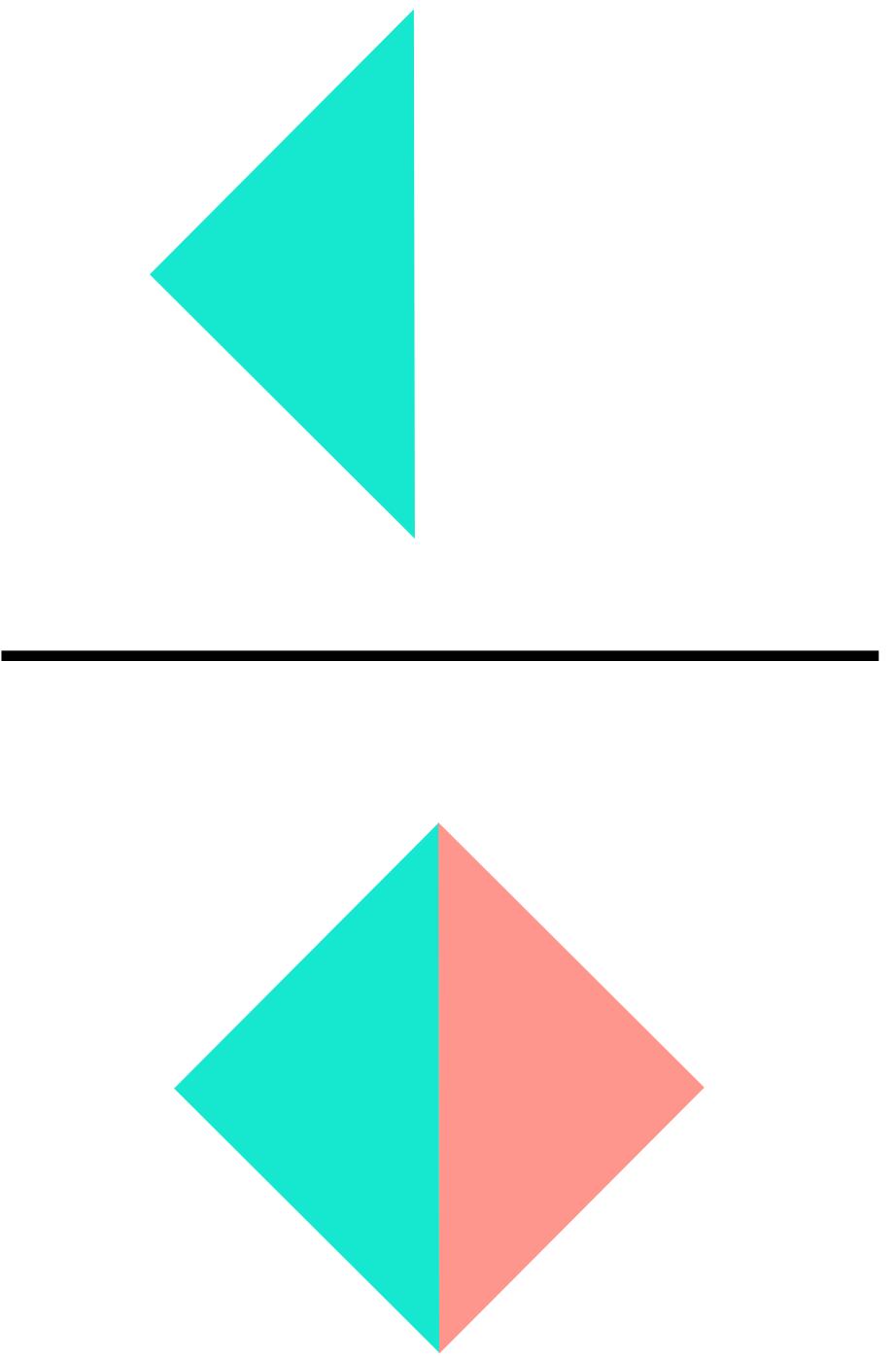
TN: Model selects **negative** and patient is **negative**

## Accuracy

Overall ability of model

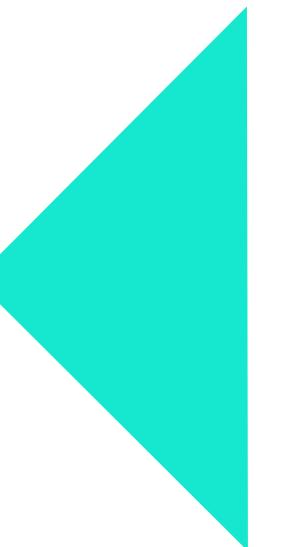
## Precision

Amount of selection  
that's actually correct.



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

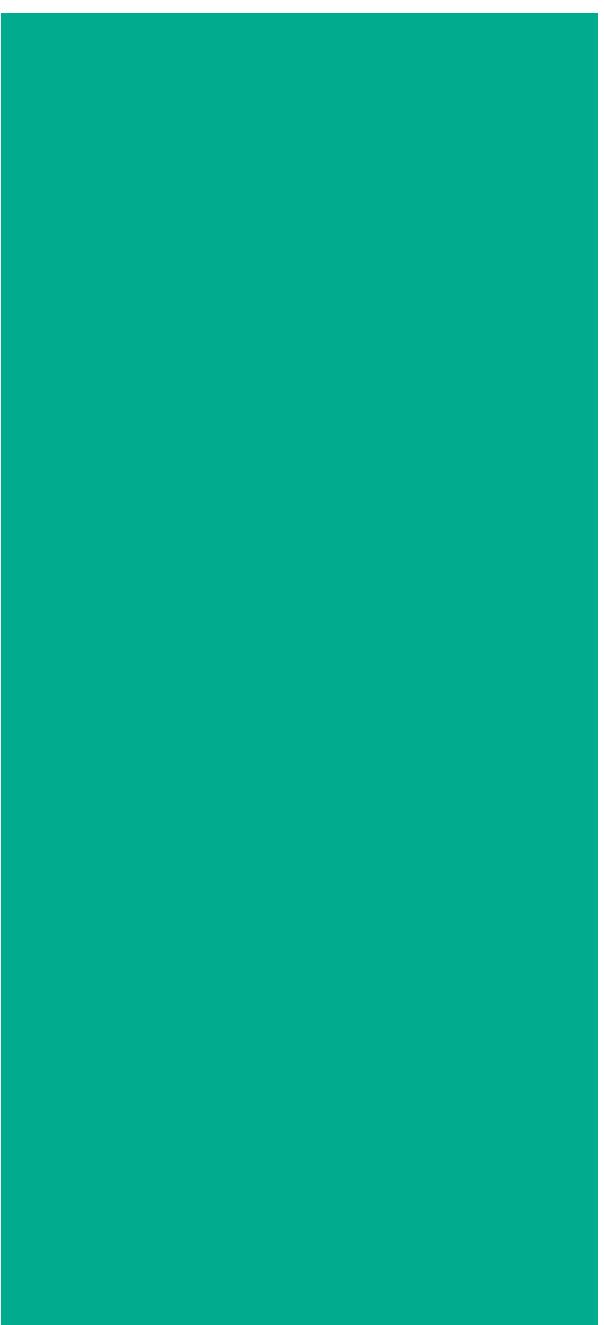
“All selected **positive** by the  
model”



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

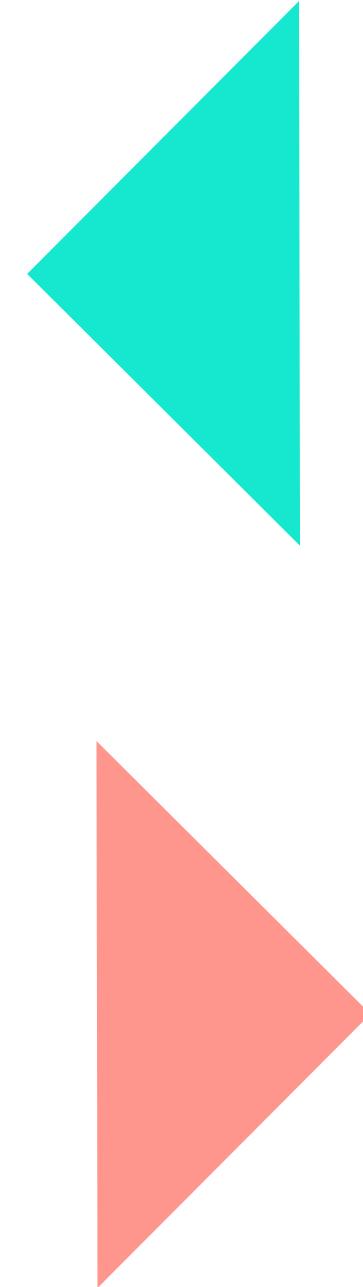
## Recall

Amount of what needs to  
be selected that is selected

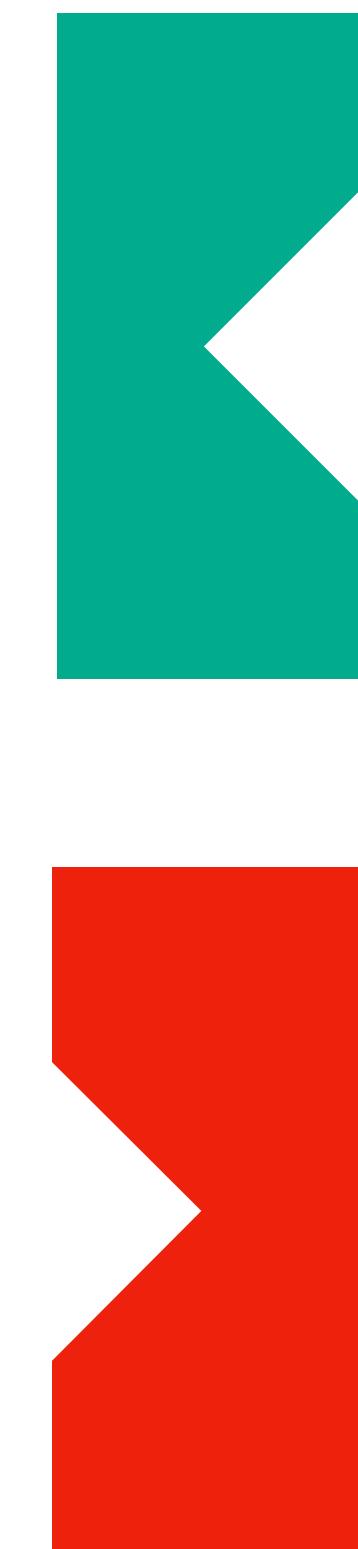
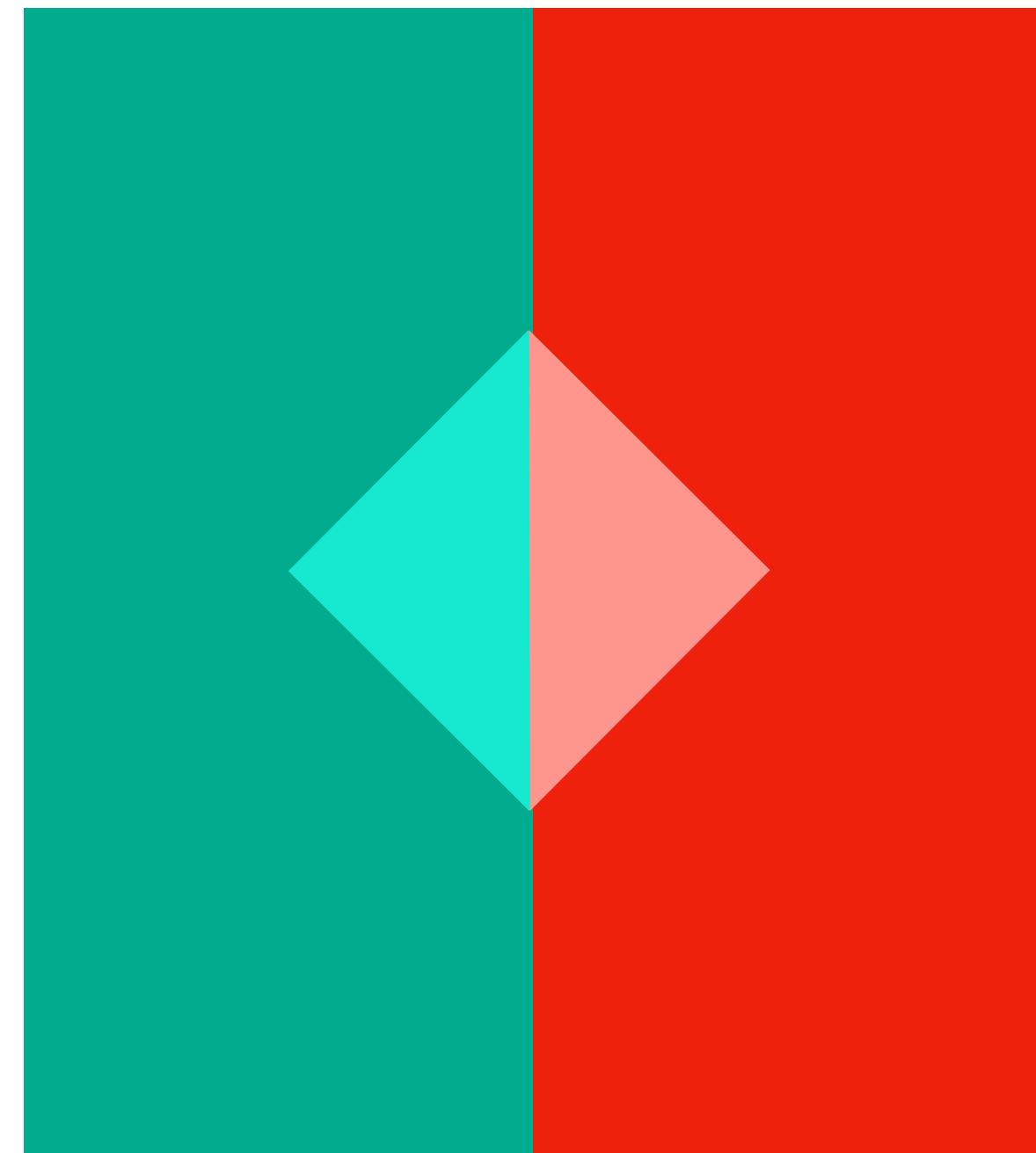


“All cases that are **positive**”

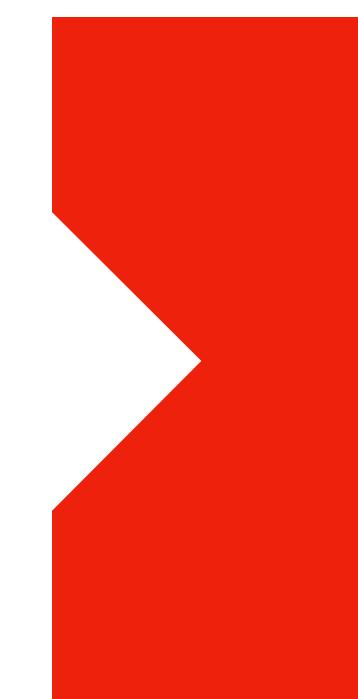
Model selects  
**positive** and  
patient is  
**positive**



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



Model selects  
**negative** and  
patient is  
**negative**



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

## Accuracy

Overall ability of model

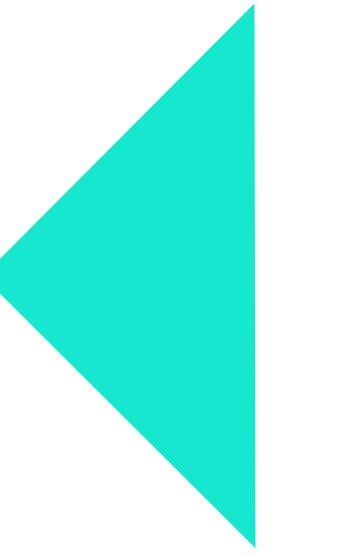
## Precision

Amount of selection  
that's actually correct.

## Recall

Amount of what needs to  
be selected that is selected

**TRUE POSITIVE**

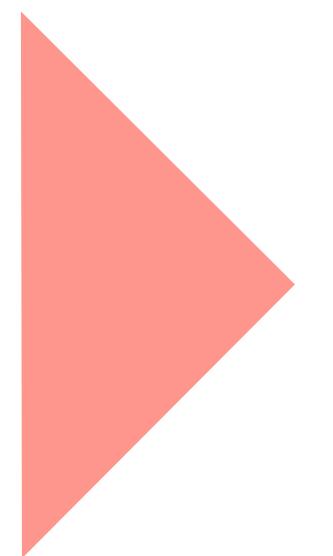


*TP*

*FN*

**False NEGATIVE**

**FALSE POSITIVE**



*FP*

*TN*

**True NEGATIVE**

### **Accuracy**

Overall ability of model

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

### **Precision**

Amount of selection  
that's actually correct.

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

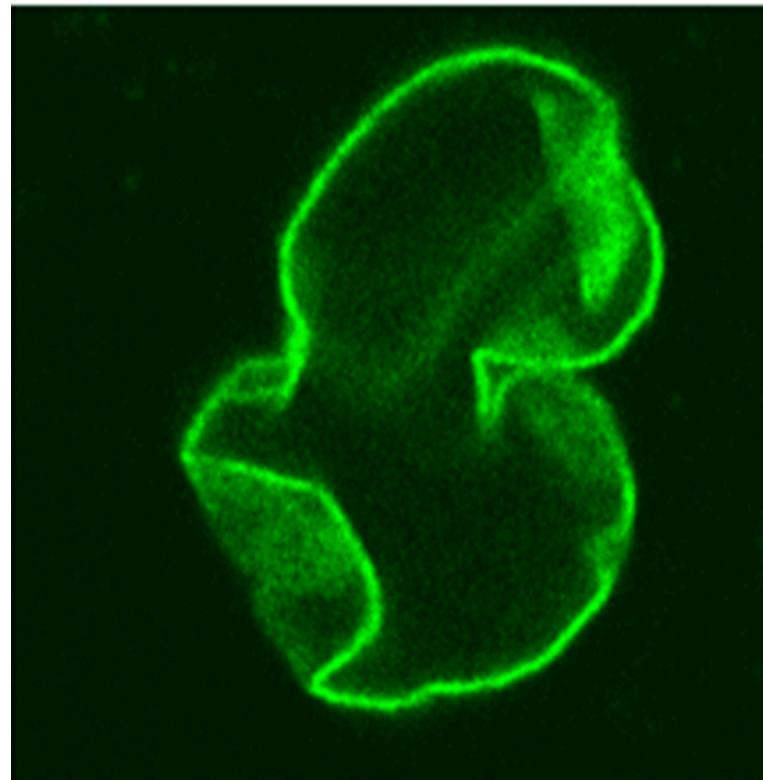
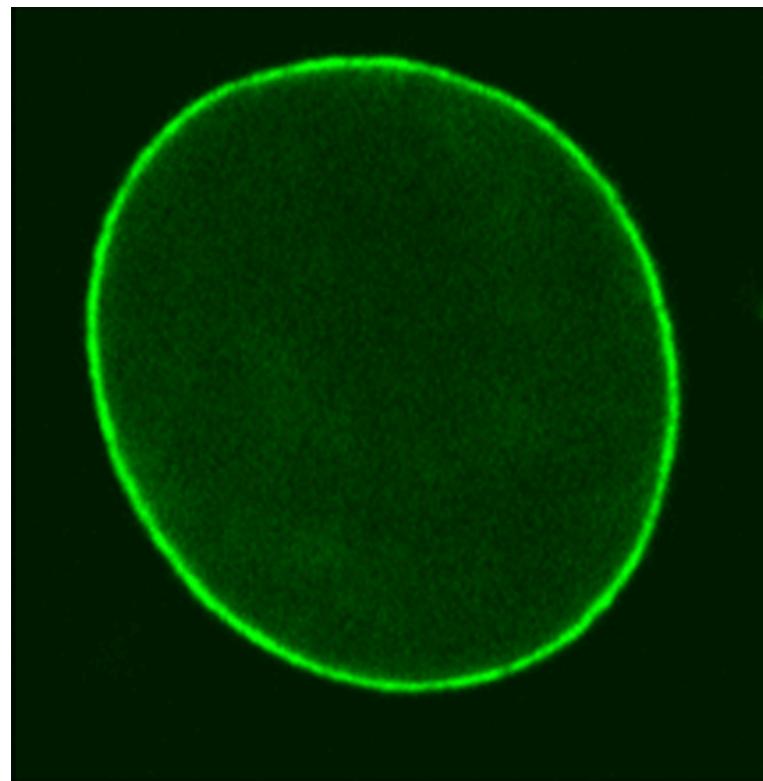
### **Recall**

Amount of what needs to  
be selected that is selected

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

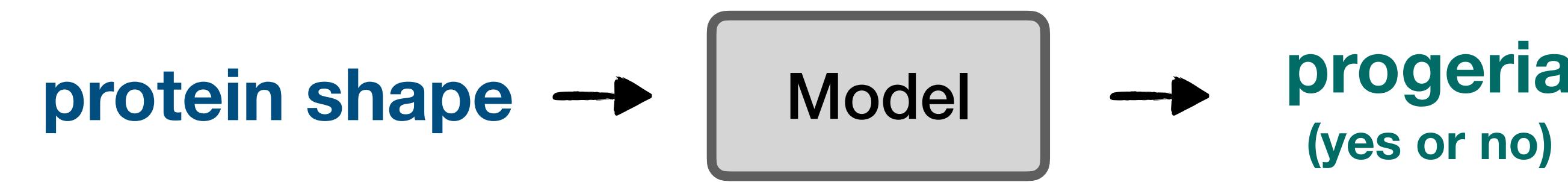
Sources: [6][7][8][9][10][11][12][13][14] [view](#) · [talk](#) · [edit](#)

Predicted condition					
Total population $= P + N$	Positive (PP)	Negative (PN)	Informedness, bookmaker informedness (BM) $= TPR + TNR - 1$	Prevalence threshold (PT) $= \frac{\sqrt{TPR \times FPR} - FPR}{TPR - FPR}$	
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 $= \frac{TP}{P} = 1 - FNR$	False negative rate (FNR), miss rate $= \frac{FN}{P} = 1 - TPR$
	Negative (N)	False positive (FP), type I error, false alarm, overestimation	True negative (TN), correct rejection	False positive rate (FPR), probability of false alarm, fall-out $= \frac{FP}{N} = 1 - TNR$	True negative rate (TNR), specificity (SPC), selectivity $= \frac{TN}{N} = 1 - FPR$
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 ( $\Delta p$ ) $= PPV + NPV - 1$	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 $= \frac{TP}{TP + FN + FP}$	



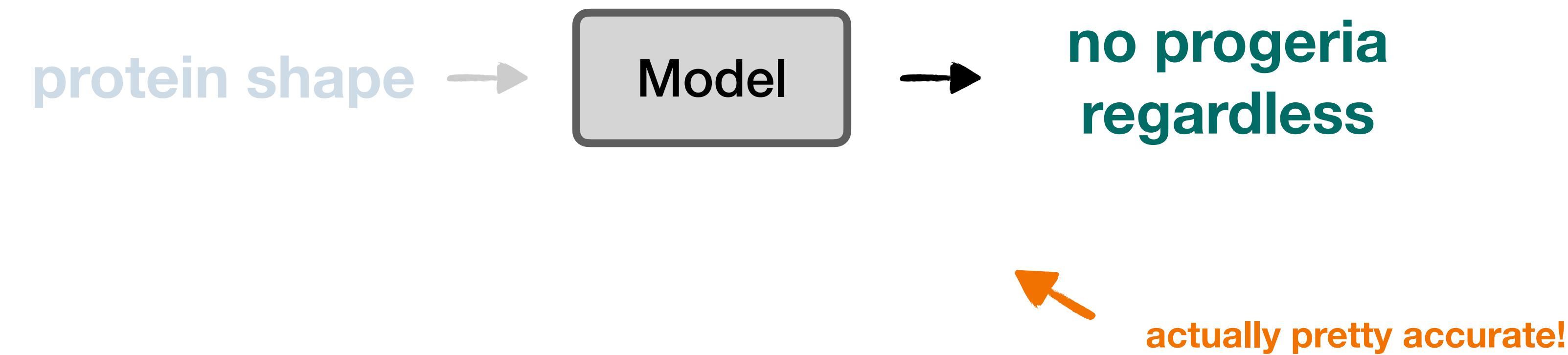
**Progeria affects ~159 patients in the US**  
we have a dataset of all American pediatric patients

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

Overall ability of model

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

exact zero

## Precision

Amount of selection that's actually correct.

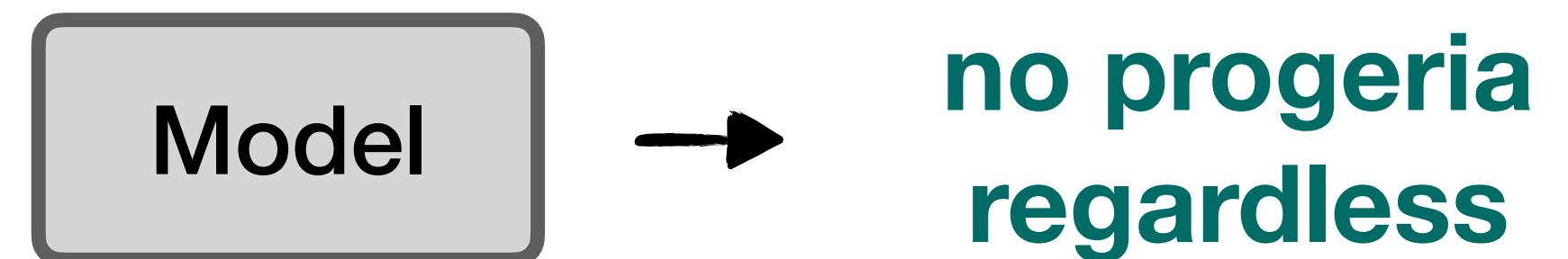
$$\frac{TP}{TP + FP}$$

## Recall

Amount of what needs to be selected that is selected

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

← scaled properly!

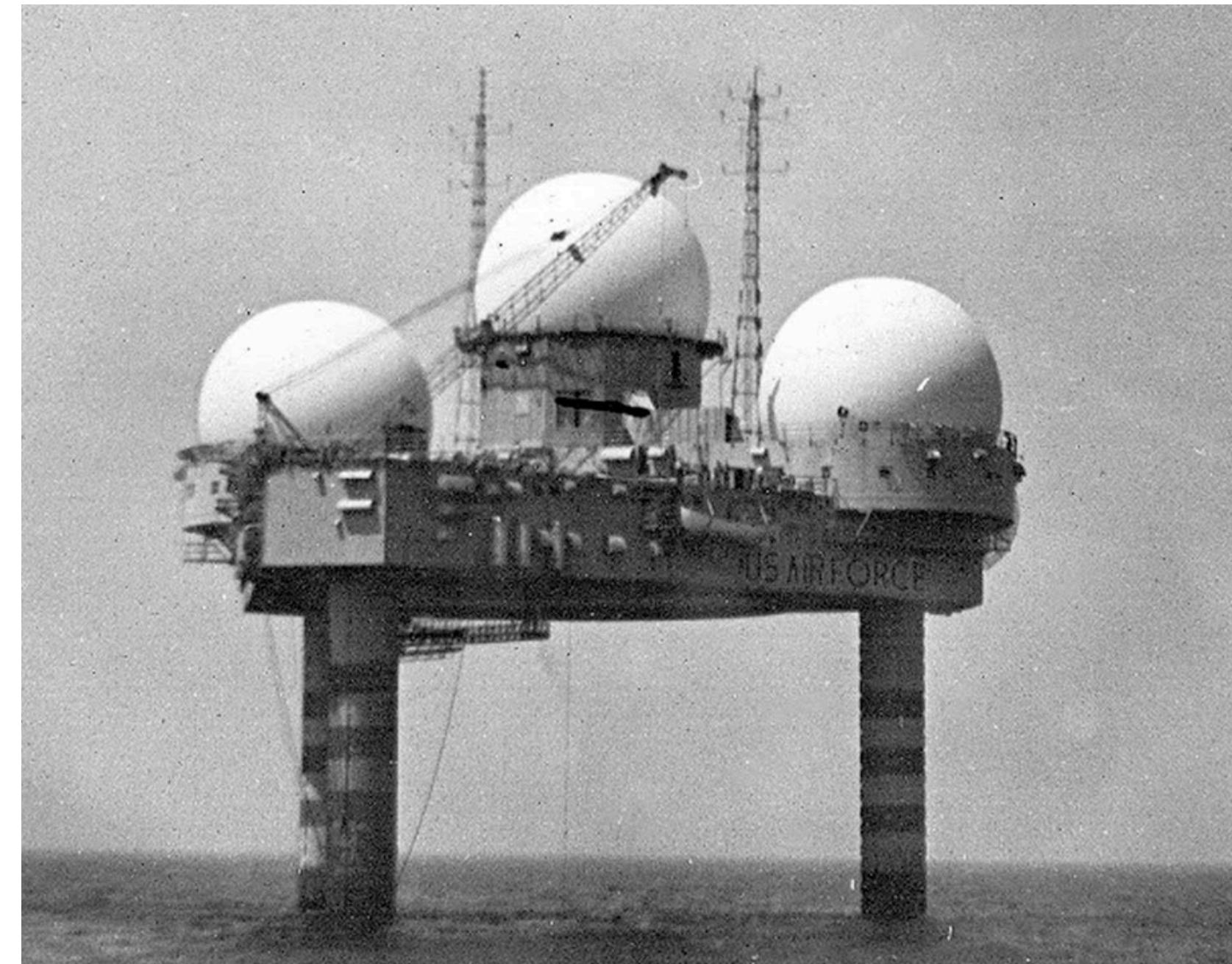


**Progeria affects ~159 patients in the US**

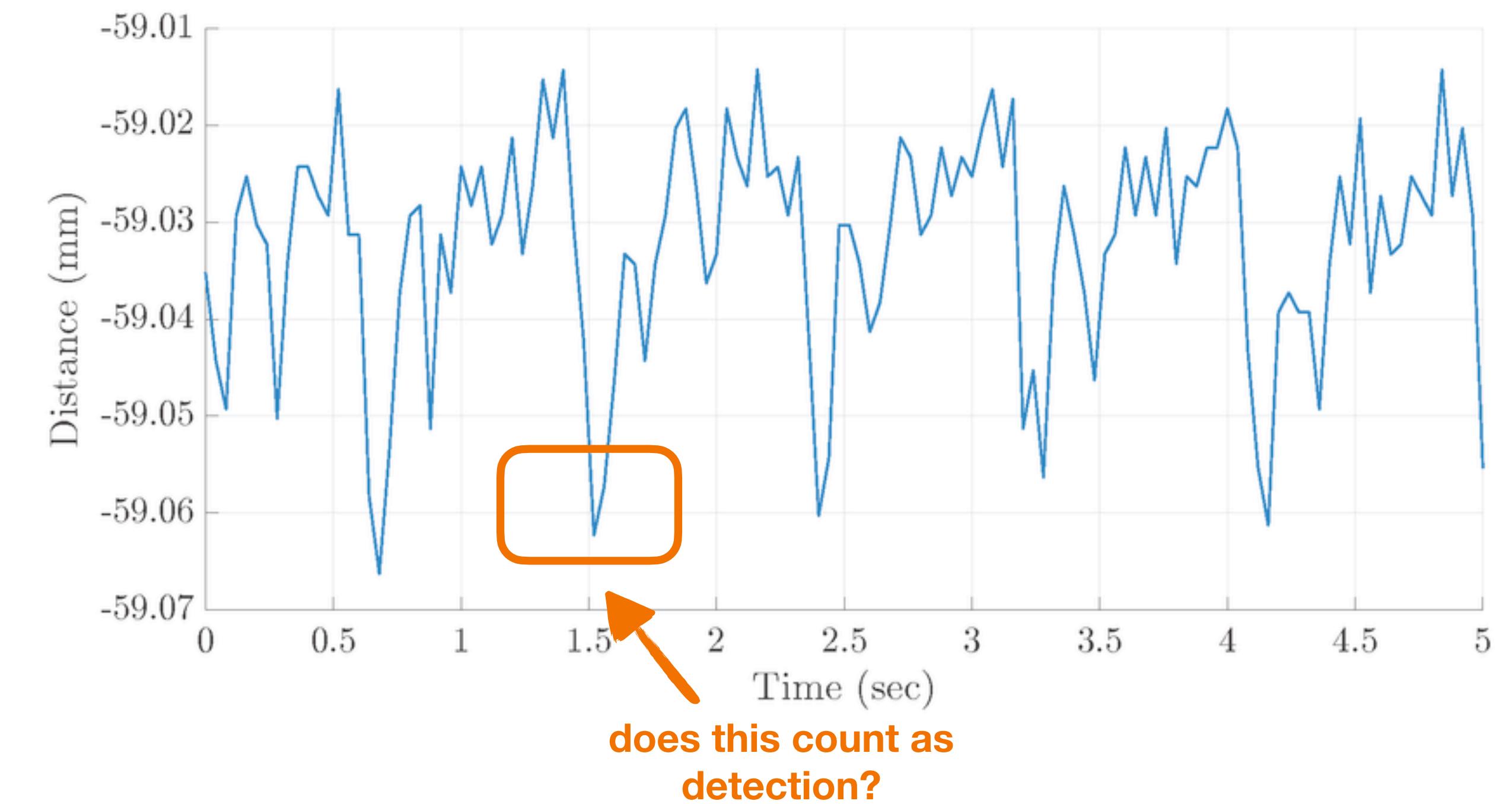
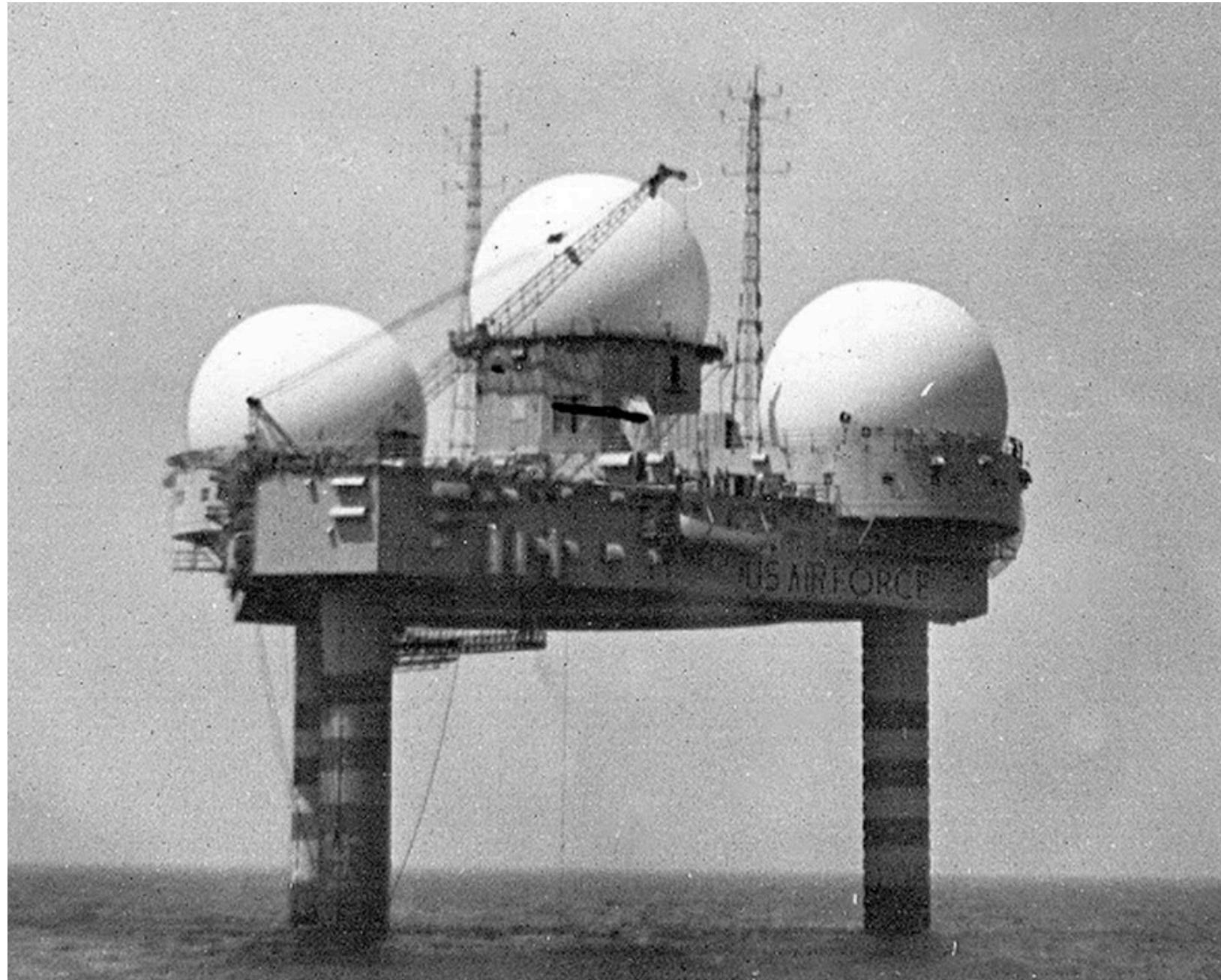
we have a dataset of all American pediatric patients

# **storytime!**

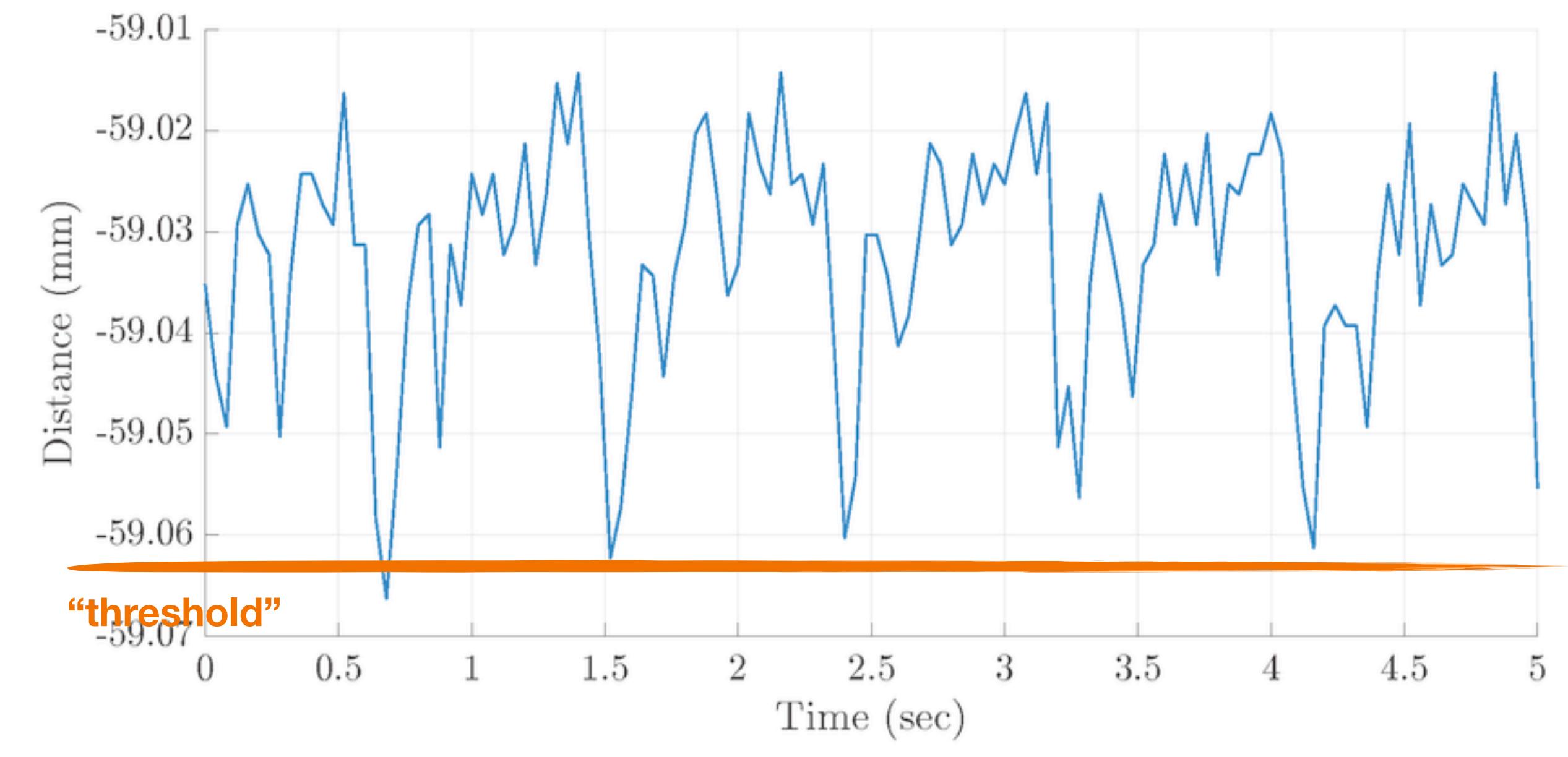
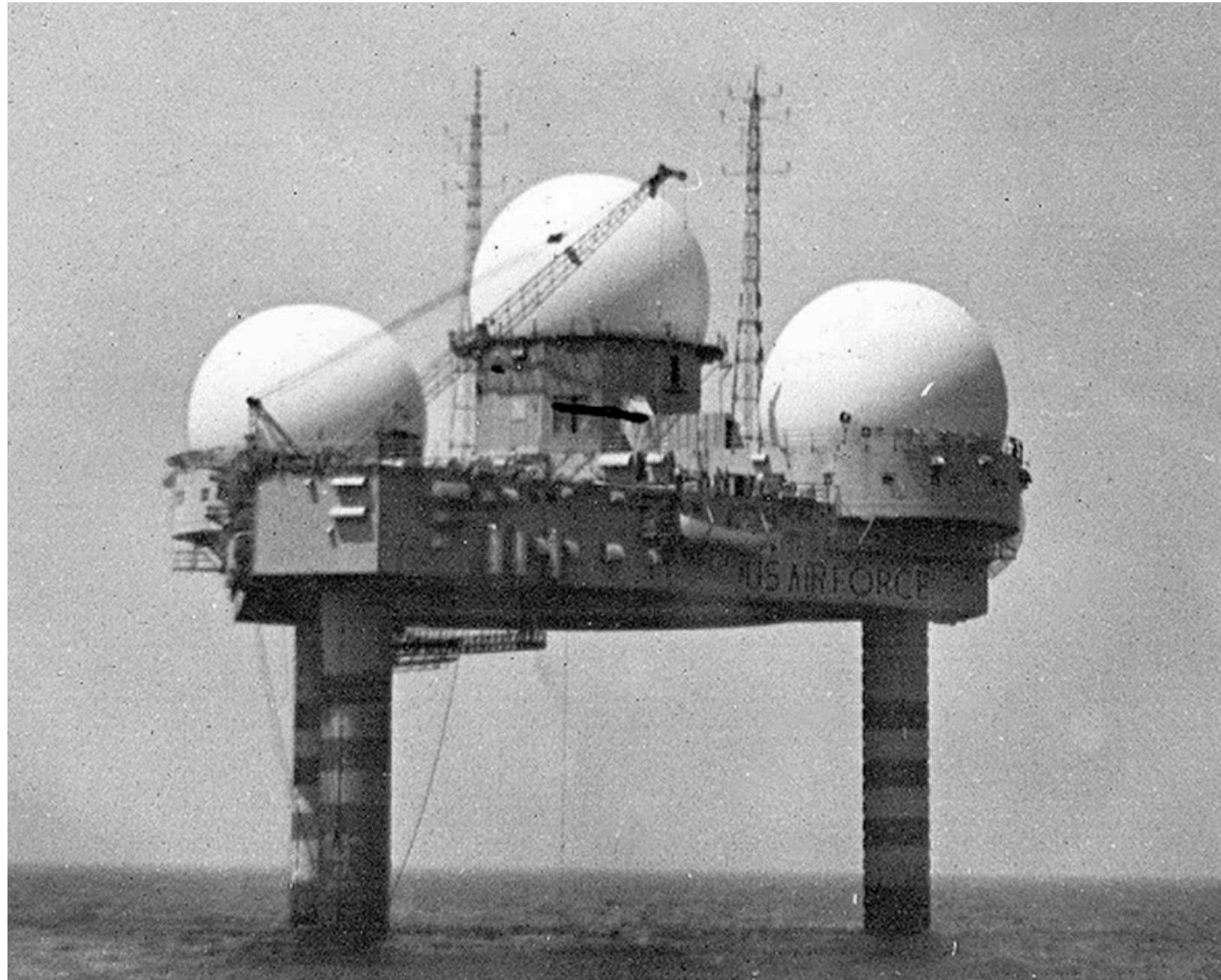
**storytime!**



# storytime!

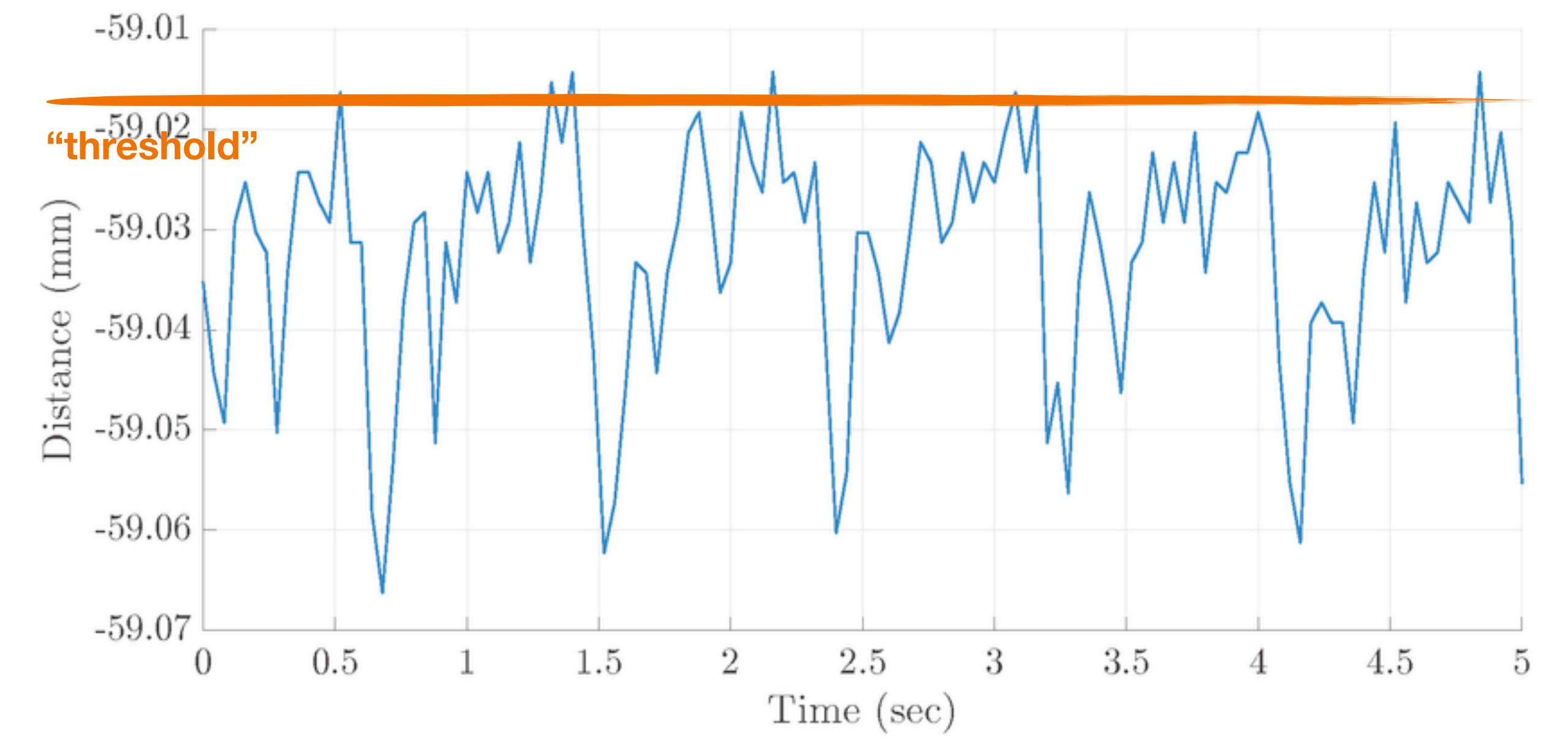
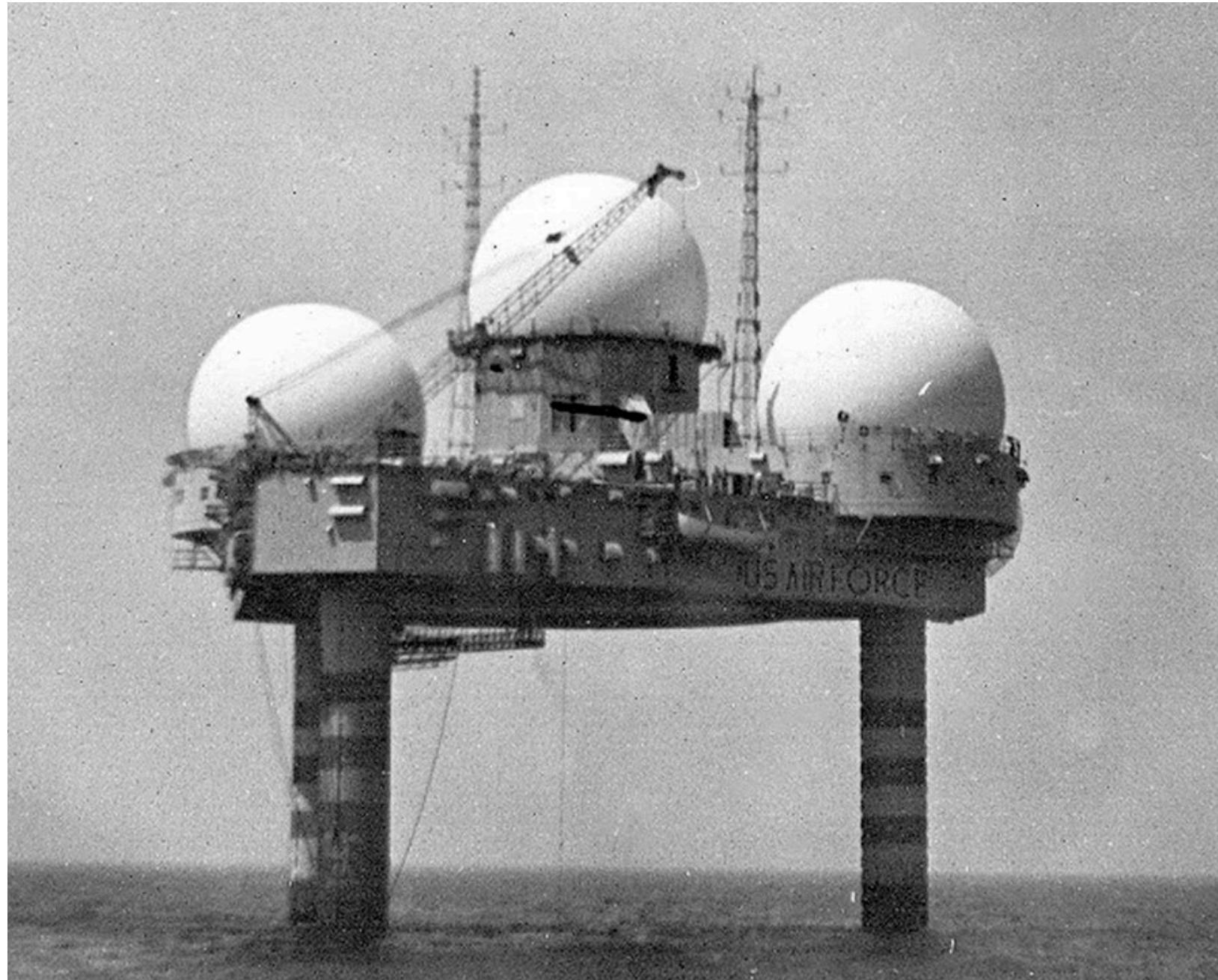


# storytime!



high recall, low precision

# storytime!

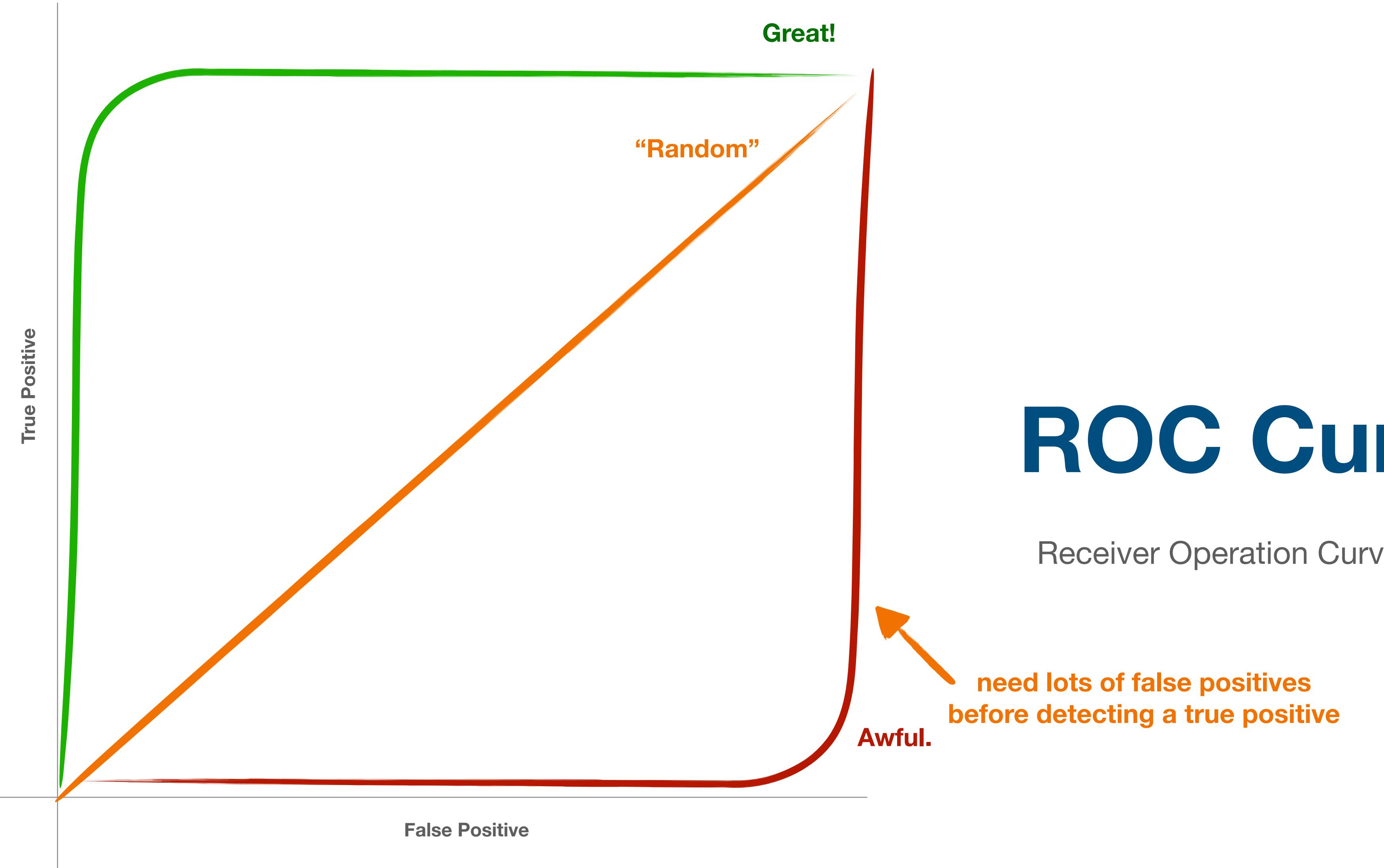


high precision, low recall

# **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

- AUC and also Precision-Recall Area Under Curve (PR AUC).

# **what makes models fit better**

- more data
- balanced data
- normalized data

**more data**

**balanced data**

**normalized data**

**more data**

balanced data

normalized data

more data

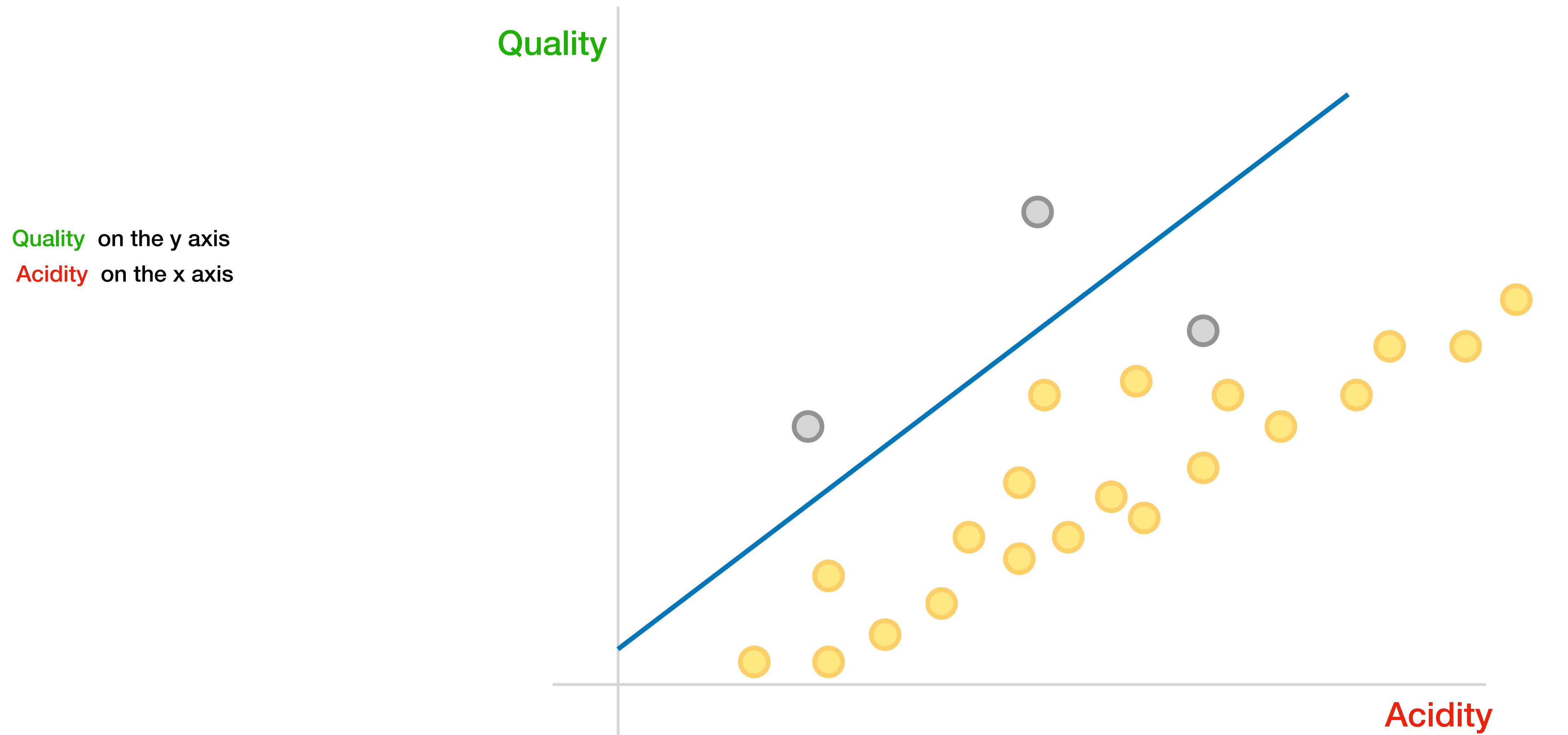
let's say we have a simpler wine dataset

Quality on the y axis

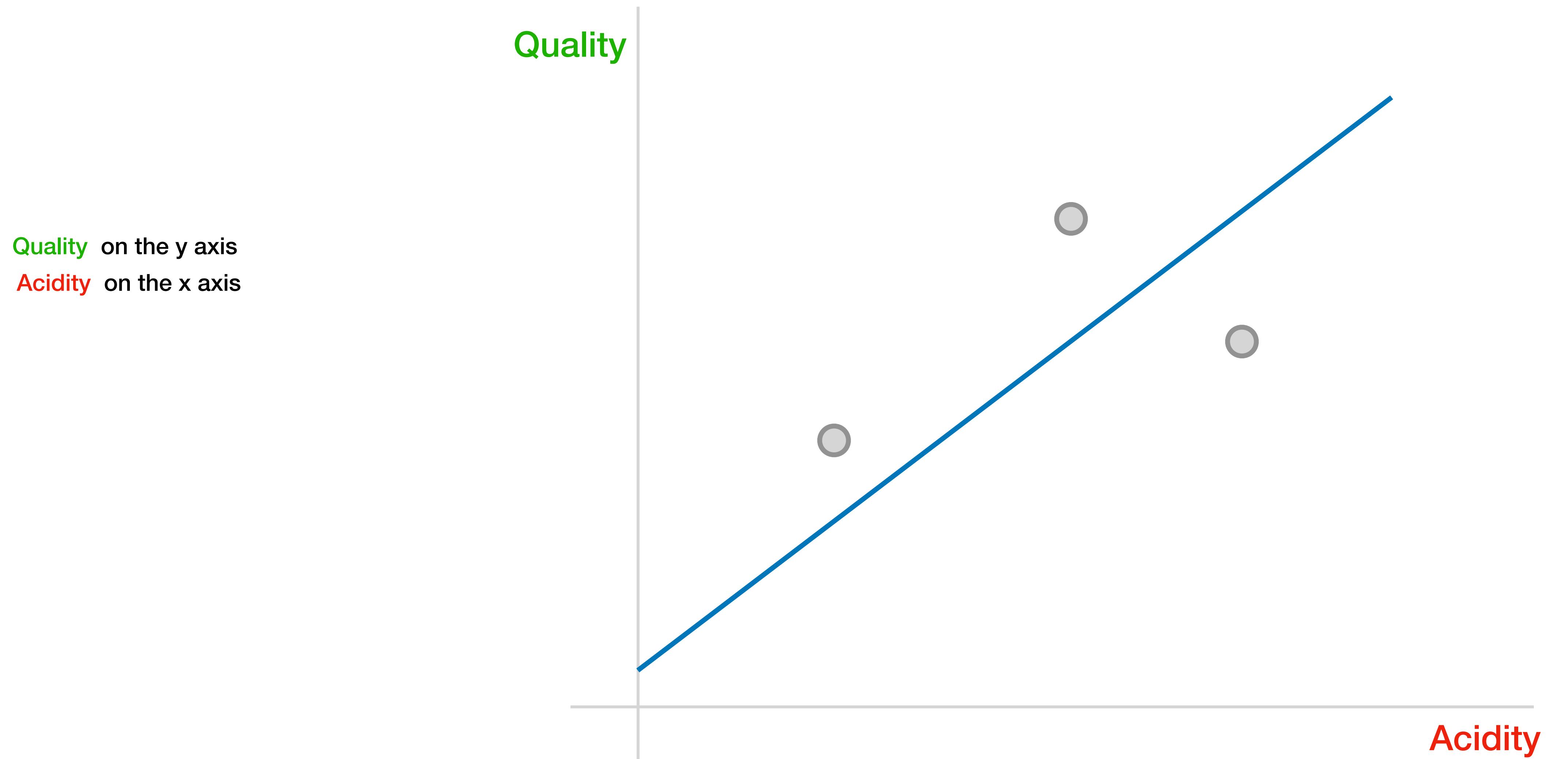
Acidity on the x axis



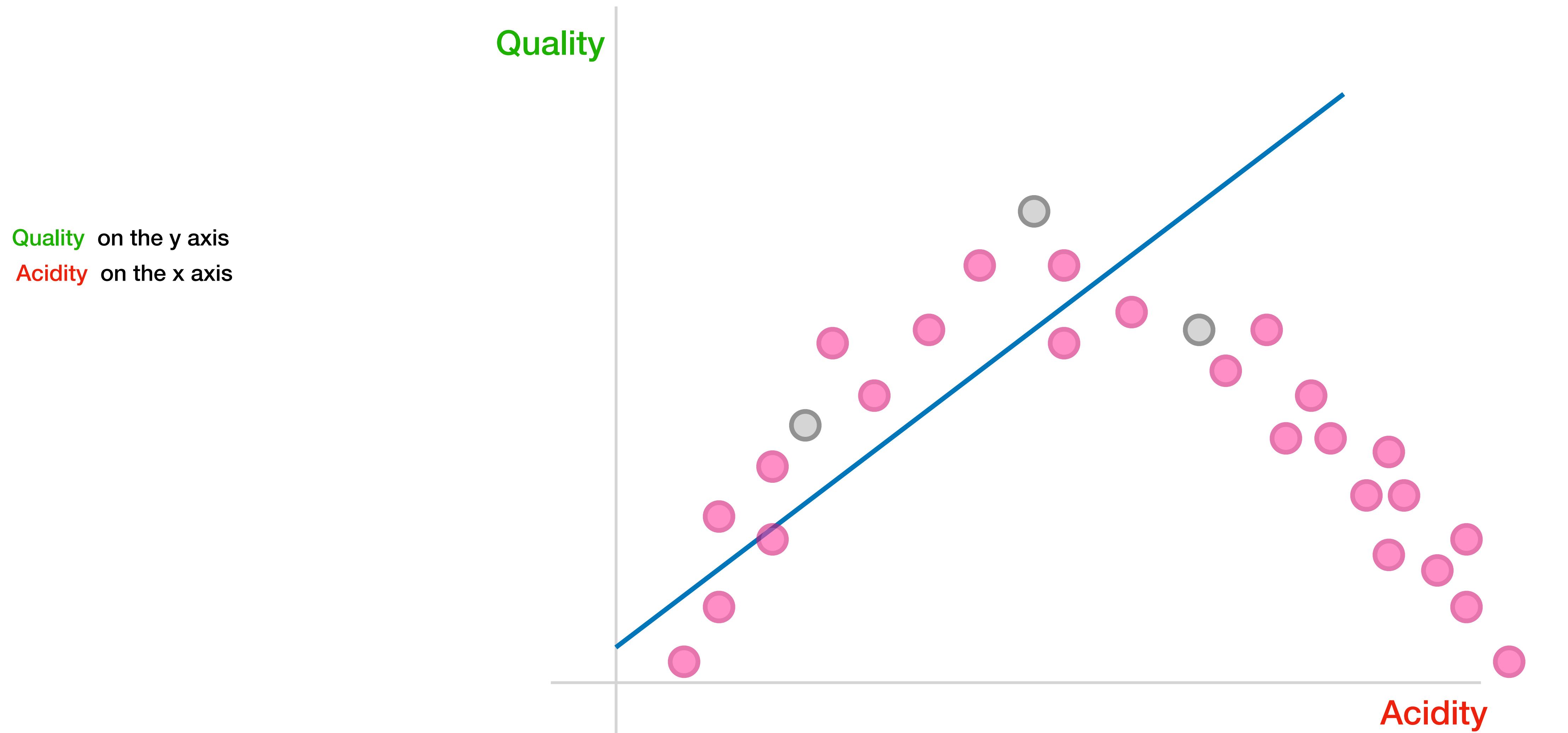
more data



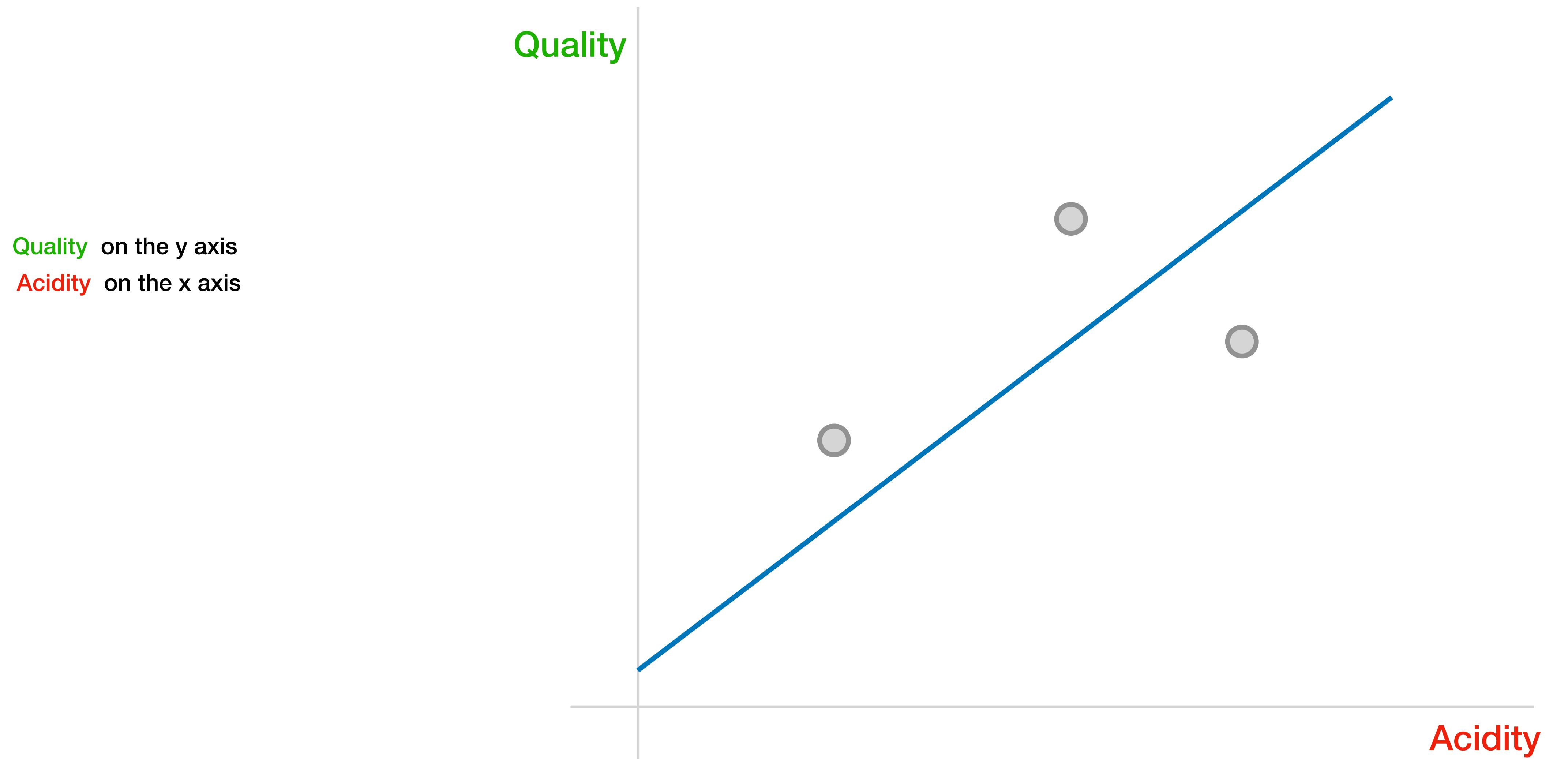
more data



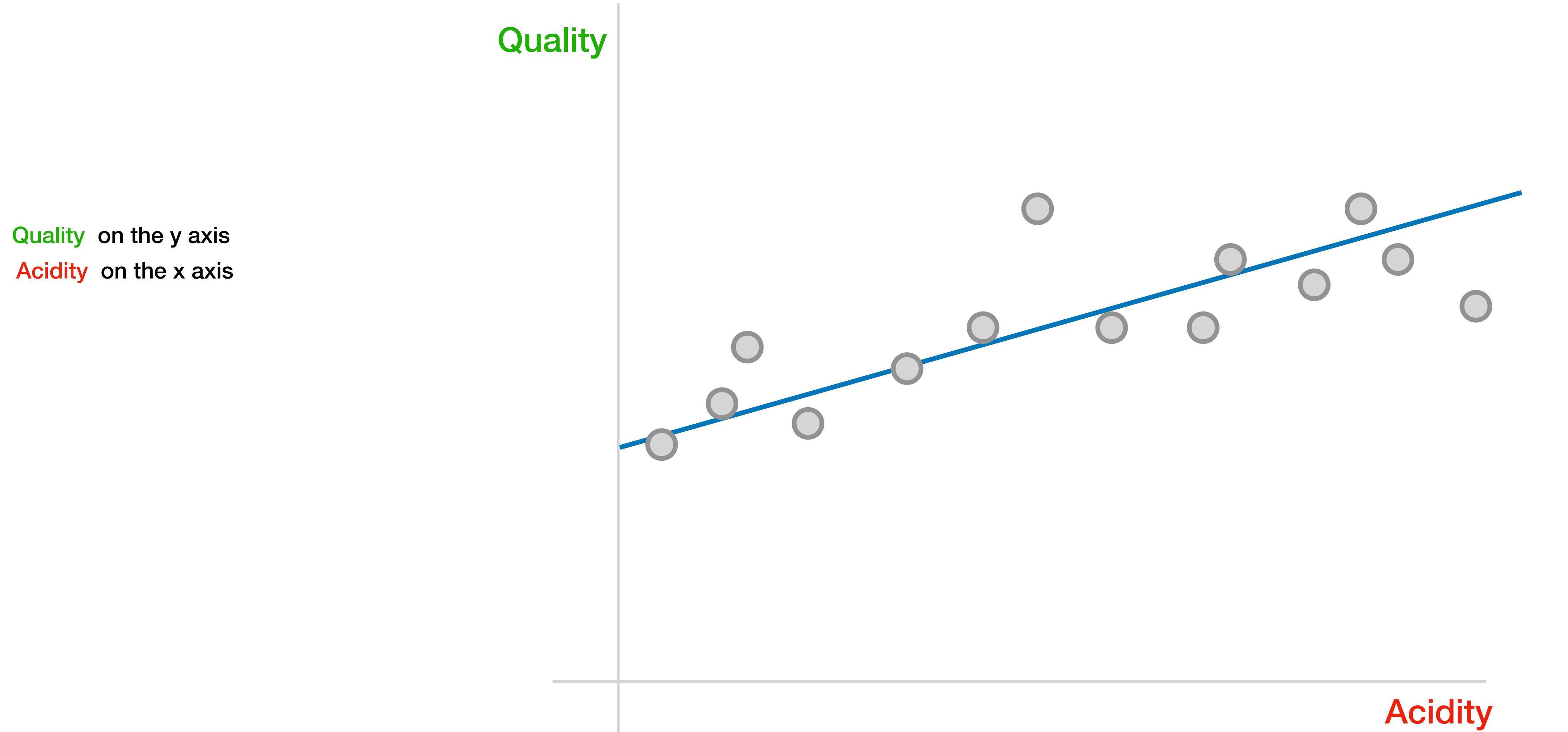
more data



more data



# more data



- use more data, get more accurate results

**more data**

balanced data

normalized data

more data

**balanced data**

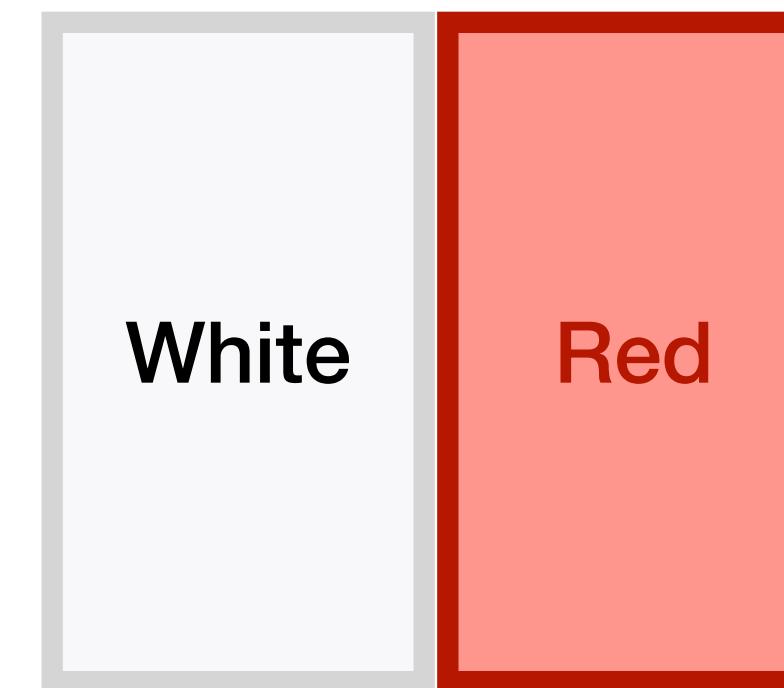
normalized data

**balanced data**

**Let's think about logistic functions!**

**balanced data**

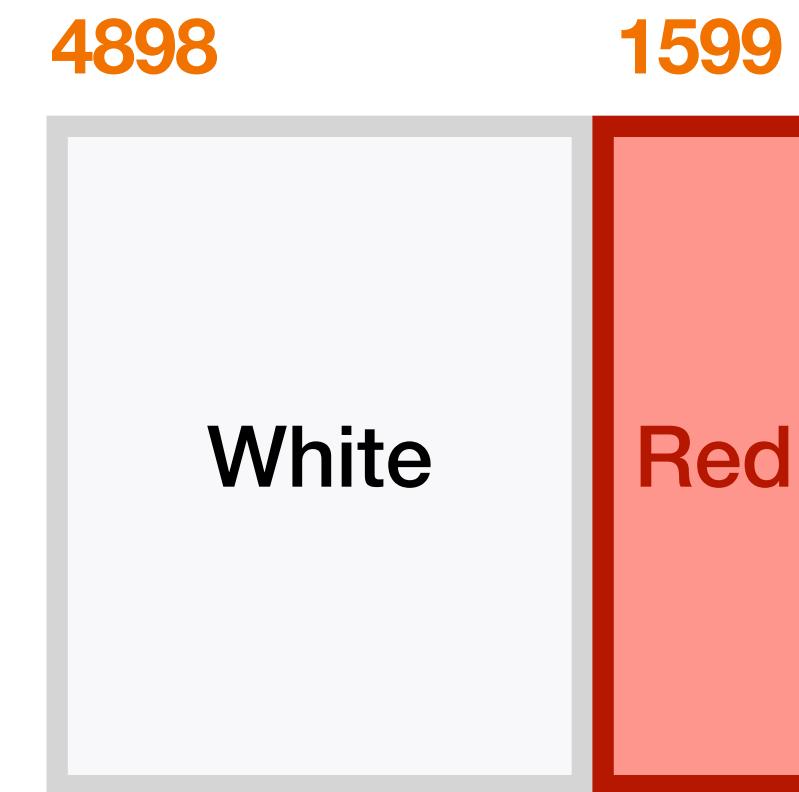
**Let's think about logistic functions!**



**in an ideal world**  
**...but no**

**balanced data**

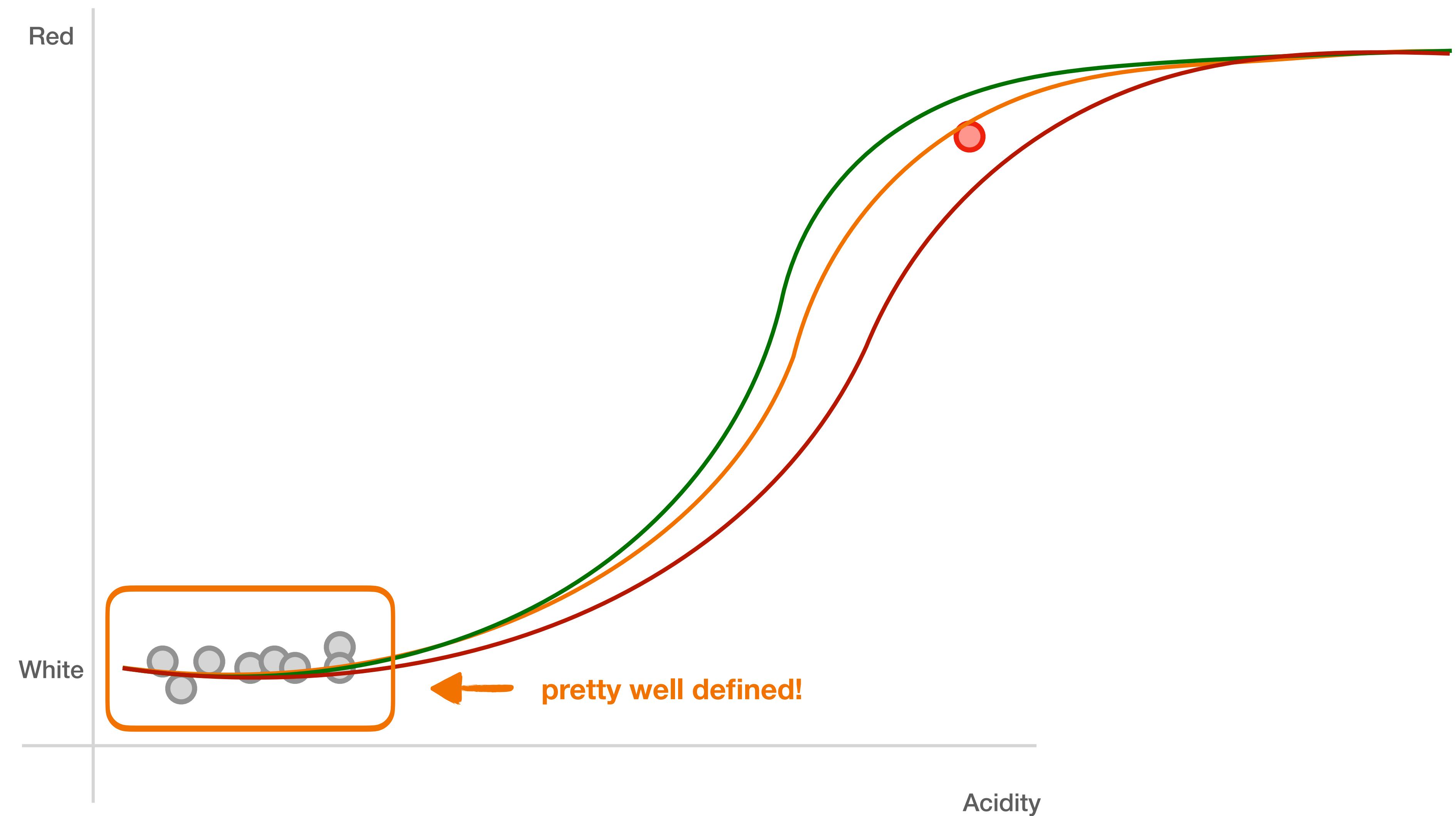
**Let's think about logistic functions!**



**What happens when we fit this dataset entirely?**

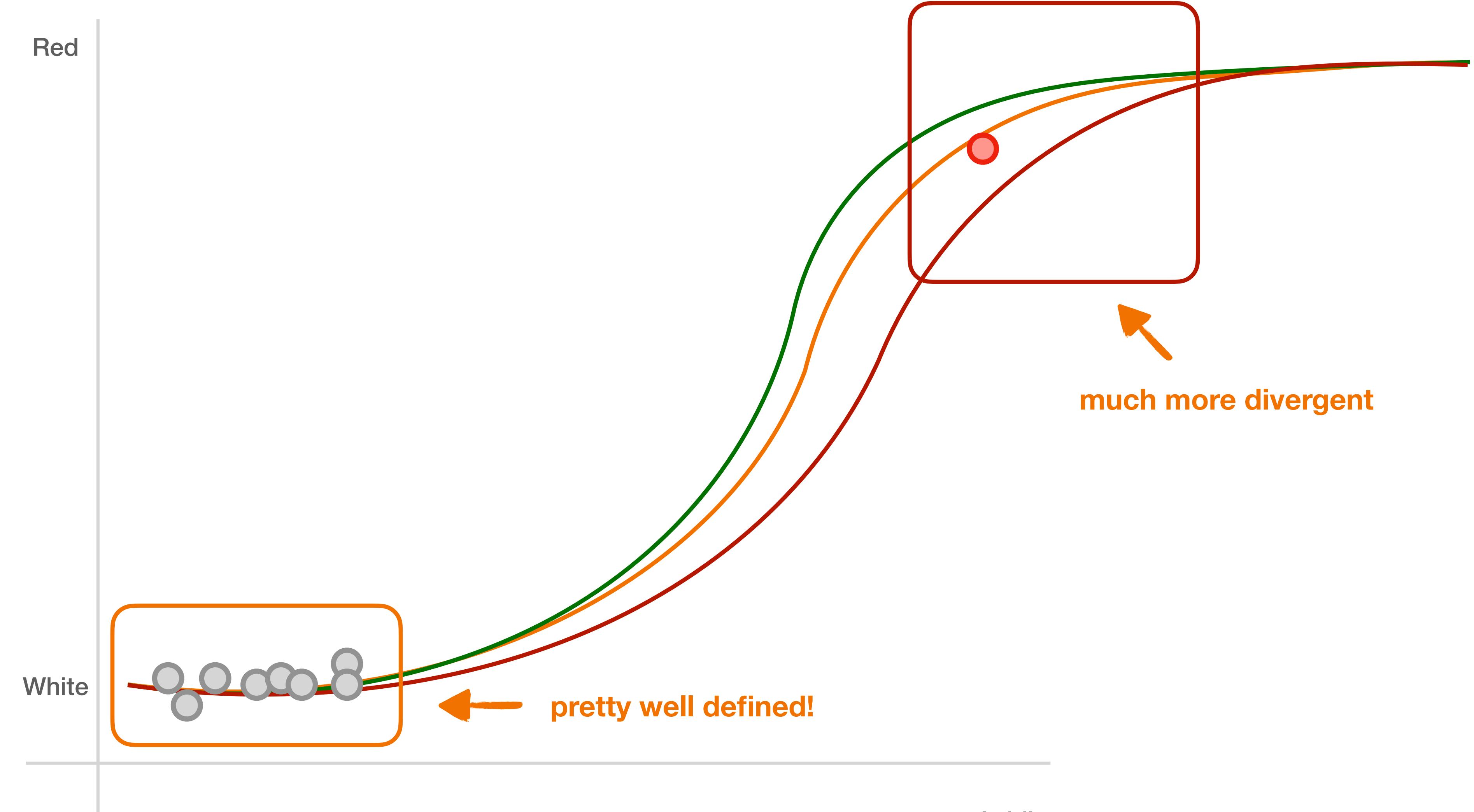
balanced data

Let's think about logistic functions!



balanced data

Let's think about logistic functions!



■ balanced data, more accurate results

more data

**balanced data**

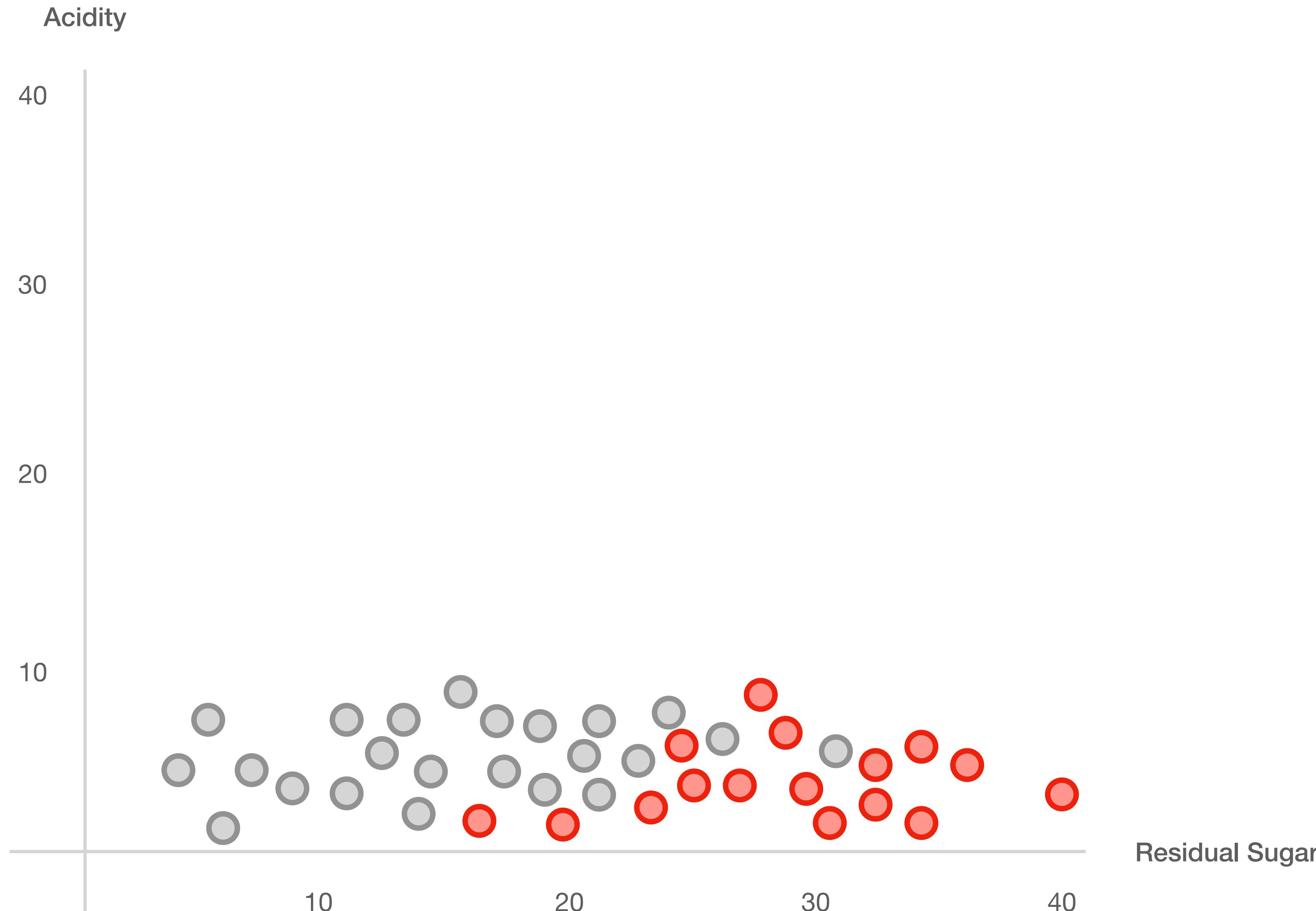
normalized data

more data

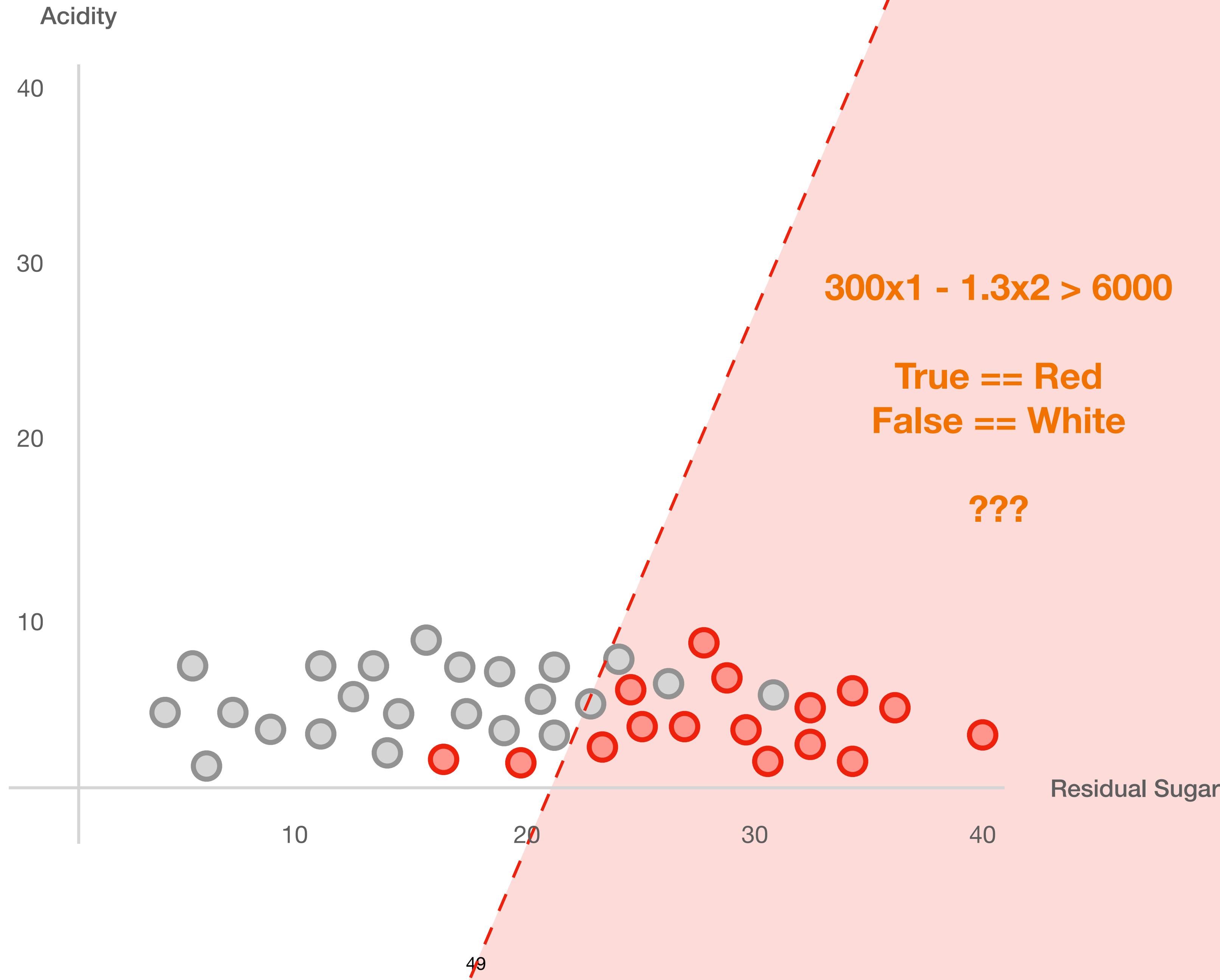
balanced data

**normalized data**

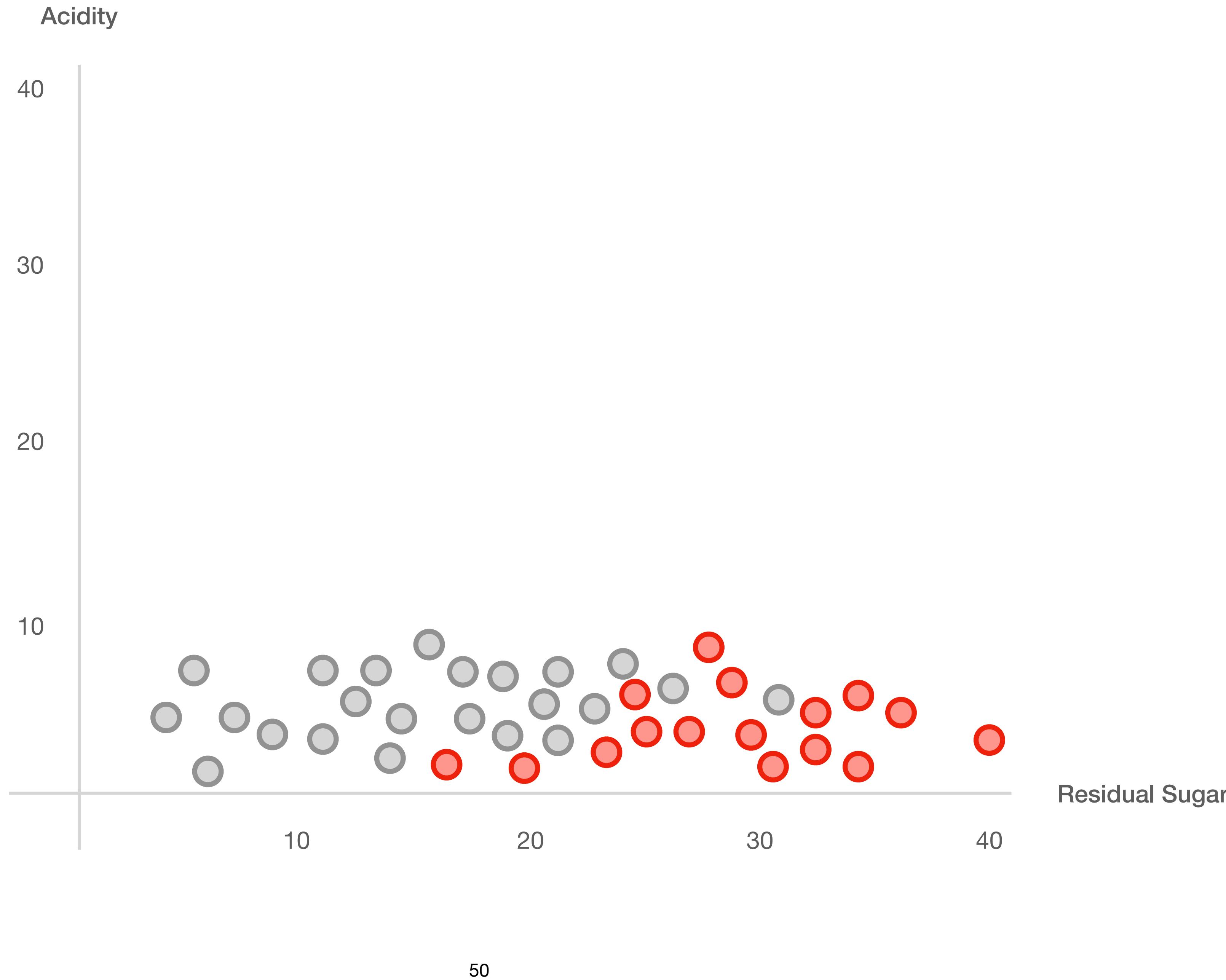
# normalized data



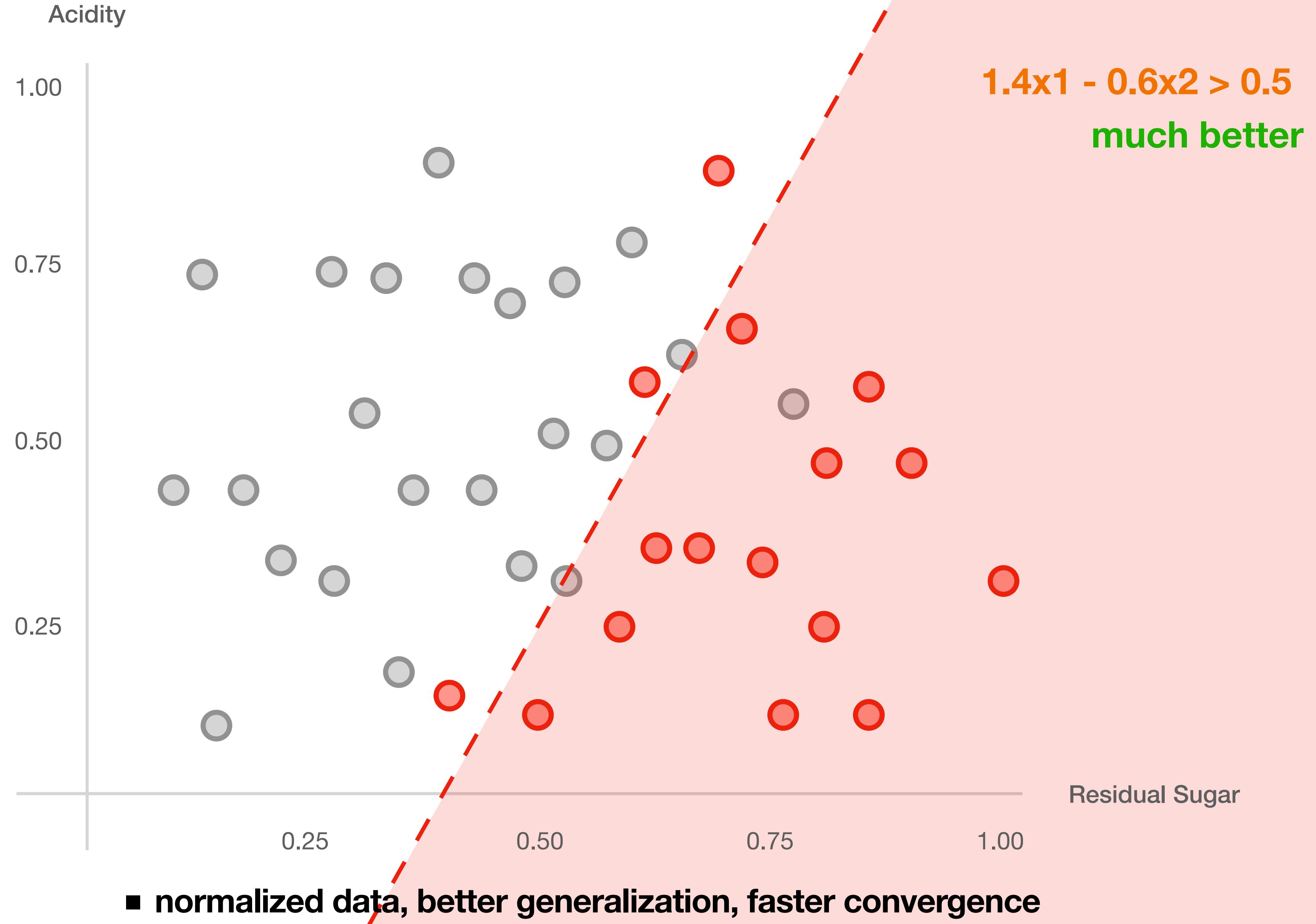
# normalized data



# normalized data



## normalized data



more data

balanced data

**normalized data**

**more data**

**balanced data**

**normalized data**

**let's clean some data!**