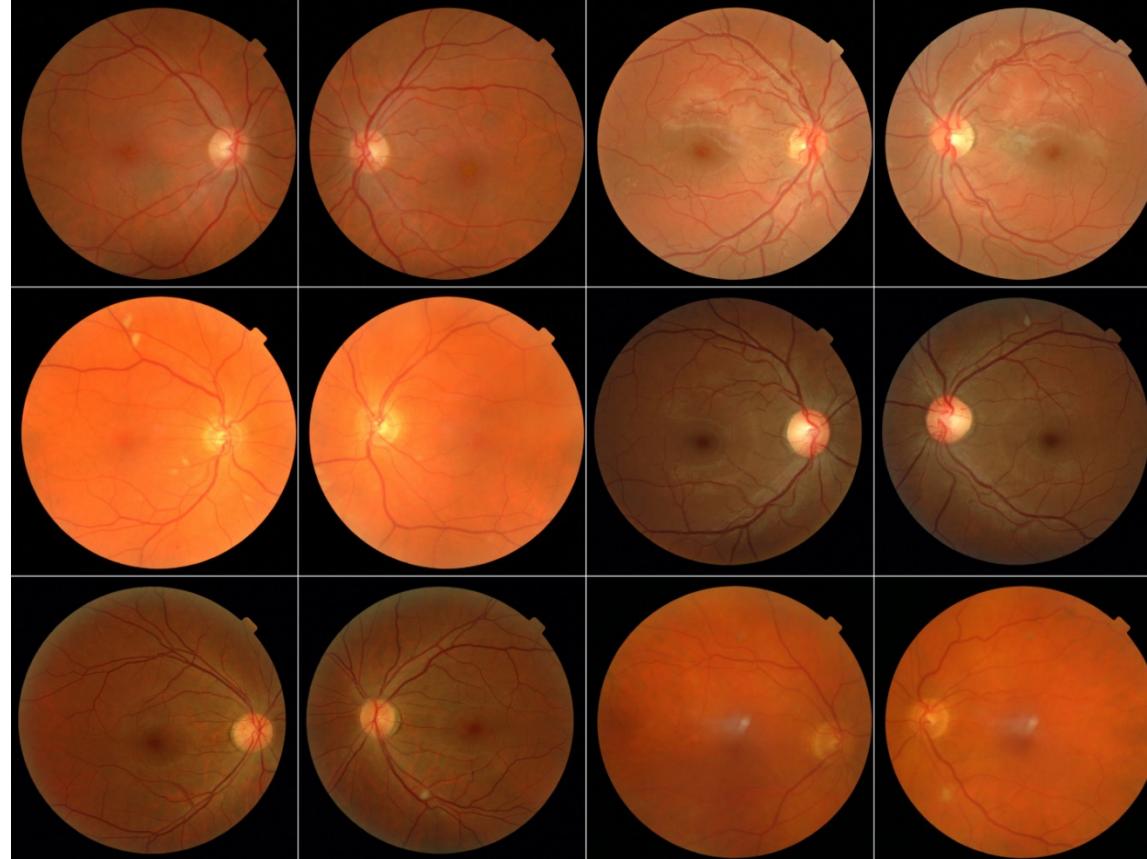


What is a Predictive Model?

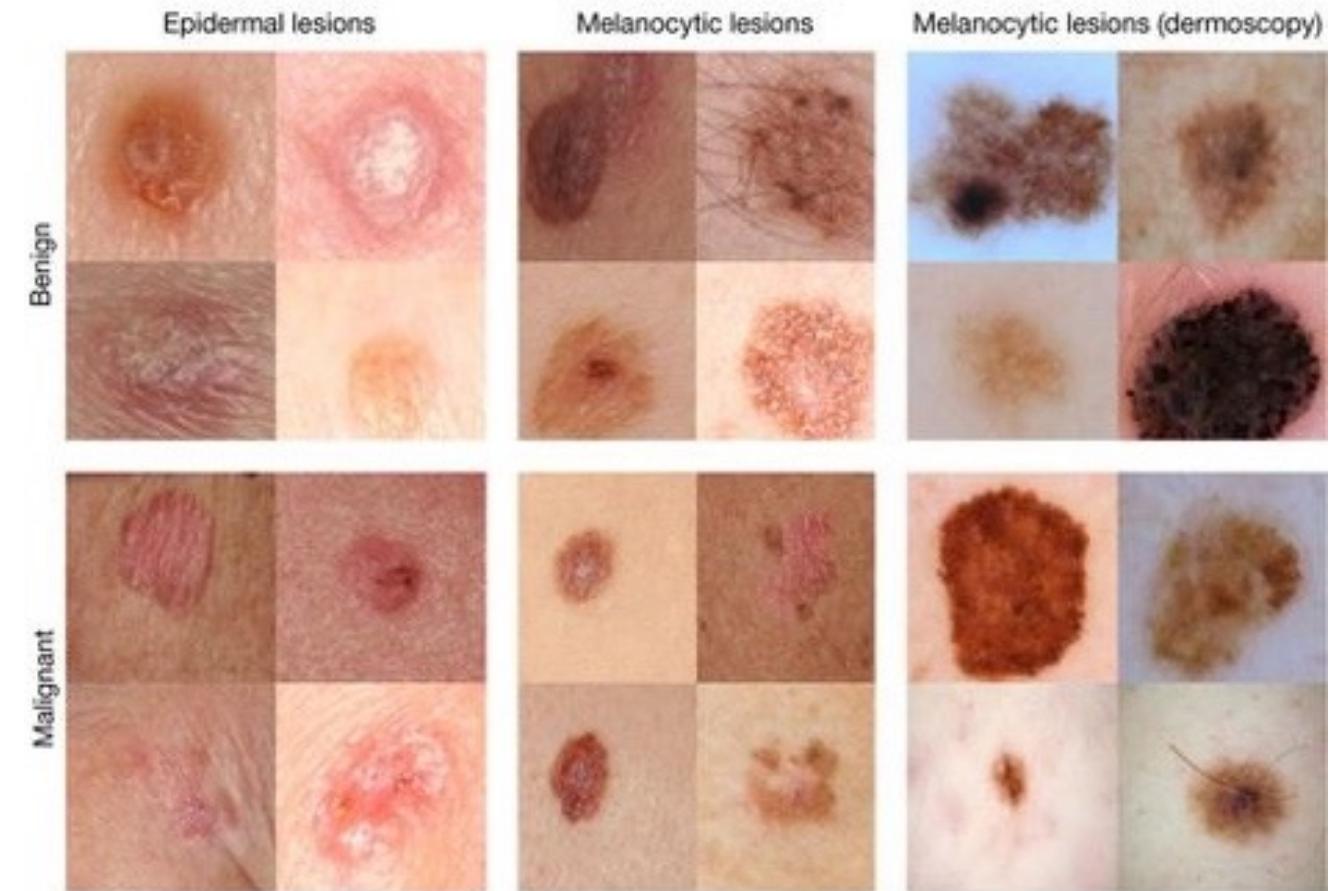
Matthew Engelhard

Medical Image Analysis with ConvNets



Improved Automated Detection of Diabetic Retinopathy

Invest. Ophthalmol. Vis. Sci.. 2016;57(13):5200-5206. doi:10.1167/iovs.16-19964



Dermatologist-level classification of skin cancer

Nature volume 542, pages 115–118 (02 February 2017)

Biomedical Text Processing

Classification of radiology reports using neural attention models, IJCNN 2017



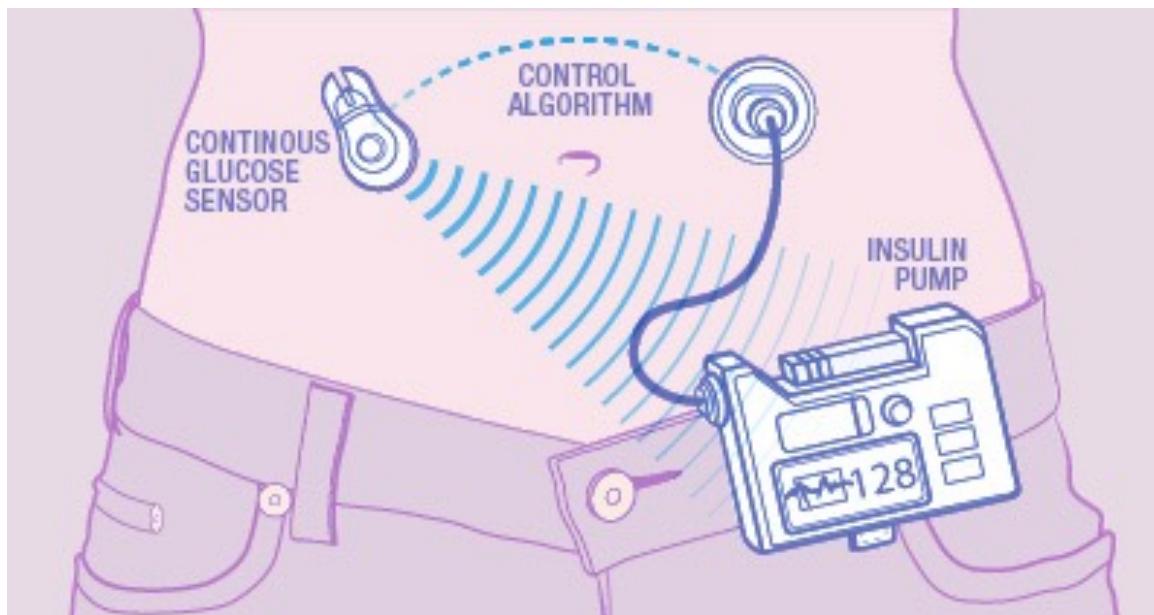
Table 5. Examples of correctly detected PHI instances (in bold) by the ANN

PHI category	ANN
AGE	Father had a stroke at <u>80</u> and died of?another stroke at age Personal data and overall health: Now <u>63</u> , despite his FH: Father: Died @ <u>52</u> from EtOH abuse (unclear exact etiology) Tobacco: smoked from age 7 to <u>15</u> , has not smoked since 15.
CONTACT	History of Present Illness <u>86F</u> reports worsening b/l leg pain. by phone, Dr. Ivan Guy. Call w/ questions <u>86383</u> . Keith Gilbert, H/O paroxysmal afib VNA <u>171-311-7974</u> ===== Medications
DATE	During his <u>May</u> hospitalization he had dysphagia Social history: divorced, quit smoking in <u>08</u> , sober x 10 yrs, She is to see him on the <u>29th</u> of this month at 1:00 p.m. He did have a renal biopsy in teh late <u>60s</u> adn thus will look for results, Results <u>02/20/2087</u> NA 135, K 3.2 (L), CL 96 (L), CO2 30.6, BUN 1 Jose Church, M.D. /ray DD: 01/18/20 DT: <u>01/19:0</u> DV: 01/18/20

De-identification of patient notes with recurrent neural networks
JAMIA 24(3), 2017, 596–606

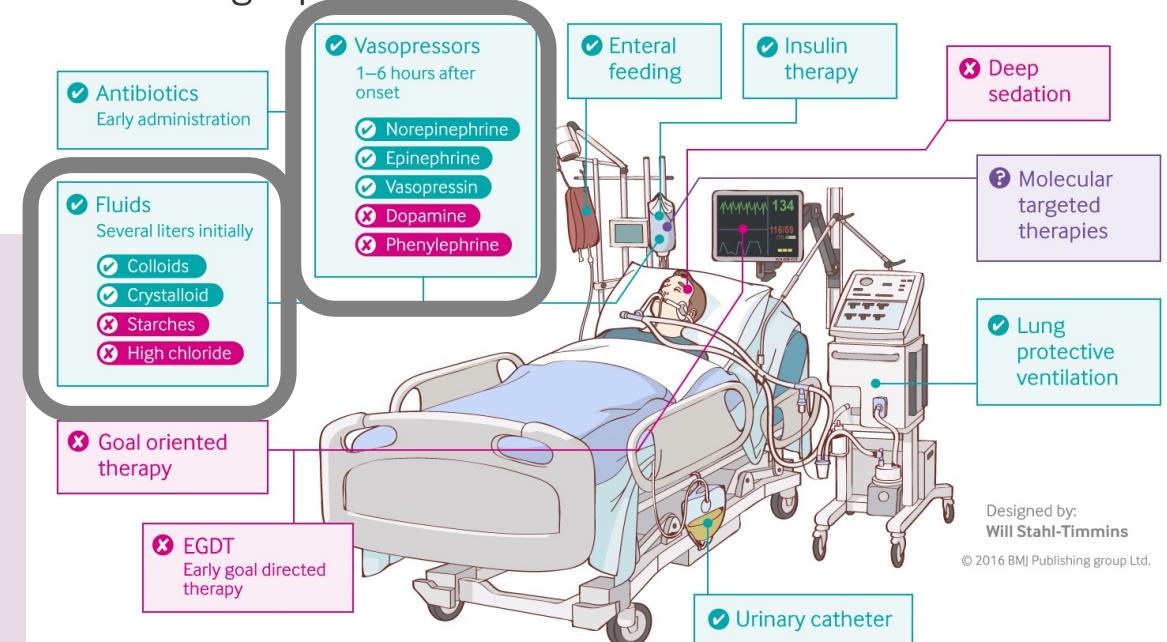
Sequential Prediction and Decision-Making Algorithms

Closed-loop blood glucose control (“artificial pancreas”)



<https://www.mayo.edu/research/labs/artificial-pancreas/overview>

Treating sepsis: the latest evidence



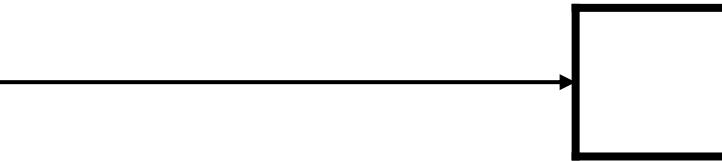
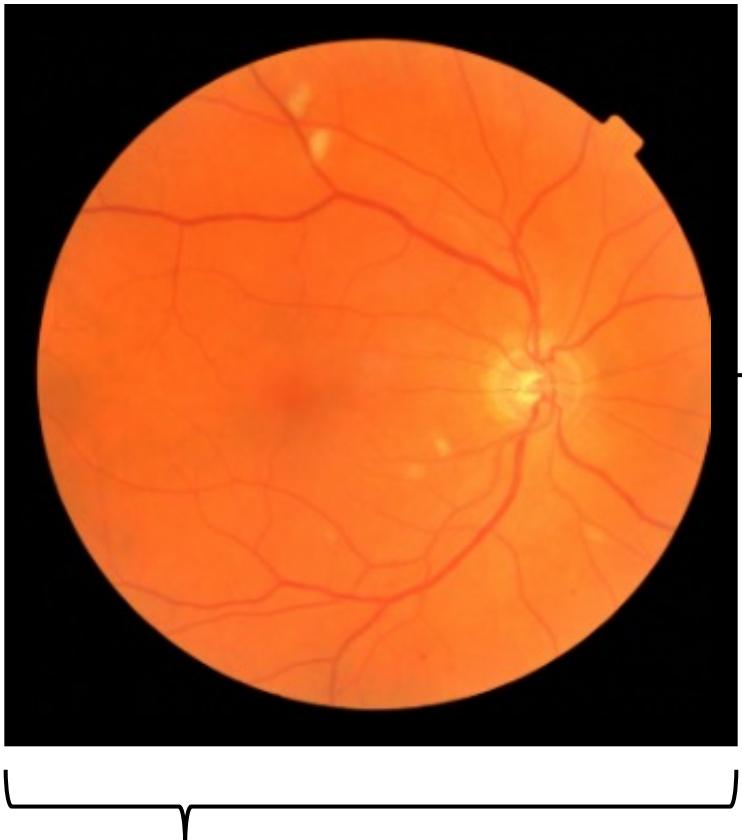
Fluid and vasopressor administration for sepsis treatment

Gotts JE, Matthay MA. Sepsis: pathophysiology and clinical management. *bmj*. 2016 May 23;353(i1585).

In each of these cases, we have a machine that receives data and makes a related prediction:

a “predictive model”

image -> prediction: computer vision



y , referable diabetic
retinopathy

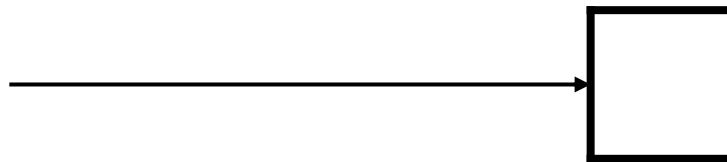
x , retinal image

End goal: predict y from x

text -> prediction: natural language processing

psychologist presenting problem NAME is a 3 year, 4 month old female who was referred for a neurodevelopmental assessment due to concerns regarding her overall development, behavior, and social emotional functioning and to

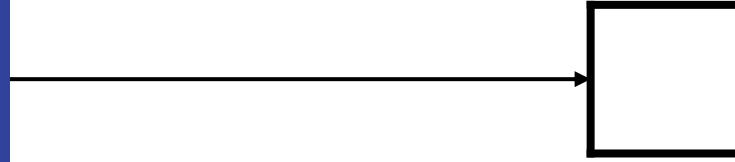
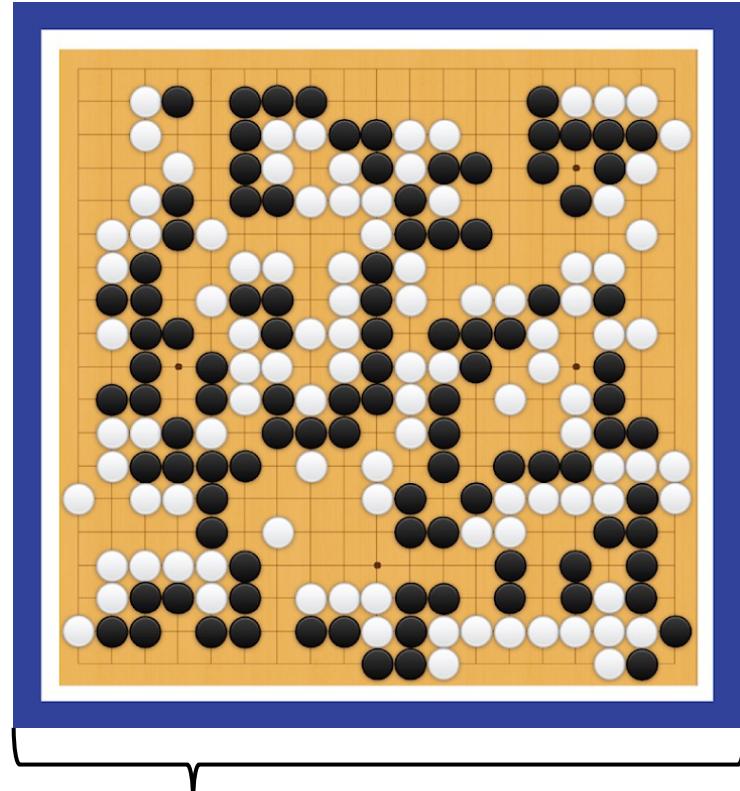
x , clinical note



y , autism risk

End goal: predict y from x

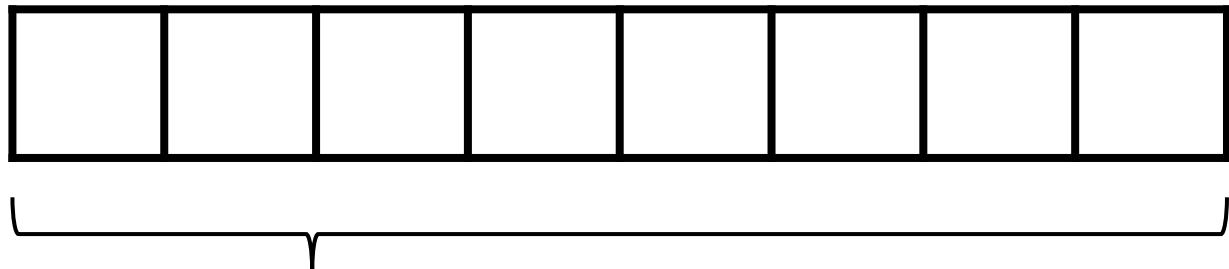
“state of the world” -> next action: reinforcement learning



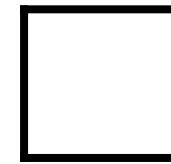
y , next move

End goal: predict y from x

features $x \rightarrow$ prediction y : a predictive model



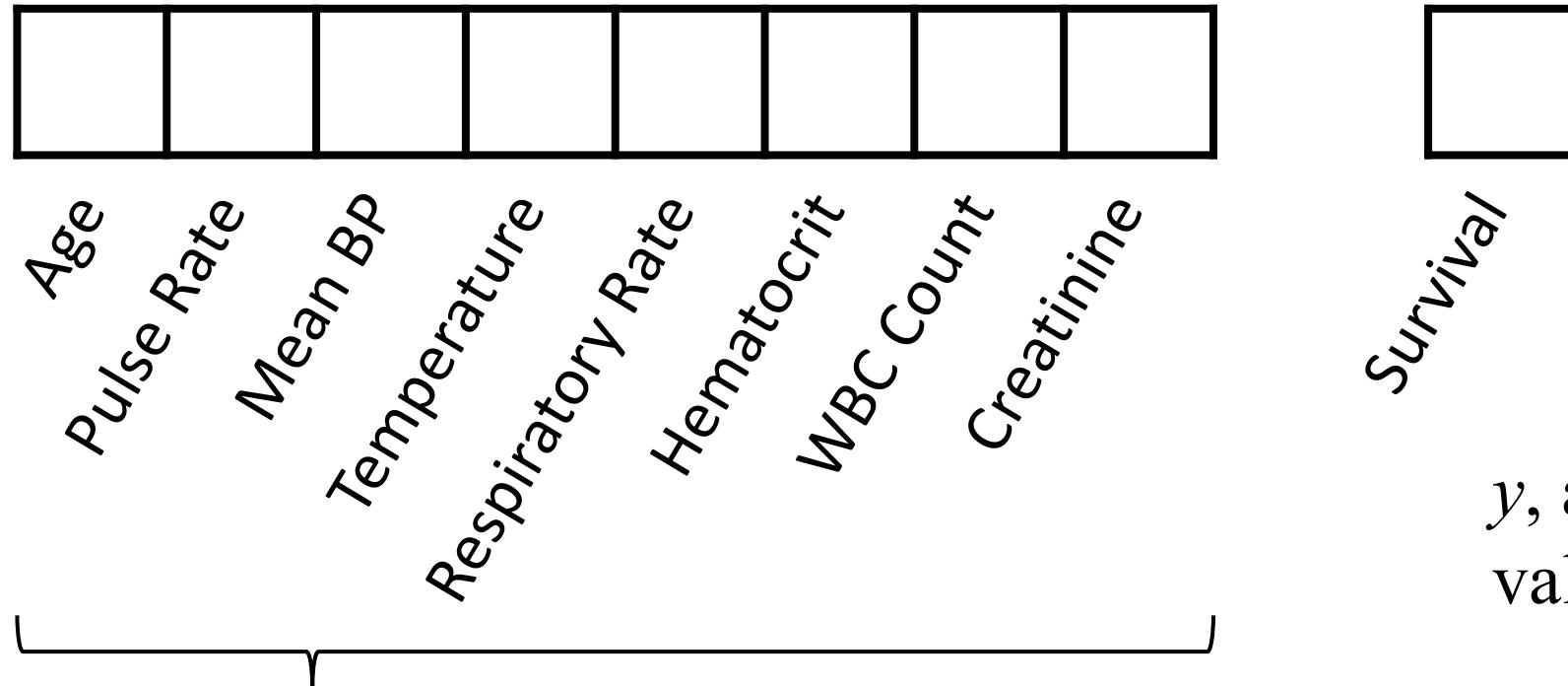
x , data/features for
a subject or patient



y , associated
value or label

End goal: predict y from x

Simple models often work well for clinical data!

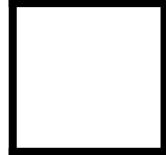


x , data/features for
a subject or patient

y , associated
value or label

End goal: predict odds
of hospital mortality
(APACHE III)

Before we tackle complex models,
let's carefully examine a very simple one.



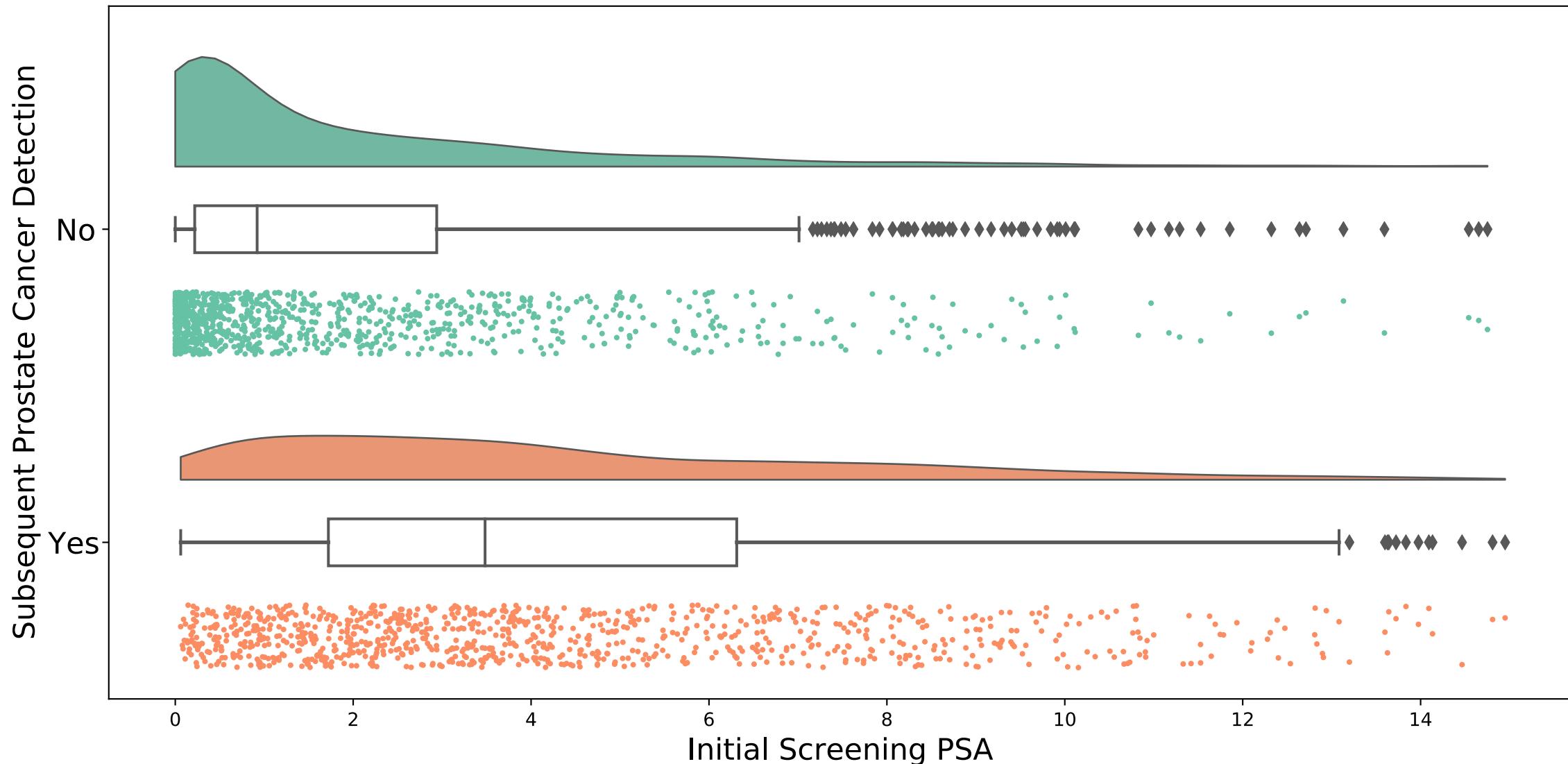
x , a single measurement:
prostate specific antigen



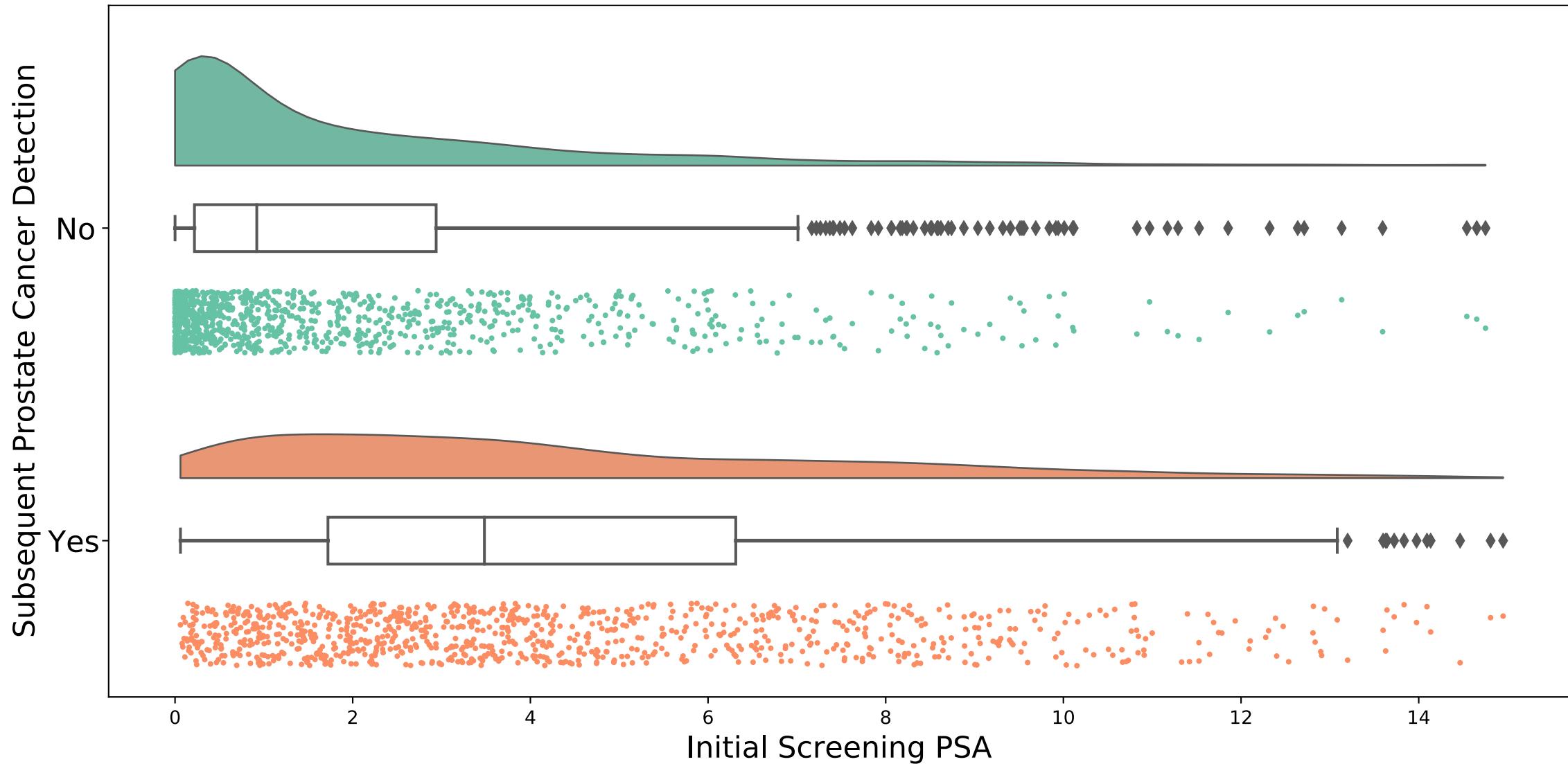
y , associated label:
prostate cancer
(0 = absent, 1 = present)

End goal: predict y from x

Prostate specific antigen measurement in individuals with vs without prostate cancer

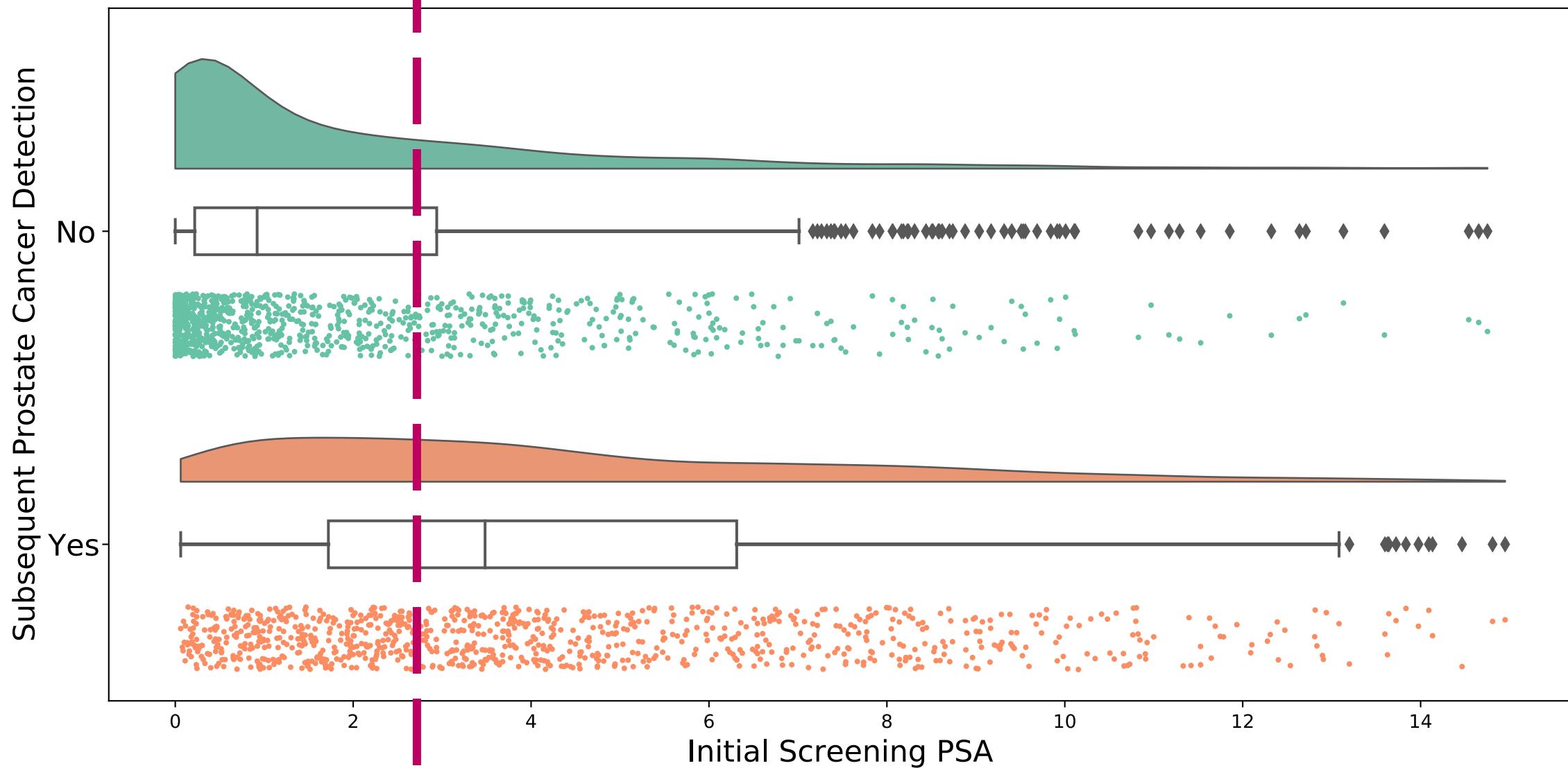


End Goal: predict cancer status (y) based on PSA (x)



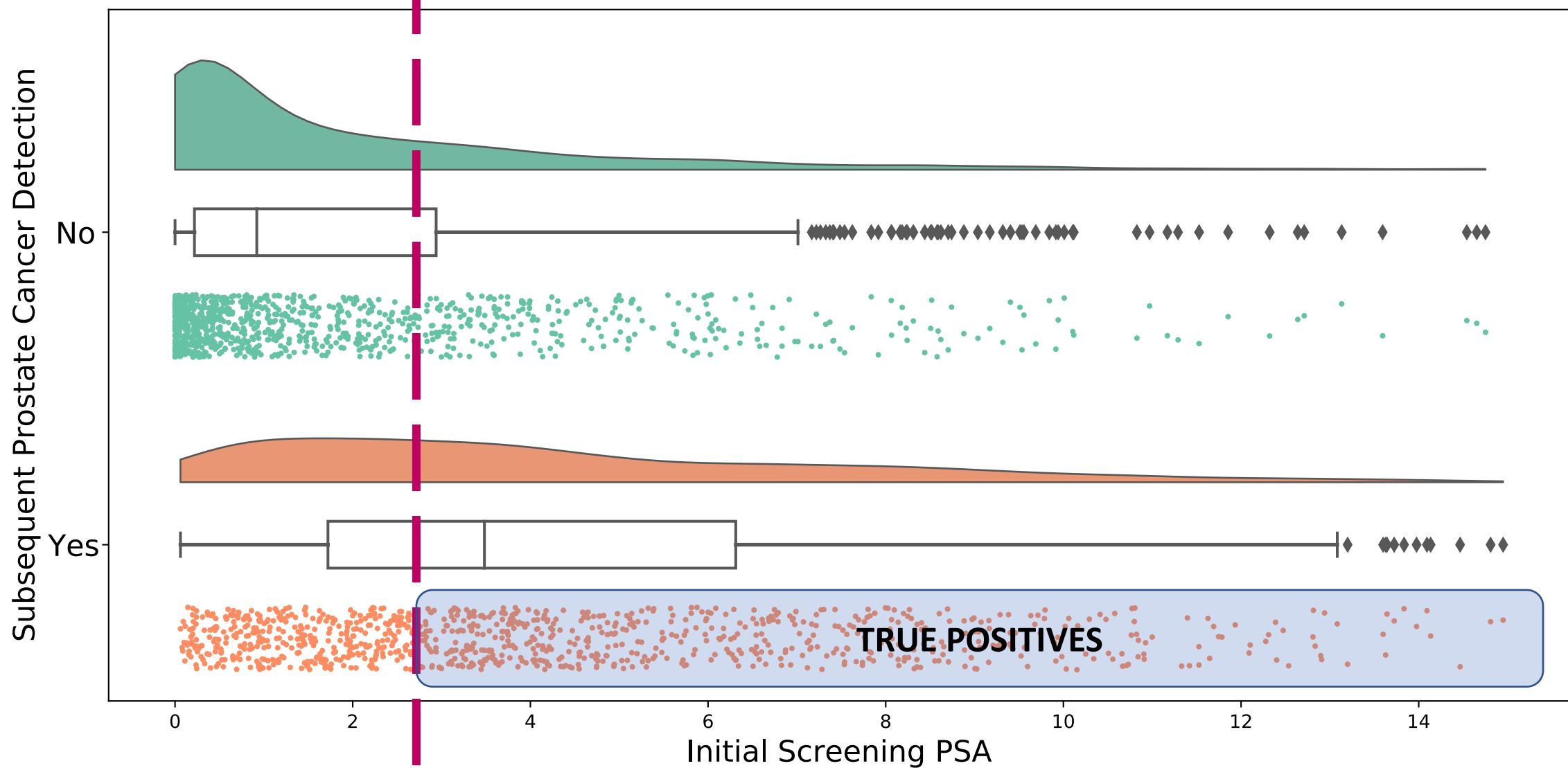
End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive



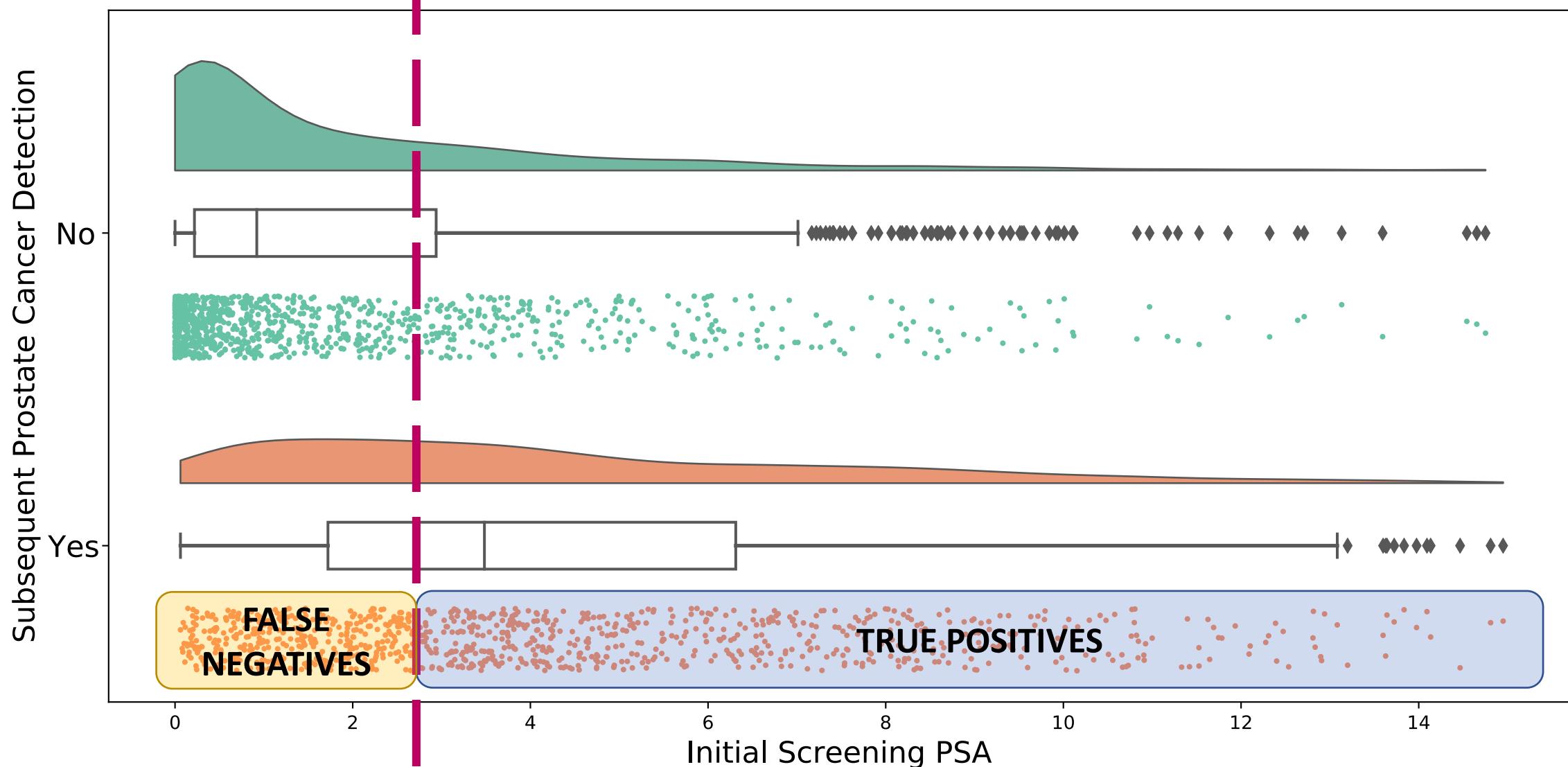
End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive

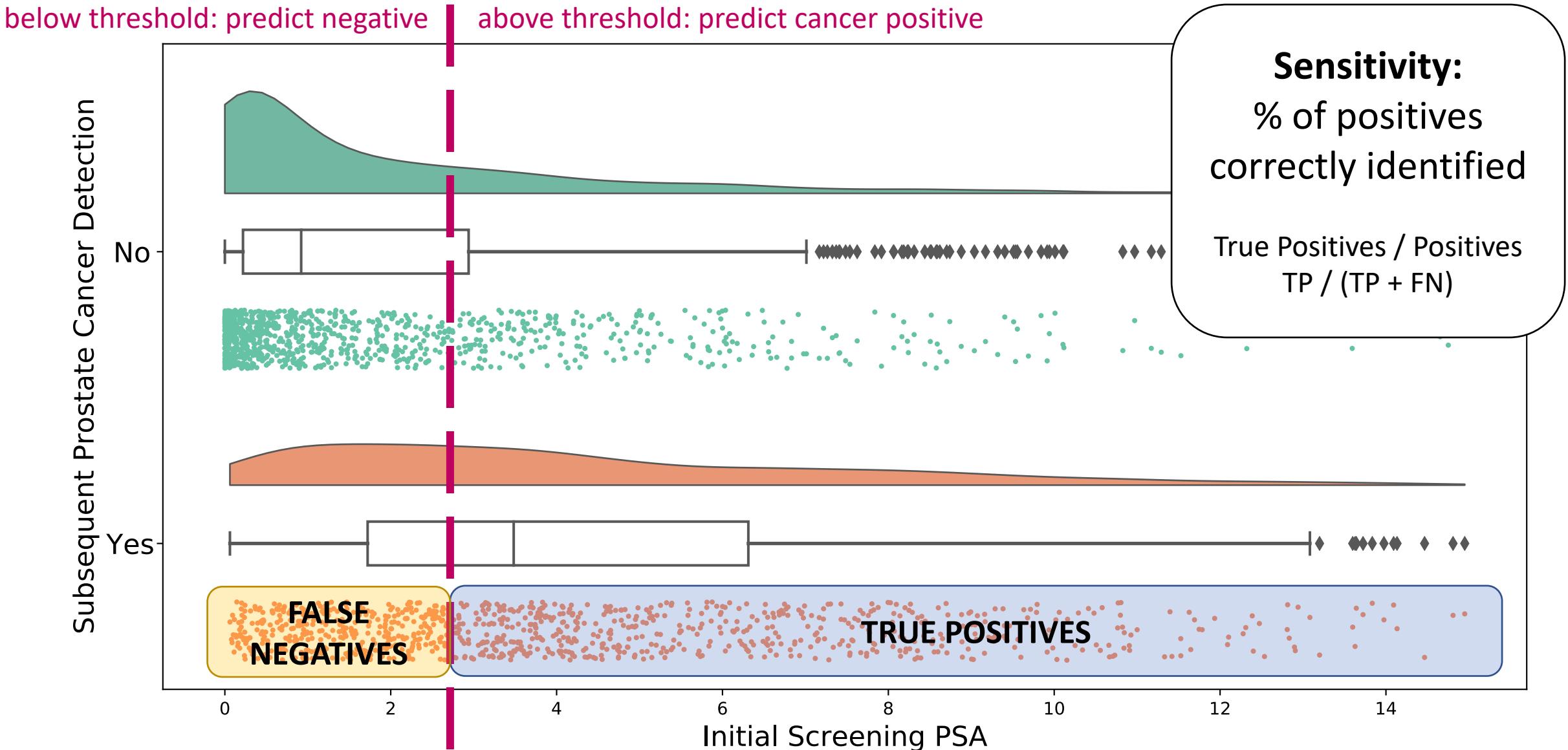


End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive

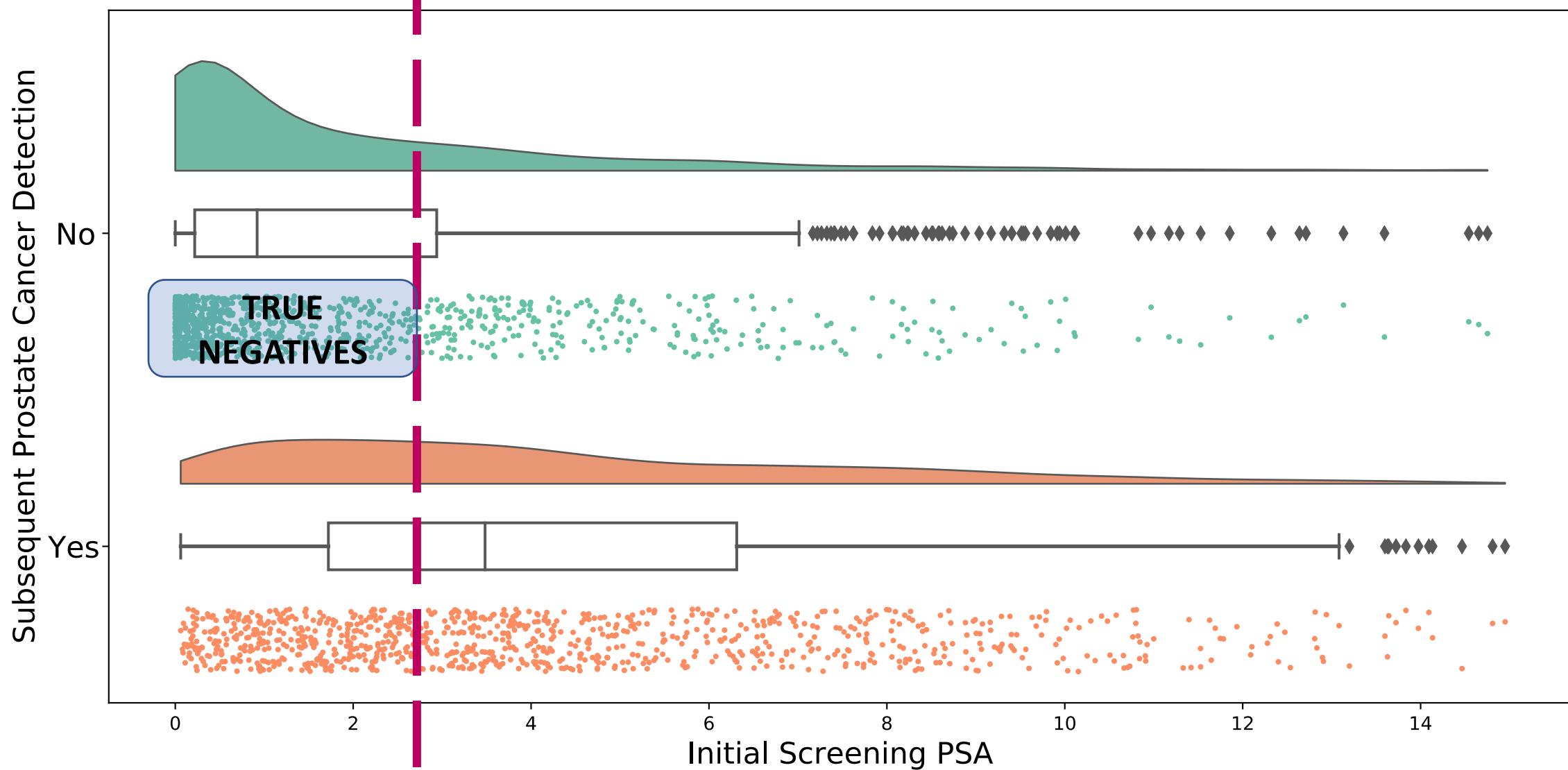


End Goal: predict cancer status (y) based on PSA (x)



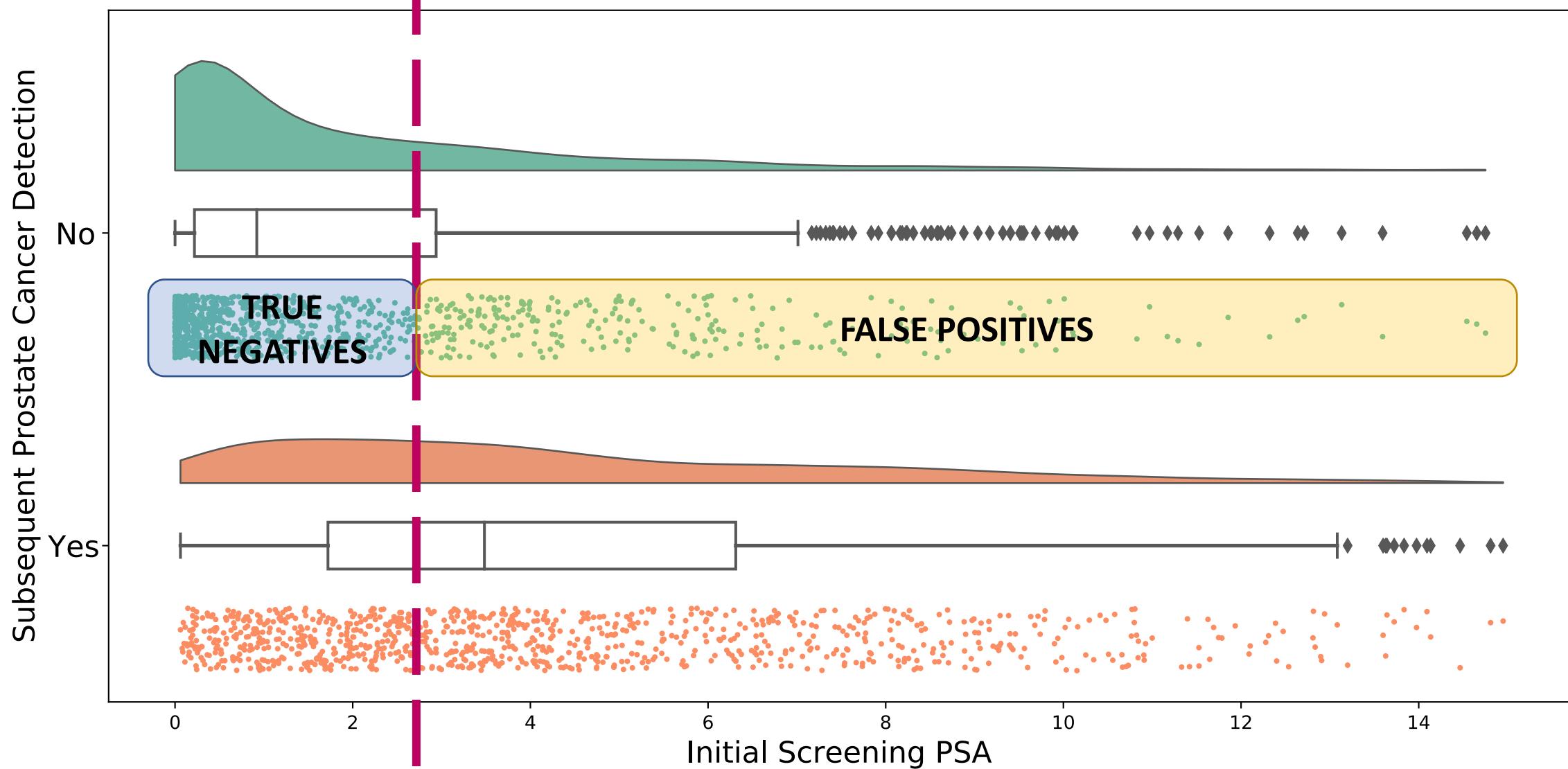
End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive



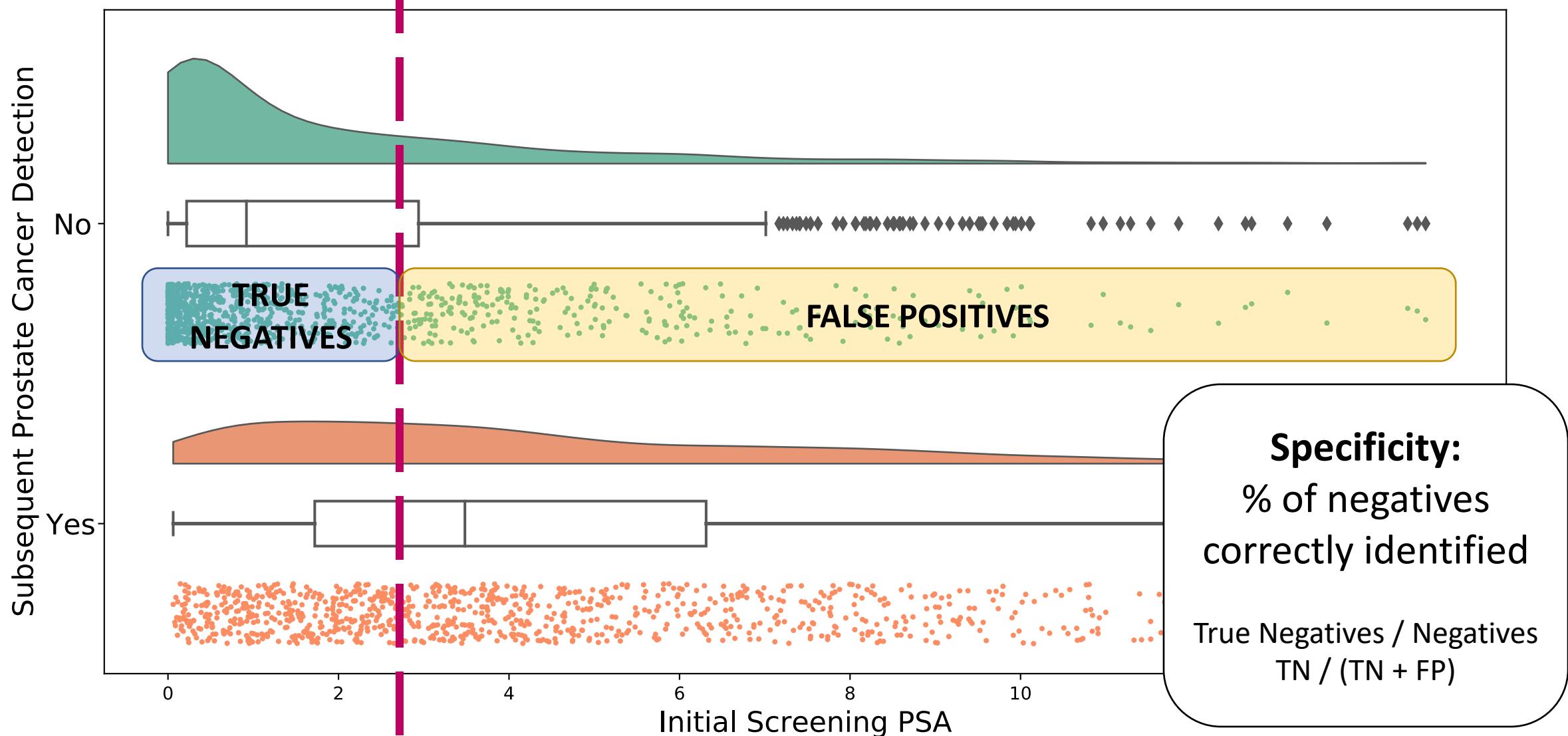
End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive

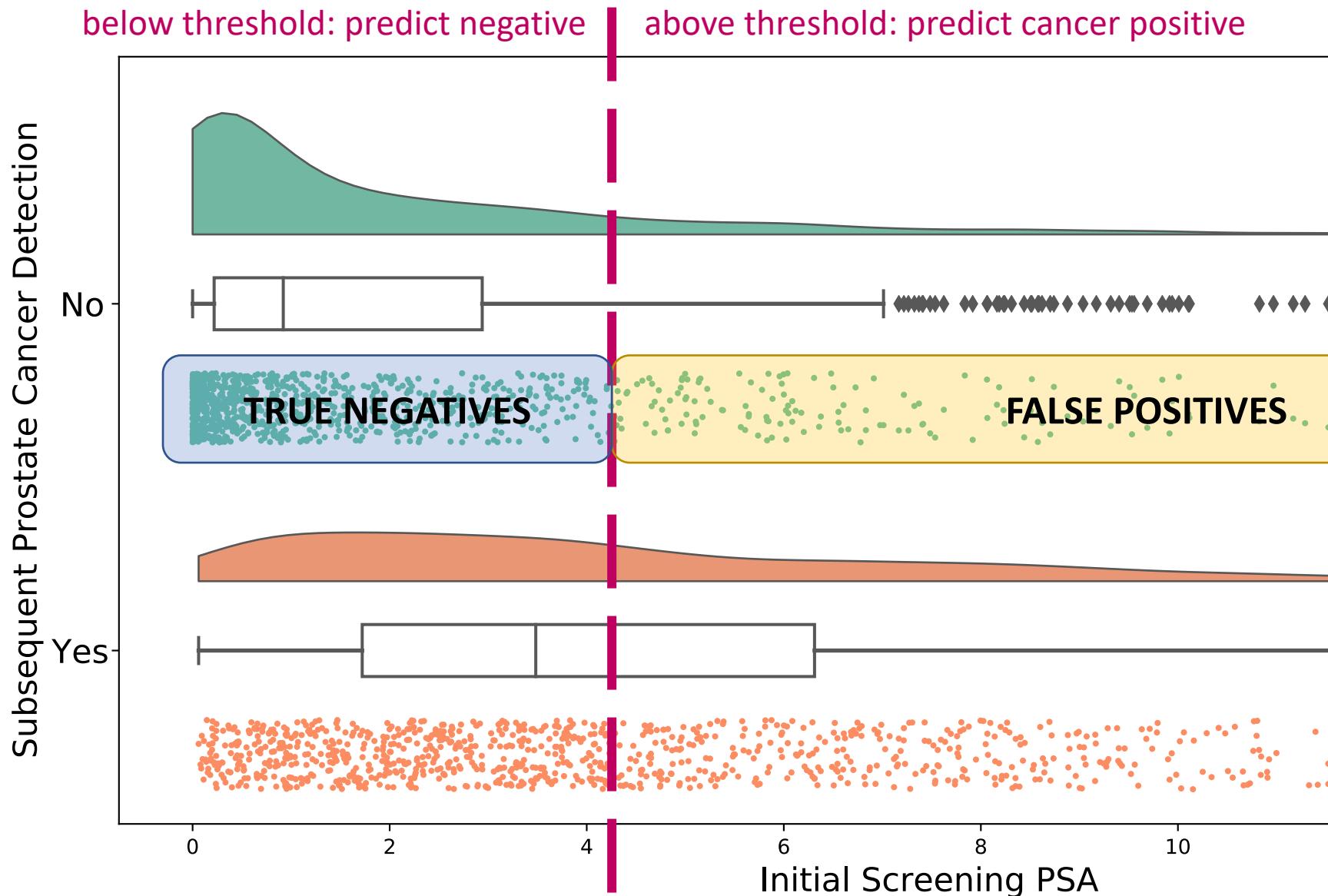


End Goal: predict cancer status (y) based on PSA (x)

below threshold: predict negative | above threshold: predict cancer positive



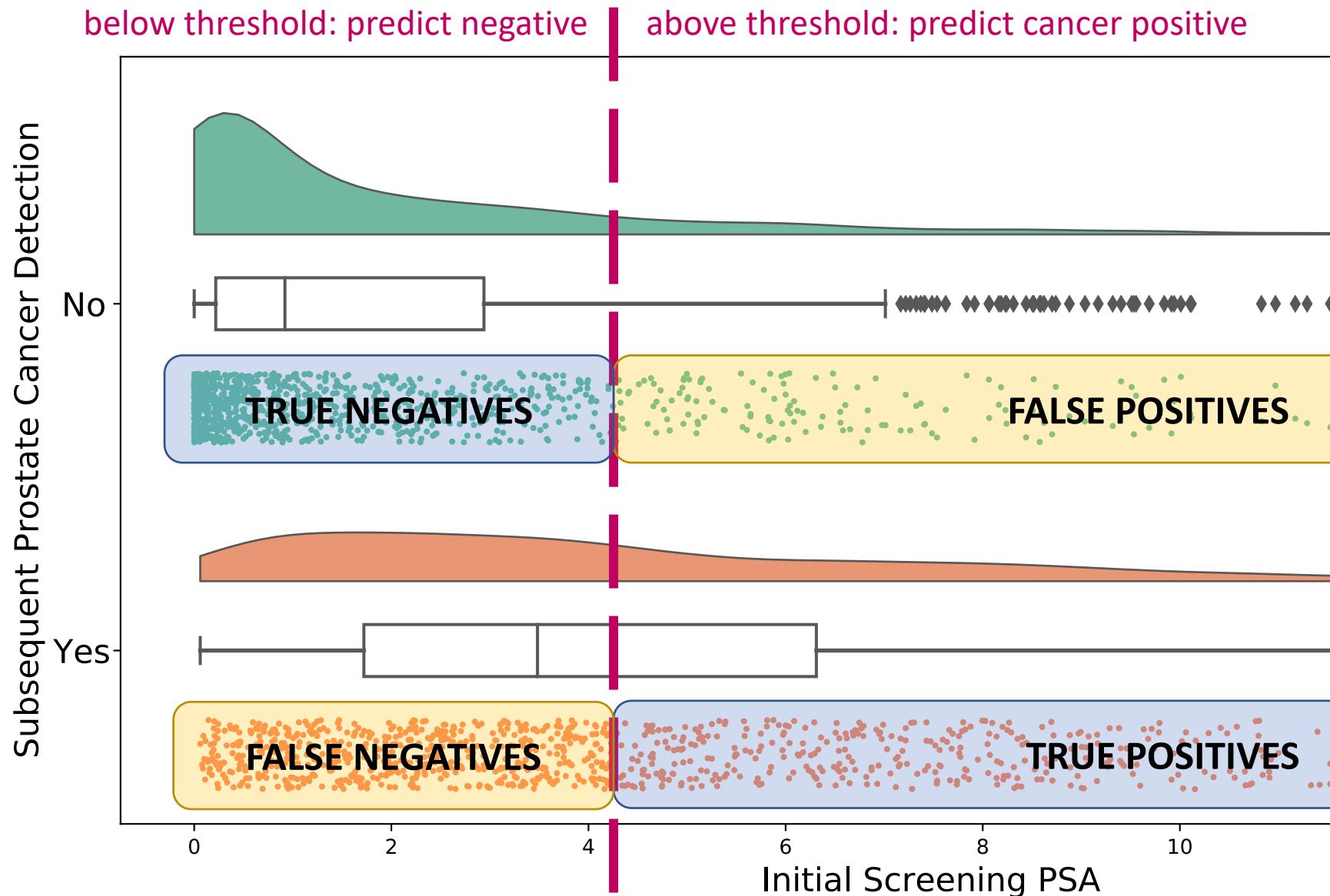
End Goal: predict cancer status (y) based on PSA (x)



Increase the threshold:

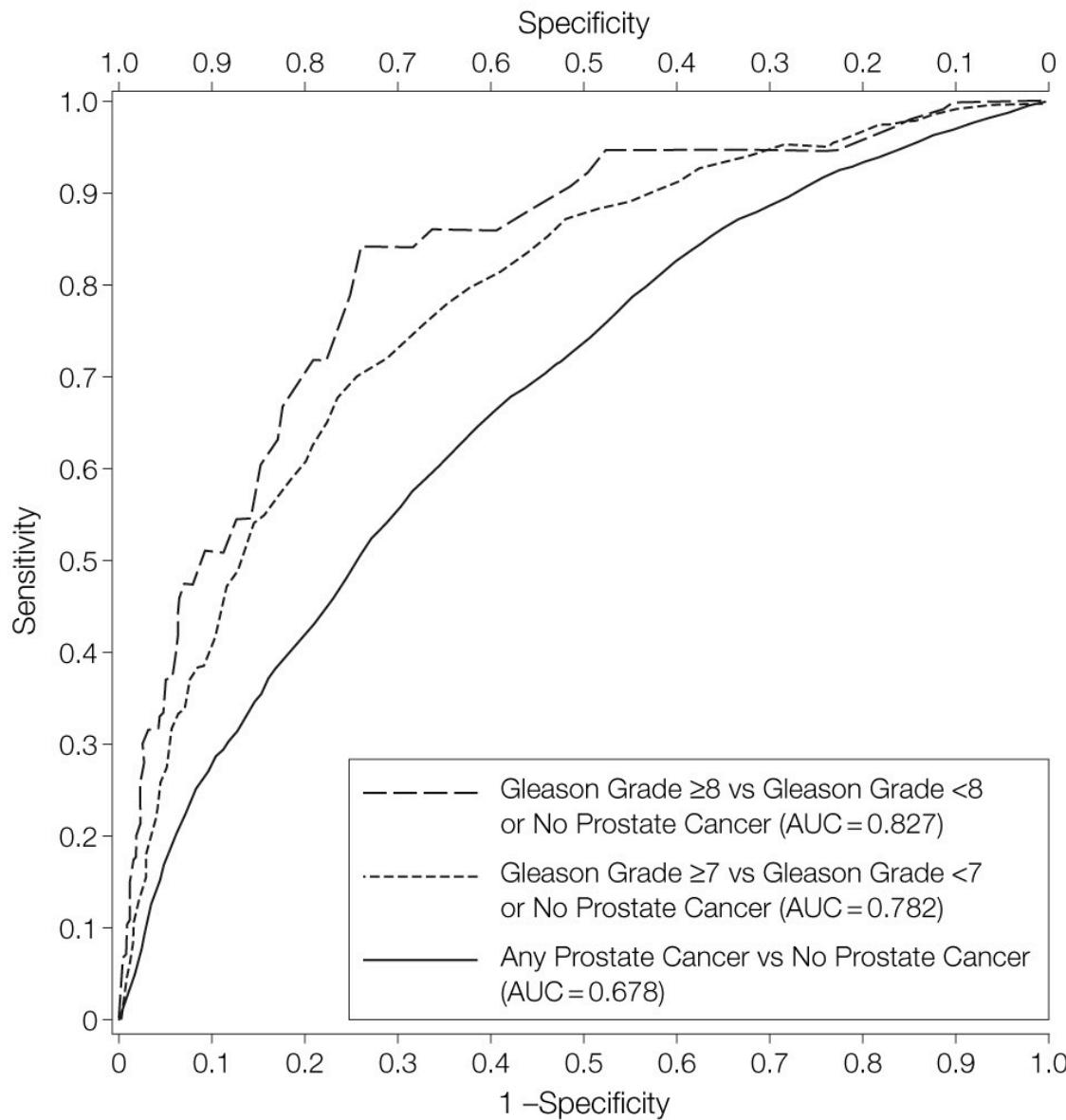
1. Specificity goes up.
(we're catching more negative cases)

End Goal: predict cancer status (y) based on PSA (x)



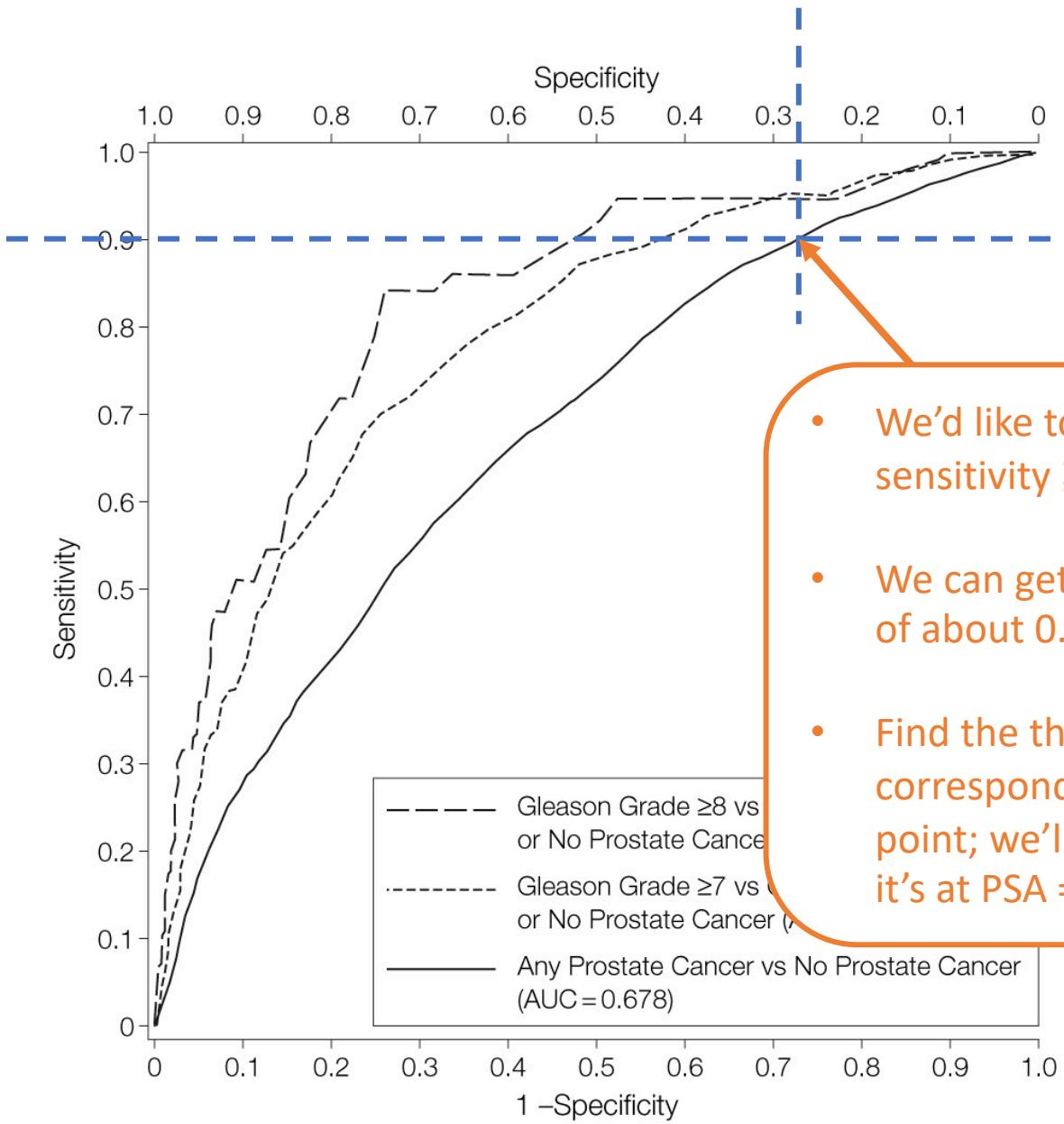
Increase the threshold:

1. Specificity goes up.
(we're catching more negative cases)
2. Sensitivity goes down.
(we're catching fewer positive cases)



The ROC curve
(i.e. sensitivity/specificity curve)
quantifies performance across
all possible thresholds

Thompson IM, Ankerst DP, Chi C, et al. Operating Characteristics of Prostate-Specific Antigen in Men With an Initial PSA Level of 3.0 ng/mL or Lower. *JAMA*. 2005;294(1):66–70.
doi:10.1001/jama.294.1.66



The ROC curve
(i.e. sensitivity/specificity curve)
identifies performance across
possible thresholds

- We'd like to have sensitivity ≥ 0.9
- We can get specificity of about 0.27
- Find the threshold corresponding to this point; we'll suppose it's at PSA = 2.0

Thompson IM, Ankerst DP, Chi C, et al. Operating Characteristics of Prostate-Specific Antigen in Men With an Initial PSA Level of 3.0 ng/mL or Lower. *JAMA*. 2005;294(1):66–70.
doi:10.1001/jama.294.1.66

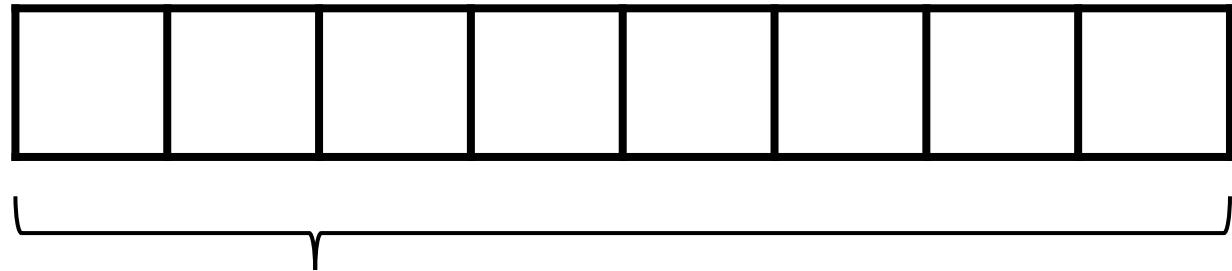
Our first, very simple predictive model

End Goal: predict cancer
status (y) based on PSA (x)

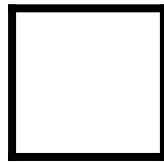
Our rule:

**if PSA > 2.0, predict positive
else predict negative**

Learning a Predictive Model from Labeled Data



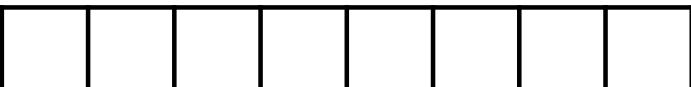
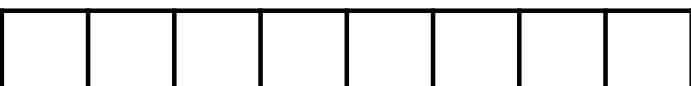
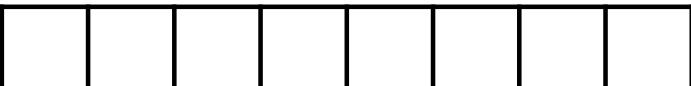
x , data/features for
a subject or patient



y , associated
value or label

The learning process: find the equation that best predicts y based on x

Training Set (Historical Data)

x_1		 y_1
x_2		 y_2
x_3		 y_3
x_4		 y_4
	\vdots	\vdots
x_{N-1}		 y_{N-1}
x_N		 y_N

Find an equation that predicts y based on x across the training set

We'll begin by supposing y is binary
(i.e. $y \in \{0, 1\}$)

Making Predictions for New x

x_1	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

x_2	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

x_3	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

x_4	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

:

x_{N-1}	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

x_N	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>								

<table border="1"><tr><td></td></tr></table>		y_1

<table border="1"><tr><td></td></tr></table>		y_2

<table border="1"><tr><td></td></tr></table>		y_3

<table border="1"><tr><td></td></tr></table>		y_4

:

<table border="1"><tr><td></td></tr></table>		y_{N-1}

<table border="1"><tr><td></td></tr></table>		y_N

Find an equation that
predicts y based on x
across the training set

We'll begin by supposing
 y is binary
(i.e. $y \in \{0, 1\}$)

x_{N+1}	<table border="1"><tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr></table>									<table border="1"><tr><td></td></tr></table>		y_{N+1}

<- Learn to predict new y

Summary

- The data science techniques we will consider in this course, from computer vision to natural language processing, are all examples of *predictive models*.
- The predictive model is the *machine* in machine learning. It is a specific mathematical equation that is learned from historical data and evaluated by applying it to additional data not used in training.
- Predictive models can be very simple or very complex. As a rule of thumb, we want to use the simplest model that performs well.