Performance Measures

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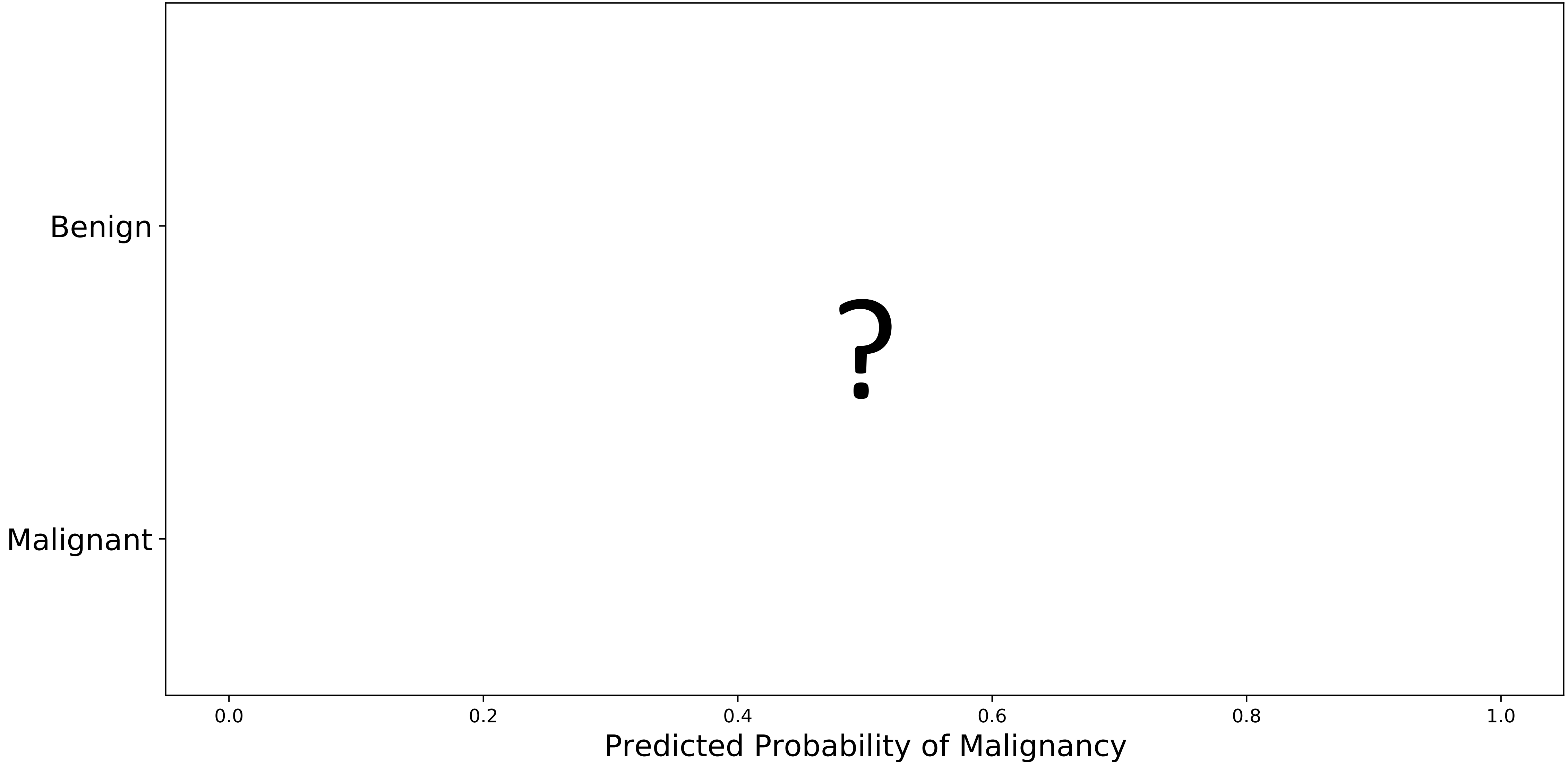
Goals

- Understand and calculate common performance measures for binary classification
- Contextualize performance against that of a *no information* classifier
- Recognize that *good* performance depends on existing alternatives
- Match clinical scenarios to performance measures important in that scenario

<u>Back to cancer prediction</u>. Suppose our features are highly informative. What might our model's predictions look like?



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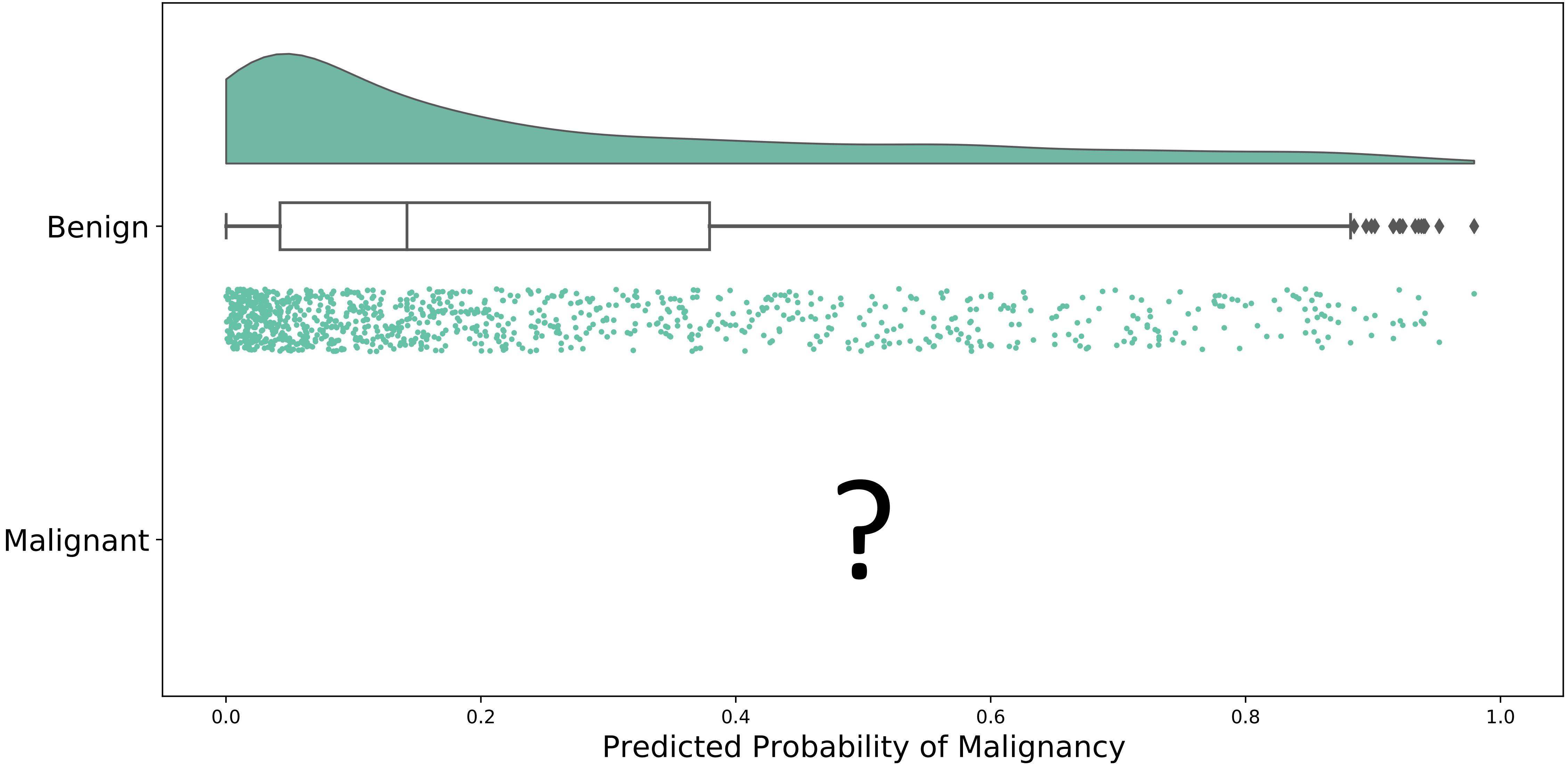

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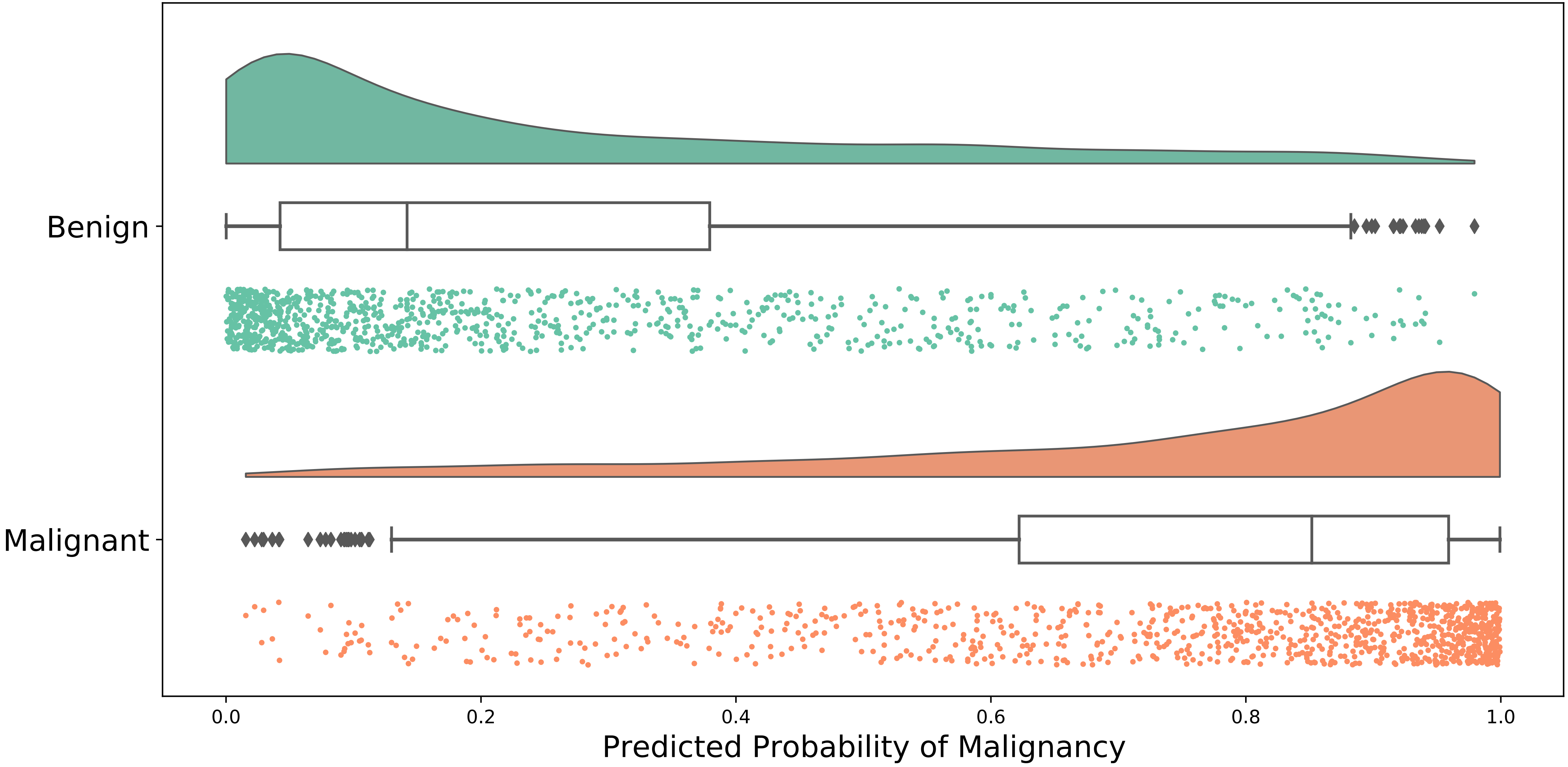
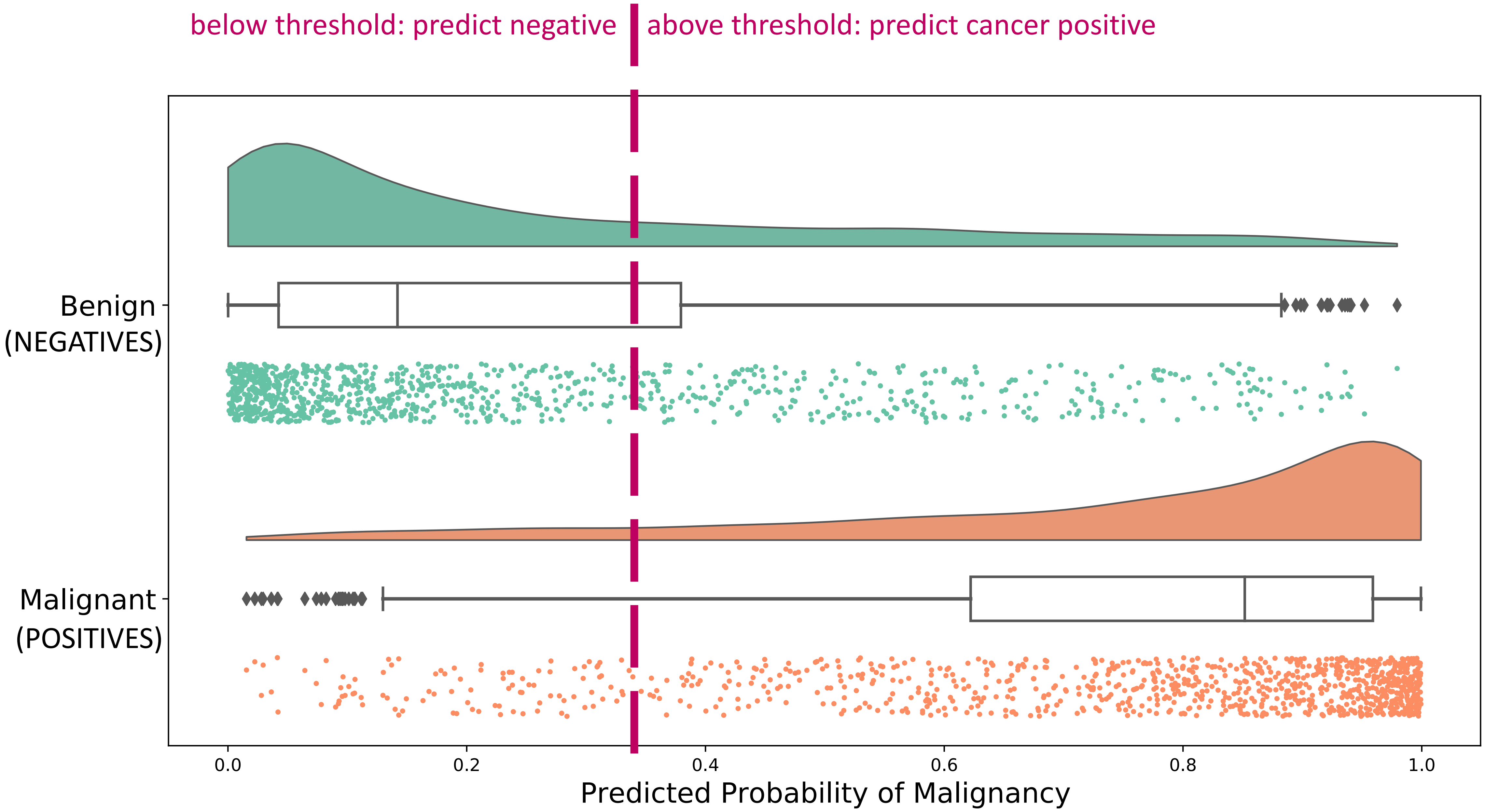
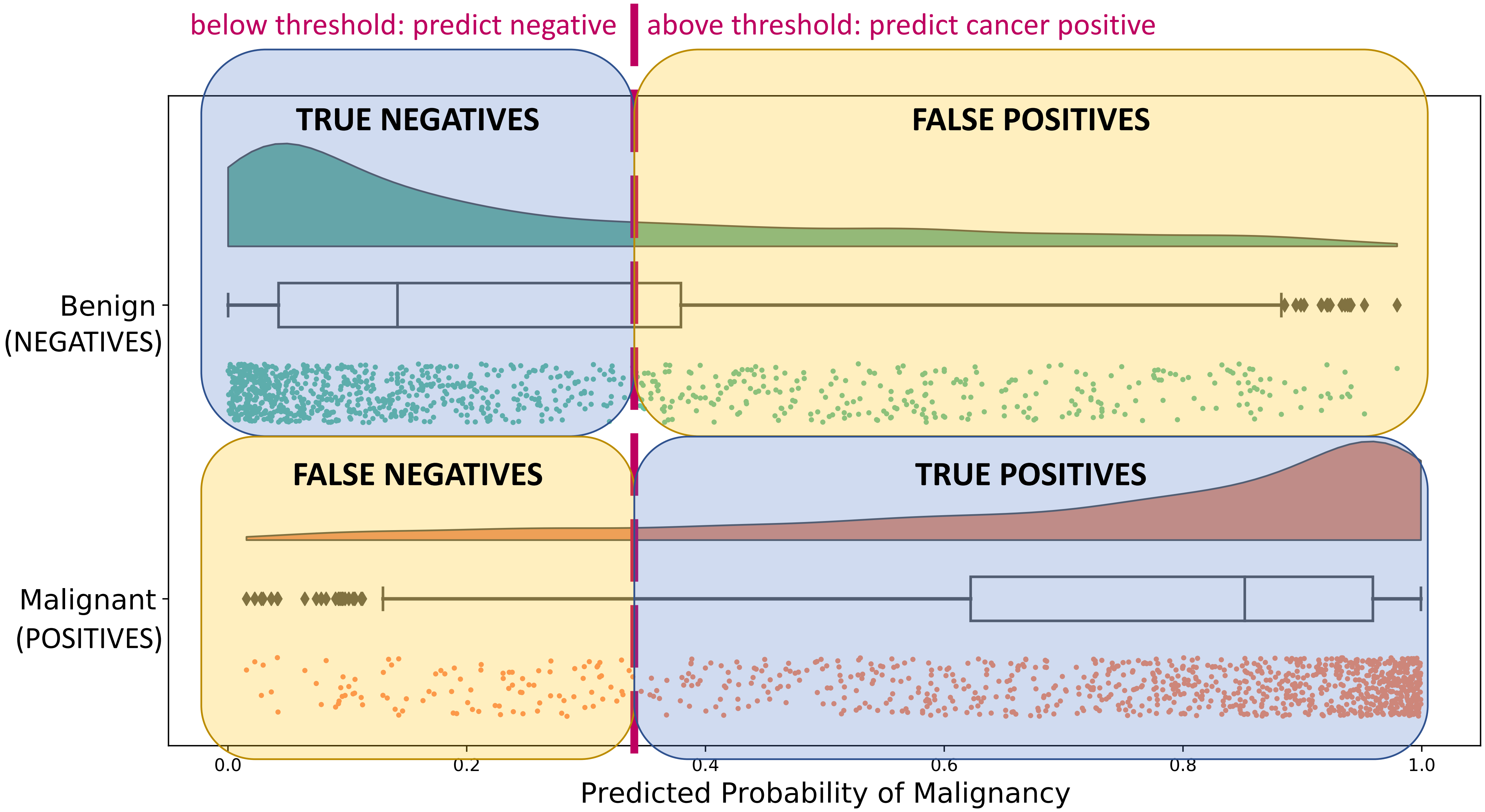



below threshold: predict negative
above threshold: predict cancer positive
Benign
(NEGATIVES)
Malignant
(POSITIVES)
0.0
0.2
0.4
0.6
0.8
1.0
Predicted Probability of Malignancy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TRUE NEGATIVES
FALSE POSITIVES
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(NEGATIVES)
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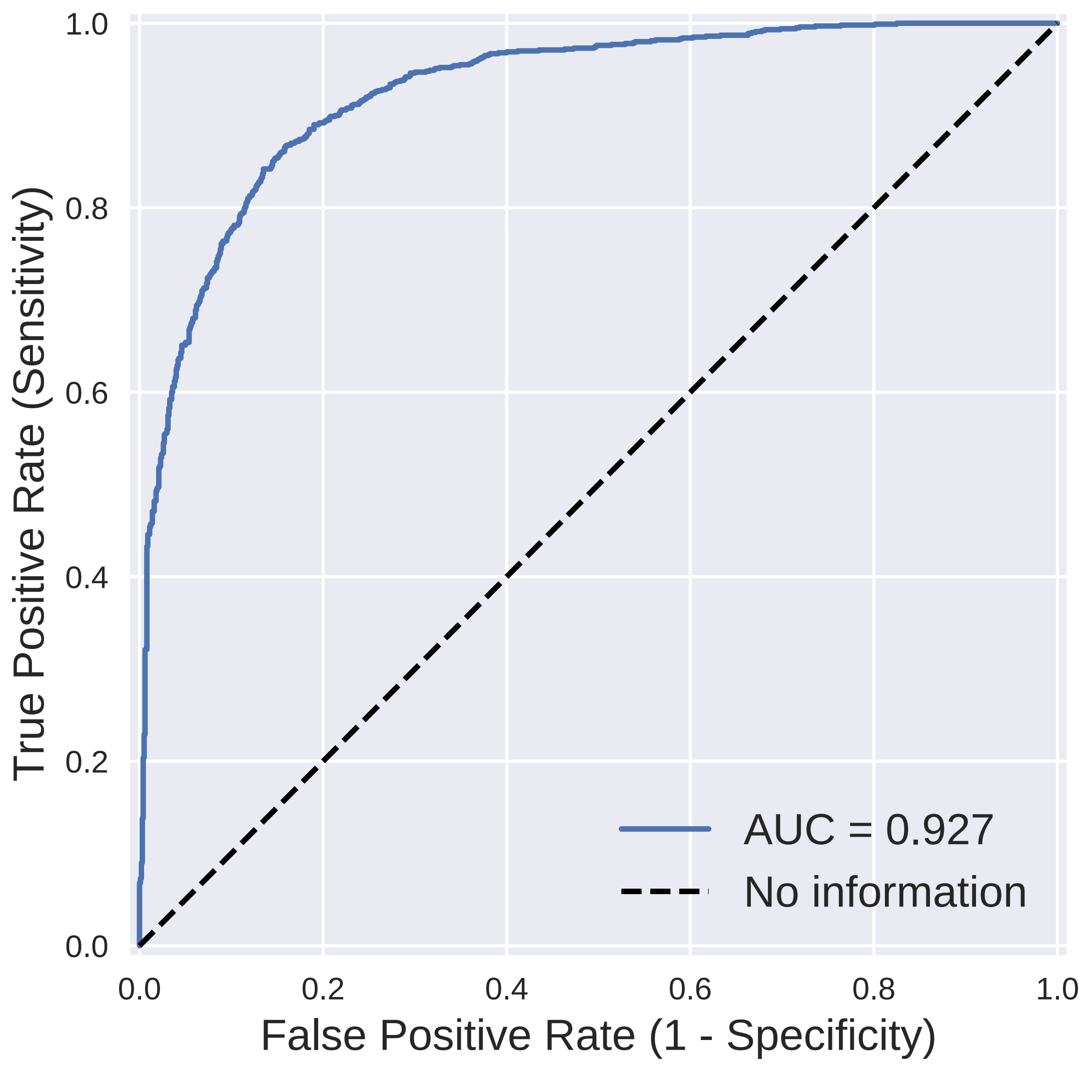
Predicted Probability of Malignancy

Receiver Operating Characteristic Curve

- Illustrates the tradeoff between the true positive rate (i.e., sensitivity) and the false positive rate (i.e., 1– specificity) as we vary the threshold.

- The area under this curve (AUC) provides a single summarizing this tradeoff.

- Note that to get the sensitivity versus specificity curve, we simply rotate the ROC curve clockwise by 90 degrees. The areas under the two curves are the same.

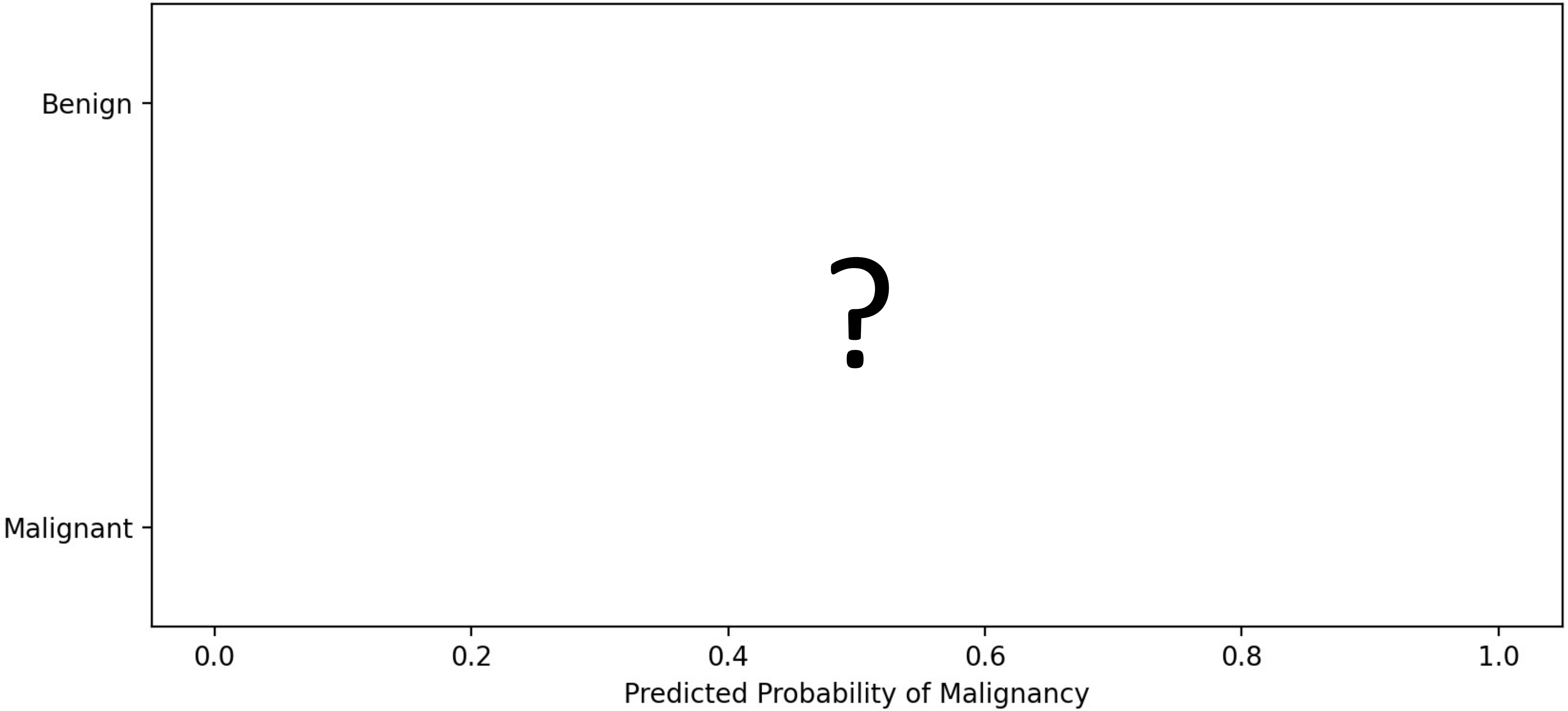


So, what's a *good* AUC value?

(i.e., *good* performance)?

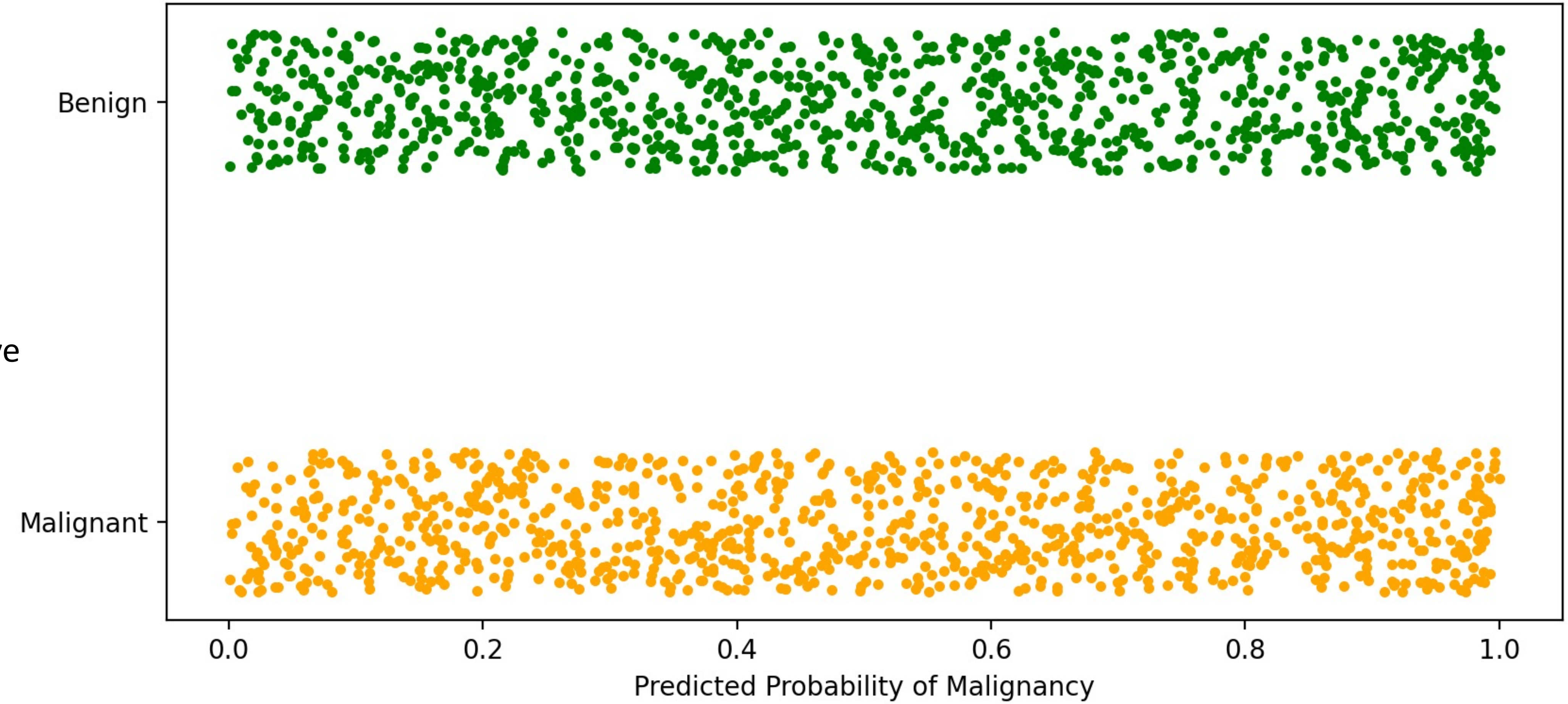
We'll start to answer this question by taking a look at *bad* performance.

Suppose our features contain *no information* about the label. What might our model's predictions look like?

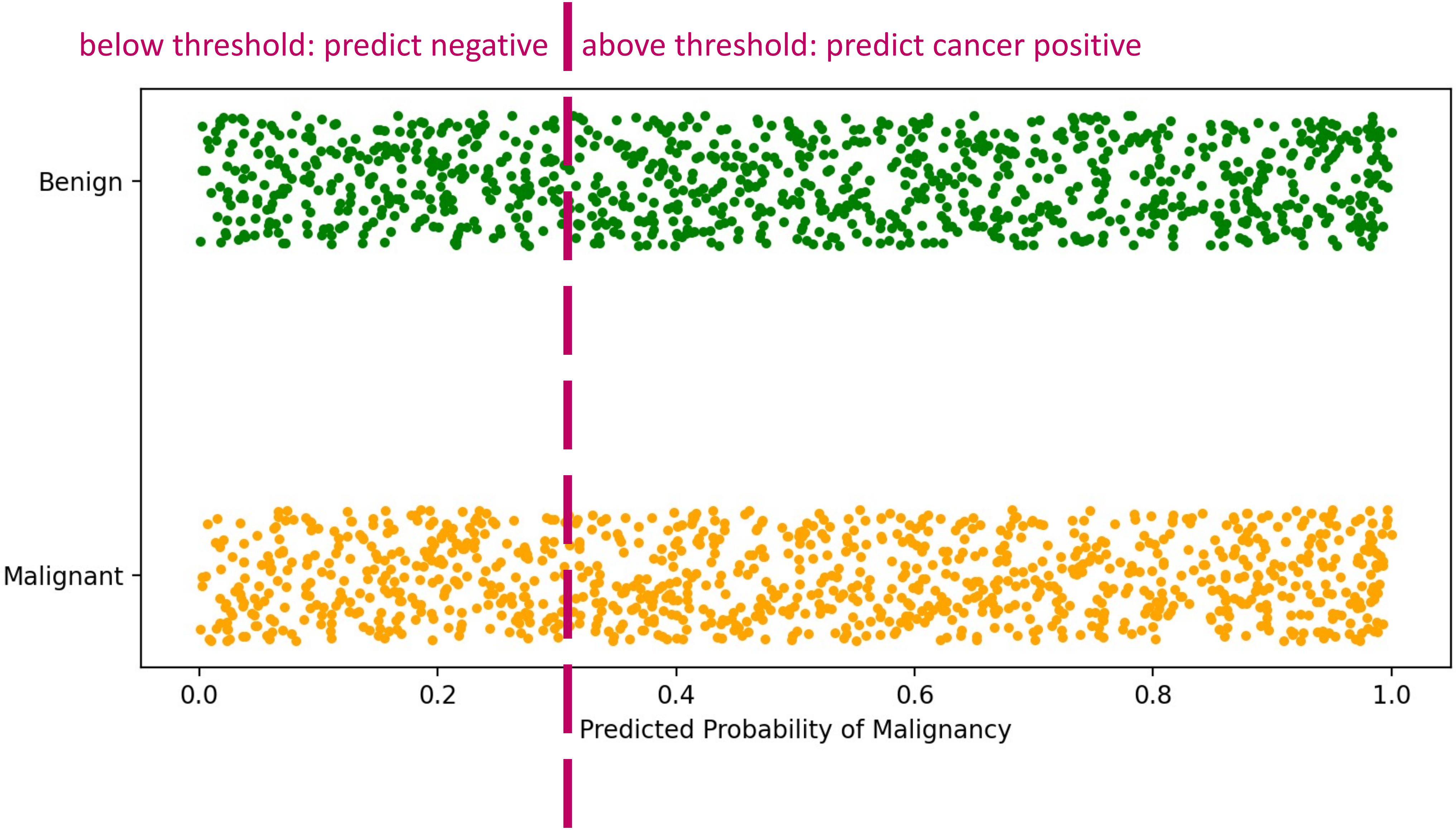


Suppose our features contain no information about the label. What might our model's predictions look like?

- Similar distributions between positive and negative cases.
- The predicted value tells you nothing about which one it's more likely to be.



We’ll try placing a threshold just like before



What is the:

(a) Sensitivity?
(b) Specificity?
(c) Positive predictive value?

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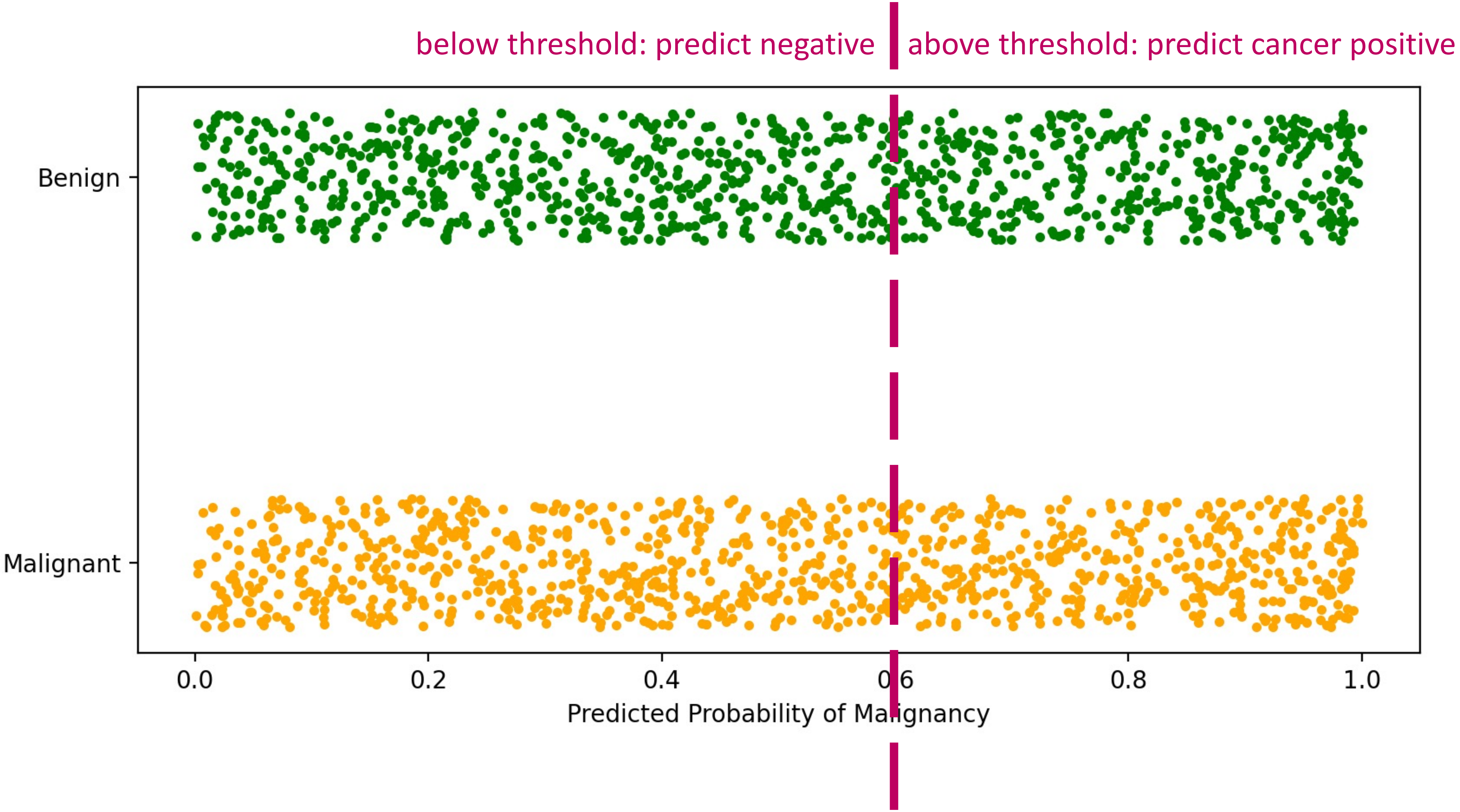


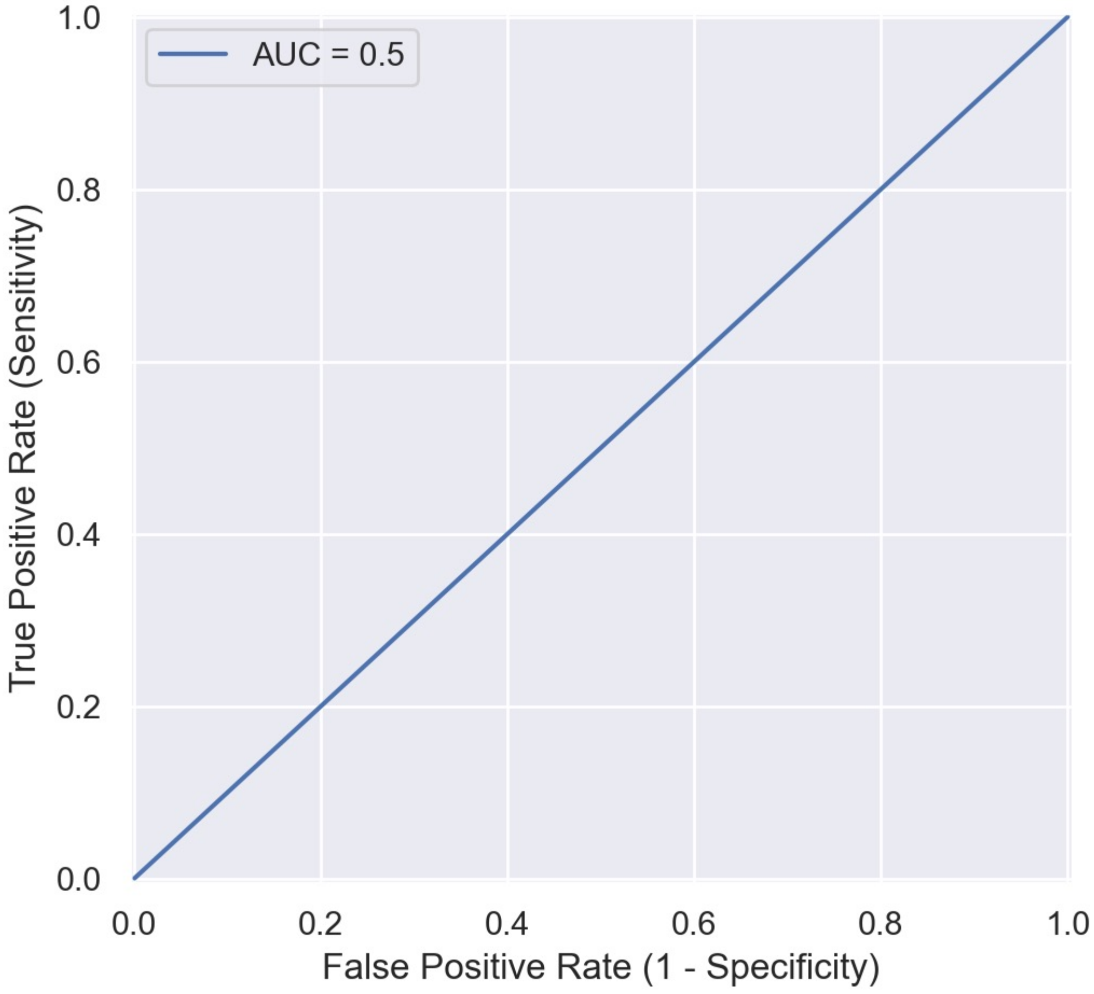
What is the:

(a) Sensitivity?
(b) Specificity?
(c) Positive predictive value?

Our *no information* predictive model:

- Place threshold at .3
  - Sensitivity = .7
  - False positive rate = .7
  - Specificity = 1-.7

- Place threshold at p
  - Sensitivity = $1-p$
  - False positive rate = $1-p$
  - Specificity = p



Let’s think about it a different way.

- Suppose we have no predictors – again, no information – so we decide we’ll just flip a coin instead of building a model.
    - If the coin comes up *heads*, we’ll predict *positive*.
    - If the coin comes up *tails*, we’ll predict *negative*.

Fair Coin: $P(\text{heads}) = .5$

- Sensitivity = ?
- False positive rate = ?
- Specificity = ?

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Fair Coin: $P(\text{heads}) = .5$

- Sensitivity = .5
- False positive rate = .5
- Specificity = .5

Let’s think about it a different way.

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Fair Coin: $P(\text{heads}) = .5$

- Sensitivity = .5
- False positive rate = .5
- Specificity = .5

Biased Coin: $P(\text{heads}) = p$

- Sensitivity = ?
- False positive rate = ?
- Specificity = ?

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Fair Coin: $P(\text{heads}) = .5$

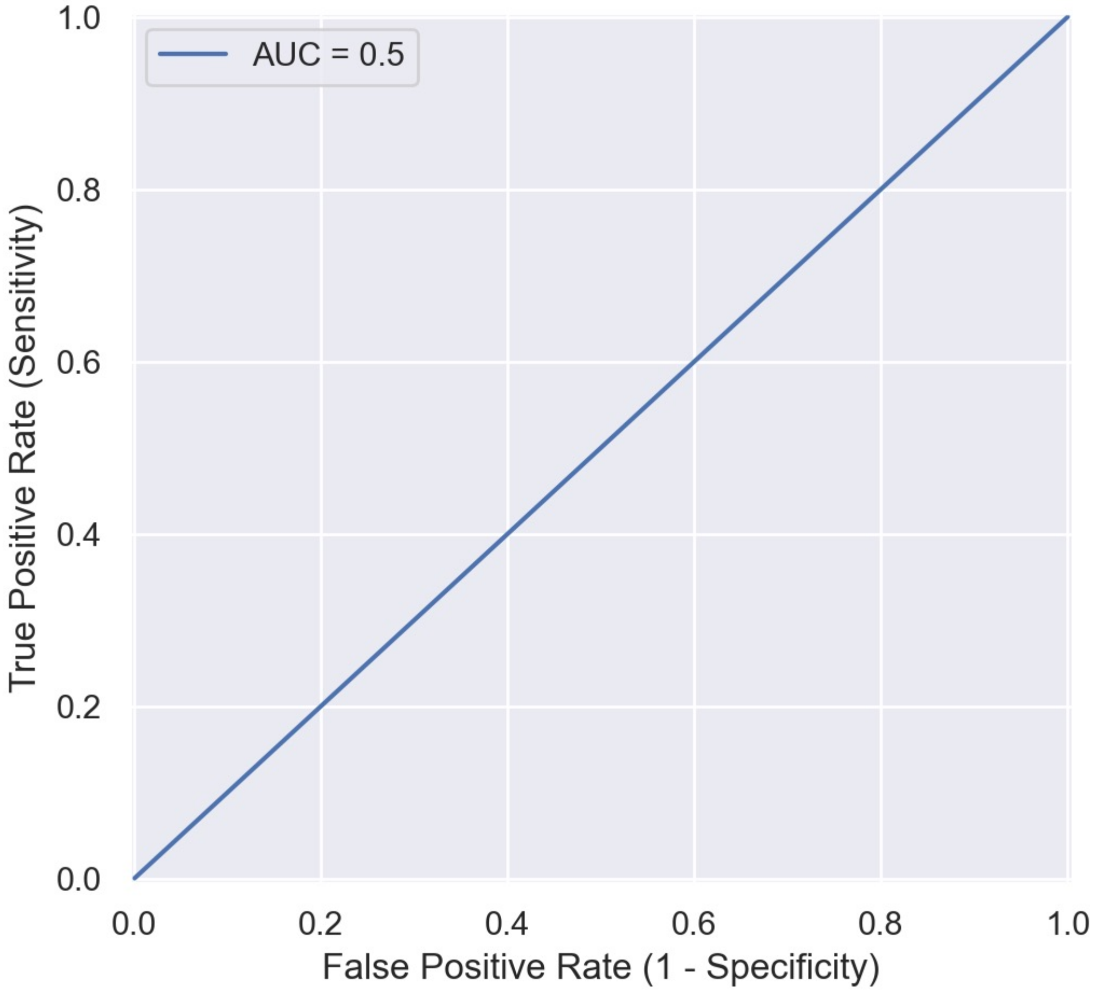
- Sensitivity = .5
- False positive rate = .5
- Specificity = .5

Biased Coin: $P(\text{heads}) = p$

- Sensitivity = 1-*p*
- False positive rate = 1-*p*
- Specificity = *p*

Again, we arrive at the following *no information* curve

- We may choose any *p* between 0 and 1 to get:
  - Sensitivity = *p*
  - False positive rate = *p*
  - Specificity = *1-p*
- What's the area under this curve (AUC)? --> 0.5



So, what’s a *good* AUC value?
(i.e., *good* performance)?

It depends.

- Are predictions better than random?
- Are predictions than the previous best performing model?
- Are predictions better than expert performance?
- Does performance exceed our (informed) expectations?

- <u>**Is the model clinically useful?**</u>

OK, we've quantified performance across all thresholds. But how do we use the model?

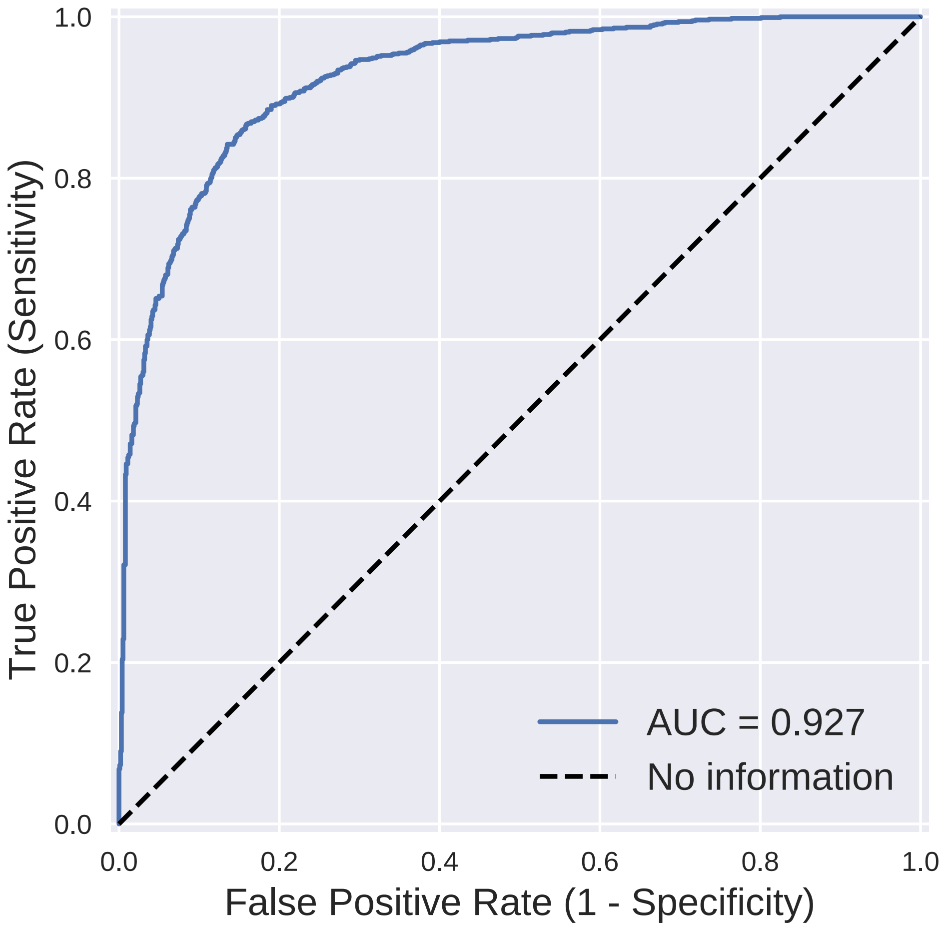
Sometimes the predicted probability really is what we care about.

- *Example*: probability of heart attack
- If so, we need to make sure our model is *calibrated*

More often, we need to pick a threshold so we can decide whether to:

- Alert a provider
- Get a biopsy
- Refer the patient
- etc

What threshold should we pick? What's the right tradeoff?



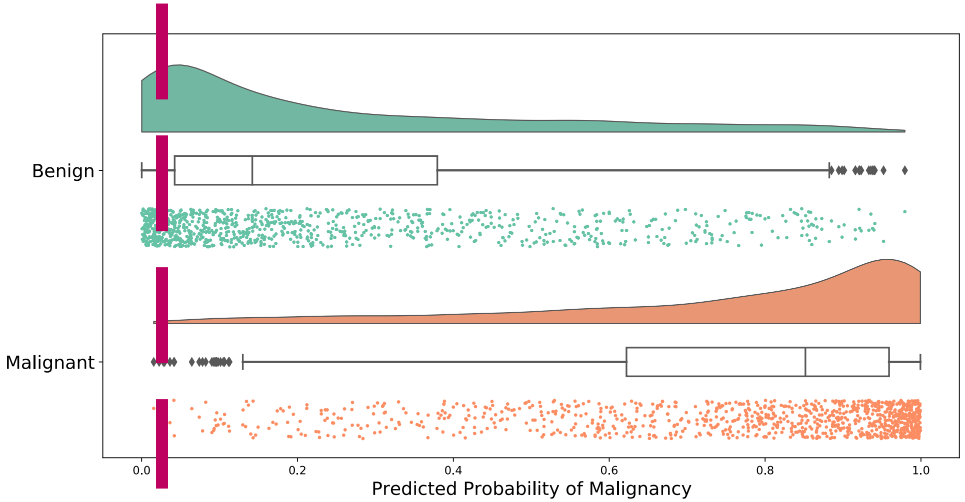
Healthcare Scenarios

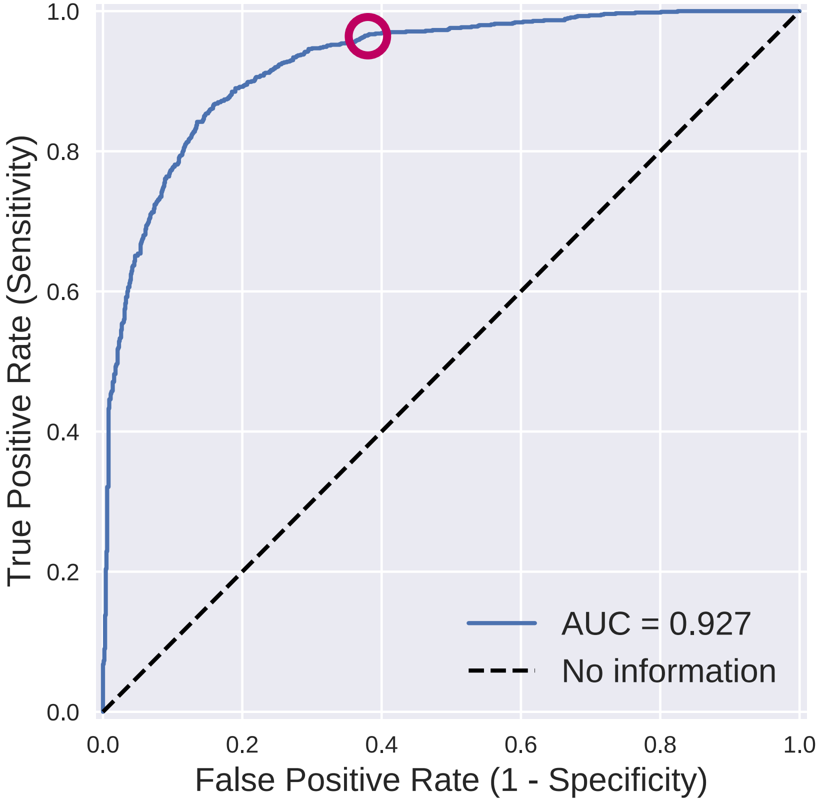
Which performance measure is most important?

1. A computer vision model that detects carcinoma

Operating Point:

high sensitivity





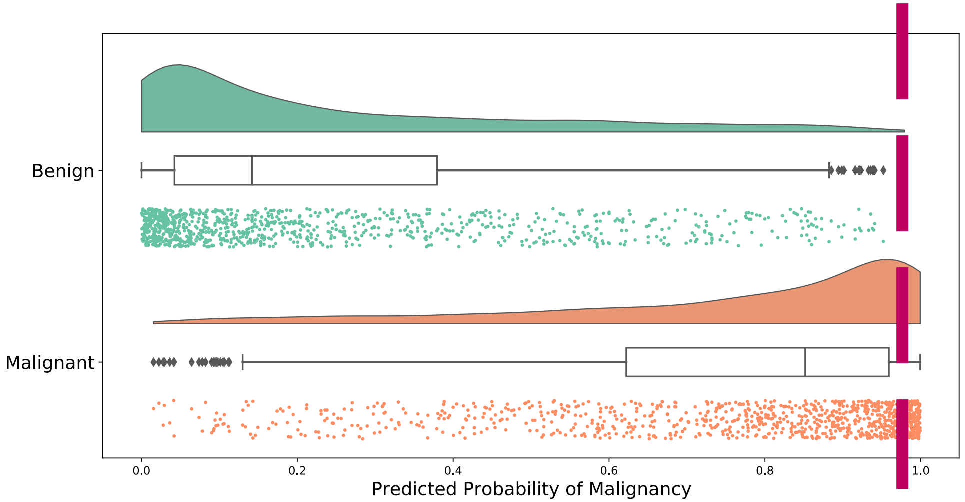
Healthcare Scenarios

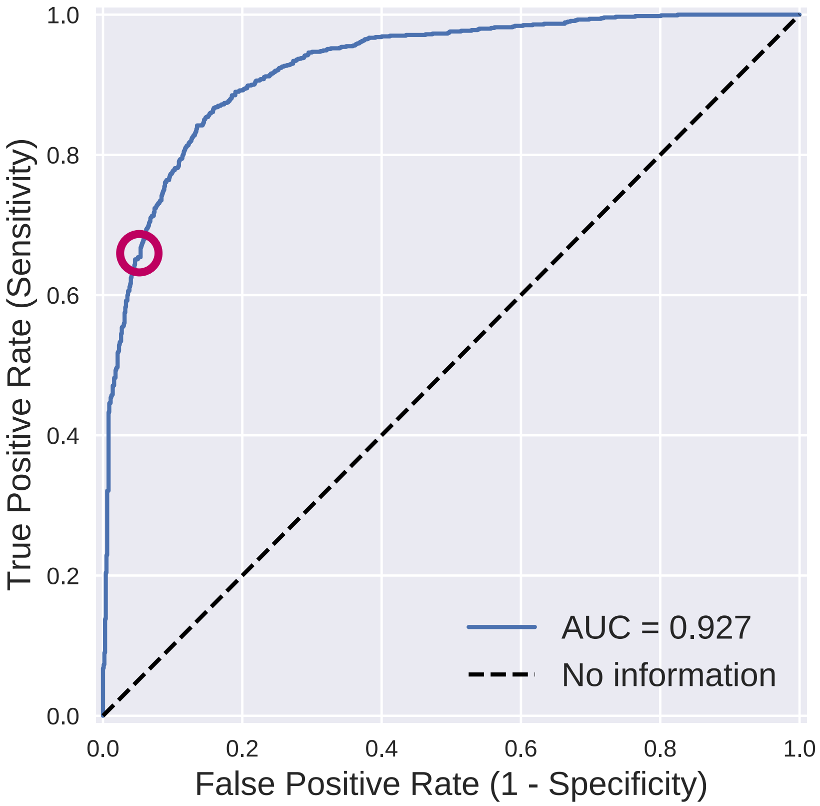
1. A computer vision model that detects carcinoma

2. An algorithm that detects atrial fibrillation in Apple Watch users

Operating Point:

high specificity



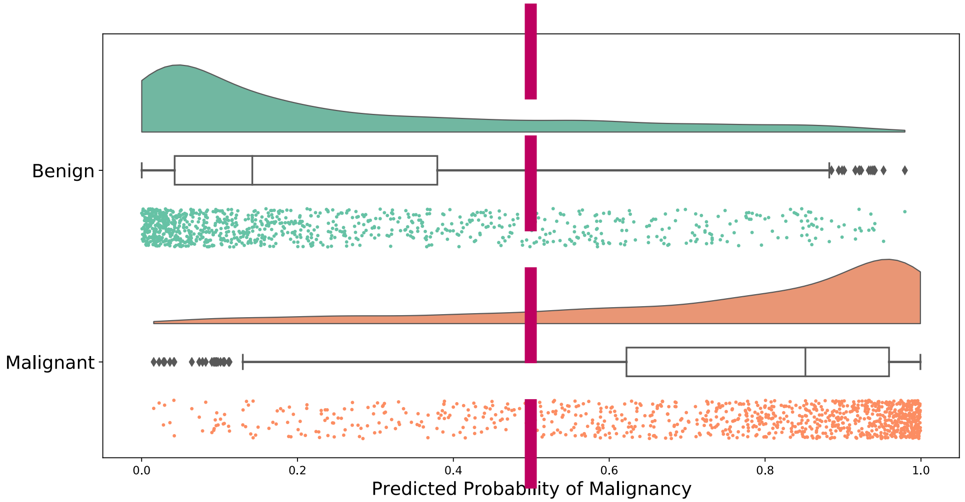


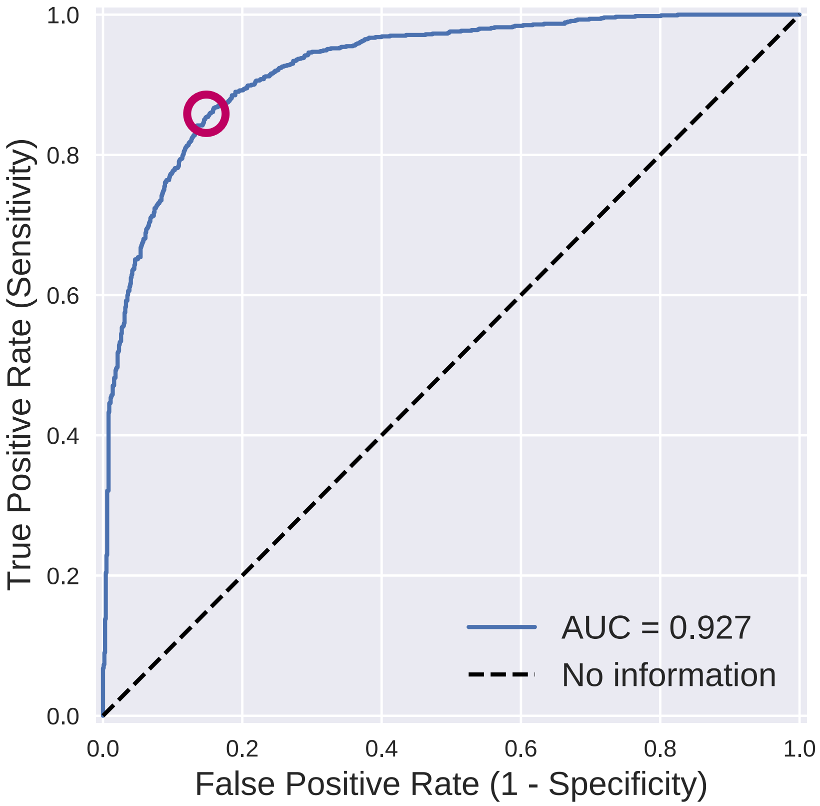
Healthcare Scenarios

1. A computer vision model that detects carcinoma
2. An algorithm that detects atrial fibrillation in Apple Watch users
3. An EHR-based model that monitors autism risk

Operating Point:

balanced





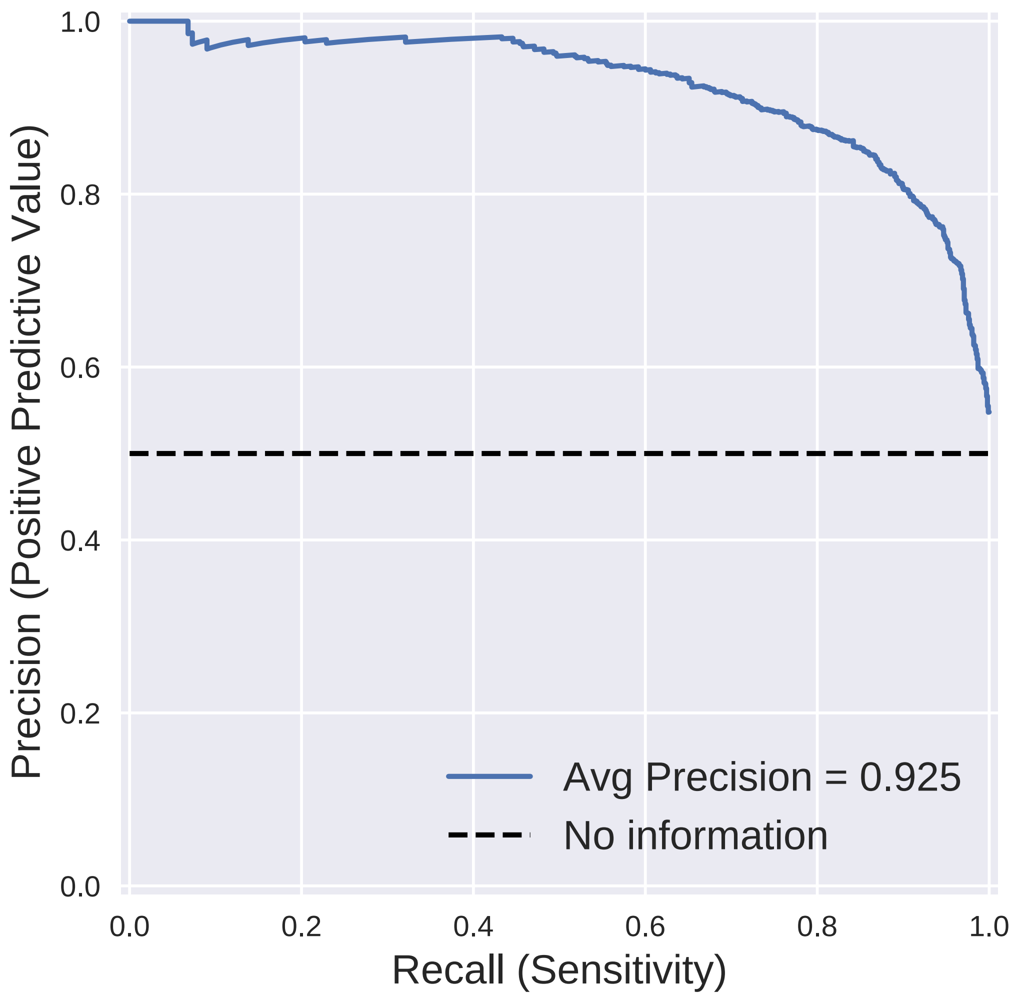
Healthcare Scenarios

1. A computer vision model that detects carcinoma
2. An algorithm that detects atrial fibrillation in Apple Watch users
3. An EHR-based model that monitors autism risk

- Sometimes specificity and sensitivity are difficult to interpret, particularly for rare conditions or events.
- The most clinically relevant measure is often the positive predictive value (or negative predictive value).

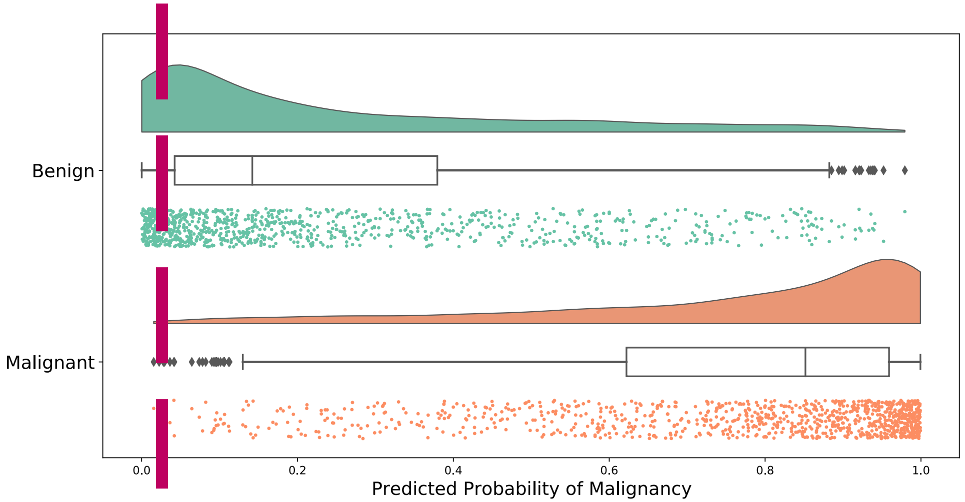
The Precision-Recall Curve
(i.e., PPV-Sensitivity Curve)

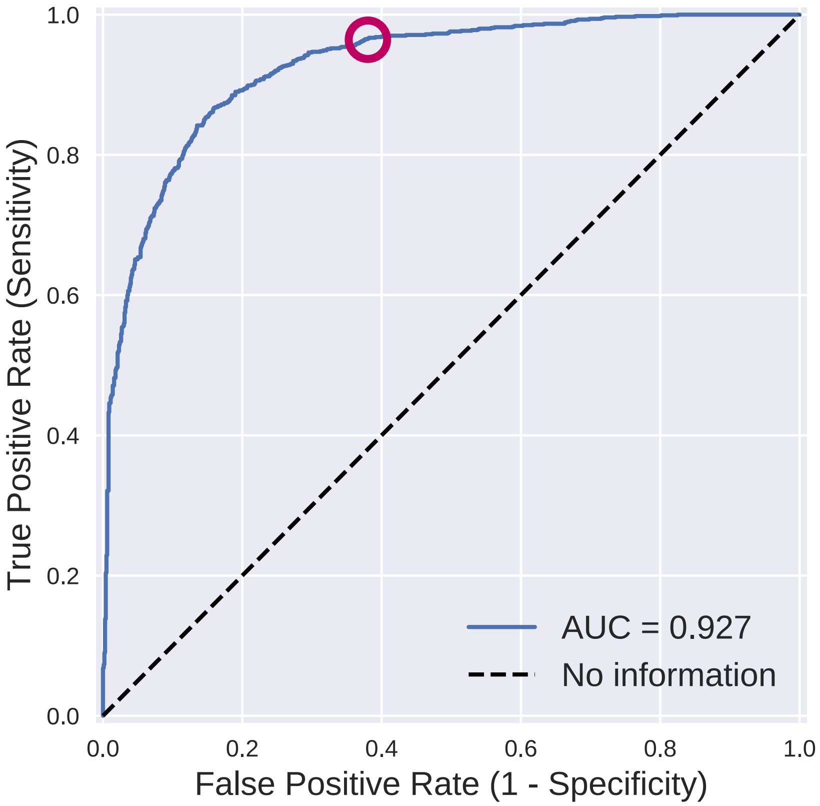
- Often has greater direct clinical relevance than the ROC curve
- The *no information* classifier always achieves PPV equal to the *base rate*, or *prevalence* (why?)
- PPV as well as the area under this curve (average precision) must be interpreted relative to prevalence

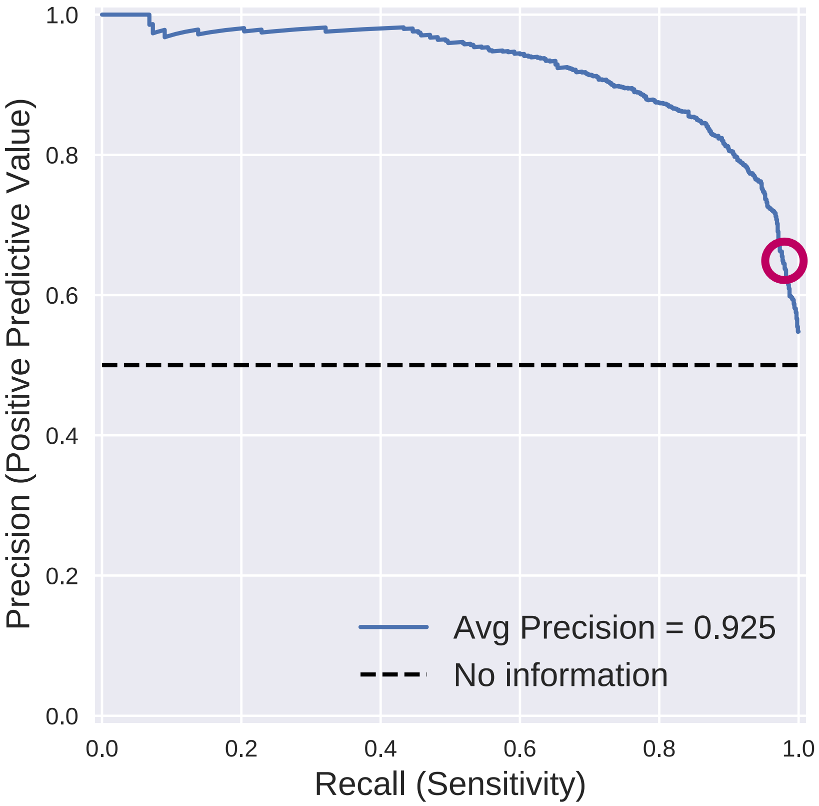


Operating Point:

high sensitivity

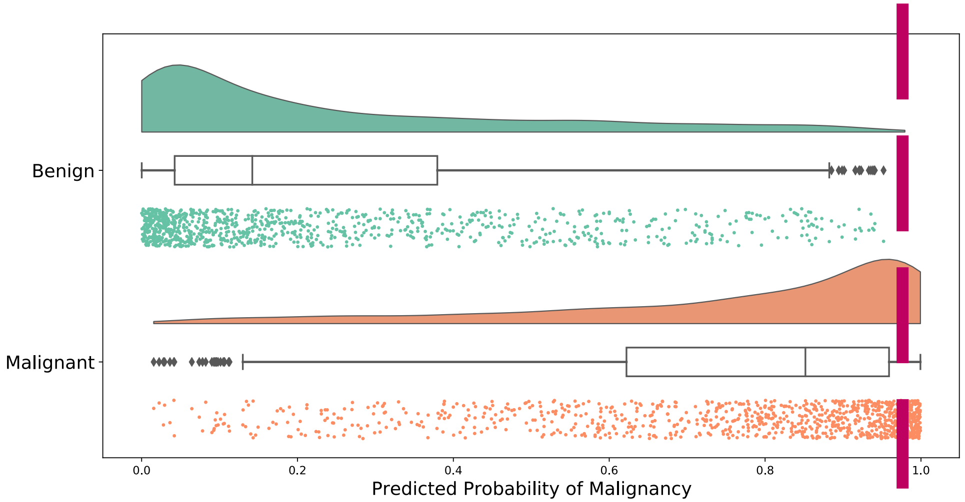


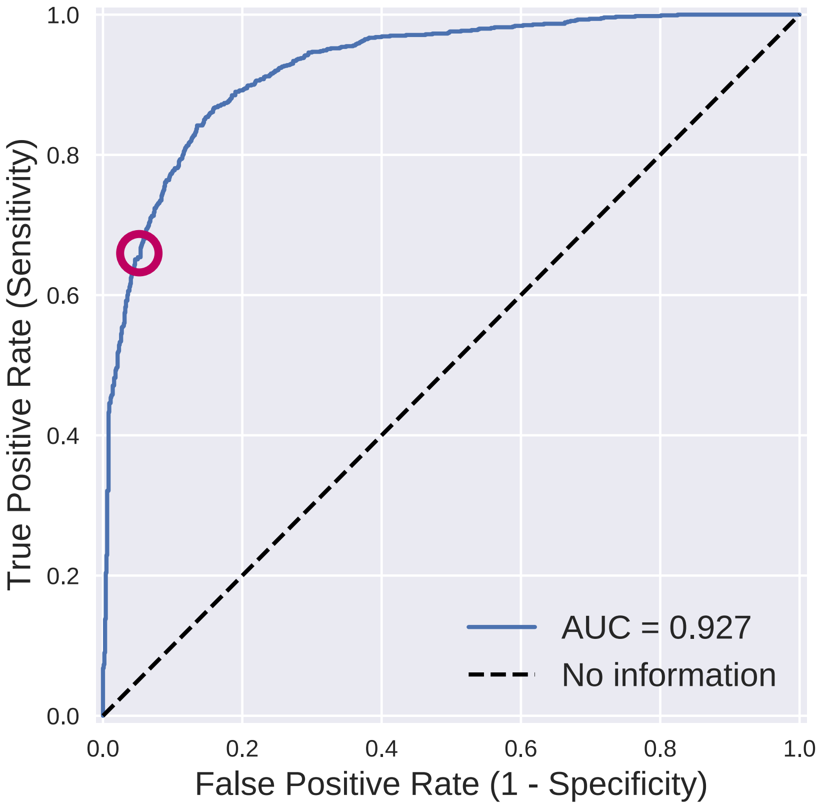


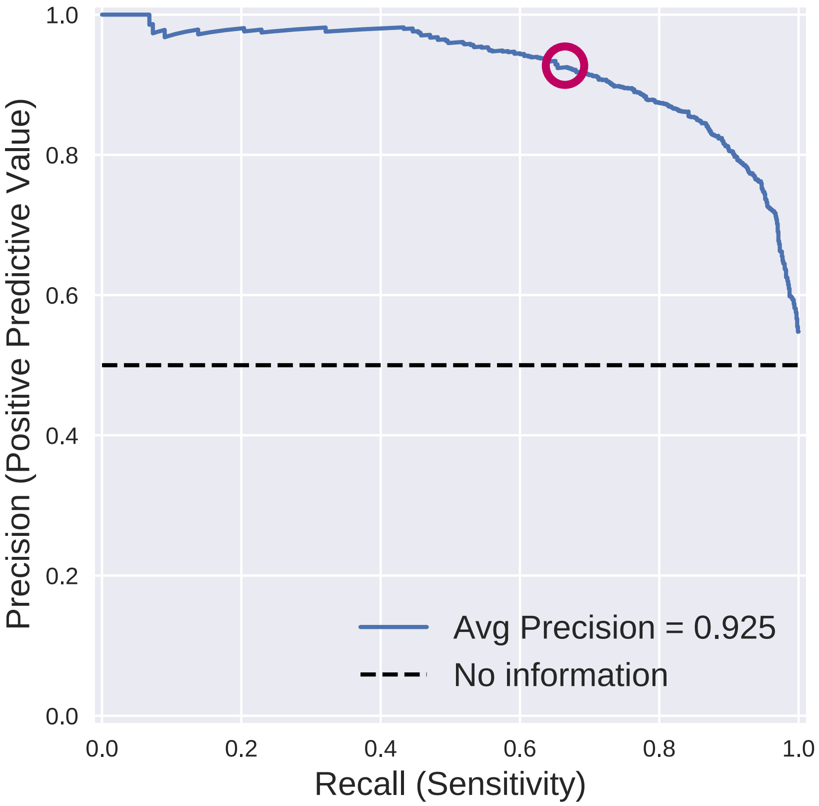


Operating Point:

high specificity

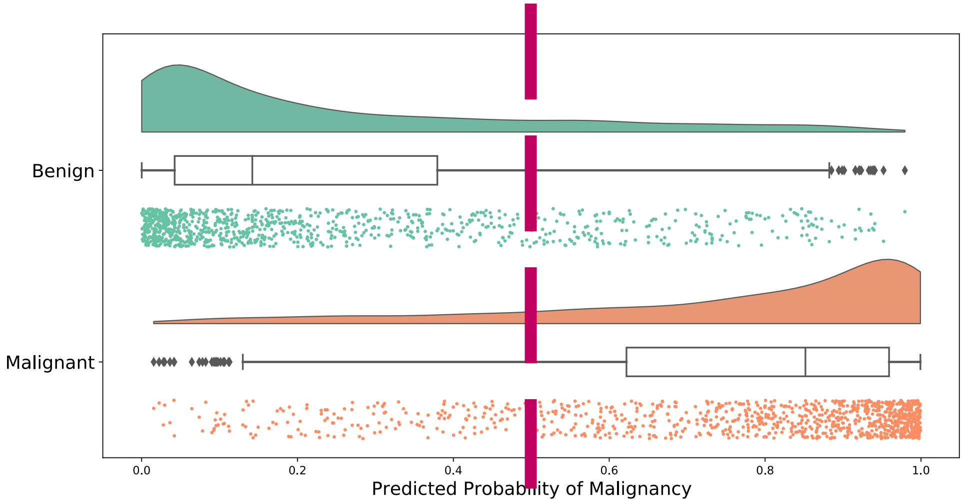


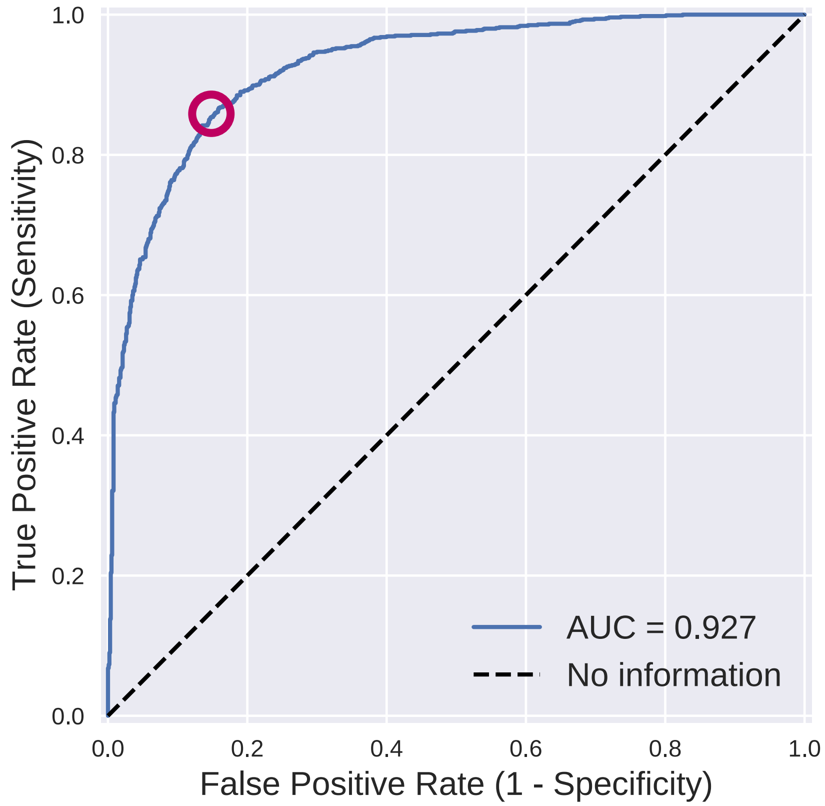


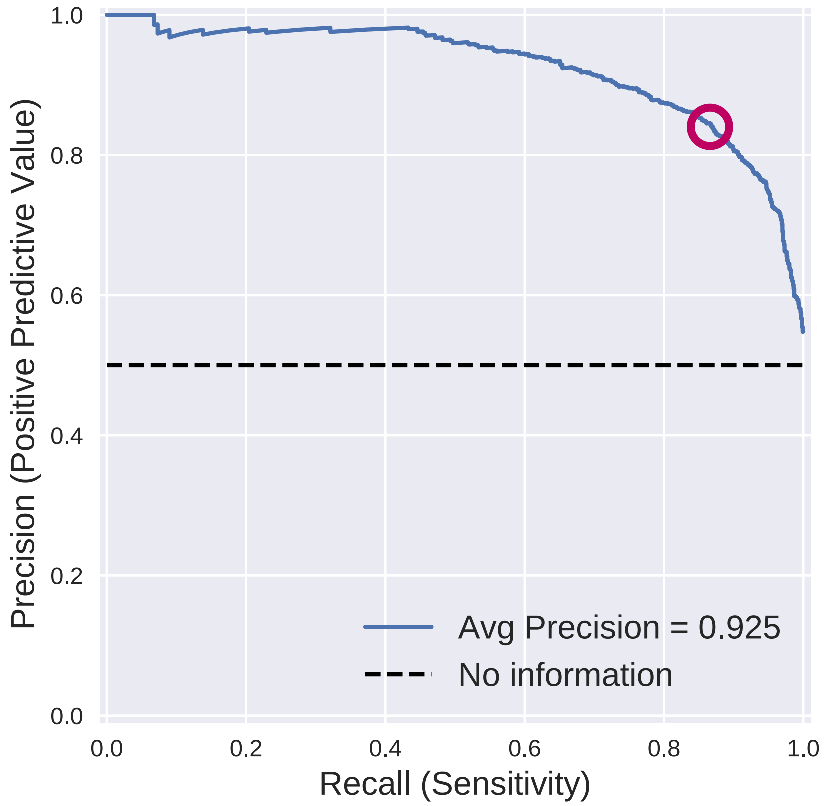


Operating Point:

balanced







Summary

- It is critical to understand performance measures in order to critically evaluate models and put them to clinical/healthcare use.

- To contextualize performance, we often compare models to a *no information* model whose predictions are random.

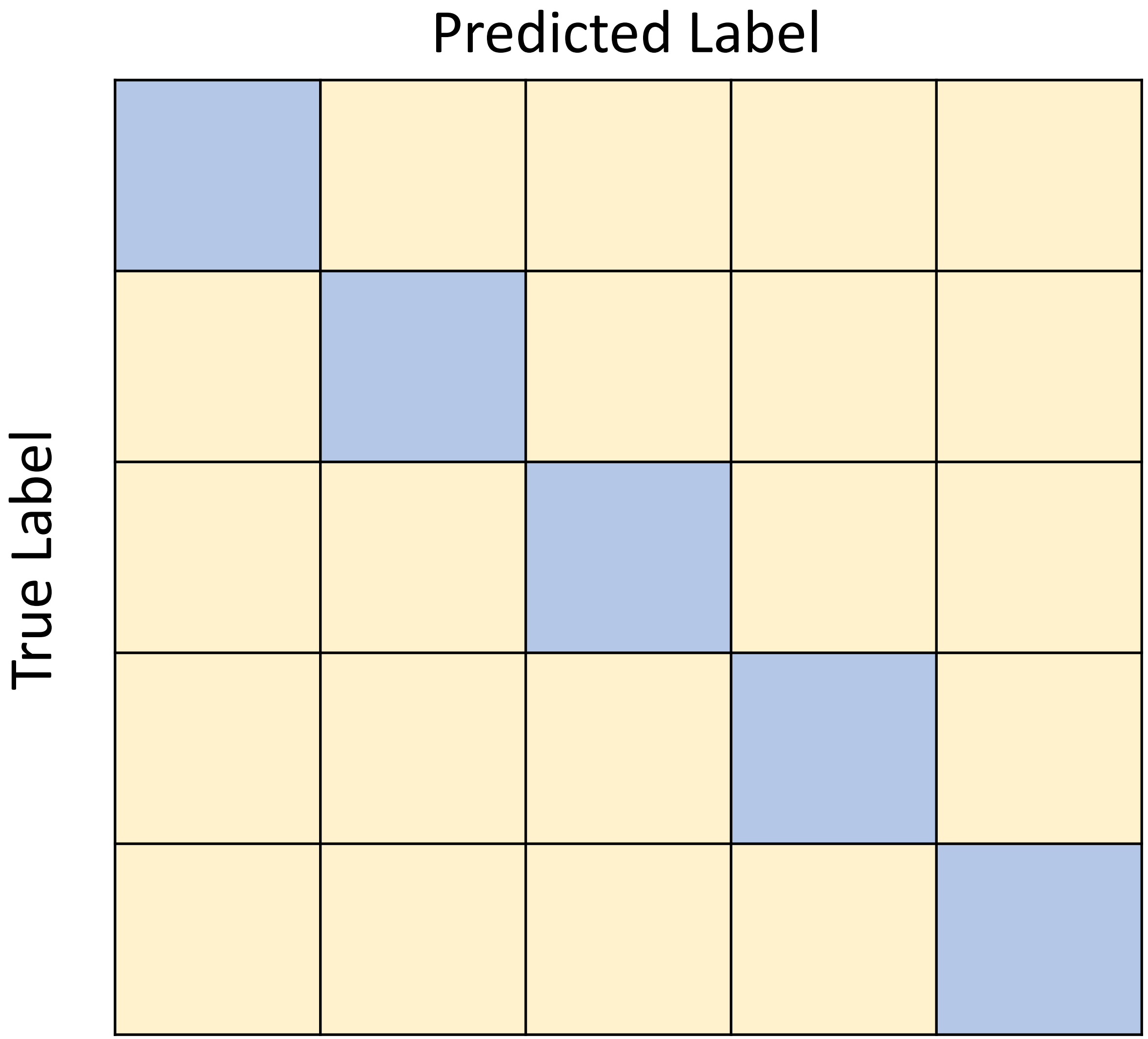
- However, *good* performance depends on existing alternative approaches, both tech- and non-tech-based, and the clinical scenario.

- Which measure is most important also depends on the clinical scenario.

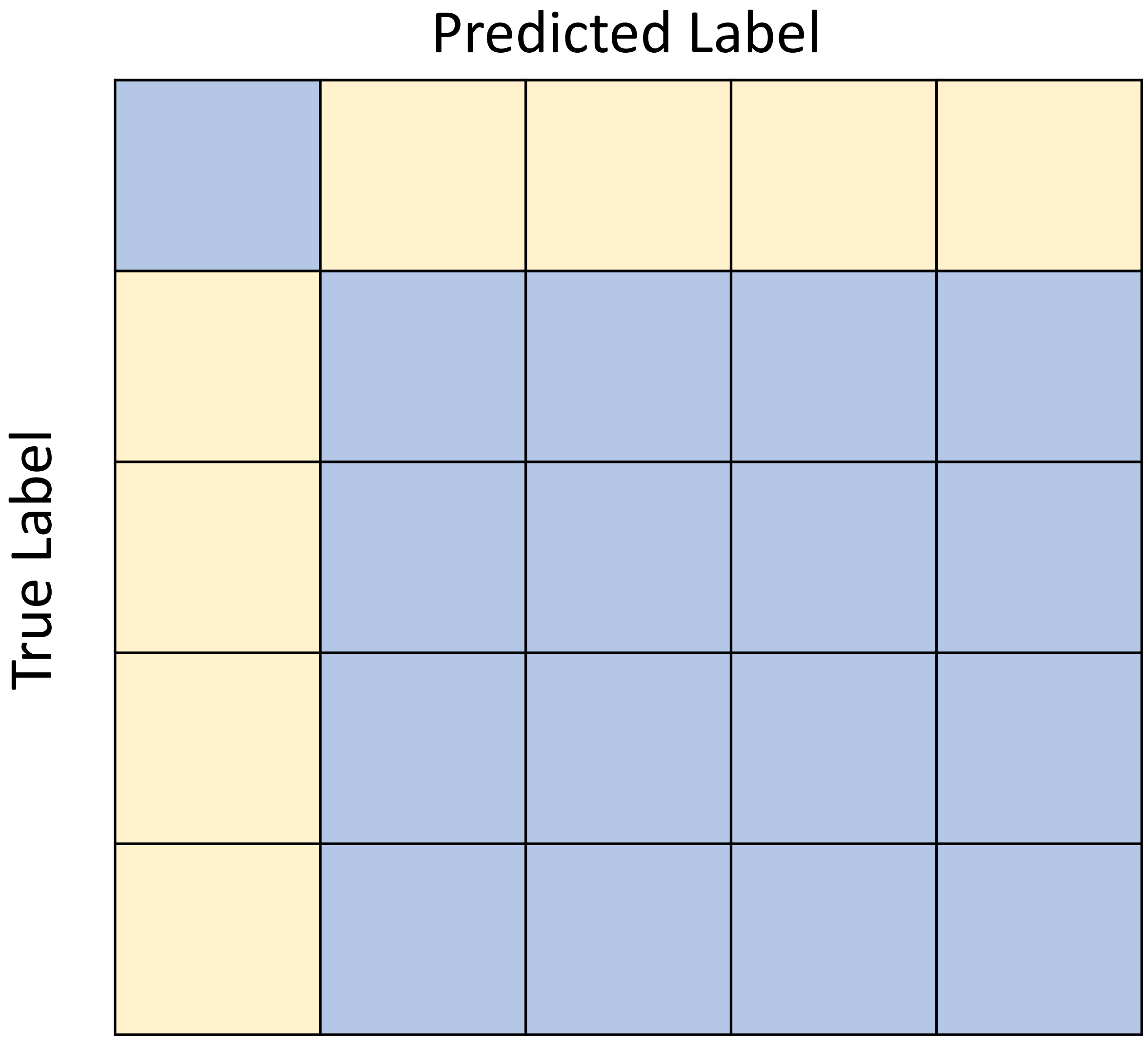
Confusion Matrix for Multi-Class Problems

If time allows.

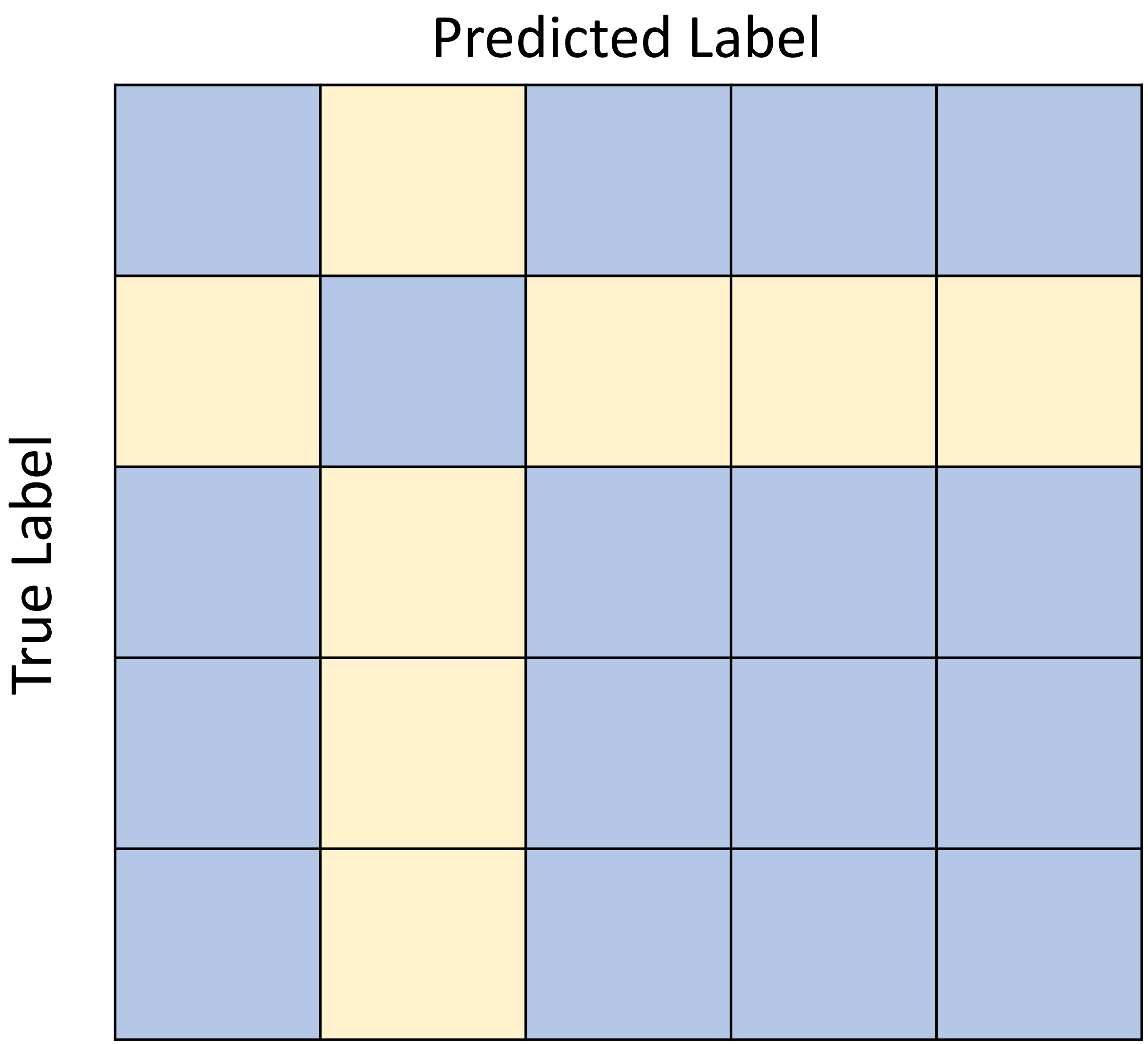
Multi-class problems: “Confusion Matrix”



Multi-class problems: Binary for Label 1



Multi-class problems: Binary for Label 2



There are many more, of course, but classification metrics go a long way.

- Regression
  - Mean squared error (MSE)
  - Mean absolute error (MAE)
  - R^2

- Survival Analysis (i.e. failure time)
  - Concordance index
  - MSE, MAE
  - Brier Score
  - AUC_t