Probability and Classification

DS-6030 | Spring 2026

classification.pdf

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1 Probability/Risk and Classification (and Ranking)

1.1 Set-up

- The outcome variable is categorical and denoted $G \in \mathcal{G}$
  - Default Credit Card Example: $\mathcal{G} = \{\text{"Yes", "No"}\}$
  - Medical Diagnosis Example: $\mathcal{G} = \{\text{"stroke", "heart attack", "drug overdose", "vertigo"}\}$
- The training data is $D = \{(X_1, G_1), (X_2, G_2), \ldots, (X_n, G_n)\}$
- The optimal decision/classification is often based on the posterior probability $\Pr(G = g \mid \mathbf{X} = \mathbf{x})$

1.2 Risk Scoring vs. Classification

Most of the models we will encounter can output a predicted probability $\hat{p}_k(x) = \widehat{\Pr}(G = k \mid X = x)$ for every class $k \in \mathcal{G}$.

Sometimes a *hard classification* needs to be made, i.e., decide on single label/class to assign the observation.

1. Hard Classification:
   - Use training data to estimate the *label* $\hat{G}(X)$
   - The loss/cost $L(G, \hat{G}(X))$ is the loss incurred by estimating G with $\hat{G}$
2. Risk Scoring (Soft-Classification/Probability Prediction):
   - Use training data to estimate the *probability* $\hat{p}_k(X)$
   - The loss/cost $L(G, \hat{p}(X))$ is the loss incurred by estimating G with $\hat{p}_k(X)$, where $\hat{p}(X) = [\hat{p}_1(X), \ldots, \hat{p}_K(X)]$
3. Ranking:
   - Use the training data to rank the test observations according to estimated risk level.
   - The loss/cost is based on the number of outcomes of interest in the top proportion of risk.

1.2.1 Example: Recidivism Prediction

Recently the National Institute of Justice hosted a Recidivism Forecasting Challenge which challenged contestants to predict if a parolee would be arrested for another offense within the next few years. The motivation is not to determine who should be released on parole, but rather which parolees should get additional assistance/supervision.

Objective	Model Output
Classification	Predict {Yes, No} for re-offending
Scoring	Predict probability of re-offending
Ranking	Order from highest risk level to lowest

Your Turn #1 : Recidivism Prediction

1. How could you use the probability/score to make a hard classification?
2. Do you think a hard classification or probability/score is better for this scenario?
3. If there were limited resources (e.g., only N parolees could get extra assistance), which type of model output would be more useful?

2 Probability Modeling Intro

2.1 Credit Card Default data (`Default`)

The textbook *An Introduction to Statistical Learning (ISL)* has a description of a simulated credit card default dataset. The goal is to *predict the probability* an individual will default on their credit card payment.

The variables are:

- *outcome variable* (`default`) is categorical (factor) with values `Yes` or `No`.
- the categorical (factor) variable (`student`) is either `Yes` or `No`.
- the average balance a customer has after making their monthly payment (`balance`).
- the customer's income (`income`).

default	student	balance	income
No	No	396.5	41970
No	No	913.6	46907
No	Yes	561.4	21747
Yes	Yes	1889.3	22652
No	No	491.0	37836
No	Yes	282.2	19809

Your Turn #2 : Credit Card Default Modeling

How would you construct a model to predict the risk of default?

2.2 Binary Probability/Risk Modeling

- Predictive modeling of a categorical outcome is simplified when there are only 2 classes.
  - Many multi-class problems can be addressed by solving a set of binary classification problems (e.g., one-vs-rest).
- It is often convenient to transform the outcome variable to a binary $\{0, 1\}$ variable, where $Y = 1$ is the *outcome of interest*:

$$Y_i = \begin{cases} 1 & G_i = \mathcal{G}_1 \quad \text{(outcome of interest)} \\ 0 & G_i = \mathcal{G}_2 \end{cases}$$

- In the `Default` data, it would be natural to set `default=Yes` to 1 and `default=No` to 0.

2.2.1 Linear Regression

- In this set-up we can run linear regression

$$\hat{y}(\mathbf{x}) = \hat{\beta}_0 + \sum_{j=1}^{p} \hat{\beta}_j x_j$$

term	estimate	std.error	statistic	p.value
(Intercept)	-0.08118	0.00838	-9.685	0.00000
studentYes	-0.01033	0.00566	-1.824	0.06817
balance	0.00013	0.00000	37.412	0.00000
income	0.00000	0.00000	1.039	0.29896

Your Turn #3 : OLS for Binary Responses

1. For the binary Y, what is linear regression estimating?

2. What is the *loss function* that linear regression is using?

3. How could you create a *hard classification* from the linear model?

4. Does is make sense to use linear regression for binary risk modeling and classification?

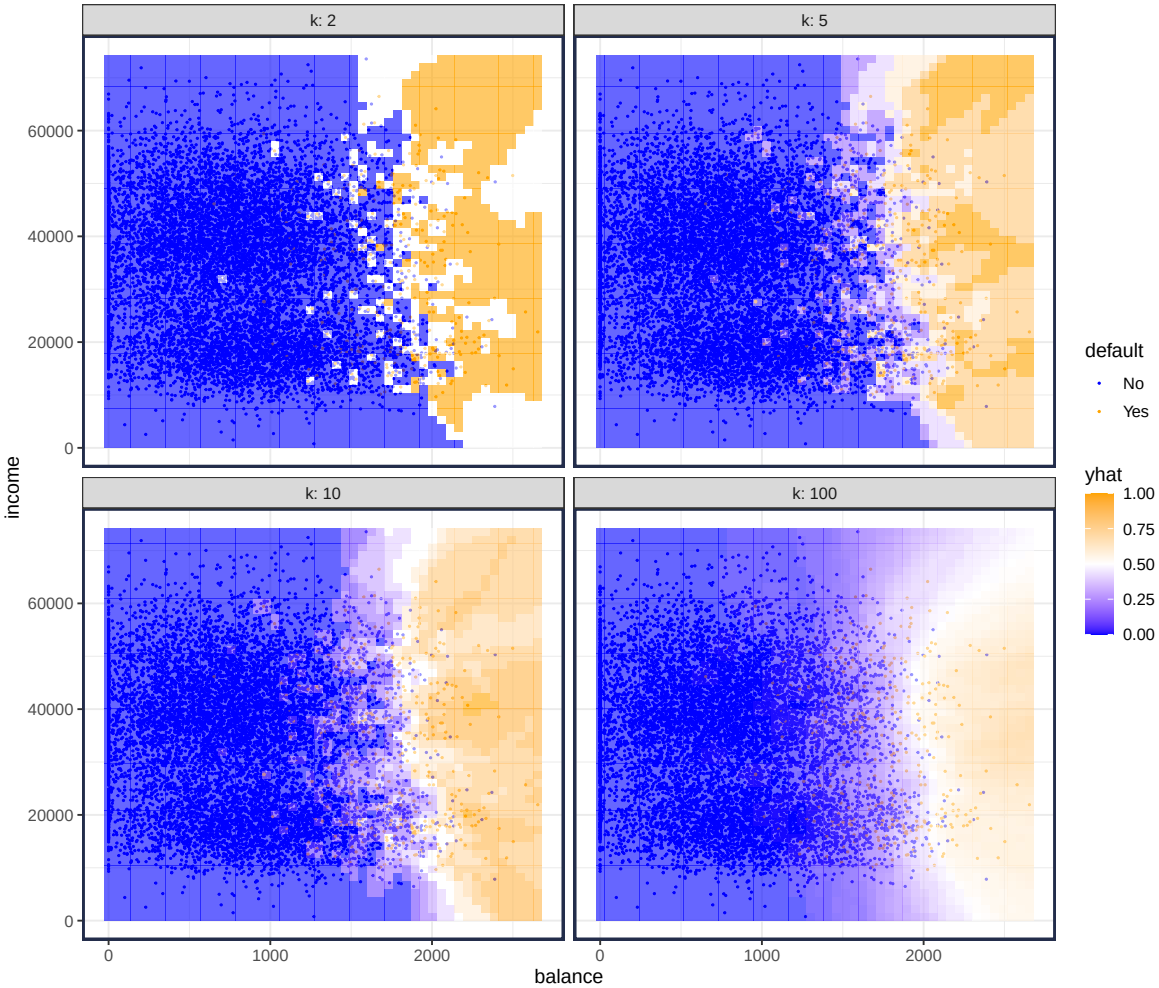
2.2.2 k-nearest neighbor (kNN)

- The k-NN method is a non-parametric *local* method, meaning that to make a prediction $\hat{y}|x$, it only uses the training data in the *vicinity* of x.
  - contrast with OLS linear regression, which uses all X's to get prediction.
- The model (for regression and binary classification) is simple to describe

$$\begin{aligned} f_{\text{knn}}(x; k) &= \frac{1}{k} \sum_{i: x_i \in N_k(x)} y_i \\ &= \text{Avg}(y_i \mid x_i \in N_k(x)) \end{aligned}$$

  - $N_k(x)$ are the set of k nearest neighbors
  - only the k closest y's are used to generate a prediction
  - it is a *simple mean* of the k nearest observations
- When y is binary (i.e., $y \in \{0, 1\}$), the kNN model estimates

$$f_{\text{knn}}(x; k) \approx p(x) = \Pr(Y = 1|X = x)$$



Your Turn #4 : Thoughts about kNN

The above plots show a kNN model using the *continuous* predictors of `balance` and `income`.

- How could you use kNN with the categorical `student` predictor?

- The k-NN model also has a more general description when the outcome variable is categorical $G_i \in \mathcal{G}$

$$f_g^{\text{knn}}(x;k) = \frac{1}{k} \sum_{i:x_i \in N_k(x)} \mathbb{1}(g_i = g)$$
$$= \widehat{\Pr}(G_i = g \mid x_i \in N_k(x))$$

  - $N_k(x)$ are the set of k nearest neighbors
  - only the k closest y's are used to generate a prediction
  - it is a *simple proportion* of the k nearest observations that are of class g

Your Turn #5 : kNN for multi-class outcomes

If using a categorical outcome, kNN models will output a *vector* of probabilities that sum to 1. For small k or if many categories, this vector may be *sparse* meaning that most entries are 0.

- How could we use concepts like Laplace smoothing to produce better predictions in these scenarios?

3 Logistic Regression

3.1 Description

Logistic regression refer to a class of *linear* models where the output (predicted value) is a **function of the** linear combination (weighted sum) of the input variables

$$\begin{aligned}
\eta(x;\beta) &= \beta_0 + \sum_{j=1}^{p} \beta_j x_j \\
&= x^\mathsf{T}\beta \\
f(x;\beta) &= \frac{\exp\left(\beta_0 + \sum_{j=1}^{p} \beta_j x_j\right)}{1 + \exp\left(\beta_0 + \sum_{j=1}^{p} \beta_j x_j\right)} \\
&= \frac{\exp\left(\eta(x;\beta)\right)}{1 + \exp\left(\eta(x;\beta)\right)} \\
&= \left(1 + \exp(-\eta(x;\beta))\right)^{-1} \\
&= \left(1 + \exp(-x^\mathsf{T}\beta)\right)^{-1}
\end{aligned}$$

where $x = [x_1, \ldots, x_p]^\mathsf{T}$ is a vector of features/variables/attributes and $\hat{Y}|x = f(x;\hat{\beta}) = \left(1 + \exp(-\eta(x;\beta))\right)^{-1}$ is the predicted outcome at $X = x$.

- the *model parameters* for linear (or coefficients or weights), $\hat{\beta}$ determine how much influence each feature has on the predicted output.

3.1.1 Model Structure

- Outcome variable: $y \in \{0, 1\}$
- Predictor variables $\mathbf{x} \in \mathbb{R}^p$
- Model parameters: $\beta = (\beta_0, \beta_1, \ldots \beta_p)$
- Prediction function: $f(\mathbf{x};\hat{\beta}) = \frac{\exp\left(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_1 x_2 + \ldots + \hat{\beta}_1 x_p\right)}{1 + \exp\left(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_1 x_2 + \ldots + \hat{\beta}_1 x_p\right)} = \frac{e^{\mathbf{x}^\mathsf{T}\beta}}{1 + e^{\mathbf{x}^\mathsf{T}\beta}} = \left(1 + e^{-\mathbf{x}^\mathsf{T}\beta}\right)^{-1}$

3.1.2 Model Fitting (or Parameter estimation)

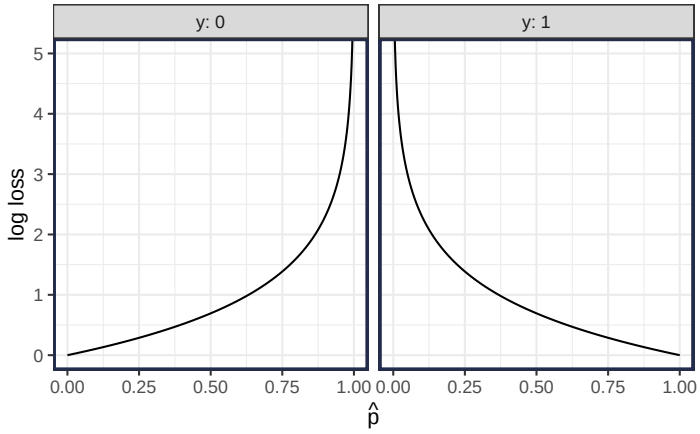
- The model is fitted by minimizing the *Log Loss* (also called *Cross-Entropy*), which is the negative log-likelihood of the Bernoulli/Binomial pmf.
  - Even better, add a penalty to the loss (e.g., elasticnet) to prevent over-fitting.
- Bernoulli Likelihood Function

$$\begin{aligned}
L(\beta) &= \prod_{i=1}^{n} p_i(\beta)^{y_i} (1 - p_i(\beta))^{1-y_i} \\
&= \sum_{i=1}^{n} \begin{cases} p_i(\beta) & y_i = 1 \\ 1 - p_i(\beta) & y_i = 0 \end{cases}
\end{aligned}$$

- Bernoulli Log-Likelihood Function

$$\begin{aligned}\log L(\beta) &= \sum_{i=1}^{n} \{y_i \ln p_i(\beta) + (1-y_i)\ln(1-p_i(\beta))\} \\ &= \sum_{i=1}^{n} \begin{cases} \ln p_i(\beta) & y_i = 1 \\ \ln(1-p_i(\beta)) & y_i = 0 \end{cases} \\ &= \sum_{i:y_i=1} \ln p_i(\beta) + \sum_{i:y_i=0} \ln(1-p_i(\beta)\end{aligned}$$

- Note: $-\log(p) = \log(1/p)$



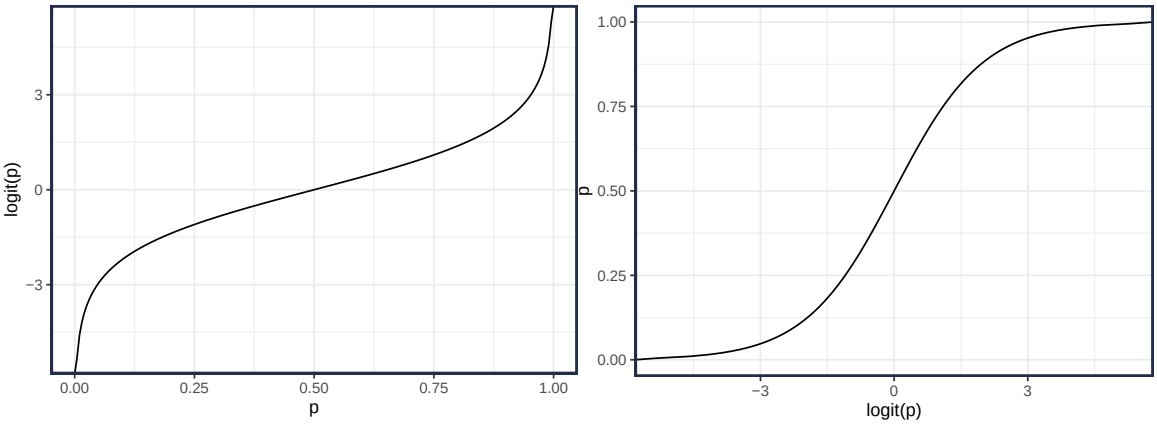
3.2 Details

- Let $0 \leq p \leq 1$ be a probability.
- The log-odds of p is called the *logit*

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

- The inverse logit is the *logistic function* (or *sigmoid function*). Let $f = \text{logit}(p)$, then

$$\begin{aligned} p &= \frac{e^f}{1+e^f} \\ &= \frac{1}{1+e^{-f}} \end{aligned}$$



Logistic vs. Linear Regression

For binary $Y \in \{0, 1\}$:

- Logistic Regression:

$$\text{logit}\Pr(Y = 1 \mid X = x) = \log\left(\frac{\Pr(Y = 1 \mid X = x)}{1 - \Pr(Y = 1 \mid X = x)}\right) = \beta^{\mathsf{T}} x$$

  and thus,

$$\begin{aligned}\Pr(Y = 1 \mid X = x) &= \frac{e^{\beta^{\mathsf{T}} x}}{1 + e^{\beta^{\mathsf{T}} x}} \\ &= \left(1 + e^{-\beta^{\mathsf{T}} x}\right)^{-1}\end{aligned}$$

- Linear Regression:

$$\mathrm{E}[Y \mid X = x] = \Pr(Y = 1 \mid X = x) = \beta^{\mathsf{T}} x$$

  and thus,

$$\Pr(Y = 1 \mid X = x) = \beta^{\mathsf{T}} x$$

3.2.1 Logistic vs. Linear Regression predictions

Logistic

term	estimate	std.error	statistic	p.value
(Intercept)	-10.869	0.492	-22.080	0.000
studentYes	-0.647	0.236	-2.738	0.006
balance	0.006	0.000	24.738	0.000
income	0.000	0.000	0.370	0.712

Linear

term	estimate	std.error	statistic	p.value
(Intercept)	-0.08118	0.00838	-9.685	0.00000
studentYes	-0.01033	0.00566	-1.824	0.06817
balance	0.00013	0.00000	37.412	0.00000
income	0.00000	0.00000	1.039	0.29896

Compare predictions:

student	balance	income	logistic_p	linear_p
Yes	1000	40000	0.003	0.049
No	1000	40000	0.007	0.059

4 Evaluating Binary Risk Models

4.1 Common Binary Loss Functions

- Suppose we are going to predict a binary outcome $Y \in \{0, 1\}$ with $0 \leq \hat{p}(x) \leq 1$.
  - Call $\hat{p}(x)$ the *risk score*
- **Brier Score / Squared Error**

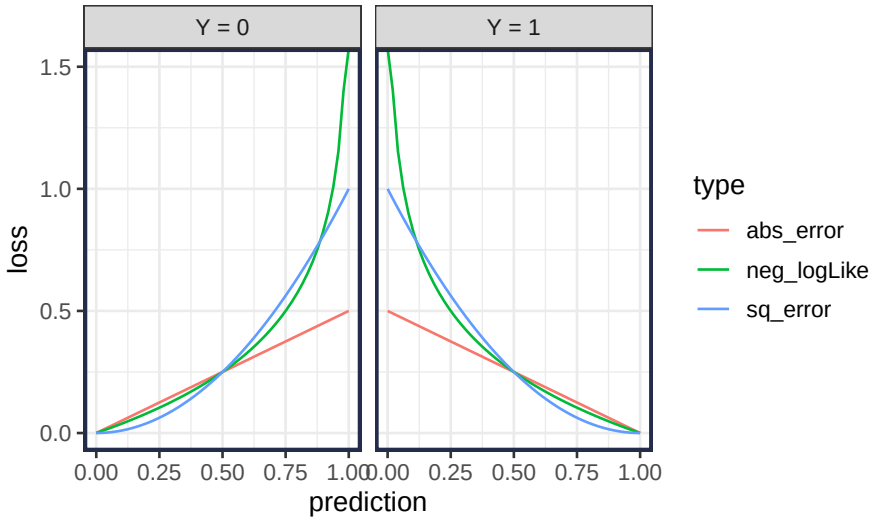
$$\begin{aligned} L(y, \hat{p}) &= (y - \hat{p})^2 \\ &= \begin{cases} (1-\hat{p})^2 & y = 1 \\ \hat{p}^2 & y = 0 \end{cases} \end{aligned}$$

- **Absolute Error**

$$\begin{aligned} L(y, \hat{p}) &= |y - \hat{p}| \\ &= \begin{cases} 1 - \hat{p} & y = 1 \\ \hat{p} & y = 0 \end{cases} \end{aligned}$$

- **Bernoulli negative log-likelihood (Log-Loss / Cross-entropy)**
  - This is the loss function used in Logistic Regression

$$\begin{aligned} L(y, \hat{p}) &= -\{y \log \hat{p} + (1-y) \log(1-\hat{p})\} \\ &= \begin{cases} -\log \hat{p} & y = 1 \\ -\log(1-\hat{p}) & y = 0 \end{cases} \end{aligned}$$



Loss functions scaled to be equal at .50

4.2 Area under the ROC curve (AUC, AUROC)

The AUROC of a risk model is: the probability that the model will score a randomly chosen positive example ($Y = 1$) higher than a randomly chosen negative example ($Y = 0$), i.e.

$$\text{AUROC} = \Pr(\hat{p}(\tilde{X}_1) > \hat{p}(\tilde{X}_0))$$

where $\tilde{X}_k$ is a randomly chosen example from class $Y = k$ and $\hat{p}(x) = \widehat{\Pr}(Y = 1 \mid X = x)$ is the estimated probability from a fitted model.

4.2.1 Naive AUC estimator

To *estimate* the AUROC you will fit a model to training data and make predictions on hold-out (test) data with known labels. Hopefully the model will assign large probabilities to the outcome of interest ($Y = 1$) and low probabilities to the other class.

The *naive AUC estimator* compares the probabilities between all pairs of observations where one comes from the $Y = 1$ set and the other from the $Y = 0$ set. The estimated AUROC is the proportion of the pairs where the estimated probability for the outcome of interest is larger then the probability for the other outcome.

$$\widehat{\text{AUROC}} = \frac{1}{n_1 n_0} \sum_{i:y_i=1} \sum_{j:y_j=0} \mathbb{1}(\hat{p}_i > \hat{p}_j) + \frac{1}{2}\mathbb{1}(\hat{p}_i = \hat{p}_j)$$

- The extra term ($\frac{1}{2}\mathbb{1}(\hat{p}_i = \hat{p}_j)$) is to handle ties in predicted probability.

- Note: see below for a more efficient way to estimate AUC using the ranked order of test predictions

4.2.2 AUC properties

- The AUROC assesses the *discrimination ability* of the model. It gives a different assessment on model performance from *calibration*.
- Notice that the AUROC is the same for any monotonic transformation of the estimated probabilities. E.g., we can use $\hat{p}$ or $\log(\hat{p})$ or $\text{logit}(\hat{p})$ or $\hat{p}/10$ and still get the same AUROC.
- We will discuss the Receiver Operating Curves (ROC) during Classification: Decision Theory lesson.
- Note: calibration assesses how closely the estimated probabilities match the actual probabilities as well as helping to identify the regions in feature space where the predictions are poor.

Calculating AUC from Ranked Sums

The AUC is related to the test statistic form a Wilcoxon rank-sum test (also known as the Mann-Whitney U test). Steps:

1. Rank all predictions $\{\hat{p}(x_i)\}$ from *smallest to largest*.
2. Calculate R_1, the sum of the ranks for the observations correspond to the outcome of interest ($Y = 1$). Hopefully, the sum of the ranks is large.

3. Estimate the AUC as

$$\widehat{\text{AUC}} = \frac{R_1 - n_1(n_1+1)/2}{n_1 n_0}$$

This calculation makes it clear that AUC may be better viewed as a ranking metric rather than a probability assessment.

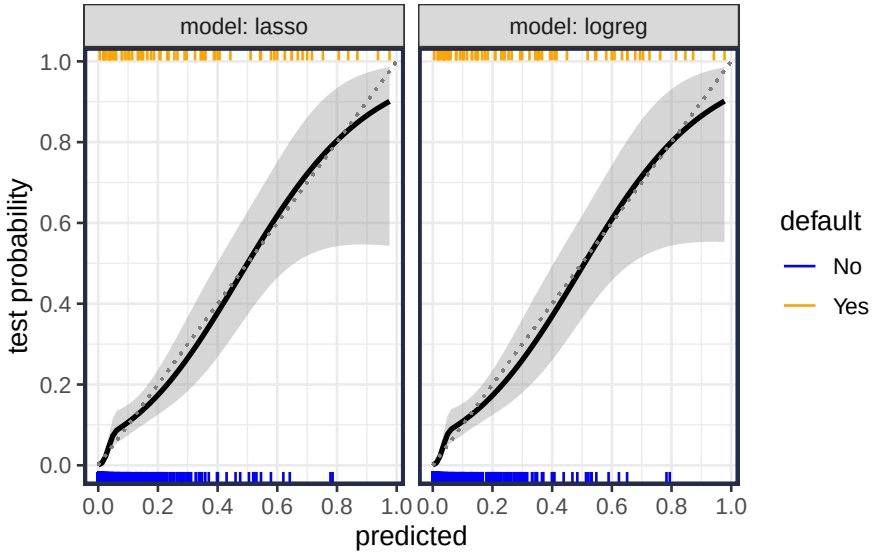
- If your problem is not fundamentally based on *ranking a set of unlabeled observations*, then AUC may not be the best metric for the problem.

A helpful discussion on AUROC (including calculation): https://stats.stackexchange.com/questions/145566/how-to-calculate-area-under-the-curve-auc-or-the-c-statistic-by-hand

4.3 Calibration

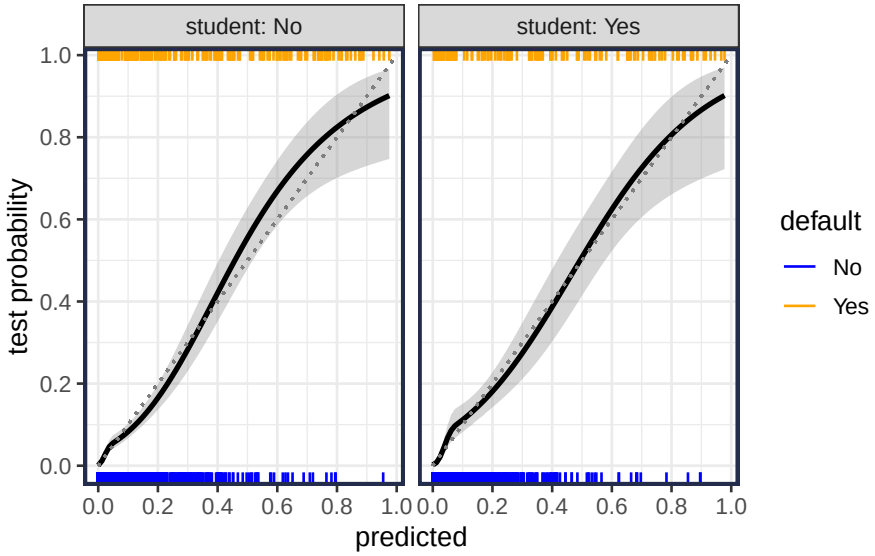
A risk model is said to be calibrated if the *predicted* probabilities are equal to the *true* probabilities.

$$\Pr(Y = 1 \mid \hat{p} = p) = p \qquad \text{for all } p$$



Calibration plots can be used to measure drift, fairness, and model/algorithmic bias. Consider comparing the predictive performance of our models for Students and Non-Students.

$$\Pr(Y = 1 \mid \hat{p} = p, X = x) = p \qquad \text{for all } p \text{ and } x$$



4.3.1 Estimating Calibration

To measure mis-calibration, we can treat the *predictions as features* while using the logit of the predictions as an offset. E.g., to check for a *linear deviation*

$$\text{logit } p(x) = \beta_0 + \beta_1 \hat{p}(x) + \text{logit } \hat{p}(x)$$

fit on a hold-out set, and check how far β_0 and β_1 are from 0.

We will dive into calibration later in the course.

5 Binary Classification

5.1 Decision Theory

- We are considering *binary* outcomes, so the outcomes $G \in \{0, 1\}$
- Let $p(x) = \Pr(G = 1 \mid X = x)$
- Loss Function: $L(\text{True Label}, \text{Estimated Label}) = L(G, \hat{G})$

Loss	Description	Name
$L(G = 0, \hat{G} = 0)$	True class is 0, Predicted class is 0	True Negative
$L(G = 1, \hat{G} = 1)$	True class is 1, Predicted class is 1	True Positive
$L(G = 0, \hat{G} = 1)$	True class is 0, Predicted class is 1	False Positive
$L(G = 1, \hat{G} = 0)$	True class is 1, Predicted class is 0	False Negative

- A model's *Expected Prediction Error (EPE)* at input X is the expected loss on new data with input X.
- The EPE (for a binary outcome) is:

$$\begin{aligned}\text{EPE}_x(\hat{g}) &= \text{E}_{G|X=x}\left[L(G, \hat{G}(x) = \hat{g}) \mid X = x\right] \\ &= L(1, \hat{g}) \Pr(G = 1 \mid X = x) + L(0, \hat{g})(1 - \Pr(G = 1 \mid X = x)) \\ &= L(1, \hat{g})p(x) + L(0, \hat{g})(1 - p(x))\end{aligned}$$

- Hard Decision ($\hat{G}(x) \in \{0, 1\}$): choose $\hat{G}(x) = 1$ if

$$\begin{aligned}\text{EPE}_x(\hat{g} = 1) &< \text{EPE}_x(\hat{g} = 0) \\ L(1,1)p(x) + L(0,1)(1 - p(x)) &< L(1,0)p(x) + L(0,0)(1 - p(x)) \\ p(x)\left(L(1,1) - L(1,0)\right) &< (1 - p(x))\left(L(0,0) - L(0,1)\right) \\ p(x)\left(L(1,0) - L(1,1)\right) &\geq (1 - p(x))\left(L(0,1) - L(0,0)\right) \qquad (\textit{multiply both sides by } -1) \\ \frac{p(x)}{1 - p(x)} &\geq \frac{L(0,1) - L(0,0)}{L(1,0) - L(1,1)}\end{aligned}$$

Note

In most cases, there will be no loss/cost for making a correct classification. Thus it is convention to set $L(0, 0) = L(1, 1) = 0$ in these scenarios.

5.1.1 Example: Cancer Diagnosis

- Say we have a goal of estimating if a patient has cancer using medical imaging
  - Let $G = 1$ for cancer and $G = 0$ for no cancer
- Suppose we have solicited a loss function with the following values
  - $L(G = 0, \hat{G} = 0) = 0$: There is no loss for correctly diagnosis a patient without cancer.

  - $L(G = 1, \hat{G} = 1) = 0$: There is no loss (for our model) for correctly diagnosis a patient with cancer.
  - $L(G = 0, \hat{G} = 1) = C_{\text{FP}}$: There is a cost of C_{FP} units if the model issues a *false positive*, estimating the patient has cancer when they don't.
  - $L(G = 1, \hat{G} = 0) = C_{\text{FN}}$: There is a cost of C_{FN} units if the model issues a *false negative*, estimating the patient does not have cancer when they really do.
  - In these scenarios C_{FN} is often much larger than C_{FP} ($C_{\text{FN}} >> C_{\text{FP}}$) because the the effects of not promptly treating (or further testing, etc) a patient is more severe than starting a treatment path for patients that don't actually have cancer.

- The optimal decision is to issue a positive indication for cancer if $\text{EPE}_x(1) < \text{EPE}_x(0)$. This occurs when

$$\frac{p(x)}{1-p(x)} \geq \frac{C_{\text{FP}}}{C_{\text{FN}}} \quad \text{OR} \quad p(x) \geq \frac{C_{\text{FP}}}{C_{\text{FP}} + C_{\text{FN}}} \quad \text{OR} \quad \log\left(\frac{p(x)}{1-p(x)}\right) \geq \log\left(\frac{C_{\text{FP}}}{C_{\text{FN}}}\right)$$

- The ratio of C_{FP} to C_{FN} is all that matters for the decision. Let's say that $C_{\text{FP}} = 1$ and $C_{\text{FN}} = 10$. Then if $p(x) \geq 1/11$, our model will diagnose cancer.
  - Note: $p(x) = \Pr(Y = 1|X = x)$ is affected by the class prior $\Pr(Y = 1)$ (e.g., the portion of the population tested who have cancer), which is usually going to be small.

5.1.2 Optimal Threshold

- Recall, the optimal *hard classification* decision is to choose $\hat{G} = 1$ if:

$$\frac{p(x)}{1-p(x)} \geq \frac{L(0,1) - L(0,0)}{L(1,0) - L(1,1)}$$

- It can be convenient to use model output other than $p(x)/(1-p(x))$ to make decisions
- Some models directly output $\hat{p}(x)$
- Other models, like logistic regression, naturally work with the link function (linear part)
  - Denote $\gamma(x)$ as the *logit* of $p(x)$:

$$\gamma(x) = \log\frac{p(x)}{1-p(x)} = \log\frac{\Pr(G = 1 \mid X = x)}{\Pr(G = 0 \mid X = x)}$$

Notation

$$\gamma(x) = \log\frac{p(x)}{1-p(x)}$$
$$p(x) = \frac{e^{\gamma(x)}}{1+e^{\gamma(x)}}$$

- Table of equivalent representations:

Score	Threshold	Threshold (simplified)
$\dfrac{p(x)}{1-p(x)}$	$\dfrac{L(0,1)-L(0,0)}{L(1,0)-L(1,1)}$	$\dfrac{C_{\text{FP}}}{C_{\text{FN}}}$
$\gamma(x) = \log \dfrac{p(x)}{1-p(x)}$	$\log\left(\dfrac{L(0,1)-L(0,0)}{L(1,0)-L(1,1)}\right)$	$\log\left(\dfrac{C_{\text{FP}}}{C_{\text{FN}}}\right)$
$p(x)$	$\dfrac{L(0,1)-L(0,0)}{L(0,1)-L(0,0)+L(1,0)-L(1,1)}$	$\dfrac{C_{\text{FP}}}{C_{\text{FP}}+C_{\text{FN}}}$

The *Threshold (simplified)* assumes $L(0,0) = L(1,1) = 0$

5.1.3 Using estimated values

- We will never have the actual $p(x)$ or $\gamma(x)$, so replace them with the estimated values.
- For a given threshold t and input x, the hard classification rule is $\hat{G}_t(x) = \mathbb{1}(\hat{p}(x) \geq t)$ (or $\hat{G}_t(x) = \mathbb{1}(\hat{\gamma}(x) \geq t)$ if using $\hat{\gamma}$ instead of $\hat{p}$).

Note

Because we have to estimate $\hat{p}(x)$ or $\hat{\gamma}(x)$, the best threshold t^* may differ from the theoretical optimal and need to be estimated. (more info about this below)

5.2 Common Binary Loss Functions

- Setting: estimate a binary outcome $G \in \{0, 1\}$ with a predicted label $\hat{G}(x)$
- **Mis-Classification Cost**

$$L(G, \hat{G}(x)) = \begin{cases} C_{\text{FP}} & G = 0, \hat{G}(x) = 1 \\ C_{\text{FN}} & G = 1, \hat{G}(x) = 0 \\ 0 & \text{otherwise} \end{cases}$$

  - This requires that a *hard classification* is made.
  - The theoretically optimal prediction is:

$$G^*(x) = \mathbb{1}(p(x) > C_{\text{FP}}/(C_{\text{FP}} + C_{\text{FN}}))$$

- **0-1 Loss** or **Misclassification Error**

$$L(G, \hat{G}(x)) = \mathbb{1}(y \neq \hat{G}(x)) = \begin{cases} 0 & G = \hat{G}(x) \\ 1 & G \neq \hat{G}(x) \end{cases}$$

  - This assumes $L(0,1) = L(1,0)$ (i.e., false positive costs the same as a false negative)
  - This requires that a *hard classification* is made.
  - The theoretically optimal prediction is:

$$\begin{aligned} G^*(x) &= \mathbb{1}(p(x) > 1 - p(x)) \\ &= \mathbb{1}(p(x) > 0.50) \end{aligned}$$

5.3 Performance Metrics

5.3.1 Confusion Matrix

- Given a threshold t, we can make a *confusion matrix* to help analyze our model's performance on data
  - Data = $\{(X_i, G_i)\}_{i=1}^{N}$ (ideally this is hold-out/test data)
  - N_k is number of observations from class k ($N_0 + N_1 = N$)

		Model Outcome $\hat{G}_t = 1$	$\hat{G}_t = 0$	**total**
True Outcome	$G = 1$	True Positive (TP)	False Negative (FN)	N_1
	$G = 0$	False Positive (FP)	True Negative (TN)	N_0
	total	$\hat{N}_1(t)$	$\hat{N}_0(t)$	N

Table from: https://tex.stackexchange.com/questions/20267/how-to-construct-a-confusion-matrix-in-latex

To illustrate a confusion table in practice let's go back to the `Default` data and see how the basic logistic regression models performs.

- In order to evaluate on hold-out data, split the data into train/test (used 8000 training, 2000 testing), fit a logistic regression model on training data, and make predictions on the test data
- Note that only 3.3% of the data is default.
  - Using a threshold of $\hat{p}(x) \geq 0.10$ to make a hard classification.
  - Equivalent to $\hat{\gamma}(x) \geq \log(.10) - \log(1 - .10) = -2.1972$

```
#: train/test split
set.seed(2019)
test.ind = sample(nrow(Default), size=2000)
train.ind = -test.ind

#: fit model on training data
fit_lm = glm(y~student + balance + income, family='binomial',
             data=Default[train.ind, ])

#: Get predictions (of p(x)) on test data
p_hat = predict(fit_lm, Default[test.ind, ], type='response')

#: Make Hard classification (use .10 as cut-off)
G_hat = ifelse(p_hat >= .10, 1, 0)

#: Make Confusion Table
G_test = Default$y[test.ind]  # true values

table(truth = G_test, predicted = G_hat) %>% addmargins()
#>       predicted
#> truth    0    1  Sum
```

```
#>   0    1805  128 1933
#>   1      17   50   67
#>   Sum 1822  178 2000
```

5.3.2 Metrics

There are several standard evaluation metrics that can be calculated from the confusion matrix:

Metric	Definition	Estimate
Expected Cost	$\sum_{i=0}^{1}\sum_{j=0}^{1} L(i,j)P_X(G(X)=i,\hat{G}_t(X)=j)$	$\frac{1}{N}\sum_{i=1}^{N} L(G_i,\hat{G}_t(x_i))$
Mis-classification Rate	$P_{XG}(\hat{G}_t(X)\neq G(X)) =$ $P_X(\hat{G}_t(X)=0,G(X)=1)+$ $P_X(\hat{G}_t(X)=1,G(X)=0)$	$\frac{1}{N}\sum_{i=1}^{N}\mathbb{1}(\hat{G}_t(x_i)\neq G_i)$
False Positive Rate (FPR) {1-*Specificity*}	$P_X(\hat{G}_t(X)=1 \mid G(X)=0)$	$\frac{1}{N_0}\sum_{i:G_i=0}\mathbb{1}(\hat{G}_t(x_i)=1)$
True Positive Rate (TPR) {*Hit Rate, Recall, Sensitivity*}	$P_X(\hat{G}_t(X)=1 \mid G(X)=1)$	$\frac{1}{N_1}\sum_{i:G_i=1}\mathbb{1}(\hat{G}_t(x_i)=1)$
Precision TP/(TP + FP)	$P_X(G(X)=1 \mid \hat{G}_t(X)=1)$	$\frac{1}{\hat{N}_1(t)}\sum_{i:\hat{G}(x_i)=1}\mathbb{1}(G_i=1)$

N is the total number of predictions/observations, N_0 is the number of true class 0's in the data ($N_0 = \sum_{i=1}^{N}\mathbb{1}(y_i=0)$), N_1 is the number of true class 1's in the data ($N_1=\sum_{i=1}^{N}\mathbb{1}(y_i=1)$), $\hat{N}_1(t)$ is the number of *predicted* class 1's using a threshold of t ($\hat{N}_1(t)=\sum_{i=1}^{n}\mathbb{1}(\hat{p}_i\geq t)$).

- Note: Performance estimates are best carried out on *hold-out* data!
- See Wikipedia Page: Confusion Matrix for more metrics:

		Predicted condition		Sources: [13][14][15][16][17][18][19][20] view • talk • edit	
	Total population = P + N	**Positive (PP)**	**Negative (PN)**	Informedness, bookmaker informedness (BM) = TPR + TNR − 1	Prevalence threshold (PT) = $\frac{\sqrt{\text{TPR}\times\text{FPR}}-\text{FPR}}{\text{TPR}-\text{FPR}}$
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 = $\frac{\text{TP}}{\text{P}}$ = 1 − FNR	False negative rate (FNR), miss rate = $\frac{\text{FN}}{\text{P}}$ = 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 = $\frac{\text{FP}}{\text{N}}$ = 1 − TNR	True negative rate (TNR), specificity (SPC), selectivity = $\frac{\text{TN}}{\text{N}}$ = 1 − FPR
	Prevalence = $\frac{\text{P}}{\text{P}+\text{N}}$	Positive predictive value (PPV), precision = $\frac{\text{TP}}{\text{PP}}$ = 1 − FDR	False omission rate (FOR) = $\frac{\text{FN}}{\text{PN}}$ = 1 − NPV	Positive likelihood ratio (LR+) = $\frac{\text{TPR}}{\text{FPR}}$	Negative likelihood ratio (LR−) = $\frac{\text{FNR}}{\text{TNR}}$
	Accuracy (ACC) = $\frac{\text{TP}+\text{TN}}{\text{P}+\text{N}}$	False discovery rate (FDR) = $\frac{\text{FP}}{\text{PP}}$ = 1 − PPV	Negative predictive value (NPV) = $\frac{\text{TN}}{\text{PN}}$ = 1 − FOR	Markedness (MK), deltaP (Δp) = PPV + NPV − 1	Diagnostic odds ratio (DOR) = $\frac{\text{LR+}}{\text{LR−}}$
	Balanced accuracy (BA) = $\frac{\text{TPR}+\text{TNR}}{2}$	F_1 score = $\frac{2\text{PPV}\times\text{TPR}}{\text{PPV}+\text{TPR}}$ = $\frac{2\text{TP}}{2\text{TP}+\text{FP}+\text{FN}}$	Fowlkes–Mallows index (FM) = $\sqrt{\text{PPV}\times\text{TPR}}$	Matthews correlation coefficient (MCC) = $\sqrt{\text{TPR}\times\text{TNR}\times\text{PPV}\times\text{NPV}}$ − $\sqrt{\text{FNR}\times\text{FPR}\times\text{FOR}\times\text{FDR}}$	Threat score (TS), critical success index (CSI), Jaccard index = $\frac{\text{TP}}{\text{TP}+\text{FN}+\text{FP}}$

F1 Metric

The F1 metric is the harmonic mean of precision and recall/TPR. It was first used in the context of information retrieval where there are often a massive number of irrelevant cases (negatives). In this setting, the actual number of true negatives isn't that important and the F1 metric, which doesn't consider the number of true negatives, became popular.

$$\begin{aligned} F_1 &= \left(\frac{1/\text{precision} + 1/\text{recall}}{2}\right)^{-1} \\ &= \frac{2\text{TP}}{2\text{TP} + \text{FN} + \text{FP}} \end{aligned}$$

- But even in this setting, why not use cost? You see that here false positives and false negatives show as equally important in the denominator. Wouldn't it be better to use Score $= \text{FP} \times C_{\text{FP}} + \text{FN} \times C_{\text{FN}}$?
- More reasons to avoid F1 (and Accuracy) are provided in Common Problems With the Usage of F-Measure and Accuracy Metrics in Medical Research.
- Finally, what does F1 actually try to estimate? Using the definitions precision $= P_X(G(X) = 1 \mid \hat{G}_t(X) = 1)$ and recall $= P_X(\hat{G}_t(X) = 1 \mid G(X) = 1)$

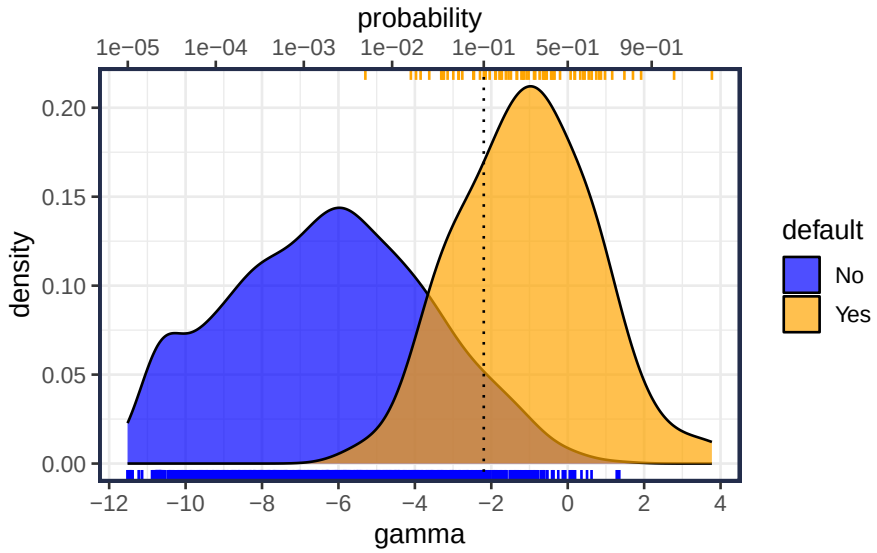
$$\begin{aligned} F_1 &= \left(\frac{1/\text{precision} + 1/\text{recall}}{2}\right)^{-1} \\ &= \frac{2}{P_X(G(X) = 1 \mid \hat{G}_t(X) = 1)^{-1} + P_X(\hat{G}_t(X) = 1) \mid G(X) = 1)^{-1}} \\ &= \frac{2}{\frac{P_X(\hat{G}_t(X)=1)}{P_X(G(X)=1, \hat{G}_t(X)=1)} + \frac{P_X(G(X)=1}{P_X(G(X)=1, \hat{G}_t(X)=1)}} \\ &= \frac{2P_X(G(X) = 1, \hat{G}_t(X) = 1)}{P_X(\hat{G}_t(X) = 1) + P_X(G(X) = 1)} \end{aligned}$$

5.4 Performance over a range of thresholds

In the previous example, a hard classification was made using a threshold of $\hat{p}(x) \geq 0.10$. But performance varies as we adjust the threshold. Let's explore!

I'll use $\hat{\gamma}(x)$ instead of $\hat{p}(x)$ for this illustration because it better separates the classes.

- The model is unable to perfectly discriminate between groups, but the *defaults* do get scored higher in general:
  - As a reference point, note that $\gamma(x) = 0 \rightarrow \Pr(Y = 1 \mid X = x) = 1/2$
  - $\gamma(x) = \log p(x)/(1 - p(x))$



- We can calculate performance over a range of thresholds:

```
# truth: {0,1} vector
# score: risk score with larger values correspond to label = 1.
# thres: vector of thresholds at which to calculate metric.
# Note: decision is 1 if score > thres, 0 if score <= thres.
perf_table <- function(truth, score, thres=NULL){
  if(is.null(thres)) thres = seq(min(score, max(score), length=1000))

  x = c(-Inf, thres, Inf) %>% unique() %>% sort() # expand and clean thresholds
  tibble(truth, score) %>%
    # create groups by threshold
    mutate(
      bin = findInterval(score, x, left.open = TRUE),
      val = x[bin+1]
    ) %>%
    # counts by group/threshold
    summarize(
      .by = val,
      n = n(),
      n.1 = sum(truth),
      n.0 = n-n.1
    ) %>%
    # add zero counts
    complete(val = thres, fill = list(n=0L, n.1=0L, n.0 = 0L)) %>%
    # calculate metrics
    arrange(val) %>%
```

```
    mutate(
      TN = cumsum(n.0),    # True negatives
      FN = cumsum(n.1),    # False negatives
      TP = sum(n.1) - FN, # True positives
      FP = sum(n.0) - TN, # False positives
      TPR = TP/sum(n.1),   # True positive rate (TP / Positives)
      FPR = FP/sum(n.0)    # False positive rate (FP / Negatives)
    ) %>%
    # drop values outside of stated thresholds
    filter(val %in% thres)  %>%
    # retain relevant metrics
    select(-n, -n.1, -n.0, score = val)
}
```

```
thresholds = seq(0, 1, length = 1000)
perf = perf_table(truth = G_test, score = p_hat, thres = thresholds) %>%
  mutate(p_hat = score, gamma_hat = log(p_hat) - log(1-p_hat), .before=1) %>%
  select(-score)
```

Here is a selection from the `perf` table

p_hat	gamma_hat	TN	FN	TP	FP	TPR	FPR
0.01	-4.594	1408	1	66	525	0.985	0.272
0.02	-3.891	1562	3	64	371	0.955	0.192
0.03	-3.475	1639	5	62	294	0.925	0.152
0.04	-3.177	1688	9	58	245	0.866	0.127
0.05	-2.943	1721	11	56	212	0.836	0.110
0.06	-2.750	1743	14	53	190	0.791	0.098
0.07	-2.586	1769	14	53	164	0.791	0.085
0.08	-2.441	1779	16	51	154	0.761	0.080
0.09	-2.313	1792	16	51	141	0.761	0.073

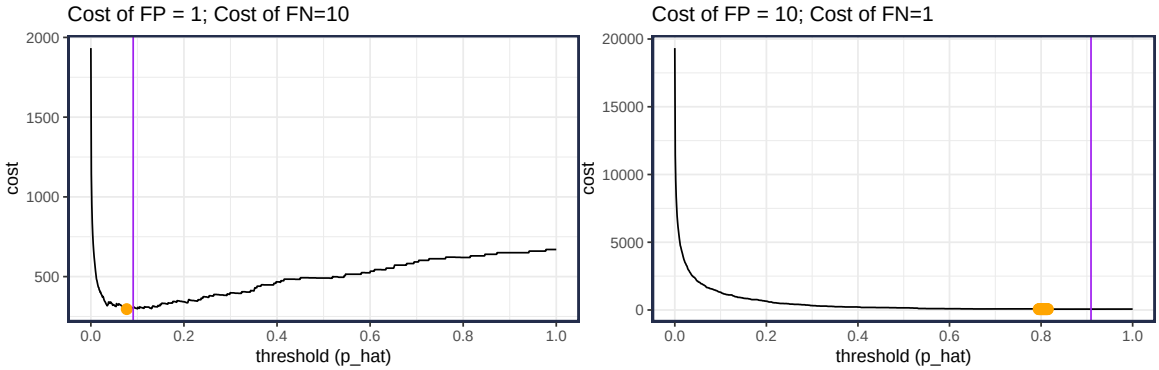
- Note: the `perf` object is *only based on the rank order* of the predictions. This means that the same results would be obtained if we used $\hat{\gamma}(x)$ or $\hat{p}(x)$ to do the ranking.
  - This is because there is a one-to-one monotone relationship between $\hat{\gamma}(x)$ and $\hat{p}(x)$.
  - The `perf` object grouped by both `gamma_hat` and `p_hat` so both thresholds are available. But we can switch back and forth from the relationship $\log(p/(1-p)) = \gamma$, so its easy to switch between the two depending on what is most convienient.

5.4.1 Cost Curves

- Under the usual scenario where $L(0,0) = L(1,1) = 0$, the cost only depends on the ratio of false positive costs (C_{FP}) to false negative costs (C_{FN}).
- note: the purple is the *theoretical* optimal threshold (using $t^* = \log C_{\text{FP}}/C_{\text{FN}}$ for $\hat{\gamma}(x)$ and $C_{\text{FP}}/(C_{\text{FP}} + C_{\text{FN}})$ for $\hat{p}(x)$) and the orange point is at the optimal value for the test data.

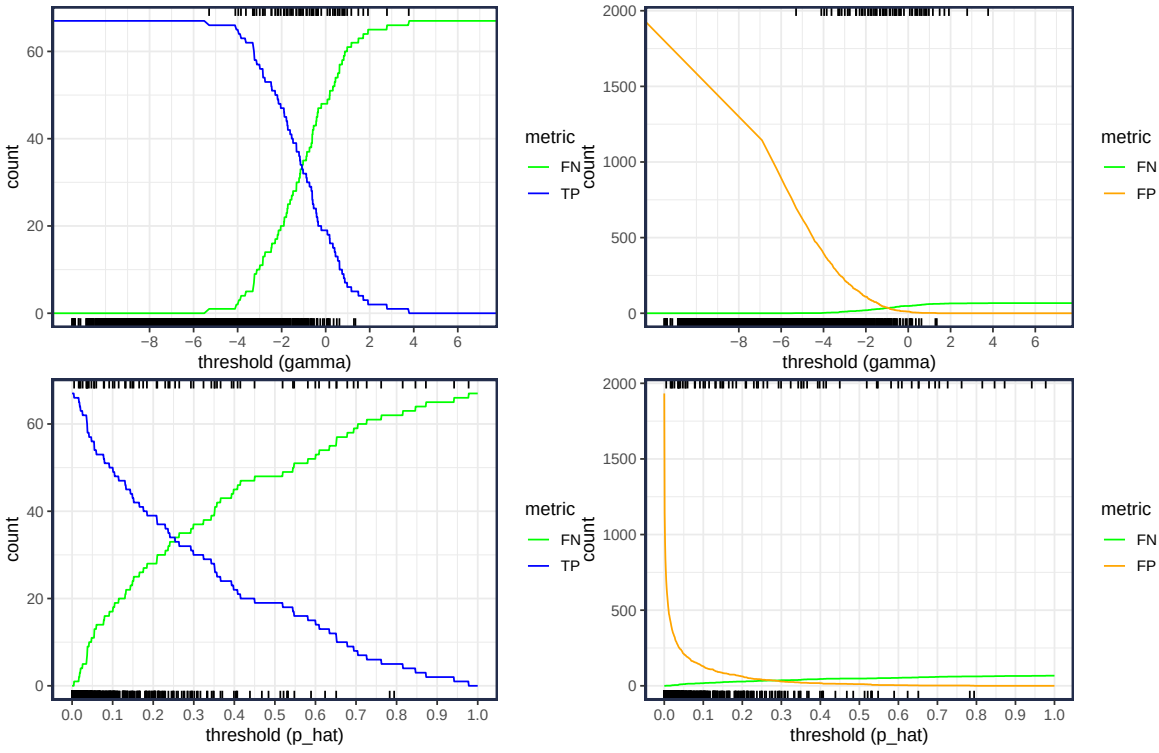
Optimal Threshold

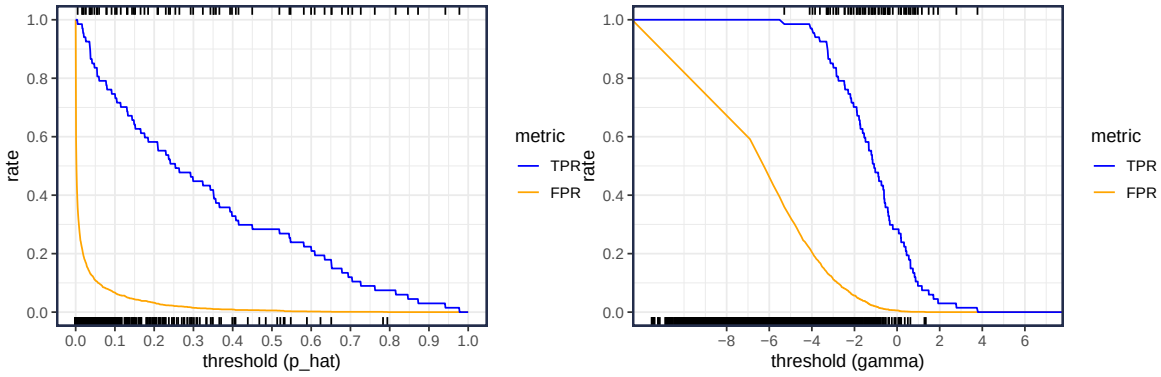
- The *theoretically* optimal threshold is based on the *true* $\gamma(x) = \log \frac{p(x)}{1-p(x)}$ (for a given cost ratio of FP to FN)



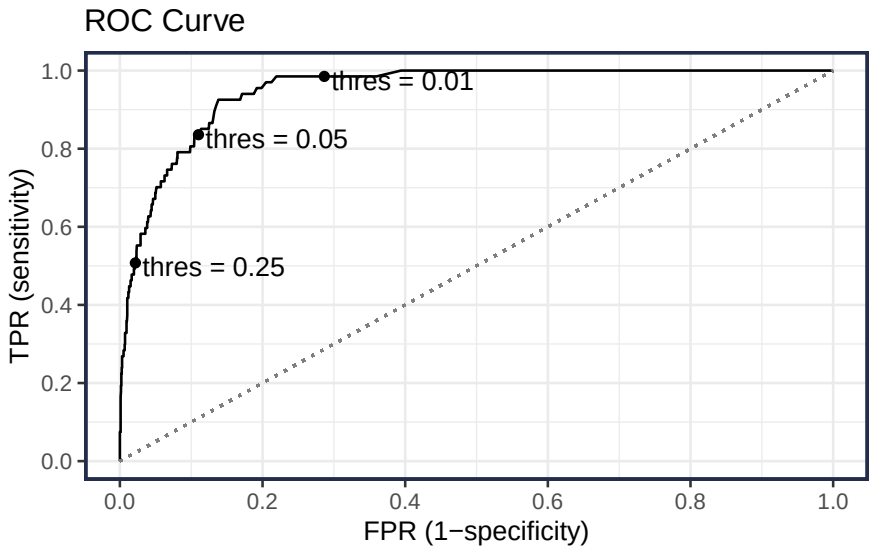
- The observed optimal threshold will differ when the model's estimate $\hat{\gamma}(x) \neq \gamma(x)$
  - Hopefully, they are close and it won't make much difference which one you use. But I'd take the estimated threshold if I had sufficient data.
- Note that the estimated values depend on the prior class probabilities. If you suspect these may differ in the future, then you should adjust the threshold.

5.4.2 General Performance as function of threshold (select metrics)





5.4.3 ROC Curve (Receiver Operating Characteristic)

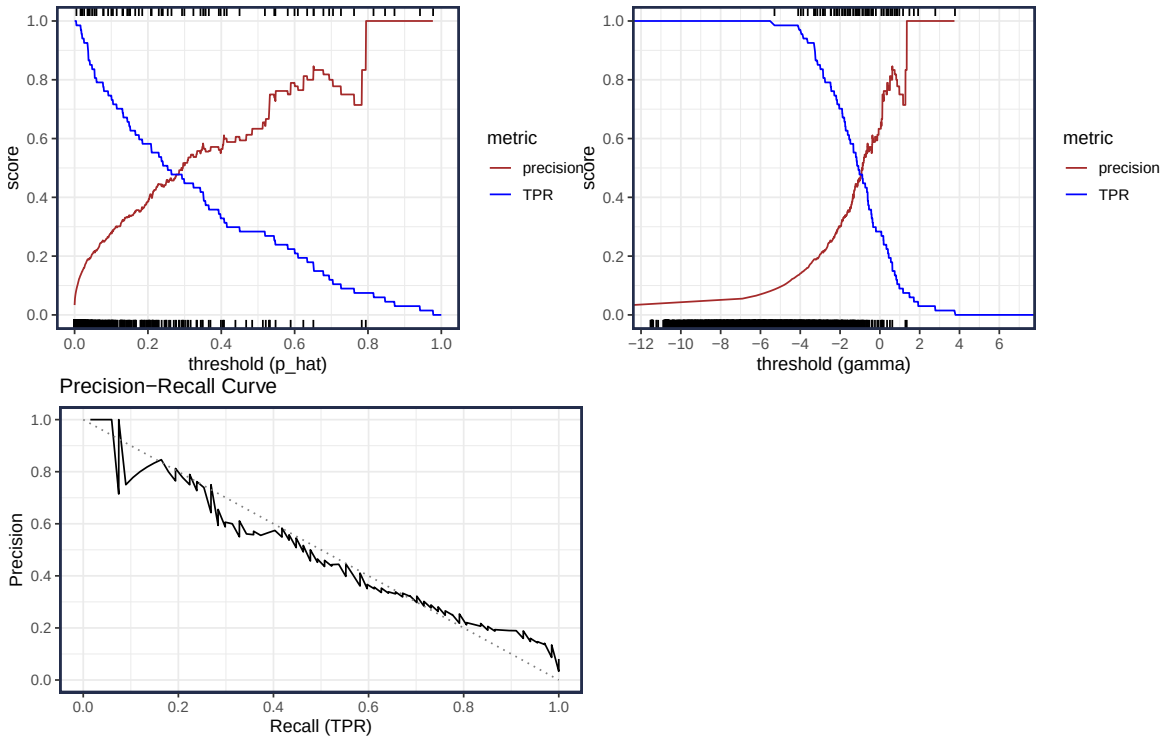


AUROC

- The *area under the ROC curve* (AUROC or AUC) is a popular performance metric
- I don't think it is a great way to compare classifiers for several reasons
  - The main reason is that in a real application you can almost always come up with an estimated cost/loss for the different decisions
  - To say it another way, comparisons should be made at a single point on the curve; the entire FPR region should not factor into the comparison.
- The AUROC is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.
  - AUROC is proportional to the Mann-Whitney U statistic

5.4.4 Precision Recall Curves

- Popular for information retrieval/ranking
- The *precision* metric is not monotonic wrt threshold, hence the sawteeth pattern.



5.5 More than two classes

Nothing really changes when there are more than two classes; we still want to choose the (hard) label that has **minimum** EPE:

$$\begin{aligned}\text{EPE}_x(g) &= \text{E}_{G|X=x}\left[L(G, \hat{G}(x) = g) \mid X = x\right] \\ &= \sum_k L(G = k, \hat{G} = g)\,\text{Pr}(G = k \mid X = x)\end{aligned}$$

$$\begin{aligned}G^*(x) &= \arg\min_g \widehat{\text{EPE}}_x(g) \\ &= \arg\min_g \sum_k L(G = k, \hat{G} = g)\widehat{\text{Pr}}(G = k \mid X = x)\end{aligned}$$

5.6 Summary of Classification Evaluation

Decision Theory

A prediction is not a decision!

- Ask yourself: do I really need to make a hard classification? Or are risk scores/probabilities better for end user (who is in charge of *making the decisions*)?

- Use cost! The other metrics are probably not going to give you what you really want.
  - Resist the pressure to use AUROC, Accuracy, F1.
  - If you don't know the exact cost(FP)/cost(FN) ratio, then report performance for a reasonable range of values.
- For Binary Classification Problems, the optimal decision is to choose $\hat{G}(x) = 1$ if

$$\begin{aligned}\frac{p(x)}{1-p(x)} &\geq \frac{L(0,1) - L(0,0)}{L(1,0) - L(1,1)} \\ &= \frac{\text{FP} - \text{TN}}{\text{FN} - \text{TP}}\end{aligned}$$

- Consider the connection to Decision Theory, make the decision that maximizes *expected utility*. The losses define the utility.
- In practice, we need to use an *estimated* $\hat{p}(x)$ or $\hat{\gamma}(x)$ and *estimated* threshold.
- Model parameters are usually estimated with a different metric than what's used for evaluation.
  - E.g., Estimate logistic regression parameters by minimizing Log-loss (i.e., maximum likelihood)
  - E.g., Hinge Loss for Support Vector Machines (SVM)
  - But Total Cost, MAE, F1, AUROC are used for evaluation (and tuning parameter estimation).
  - Reason: its difficult to estimate model parameters with such loss functions (e.g., non-differentiable, non-unique, etc.)

6 Appendix: R Code Classification

Set-up

```
#: Load Required Packages
library(ISLR)
library(glmnet)
library(yardstick)
library(tidyverse)
```

```
#------------------------------------------------------------------------------#
#: Default Data
#  From the ISLR package
#  The outcome variable is `default`
#------------------------------------------------------------------------------#
library(ISLR)
data(Default, package="ISLR")     # load the Default Data

#: Create binary column (y)
Default = Default |> mutate(y = ifelse(default == "Yes", 1L, 0L))
#: Summary Stats (Notice only 333 (3.3%) have defaulted)
summary(Default)
#>  default    student       balance          income            y
#>  No :9667   No :7056   Min.   :   0   Min.   :  772   Min.   :0.0000
#>  Yes: 333   Yes:2944   1st Qu.: 482   1st Qu.:21340   1st Qu.:0.0000
#>                        Median : 824   Median :34553   Median :0.0000
#>                        Mean   : 835   Mean   :33517   Mean   :0.0333
#>                        3rd Qu.:1166   3rd Qu.:43808   3rd Qu.:0.0000
#>                        Max.   :2654   Max.   :73554   Max.   :1.0000
```

```
#: Train/Test Split
library(rsample)
set.seed(2024)
Default_split =
  initial_split(
    Default,
    prop = 1 - 500/nrow(Default), # n_test = 500
    strata = y                    # stratify on outcome
  )
```

Penalized Logistic Regression

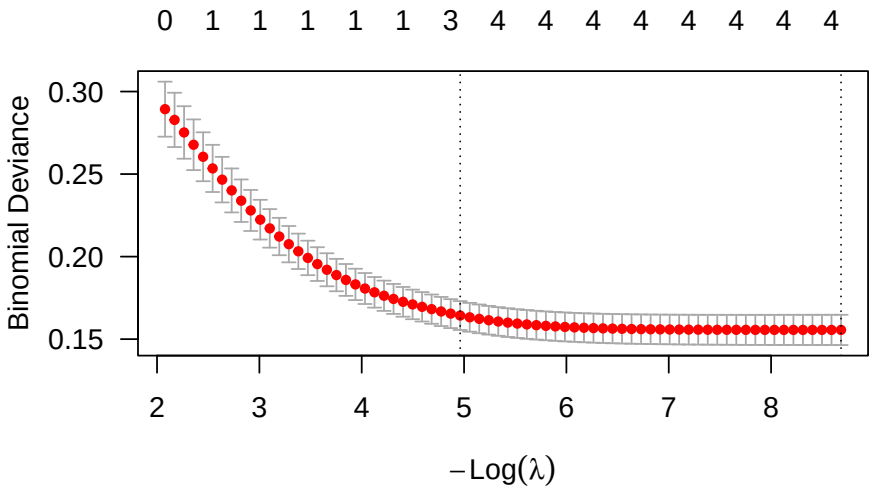
First need to convert data to numeric model matrix

```
#: using the recipe/bake method
library(tidymodels)
rec_fit = recipe(y~student + balance + income,
                 data = training(Default_split)) |>
  step_dummy(all_nominal(), one_hot = TRUE) |>
  prep()


#: training data
X.train = rec_fit  |>
  bake(
    all_predictors(),
    new_data = training(Default_split),
```

```
    composition="matrix"
  )
Y.train = training(Default_split)$y

#: testing data
X.test = rec_fit  |>
  bake(
    all_predictors(),
    new_data = testing(Default_split),
    composition="matrix"
  )
Y.test = testing(Default_split)$y
```

Now fit the elastic net

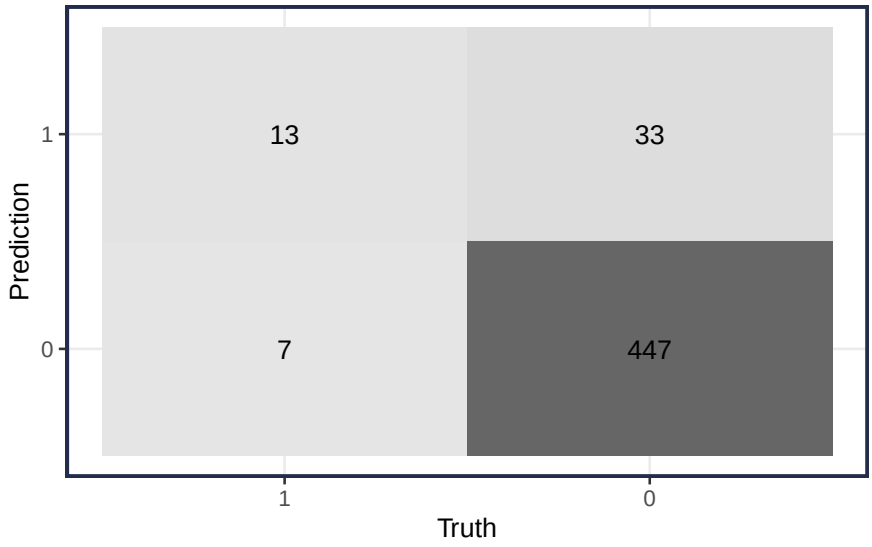
```
#: Elastic net with alpha = .5. Use CV to select lambda.
library(glmnet)
set.seed(2020)   # seed controls the cross-validation splits
fit_enet =
  cv.glmnet(X.train, Y.train,
                      alpha=.5,
                      family="binomial")

#: CV performance plot
plot(fit_enet, las=1)
```



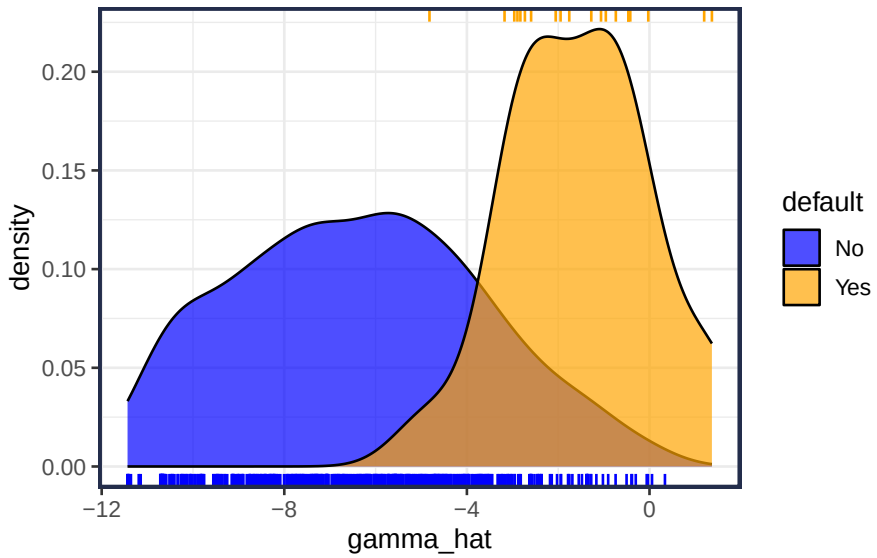
Performance Metrics and Curves

```
perf_data =
  testing(Default_split) |>
  mutate(
    # p_hat(x)
    p_hat = predict(fit_enet, X.test, s = "lambda.min", type = "response")[,1],
    # gamma_hat(x) = log(p) - log(1-p)
    gamma_hat = predict(fit_enet, X.test, s = "lambda.min", type = "link")[,1],
    # Make Hard classification (use .10 as cut-off)
    G_hat = ifelse(p_hat >= .10, 1, 0)
  ) |>
  as_tibble()
```

```r
#: Make Confusion Table (yardstick)
library(yardstick)
# Note: the yardstick package functions, like conf_mat(), requires that hard
#       classifications have *factor* inputs (instead of *character*)
cm = perf_data |>
  mutate(
    y = factor(y, levels=c("1", "0")),
    G_hat = factor(G_hat, levels=c("1", "0"))
  ) %>%
  conf_mat(truth = y, estimate = G_hat)
cm
#>            Truth
#> Prediction   1   0
#>          1  13  33
#>          0   7 447
autoplot(cm, type = "heatmap")
```




```r
#: Visualize Performance by score
perf_data |>
  ggplot(aes(gamma_hat, fill=default)) +
  geom_density(alpha=.70) +                      # add kernel density estimates
  geom_rug(data=. %>% filter(default == 'Yes'), # add rug to top
           aes(color=default), sides='t') +
  geom_rug(data=. %>% filter(default == 'No'),  # add rug to bottom
           aes(color=default), sides='b') +
  scale_fill_manual(values=c(Yes="orange", No="blue")) + # modify fill colors
  scale_color_manual(values=c(Yes="orange", No="blue"), guide="none") # modify colors
```



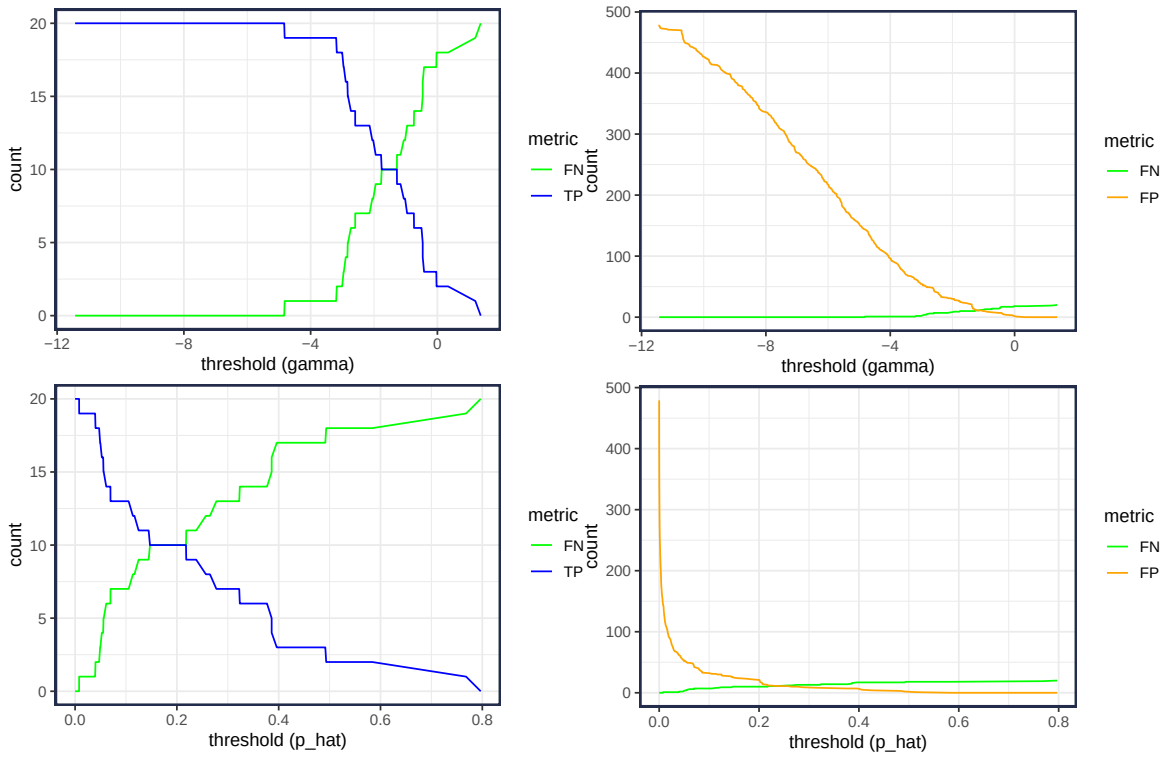

```
#: Get performance data (by threshold)
#   This table has one row for every threshold. The columns are the elements
#   of the confusion table plus FPR, TPR
perf_table =
  perf_data |>
  #- group_by() + summarize() in case of ties
  group_by(gamma_hat, p_hat)  |>
    summarize(
      n = n(),
      n.1 = sum(y),
      n.0 = n-sum(y)
    ) |>
  ungroup() |>
  #- calculate metrics
  arrange(gamma_hat) %>%
  mutate(
    FN = cumsum(n.1),     # false negatives
         TN = cumsum(n.0),     # true negatives
         TP = sum(n.1) - FN,   # true positives
         FP = sum(n.0) - TN,   # false positives
         N = cumsum(n),        # number of cases predicted to be 1
    TPR = TP/sum(n.1), FPR = FP/sum(n.0)
  ) %>%
  #- only keep relevant metrics
  select(-n, -n.1, -n.0, gamma_hat, p_hat)

## Note: gamma = log(p_hat) - log(1-p_hat) = log(p_hat / (1-p_hat))
```

```
perf_table |>
  head(10)
#> # A tibble: 10 x 9
#>   gamma_hat     p_hat    FN    TN    TP    FP     N   TPR   FPR
#>       <dbl>     <dbl> <int> <int> <int> <int> <int> <dbl> <dbl>
#> 1     -11.4 0.0000108     0     1    20   479     1     1 0.998
#> 2     -11.4 0.0000108     0     2    20   478     2     1 0.996
#> 3     -11.4 0.0000108     0     3    20   477     3     1 0.994
#> 4     -11.4 0.0000111     0     4    20   476     4     1 0.992
#> 5     -11.4 0.0000111     0     5    20   475     5     1 0.990
#> 6     -11.4 0.0000111     0     6    20   474     6     1 0.988
#> # i 4 more rows
```

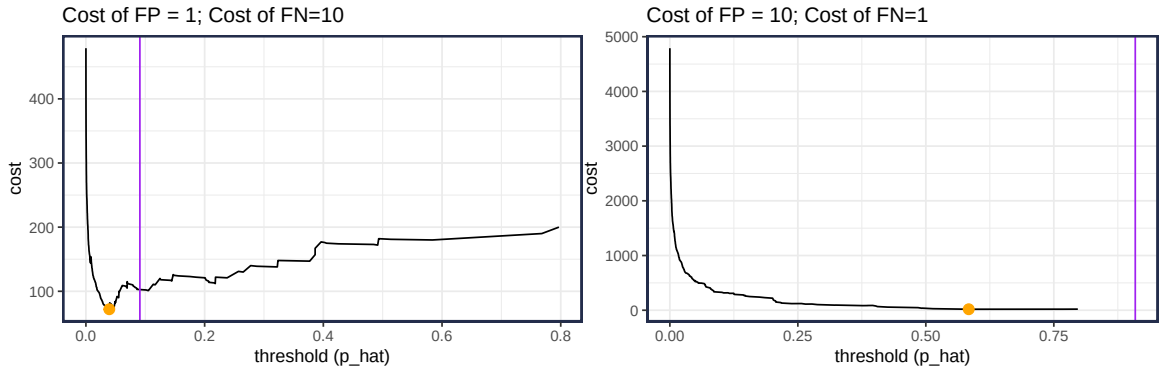
```r
## Alternatively, using yardstick::roc_curve()
perf_data |>
  mutate(
    y = factor(y, levels = c(1,0)),
  ) |>
  roc_curve(y, p_hat)
#> # A tibble: 502 x 3
#>    .threshold specificity sensitivity
#>         <dbl>       <dbl>       <dbl>
#> 1 -Inf             0                1
#> 2    0.0000108     0                1
#> 3    0.0000108     0.00208          1
#> 4    0.0000108     0.00417          1
#> 5    0.0000111     0.00625          1
#> 6    0.0000111     0.00833          1
#> # i 496 more rows
```

```r
#: Make performance curves
col_lines = c(TP = "blue", FP="orange", FN="green", TN="brown",
              TPR = "blue", FPR="orange", FNR="green", TNR="brown")

#: Make performance curves
perf_table %>%
  select(threshold = gamma_hat, FN, TP) %>%
  gather(metric, n, -threshold) %>%
  ggplot(aes(threshold, n, color=metric)) + geom_line() +
  labs(x= "threshold (gamma)", y="count") +
  scale_color_manual(values=col_lines)

perf_table %>%
  select(threshold = gamma_hat, FN, FP) %>%
  gather(metric, n, -threshold) %>%
  ggplot(aes(threshold, n, color=metric)) + geom_line() +
  labs(x= "threshold (gamma)", y="count") +
  scale_color_manual(values=col_lines)

perf_table %>%
  select(threshold = p_hat, FN, TP) %>%
  gather(metric, n, -threshold) %>%
  ggplot(aes(threshold, n, color=metric)) + geom_line() +
  labs(x= "threshold (p_hat)", y="count") +
  scale_color_manual(values=col_lines)

perf_table %>%
  select(threshold = p_hat, FN, FP) %>%
  gather(metric, n, -threshold) %>%
  ggplot(aes(threshold, n, color=metric)) + geom_line() +
  labs(x= "threshold (p_hat)", y="count") +
  scale_color_manual(values=col_lines)
```

```r
#: Make Cost curves
perf_table %>%
  mutate(cost = 1*FP + 10*FN) %>%    # use 1:10 costs
  ggplot(aes(p_hat, cost)) + geom_line() +
  geom_point(data=. %>% filter(cost==min(cost)), size=3, color='orange') + # # optimal from test data
  geom_vline(xintercept = 1/11, color='purple') +  # theoretical optimal
  ggtitle('Cost of FP = 1; Cost of FN=10') +
  labs(x="threshold (p_hat)")

perf_table %>%
```




```
  mutate(cost = 10*FP + 1*FN) %>%    # use 10:1 costs
  ggplot(aes(p_hat, cost)) + geom_line() +
  geom_point(data=. %>% filter(cost==min(cost)), size=3, color='orange') + # optimal from test data
  geom_vline(xintercept = 10/11, color='purple') + # theoretical optimal
  ggtitle('Cost of FP = 10; Cost of FN=1') +   labs(x="threshold (p_hat)")
```

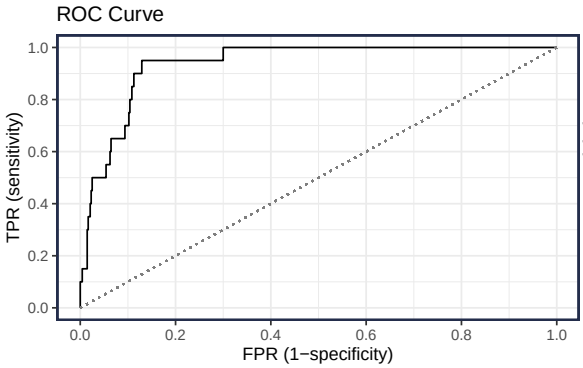


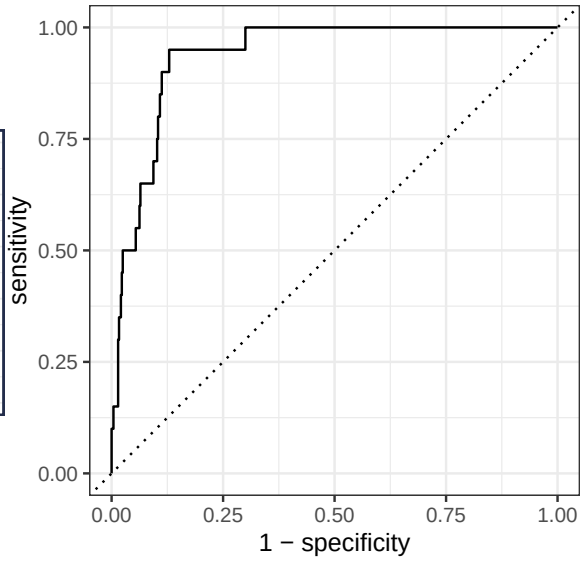

```
#: Make ROC curve
perf_table %>%
  ggplot(aes(FPR, TPR)) +
  geom_path() +
  labs(x='FPR (1-specificity)', y='TPR (sensitivity)') +
  geom_segment(x=0, xend=1, y=0, yend=1, lty=3, color='grey50') +
  scale_x_continuous(breaks = seq(0, 1, by=.20)) +
  scale_y_continuous(breaks = seq(0, 1, by=.20)) +
  ggtitle("ROC Curve")


## Using yardstick package
library(yardstick)  # for evaluation functions
# Notes:
```

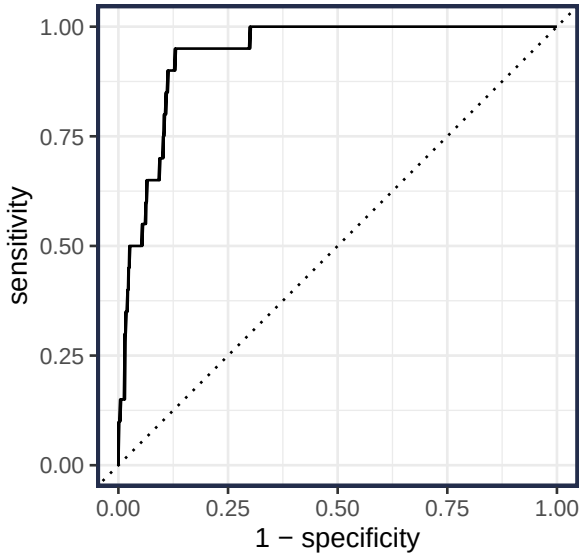
```
# - for ROC curve and AUROC, it doesn't matter if the estimates/predictions
#   are p_hat or gamma_hat
# - for


#: ROC plots
ROC =
  perf_data %>%
  mutate(y = factor(y, levels=c(1,0))) %>%
  yardstick::roc_curve(y, gamma_hat)

autoplot(ROC)  # autoplot() method

ROC |>         # same as autoplot()
  ggplot(aes(1-specificity, sensitivity)) + geom_line() +
  geom_abline(lty=3) +
  coord_equal()


#: Area under ROC (AUROC)
perf_data |>
  mutate(y = factor(y, levels=c(1,0))) |>
  roc_auc(y, gamma_hat)
#> # A tibble: 1 x 3
#>   .metric .estimator .estimate
#>   <chr>   <chr>          <dbl>
#> 1 roc_auc binary         0.937

yardstick::roc_auc_vec(factor(perf_data$y, 1:0), perf_data$gamma_hat)
#> [1] 0.9368
```

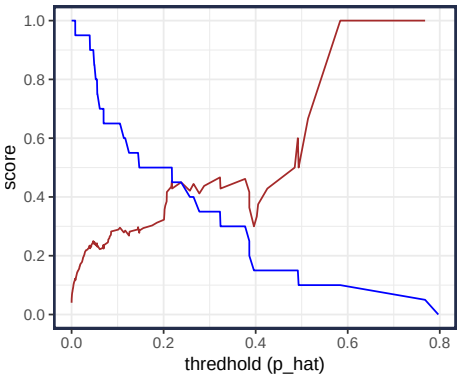
```
#: Log Loss Metric
perf_data |>
  mutate(y = factor(y, levels=c(1,0))) |>
  mn_log_loss(y, p_hat)
#> # A tibble: 1 x 3
#>   .metric     .estimator .estimate
#>   <chr>       <chr>          <dbl>
#> 1 mn_log_loss binary         0.104
```

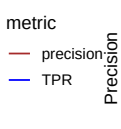
```
#: Precision-Recall
perf_table %>%
  mutate(threshold = p_hat, precision = TP/(TP + FP)) %>%
  select(threshold, TPR, precision) %>%
  gather(metric, n, -threshold) %>%
  ggplot(aes(threshold, n, color=metric)) + geom_line() +
  scale_x_continuous(breaks = seq(0, 1, by=.20)) +
  scale_y_continuous(breaks = seq(0, 1, by=.20)) +
  scale_color_manual(values = c(TPR="blue", precision="brown")) +
  labs(x="thredhold (p_hat)", y="score")

perf_table %>%
  mutate(threshold=p_hat, precision = TP/(TP + FP)) %>%
  ggplot(aes(TPR, precision)) + geom_line() +
  scale_x_continuous(breaks = seq(0, 1, by=.20)) +
  scale_y_continuous(breaks = seq(0, 1, by=.20)) +
  labs(x='Recall (TPR)', y='Precision', # (TP/(TP+FP))
       title="Precision-Recall Curve")
```

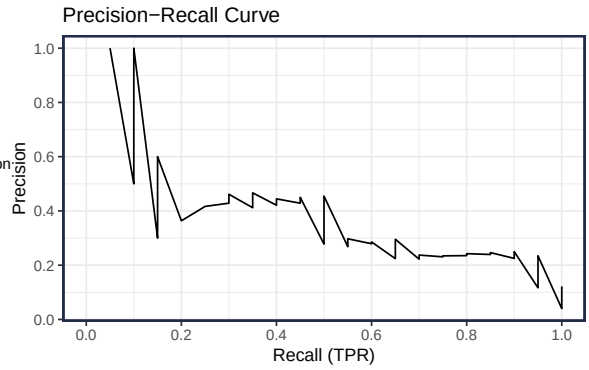

ROC Curve
TPR (sensitivity)
FPR (1−specificity)
0.0
0.2
0.4
0.6
0.8
1.0


sensitivity
1 − specificity
0.00
0.25
0.50
0.75
1.00


sensitivity
1 − specificity
0.00
0.25
0.50
0.75
1.00


score
thredhold (p_hat)
0.0
0.2
0.4
0.6
0.8
1.0


metric
precision
TPR


Precision−Recall Curve
Precision
Recall (TPR)
0.0
0.2
0.4
0.6
0.8
1.0