

Lesson 12: Assessing Model Fit (and comparing non-nested models)

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Learning Objectives

1. Use the Pearson residual statistic to determine if our preliminary final model fits the data well
2. Use the Hosmer and Lemeshow goodness-of-fit statistic to determine if our preliminary final model fits the data well
3. Use the AUC-ROC to determine how well model predicts binary outcome
4. Apply AIC and BIC as a summary measure to make additional comparisons between potential models

Last class: GLOW Study with interactions

- **Outcome variable:** any fracture in the first year of follow up (FRACTURE: 0 or 1)
- **Risk factor/variable of interest:** history of prior fracture (PRIORFRAC: 0 or 1)
- **Potential confounder or effect modifier:** age (AGE, a continuous variable)
- Fitted model with interactions:

$$\text{logit}(\hat{\pi}(\mathbf{X})) = \hat{\beta}_0 + \hat{\beta}_1 \cdot I(\text{PF} = \text{"Yes"}) + \hat{\beta}_2 \cdot \text{Age} + \hat{\beta}_3 \cdot I(\text{PF} = \text{"Yes"}) \cdot \text{Age}$$

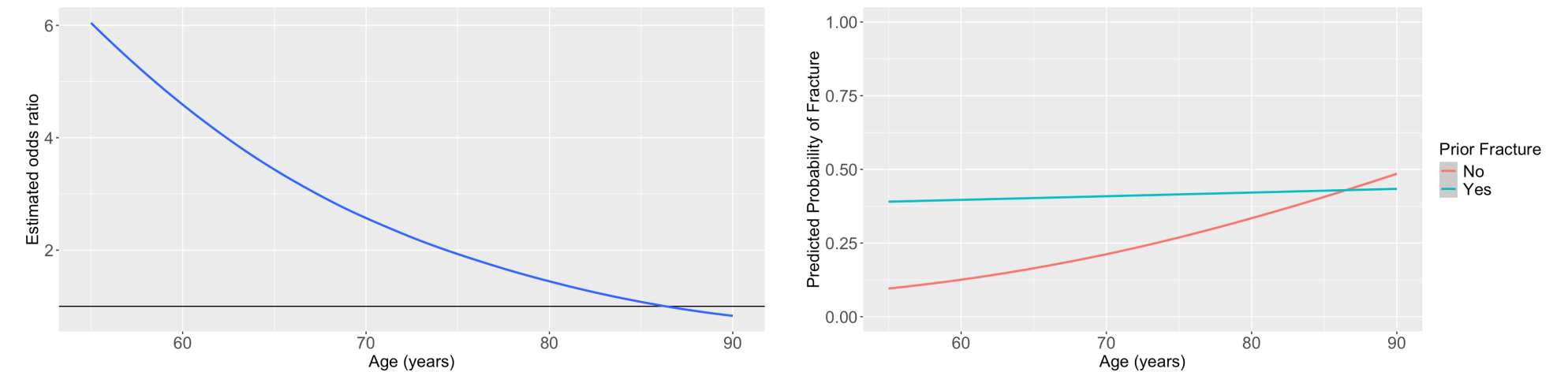
$$\text{logit}(\hat{\pi}(\mathbf{X})) = -1.376 + 1.002 \cdot I(\text{PF} = \text{"Yes"}) + 0.063 \cdot \text{Age} - 0.057 \cdot I(\text{PF} = \text{"Yes"}) \cdot \text{Age}$$

- Let's say we are considering this model for our **final model**
- Today: determine the overall fit of this model

Last class: Reporting results of GLOW Study with interactions

- Remember our main covariate is prior fracture, so we want to focus on how age changes the relationship between prior fracture and a new fracture!

For individuals 69 years old, the estimated odds of a new fracture for individuals with prior fracture is 2.72 times the estimated odds of a new fracture for individuals with no prior fracture (95% CI: 1.70, 4.35). As seen in [Figure 1 \(a\)](#), the odds ratio of a new fracture when comparing prior fracture status decreases with age, indicating that the effect of prior fractures on new fractures decreases as individuals get older. In [Figure 1 \(b\)](#), it is evident that for both prior fracture statuses, the predicted probability of a new fracture increases as age increases. However, the predicted probability of new fracture for those without a prior fracture increases at a higher rate than that of individuals with a prior fracture. Thus, the predicted probabilities of a new fracture converge at age [insert age here].



(a) Odds ratio of fracture outcome comparing prior fracture to no prior fracture

(b) Predicted probability of fracture

Figure 1: Plots of odds ratio and predicted probability from fitted interaction model

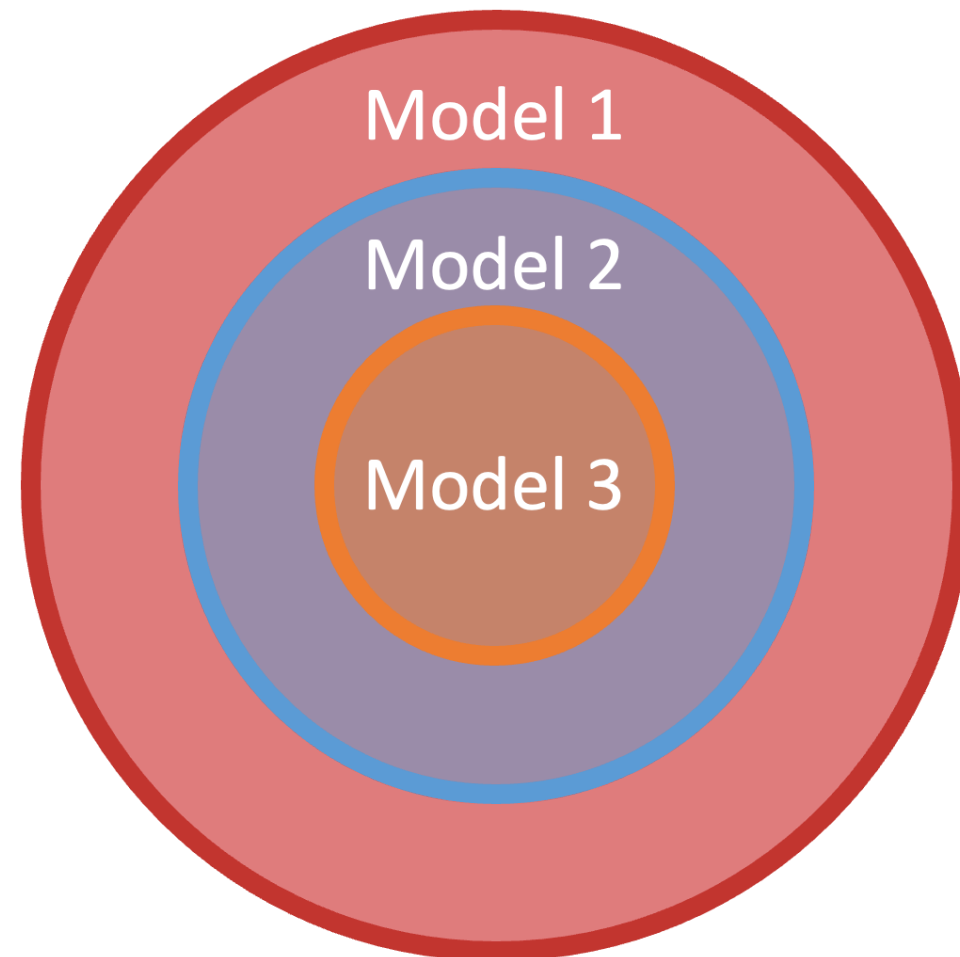
Assessing model fit: overview

- Once a potential final model has been determined, we need to assess the fit of the model
- Variable selection is no longer our focus at this stage
 - We want to find answer to whether the model fits the data adequately
- Assessing the Goodness of Fit or Assessing model fit
 - Assess how well our fitted logistic regression model predicts/estimates the observed outcomes
 - Comparison: fitted/estimated outcome vs. observed outcome

Assessing model fit: nested vs unnested models

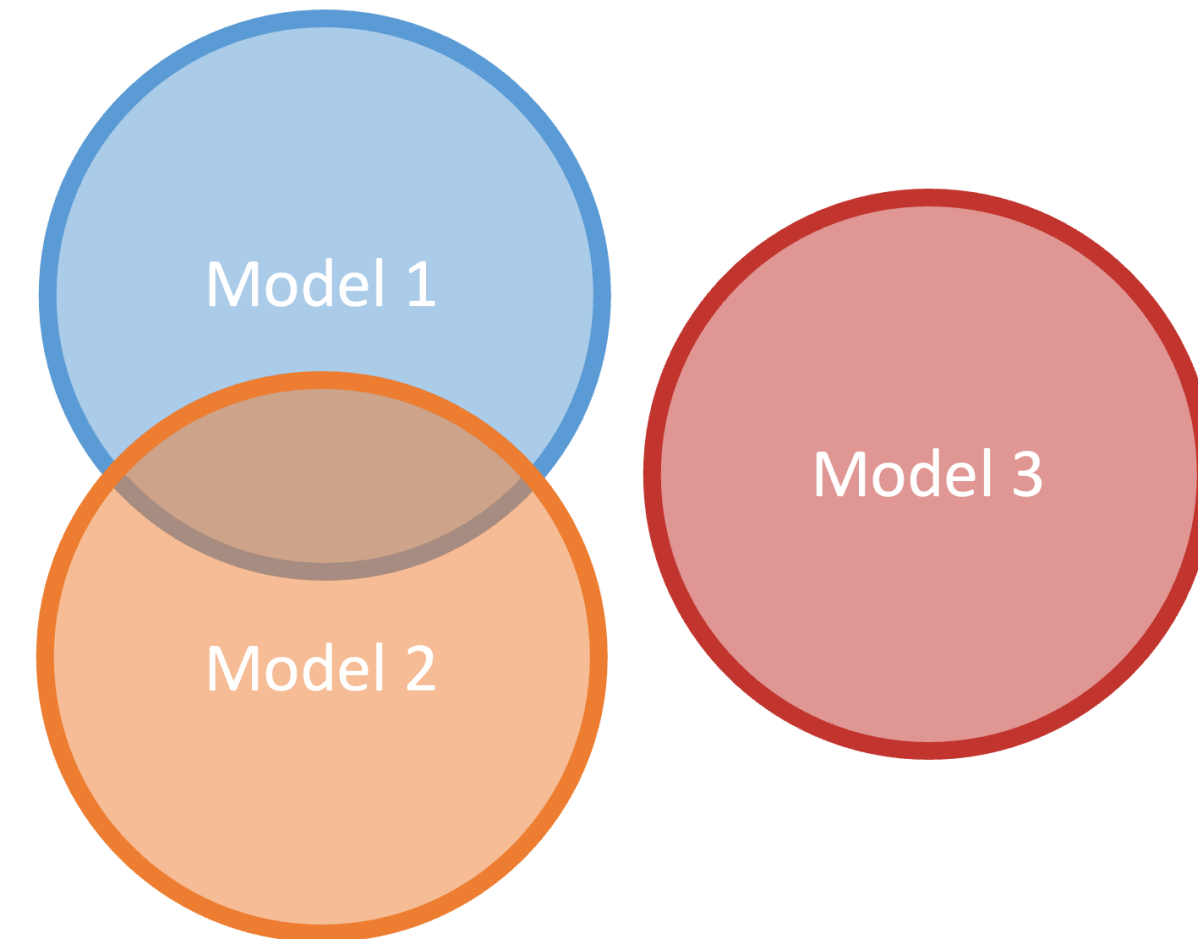
Nested models and LRT

- If we have **two nested models**, we can use likelihood ratio test to compare the fit of the two models
 - Nested models: one model's variables are a subset of the other



Unnested models and comparisons

- If we have **two unnested models**, we cannot use likelihood ratio test to compare the fit of the two models
 - Non-nested models: can have overlapping variables, but not a complete subset of variables



Some measurements for our final model(s)

- To assess the fit of the model, it is good to have a mixture of measurements

If we want to **measure the absolute fit**: not comparing to any models, but determining if the model fits the data well

- Pearson residual statistic
 - Not the best measurement
 - Does not work if continuous variables in model
- Hosmer-Lemeshow goodness-of-fit statistic
 - Need to adjust when sample size is large
- AUC-ROC (area under the curve of the receiver operating characteristic)

If we want **comparable measures of fit**: if we want to compare candidate models that are not nested

- AUC-ROC
- AIC/BIC

Poll Everywhere Question 1

Components to Assess Model Fit

- The model fits the data well if
 - **Summary measurements of model fit** tell us good fit
 - Aka: Summary measures of the distance between the predicted/estimated/fitted and observed Y are small
 - Today's lecture!!
 - No major issues in **model diagnostics**, observations fit into model and our assumptions
 - The contribution of each pair (predicted and observed) to these summary measures is unsystematic and is small relative to the error structure of the model
 - Model Diagnostics that will be covered in another lecture!
- **Need to examine both components**
 - It is possible to see a “good” summary measure of the distance between predicted and observed Y with some substantial deviation from fit for a few subjects

Summary Measures of Goodness of Fit

- Aka overall measure of fit
- What do we need to calculate them?
 - Need to calculate the fitted outcome
 - Need to calculate how close the fitted outcome is to the observed outcome
 - Summarize across all observations (or individuals' data)
- Two **tests** of goodness-of-fit
 - Pearson residual statistic
 - Hosmer-Lemeshow goodness-of-fit statistic

Comparing *fitted outcome* to observed outcome

- In logistic regression model, we estimate $\pi(\mathbf{X}) = P(Y = 1|\mathbf{X})$
 - Predicted probability, $\hat{\pi}(\mathbf{X})$, is between 0 and 1 for each subject
- However, we always observe $Y = 1$ or $Y = 0$
 - Not an observed $\pi(\mathbf{X})$
- We can determine the fitted outcome by sampling Y 's from a Bernoulli distribution with the fitted probability
 - $\hat{Y} \sim \text{Bernoulli}(\hat{\pi}(\mathbf{X}))$
- If there are groups of individuals that share the *same covariate observations*, then we can use the same $\hat{\pi}(\mathbf{X})$
 - $\sum_j \hat{Y} \sim \text{Binomial}(\sum_j, \hat{\pi}(\mathbf{X}))$
- Instead of comparing the expected vs. observed at individual level, we can compare them at “group” level

Number of Covariate Patterns

- When the logistic regression model contains only categorical covariates, we can think of the number of covariate patterns
- **For example:** model contains two binary covariates (history of fracture and smoking status), there will be 4 unique combination of these factors
 - This model has 4 covariate patterns
 - Subjects can be divided into 4 groups based on the covariates' values
- We can then compute the predicted number of individuals with $Y=1$ in each group, and compare that with the actual observed number of individuals with $Y=1$ in that group
 - We don't need to sample this
 - We use the expected value (mean) of the Binomial to determine the $\hat{Y}$ for each covariate pattern
 - For covariate pattern j with m_j observations:

$$\hat{Y}_j = m_j \hat{\pi}(\mathbf{X}_j) = m_j \hat{\pi}_j$$

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Pearson Residual

- In logistic regression model, can use Pearson residual for summary measure of goodness-of-fit Uses the $\hat{Y}_j$ fitted value from previous slide
- Pearson residual for jth covariate pattern is:

$$r(Y_j, \hat{\pi}_j) = \frac{(Y_j - m_j \hat{\pi}_j)}{\sqrt{m_j \hat{\pi}_j (1 - \hat{\pi}_j)}} = \frac{(Y_j - \hat{Y}_j)}{\sqrt{\hat{Y}_j (1 - \hat{\pi}_j)}}$$

- The summary statistics of Pearson residual is thus:

$$X^2 = \sum_{j=1}^J r(Y_j, \hat{\pi}_j)^2$$

Pearson Residual procedure

1. Set the **level of significance** α
2. Specify the **null** (H_0) and **alternative** (H_A) **hypotheses**: same for all data
 - H_0 : model fits well
 - H_1 : model does not fits well
3. Calculate the **test statistic** and **p-value**
4. Write a **conclusion** to the hypothesis test
 - Do we reject or fail to reject H_0 ?
 - Write a conclusion in the context of the problem

Not going to bother going through an example

- We can calculate this by hand and test against a chi-squared distribution
- No set R code to do this
- I do not see this as the main way to determine goodness of fit... for a binary outcome!
 - Often because of the bigger issues with it... (next slide)

Issues with Pearson Residuals

- Assume current model has p covariates...
 - then X^2 (Pearson residual) follows a chi-squared distribution
 - under the null hypothesis based on large sample theory
 - **Only appropriate if the number of covariate patterns is less than the number of observations**
- When the logistic regression model contains **one or more continuous covariates**, it is likely that the **number of covariate patterns equals to the sample size n**
- We should **not use Pearson Residuals** to evaluate goodness-of-fit test when the fitted **model contains one or more continuous variables**

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Hosmer-Lemeshow test

- If number of covariate patterns is roughly same as the number of observations
 - Whenever you include a continuous variable in your model
 - **Hosmer-Lemeshow (HL) goodness-of-fit test** should be used instead
- However, HL test does not work well if the number of covariate patterns is small
 - HL test should not be used if the number of covariate patterns ≤ 6
 - For reference: 3 binary predictors makes 8 covariate patterns
 - Pearson residuals X^2 should be used when the number of covariate patterns is small
- A large p-value from HL test suggests the model fits well

Poll Everywhere question 2

Hosmer-Lemeshow test

- HL test uses groupings from percentiles to basically measure what Pearson residual measures
- Steps to compute HL test statistic:
 1. Compute estimated probability $\hat{\pi}(\mathbf{X})$ for all n subjects ($n = 1, 2, \dots, n$)
 2. Order $\hat{\pi}(\mathbf{X})$ from largest to smallest values
 3. Divide ordered values into g percentile grouping (usually $g = 10$ based on H-L's suggestion)
 4. Form table of observed and expected counts
 5. Calculate HL test statistic from table
 6. Compare HL test statistic to chi-squared distribution (χ^2_{g-2})

Hosmer-Lemeshow test statistic

- The test statistic of Hosmer-Lemeshow goodness-of-fit test is denoted by $\hat{C}$, which is obtained by calculating the Pearson chi-squared statistic from the $g \times 2$ table of observed and estimated expected frequencies

$$\hat{C} = \sum_{k=1}^g \frac{(o_k - n'_k \bar{\pi}_k)^2}{n'_k \bar{\pi}_k (1 - \bar{\pi}_k)}$$

- where n'_k is the total number of subjects in the k th group
- Let c_k be the number of covariate patterns in the k th decile:

$$o_k = \sum_{j=1}^{c_k} y_j$$

and

$$\bar{\pi}_k = \sum_{j=1}^{c_k} \frac{m_j \hat{\pi}_j}{n'_k}$$

Hosmer-Lemeshow test procedure

1. Set the **level of significance** α
2. Specify the **null** (H_0) and **alternative** (H_A) **hypotheses**: same for all data
 - H_0 : model fits well
 - H_1 : model does not fits well
3. Calculate the **test statistic** and **p-value**
 - Note: $\hat{C} \sim \chi^2_{df=g-2}$
4. Write a **conclusion** to the hypothesis test
 - Do we reject or fail to reject H_0 ?
 - Write a conclusion in the context of the problem

GLOW Study: Hosmer-Lemeshow test

- Okay, so let's look at the interaction model from last class

$$\text{logit}(\pi(\mathbf{X})) = \beta_0 + \beta_1 \cdot I(\text{PF}) + \beta_2 \cdot \text{Age} + \beta_3 \cdot I(\text{PF}) \cdot \text{Age}$$

- We need to fit the model and use a new command:

```
1 glow_m3 = glm(fracture ~ priorfrac + age_c + priorfrac*age_c,  
2               data = glow, family = binomial)  
3 library(ResourceSelection)  
4 obs_vals = as.numeric(glow$fracture) - 1  
5 fit_vals = fitted(glow_m3)  
6 hoslem.test(obs_vals, fit_vals, g = 10)
```

Hosmer and Lemeshow goodness of fit (GOF) test

data: obs_vals, fit_vals

X-squared = 6.778, df = 8, p-value = 0.5608

Note to Nicky: do NOT make conclusion yet! In the poll everywhere!

Poll Everywhere question 3

GLOW Study: Hosmer-Lemeshow test

- Conclusion: The p-value is 0.5608, so we *fail to reject* the null hypothesis that the model fits the data well. Thus, for the GLOW study data, the model with an interaction between age and prior fracture fits the data well
- Don't forget that we still need to check individual observations (Model Diagnostics!)
- R may give results for the HL test even if it is not appropriate to use it!
 - **If number of covariate patterns ≤ 6 , do not use HL test**

Large sample size issue in H-L test

- When the sample size is really big (> 1000), it is much more likely to find the H-L reject the model fit (even when the expected vs. observed in each decile categories looks pretty similar)
- This is due to “too much” power in hypothesis testing.
 - Paul et al. (2012) for samples sizes from 1000 to 25,000, the number of groups g should be equal to

$$g = \max \left(10, \min \left\{ \frac{n_1}{2}, \frac{n - n_1}{2}, 2 + 8 \left(\frac{n}{1000} \right)^2 \right\} \right)$$

- For example, if one has a sample with $n = 10,000$ (sample size) and $n_1 = 1,000$ (number of events) then $g = 500$ groups are suggested
- For $n > 25000$, other methods, such as partitioning data into a developmental data set (with smaller n) and a validation set

Final Notes on Pearson and HL tests

- They should not be used for variable selection
 - The likelihood ratio tests for significance of coefficients are much more powerful and appropriate (when nested)
- They are not for model comparison
 - One should **not** use the p-value from goodness of fit tests of different models to decide which model is better than the other
 - Something like AUC-ROC, AIC, or BIC can be used

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ROC Curve and AUC (1/2)

- Receiver Operating Characteristics (ROC) curve is useful tool to quantify how good is our model predicting binary outcome
- It is a plot of sensitivity (true positive rate) versus (1-specificity) or false positive rate of fitted binary values

- True Positive Rate = $\frac{TP}{TP + FN}$

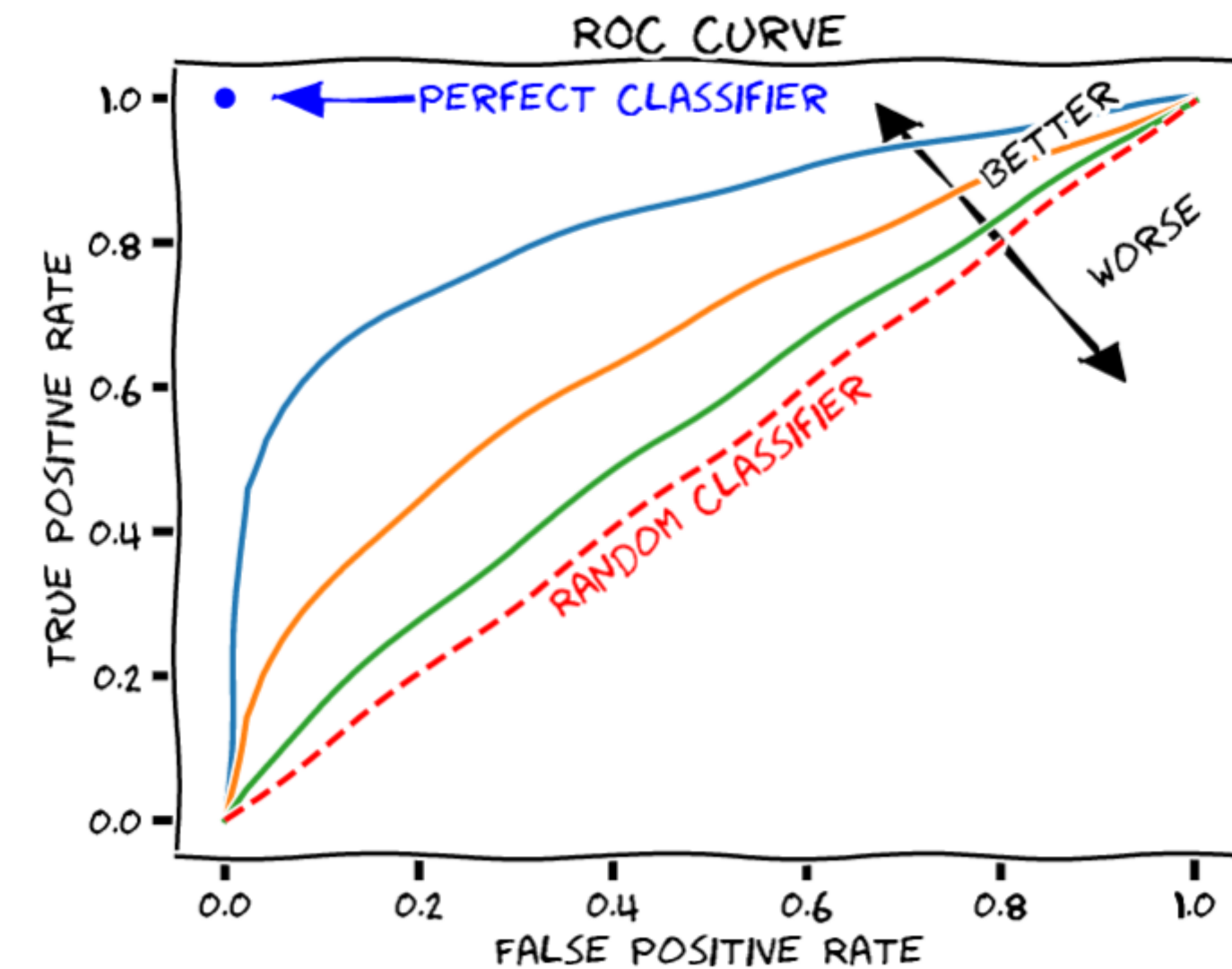
- False Positive Rate = $\frac{FP}{FP + TN}$

- The ROC curve shows the tradeoff between sensitivity and specificity

		Observed outcome	
		1	0
Predicted/fitted outcome	1	TP	FP
	0	FN	TN

ROC Curve and AUC (2/2)

- Area under the ROC curve (AUC ROC) is a reasonable summary of the overall predictive accuracy of the test
 - Accuracy means how well the predicted value matches the observed value
- The closer the curve follows the left-hand border and top border of the ROC space, the more accurate the test
 - An AUC = 1 represents 100% accuracy
- The closer the curve comes to the 45-degree diagonal line, the less accurate the test
 - An AUC = 0.5 represents an unhelpful model
 - Random predictions



Poll Everywhere Question 4

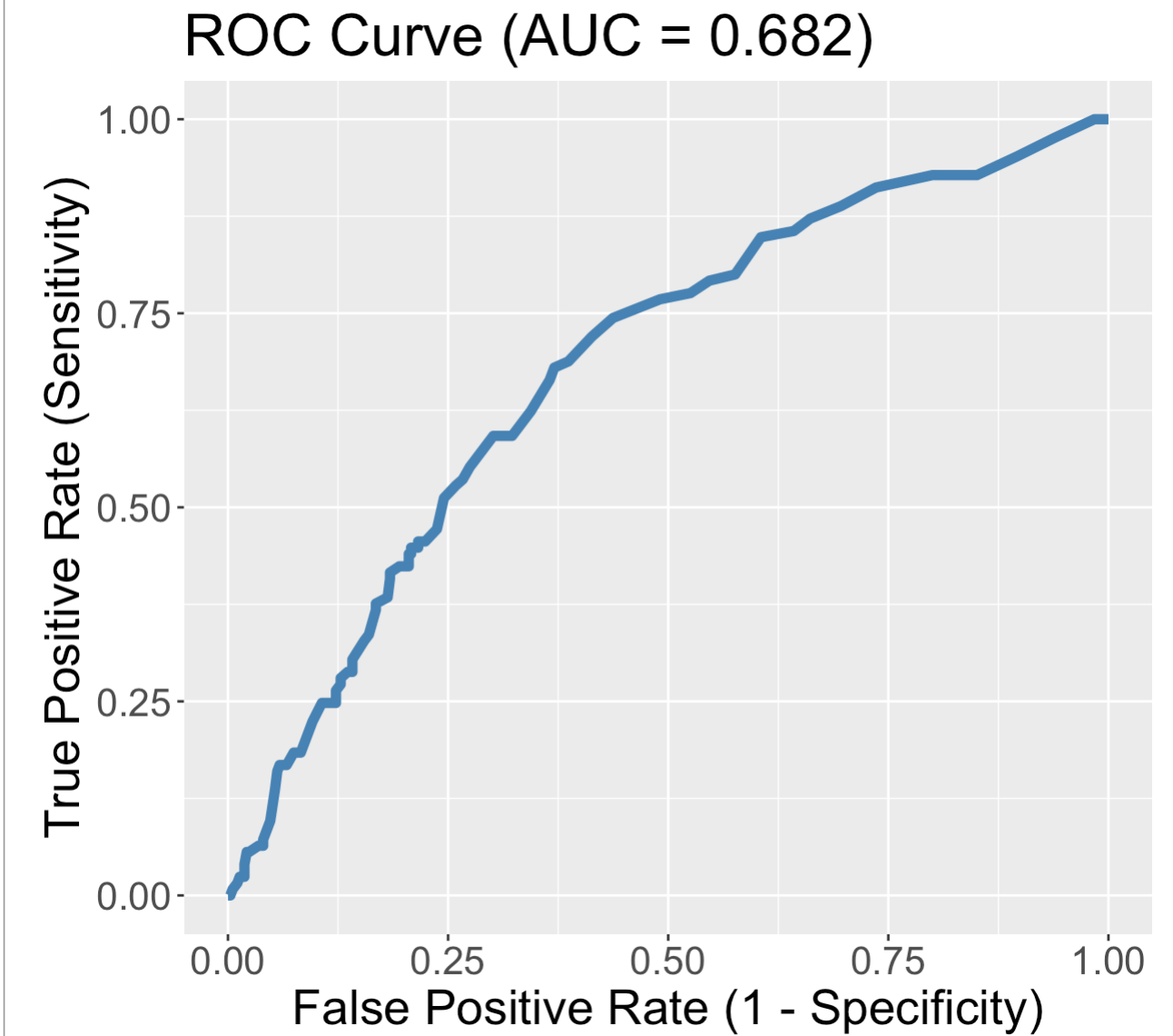
ROC Curve and AUC (3/3)

- Often only report the AUC
- Suggestions of how to interpret model fit through AUC values:

AUC Values	Fit
0.5	Useless
0.5-0.7	Poor
0.7-0.8	Acceptable
0.8-0.9	Excellent
0.9-1	Outstanding

GLOW Study: ROC of interaction model

```
1 library(pROC)
2 predicted <- predict(glow_m3, glow, type="response")
3
4 # define object to plot and calculate AUC
5 rocobj <- roc(glow$fracture, predicted)
6 auc <- round(auc(glow$fracture, predicted),4)
7
8 #create ROC plot
9 ggroc(rocobj, colour = 'steelblue',
10       size = 2, legacy.axes = TRUE) +
11   ggtitle(paste0('ROC Curve ', '(AUC = ', auc, ')')) +
12   theme(text = element_text(size = 23)) +
13   xlab("False Positive Rate (1 - Specificity)") +
14   ylab("True Positive Rate (Sensitivity)")
```



- We have a poorly fitting model
- We can take `auc` and compare it to other models: good way to pick a model based on predictive power

Another way to think about AUC

- GLOW Study: Consider the situation in which the fracture status of each individual is known
- Randomly pick one individual from fractured group and one from non-fractured outcome group
 - Based on their age and prior fracture, we will correctly predict which is from fractured group
- The AUC is the percentage of randomly drawn pairs for which we predict the pair correctly
- Therefore, AUC represents the ability of our covariates to discriminate between individuals with the outcome (fracture) and those without the outcome

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AIC and BIC

- Two widely used non-hypothesis testing based measurements that helps select a good model
 - Akaike Information Criterion (AIC)
 - Bayesian Information Criterion (BIC)
- Unlike likelihood ratio test which is only suitable for nested model, **AIC and BIC are suitable for both nested and non-nested model**
- There is no hypothesis/conclusion testing for the comparison between two models
 - So not the best for selecting covariates to include in model
 - **BUT helpful if you have a few preliminary final models that you want to compare**

Poll Everywhere Question 5

AIC and BIC

- Both AIC and BIC penalize a model for having many parameters

Measure of fit	Equation	R code
Akaike information criterion (AIC)	$AIC = -2 \cdot \log\text{-likelihood} + 2q$	<code>AIC(model_name)</code>
Bayesian information criterion (BIC)	$BIC = -2 \cdot \log\text{-likelihood} + q\log(n)$	<code>BIC(model_name)</code>

- Where q is the number of parameters in the model and n is the sample size
- Both AIC and BIC can only be used to compare models fitting the same data set
- In comparing two models, the model with **smaller AIC and/or BIC is preferred**
 - When the difference in AIC between two models exceeds 3, the difference is viewed as “meaningful”

AIC and BIC in R

- After fitting the logistic regression model, can calculate AIC and BIC
- Let's look at the AIC and BIC of our interaction model:

```
1 AIC(glow_m3)
```

```
[1] 531.2716
```

```
1 BIC(glow_m3)
```

```
[1] 548.13
```

Example of a table for model fit statistics

```
1 model1 = glow %>% glm(formula = fracture ~ age_c + height, family = binomial)
2 model2 = glow %>% glm(formula = fracture ~ priorfrac + armassist + smoke, family = binomial)
3 model3 = glow %>% glm(formula = fracture ~ priorfrac + age_c + priorfrac*age_c, family = binomial)
4 predicted1 = predict(model1, glow, type="response")
5 predicted2 = predict(model2, glow, type="response")
6 predicted3 = predict(model3, glow, type="response")
7
8 fit_stats = data.frame(Model = c("Model 1: age + height", "Model 2: prior fracture + arm assist + smoking status", "Model 3: interaction with prior fraction + age"),
9                           AUC_ROC = c(round(auc(glow$fracture, predicted1), 4), round(auc(glow$fracture, predicted2), 4), round(auc(glow$fracture, predicted3), 4)),
10                          AIC = c(AIC(model1), AIC(model2), AIC(model3)),
11                          BIC = c(BIC(model1), BIC(model2), BIC(model3)))
12
13 colnames(fit_stats) = c("Model", "AUC-ROC", "AIC", "BIC")
14
15 fit_stats %>% gt() %>% tab_options(table.font.size = 40) %>% fmt_number(decimals = 3)
```

Model	AUC-ROC	AIC	BIC
Model 1: age + height	0.642	542.036	554.680
Model 2: prior fracture + arm assist + smoking status	0.648	540.409	557.267
Model 3: interaction with prior fraction + age	0.682	531.272	548.130

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Summary (1/2)

Measure of fit	Hypothesis tested?	Equation	R code
Pearson residual	Yes	$X^2 = \sum_{j=1}^J r(Y_j, \hat{\pi}_j)^2$	Not given
Hosmer-Lemeshow test	Yes	$\hat{C} = \sum_{k=1}^g \frac{(o_k - n'_k \bar{\pi}_k)^2}{n'_k \bar{\pi}_k (1 - \bar{\pi}_k)}$	<code>hoslem.test()</code>
AUC-ROC	Kinda	Not given	<code>auc(observed, predicted)</code>
AIC	Only to compare models	$AIC = -2 \cdot \log\text{-likelihood} + 2q$	<code>AIC(model_name)</code>
BIC	Only to compare models	$AIC = -2 \cdot \log\text{-likelihood} + q \log(n)$	<code>BIC(model_name)</code>

Special notes:

- Use Hosmer-Lemshow test over Pearson residual unless number of covariate patterns is less than 6
- Cannot use Pearson residual when there is a continuous variable in the model

Summary (2/2)

- For our interaction model:

$$\begin{aligned}\text{logit}(\hat{\pi}(\mathbf{X})) &= \hat{\beta}_0 & + \hat{\beta}_1 \cdot I(\text{PF}) & + \hat{\beta}_2 \cdot \text{Age} & + \hat{\beta}_3 \cdot I(\text{PF}) \cdot \text{Age} \\ \text{logit}(\hat{\pi}(\mathbf{X})) &= -1.376 & + 1.002 \cdot I(\text{PF}) & + 0.063 \cdot \text{Age} & - 0.057 \cdot I(\text{PF}) \cdot \text{Age}\end{aligned}$$

- We can examine the overall model fit using:
 - Not comparing to any other models:
 - Pearson residual: Not appropriate for this model
 - Hosmer-Lemeshow: $\hat{C} = 6.778$, p-value = 0.56
 - AUC-ROC: 0.6819
 - Can be used to compare to other models:
 - AUC-ROC: 0.6819
 - AIC: 531.27
 - BIC: 548.13

Reference slide

- We went over model fit statistics a little in BSTA 512/612 in [Lesson 13](#)
 - Included AIC and BIC