Final Project 131

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Introduction

We want to build a model for the UCSB Division I Baseball Team that predicts slugging percentage of hitters based on exit speed and launch angle. Exit speed is the speed the ball has off the bat after the player hit it, as in how much speed did they put on the ball. Angle or launch angle is the angle that the ball flew off of the bat after the hitter made contact. We pick these two metrics because we want the model to not only be interpretable to us, but we want it to be interpretable to the players and exitspeed and launch angle are realistically the only two variables that the hitter can control are angle and exit speed.

```
#load the data
data <- read_csv_arrow("ultimategauchosresults2024.csv")
```

```
# add column for slug value
# ------------------------------
# 2. Data Preprocessing
# ------------------------------
# (Assume your data frame is named 'data' and contains PlayResult, ExitSpeed, Angle, BatterSide, etc.)
data <- data %>%
  mutate(
    SLGValue = case_when(
      PlayResult %in% c("Out") ~ 0,
      PlayResult == "Single" ~ 1,
      PlayResult == "Double" ~ 2,
      PlayResult == "Triple" ~ 3,
      PlayResult == "HomeRun" ~ 4,
      TRUE ~ NA_real_
    ),
    ExitSpeed = round(as.numeric(as.character(ExitSpeed)), 1),
    Angle = round(as.numeric(as.character(Angle)), 1)
  ) %>%
  na.omit()

# Create a binary outcome for classification tasks: Hit (SLGValue > 0) vs. NoHit
data <- data %>%
  mutate(Hit = ifelse(SLGValue > 0, "Hit", "NoHit"))

# (Optional) Print table of BatterSide
#print(batterSide)
```

Prepping the data for modeling. Ensuring that we have enough data in each column to appropriately predict slugging percentage

Cross validation

The code below ensures that we train all the models fairly using the same cross validation for each so that we can accurately compare their results.

first we split the data in order to have a test set and a train set.

```
# --------------------------------
# 1. Split the data into training and testing sets
# --------------------------------
set.seed(123)  # For reproducibility
trainIndex <- createDataPartition(data$SLGValue, p = 0.8, list = FALSE)
trainData <- data[trainIndex, ]
testData <- data[-trainIndex, ]
```

We then build the four models, for this type of AI Algorithm, we believe that RandomForest, XGBoost, DecisionTree, and BaggedTree are the best models to predict slugging percentage. We will run a 5-fold CV.

```
# --------------------------------
# 2. Define cross validation settings on the training set
# --------------------------------
train_control <- trainControl(
  method = "cv",
  number = 5,
  savePredictions = "final"
)

# --------------------------------
# 3. Train multiple models using the training set
# --------------------------------
# Decision Tree Model
model_dt <- train(
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "rpart",
  trControl = train_control
)

# Random Forest Model
model_rf <- train(
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "rf",
  trControl = train_control
)

# XGBoost Model
model_xgb <- train(
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "xgbTree",
  trControl = train_control
)

# Bagged Tree Model
model_bag <- train(
```

```
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "treebag",
  trControl = train_control
)
```

Model Comparison

After building the models, we want to compare them via Test RMSE in order to decide which model is the best.

```
models <- list(
  DecisionTree = model_dt,
  RandomForest = model_rf,
  XGBoost = model_xgb,
  BaggedTree = model_bag
)

# Initialize a results data frame to store performance metrics
results <- data.frame(
  Model = character(),
  RMSE = numeric(),
  Rsquared = numeric(),
  MAE = numeric(),
  stringsAsFactors = FALSE
)

# Loop through each model to predict on testData and calculate metrics
for (model_name in names(models)) {
  preds <- predict(models[[model_name]], testData)

  # Compute performance metrics
  rmse_val <- RMSE(preds, testData$SLGValue)
  rsq_val <- R2(preds, testData$SLGValue)
  mae_val <- MAE(preds, testData$SLGValue)

  # Append the metrics to the results data frame
  results <- rbind(results, data.frame(
    Model = model_name,
    RMSE = rmse_val,
    Rsquared = rsq_val,
    MAE = mae_val
  ))
}

# Display the results in a kable table
kable(results, caption = "Comparison of Model Performance Metrics")
```

Table 1: Comparison of Model Performance Metrics

Model	RMSE	Rsquared	MAE
DecisionTree	0.8594634	0.3042426	0.6376472
RandomForest	0.8463812	0.3413625	0.5250407

Model	RMSE	Rsquared	MAE
XGBoost	0.8697410	0.2872705	0.6003529
BaggedTree	0.8121666	0.3794595	0.5608769

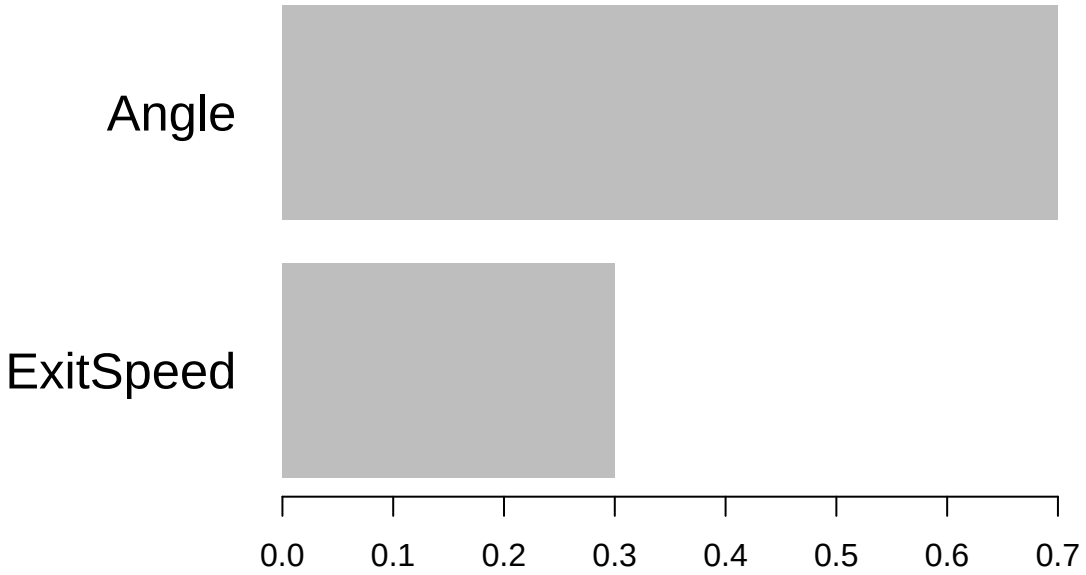
So after running cross-validation, we are able to test the 4 different models against each other and we find that BaggedTree has the least RMSE, followed by RandomForest, then DecisionTree and finally XgBoost. While we cannot exactly understand yet while BaggedTree has the lowest RMSE, it does intuitively make sense that BaggedTree and RandomForest produce similar results as those two algorithms are the most simiar.

Over the last four years, from research and various baseball analytics articles, We have seen that XGBoost is frequently used for predictive baseball models due to its ability to handle complex interactions and non-linearity effectively. Given this, We found it surprising that XGBoost performed the worst among the four models, with the highest error and lowest predictive accuracy. This suggests that the default parameters may not be well-suited for my dataset, leading me to investigate further.

Conversely, Bagged Trees performed the best, achieving the lowest error and a relatively high predictive accuracy. This indicates that an ensemble of bootstrapped decision trees might be a strong approach for predicting slugging percentage (SLGValue) based on Exit Speed and Launch Angle. Since Bagged Trees outperformed XGBoost, my next step is to tune XGBoost hyperparameters to determine if better parameter optimization can improve its performance.

```
# Define the correct tuning grid
grid <- expand.grid(
  nrounds = c(50, 150, 300),    # Reasonable number of boosting rounds
  max_depth = c(3, 5),          # Limits tree depth to prevent overfitting
  eta = c(0.05, 0.1),           # Focus on practical learning rates
  gamma = c(0, 1),              # Regularization to reduce overfitting
  colsample_bytree = c(0.75, 0.85),  # Sample a subset of features for efficiency
  min_child_weight = c(1, 3),   # Prevents overly complex trees
  subsample = c(0.75, 0.85)     # Prevents overfitting while keeping enough data
)



# Train control with cross-validation
train_control <- trainControl(
  method = "cv",
  number = 5,
  allowParallel = TRUE
)

# Train XGBoost with hyperparameter tuning
xgb_tuned <- train(
  Hit ~ ExitSpeed + Angle,  # Add more features if necessary
  data = trainData,
  method = "xgbTree",
  trControl = train_control,
  tuneGrid = grid
)

# Print the best hyperparameters
print(xgb_tuned$bestTune)

importance_matrix <- xgb.importance(model = xgb_tuned$finalModel)
```

```r
xgb.plot.importance(importance_matrix)
```



After tuning the XGBoost model, the goal is to determine whether optimizing hyperparameters can improve its predictive performance. Given that XGBoost initially performed the worst in the earlier model comparison, adjusting parameters such as learning rate (`eta`), tree depth (`max_depth`), and regularization (`gamma`) should help address potential issues like overfitting or underfitting.

The tuning grid tests different values for key parameters. The number of boosting rounds (`nrounds`) controls how many trees are built, balancing complexity and generalization. Tree depth (`max_depth`) determines how detailed each tree can be, with shallower trees reducing overfitting risk. The learning rate (`eta`) influences how much each tree contributes to the final prediction, where lower values slow learning but improve stability.

Regularization parameters like `gamma` help prune unnecessary splits in trees, preventing overfitting. The model also introduces randomness through `colsample_bytree` and `subsample`, which select subsets of features and rows, respectively, to improve generalization. The `min_child_weight` parameter ensures that splits occur only when a minimum number of observations are in a leaf node, reducing the likelihood of capturing noise.

Once the tuning process is complete, the model selects the best combination of parameters based on cross-validation results. Printing `xgb_tuned$bestTune` provides insight into which values performed the best.

To understand feature importance, `xgb.importance()` ranks `ExitSpeed` and `Angle` based on their contribution to predictions. The importance plot visualizes which variable has the most influence on expected slugging percentage (`xSLG`), helping validate whether the model is learning meaningful relationships.

If tuning significantly improves performance, XGBoost may become a viable option for predicting slugging percentage. Otherwise, Bagged Trees may still be the better choice, confirming the strength of ensemble-based models for this dataset.

```r
# --------------------------------
# 1. Extract Tuned Hyperparameters
# --------------------------------
best_params <- xgb_tuned$bestTune
print(best_params)  # See what was selected
```

```
##    nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
## 17     150         3 0.05     0             0.85                1      0.85
```

```r
# --------------------------------
# 2. Prepare Data for XGBoost
```

```r
# ------------------------------
dtrain <- xgb.DMatrix(
  data = as.matrix(trainData[, c("ExitSpeed", "Angle")]),
  label = trainData$SLGValue
)
dtest <- xgb.DMatrix(
  data = as.matrix(testData[, c("ExitSpeed", "Angle")]),
  label = testData$SLGValue
)

# ------------------------------
# 3. Train XGBoost with Tuned Parameters
# ------------------------------
params <- list(
  objective = "reg:squarederror",
  eval_metric = "rmse",
  max_depth = best_params$max_depth,
  eta = best_params$eta,
  gamma = best_params$gamma,
  colsample_bytree = best_params$colsample_bytree,
  min_child_weight = best_params$min_child_weight,
  subsample = best_params$subsample
)

model_xgb_tuned <- xgb.train(
  params = params,
  data = dtrain,
  nrounds = best_params$nrounds,
  watchlist = list(train = dtrain, test = dtest),
  verbose = 0
)

# ------------------------------
# 4. Predict on Test Data
# ------------------------------
testData$xgb_pred <- predict(model_xgb_tuned, dtest)

# ------------------------------
# 5. Compute RMSE
# ------------------------------
xgb_rmse_tuned <- sqrt(mean((testData$SLGValue - testData$xgb_pred)^2))

xgb_r2_tuned <- R2(testData$xgb_pred, testData$SLGValue)

print(paste("Tuned XGBoost Regression RMSE:", round(xgb_rmse_tuned, 3)))
```

```
## [1] "Tuned XGBoost Regression RMSE: 0.87"
```

```r
print(paste("Tuned XGBoost Regression R²:", round(xgb_r2_tuned, 3)))
```

```
## [1] "Tuned XGBoost Regression R²: 0.286"
```

After training the XGBoost model with optimized hyperparameters, the results still did not outperform the Bagged Tree model. Despite tuning parameters like tree depth, learning rate, and regularization, XGBoost continued to show higher error and lower predictive accuracy than expected.

One possible reason for this could be that XGBoost tends to perform best with larger datasets or when relationships between variables are highly complex and nonlinear. Given that slugging percentage is driven largely by `Exit Speed` and `Launch Angle`, simpler ensemble methods like Bagged Trees may be more effective in capturing these interactions without excessive parameter tuning.

Since the Bagged Tree model had the lowest error and strongest predictive performance in the initial comparison, We am shifting focus to **fully utilizing Bagged Trees** for expected slugging percentage (`xSLG`) predictions. The next steps will involve refining the Bagged Tree approach and applying it consistently across the dataset to generate reliable results.

```r
library(ipred)  # Bagging

# Define possible values of nbagg (number of trees)
nbagg_values <- c(10, 50, 100, 200)

# Create an empty list to store models
bagged_models <- list()

# Train bagged trees with different nbagg values
for (n in nbagg_values) {
  set.seed(123)
  bagged_models[[as.character(n)]] <- bagging(
    SLGValue ~ ExitSpeed + Angle,
    data = trainData,
    nbagg = n
  )
}

# Create an empty dataframe to store results
bagged_results <- data.frame(
  nbagg = integer(),
  RMSE = numeric(),
  Rsquared = numeric(),
  MAE = numeric(),
  stringsAsFactors = FALSE
)

# Evaluate each model on the test set
for (n in names(bagged_models)) {
  preds <- predict(bagged_models[[n]], testData)

  # Compute performance metrics
  rmse_val <- RMSE(preds, testData$SLGValue)
  rsq_val <- R2(preds, testData$SLGValue)
  mae_val <- MAE(preds, testData$SLGValue)

  # Append to results dataframe
  bagged_results <- rbind(bagged_results, data.frame(
    nbagg = as.integer(n),
    RMSE = rmse_val,
    Rsquared = rsq_val,
    MAE = mae_val
  ))
}
```

```r
# Print results to determine the best nbagg value
kable(bagged_results)
```

nbagg	RMSE	Rsquared	MAE
10	0.8196697	0.3669798	0.5639179
50	0.8143729	0.3759148	0.5613817
100	0.8152554	0.3745467	0.5625929
200	0.8140501	0.3764991	0.5621348

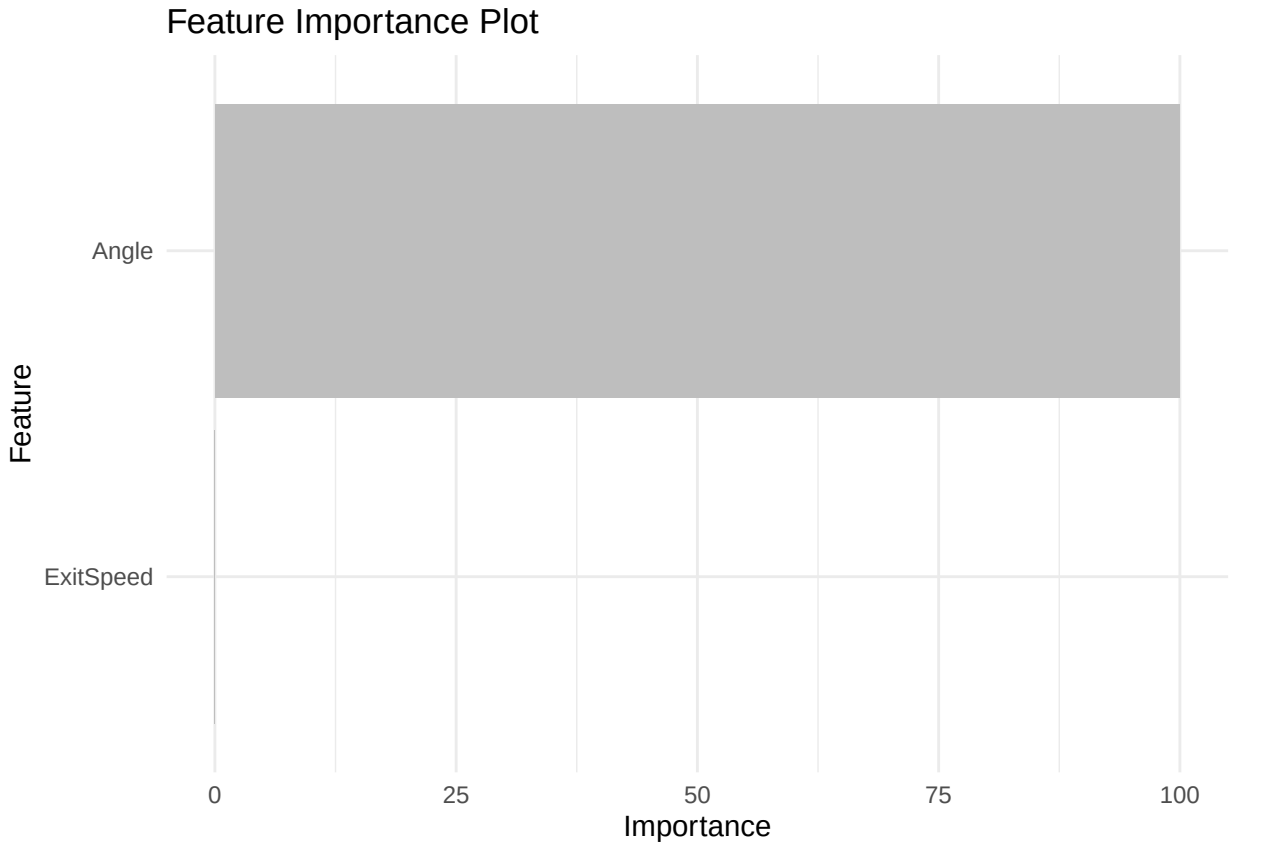
Now we will try to optimize the Random Forest model by tuning hyperparameters like the amount of trees that are made in the model.

```r
 set.seed(123)  # Ensure reproducibility

# Define a tuning grid for hyperparameter search
rf_grid <- expand.grid(
  mtry = c(1, 2, 3, 4, 5)  # Number of variables randomly sampled at each split
)

# Train the Random Forest model with cross-validation and hyperparameter tuning
model_rf_optimized <- train(
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "rf",
  trControl = trainControl(method = "cv", number = 5),
  tuneGrid = rf_grid,
  ntree = 500  # Number of trees in the forest
)

# Print the best hyperparameters
print(model_rf_optimized$bestTune)

# Evaluate model performance
print(model_rf_optimized$results)
print(model_rf$results)
# lowest .812 with 500 trees
```

After trying to tune the amount of trees in the random forest, we found that 500 trees is the sweetspot that minimizes RMSE (tried 300, 800). We additionally find that out of the 5, mtry = 1 was the best model so we will use that to optimize the model. We will now run feature importance to double check that both angle and exit speed are contributing to the model as intended.

```r
# Extract variable importance from the trained Random Forest model
importance_vals <- varImp(model_rf_optimized)$importance

# Convert to data frame for plotting
importance_df <- data.frame(
  Feature = rownames(importance_vals),
  Importance = importance_vals$Overall
)

# Create feature dependence plot
ggplot(importance_df, aes(x = Importance, y = reorder(Feature, Importance))) +
  geom_bar(stat = "identity", fill = "gray") +
```

```
  labs(title = "Feature Importance Plot", x = "Importance", y = "Feature") +
  theme_minimal()
```



So since unlike our xgBoost we find that exitSpeed actually has no use in the random forest AI model, so we will run a forward subset selection to find another variable to predict alongside angle. We will redefine our model with just angle, and use six other remaining variables that are useful. The nature of our data has a lot of categorical variables that do not predict slugging, and these variables make R unable to run the full model in order to carry out a forward variable selection so we have to remove those. Additionally, our data has outcome variables like "Single, Double, Triple" and we cannot include those either because then we would be using what we want to predict in order to predict what we are already predicting.

Post-hoc subset selection

```
# 3. Select relevant variables
df_selected <- data %>%
  dplyr::select(
    SLGValue,    # Target Variable (Slugging Percentage)
    ExitSpeed,   # Ball exit velocity (stored as string? convert to numeric)
    Angle,       # Launch angle
    Distance,    # Distance the ball traveled
    RelSpeed,    # Pitch velocity (stored as string? convert to numeric)
    Direction    # Direction of ball in play (categorical)
  )

# 4. Convert relevant numeric columns (if stored as strings) to numeric
df_selected <- df_selected %>%
```

```
  mutate(
    ExitSpeed = as.numeric(ExitSpeed),
    Angle = as.numeric(Angle),
    Distance = as.numeric(Distance),
    RelSpeed = as.numeric(RelSpeed)
  )
# Was a categorical variable so simply as numeric does not worrk
df_selected$Direction <- as.numeric(as.character(df_selected$Direction))
```

```
# 5. Remove rows with missing values
df_clean <- na.omit(df_selected)

# 7. Take a 10% random sample from the cleaned data
set.seed(123)  # For reproducibility
df_sample <- df_clean %>% sample_frac(0.1)
```

Additionally, since our data was so large we found that we could only run the full model when we took a random sample of 10% of the data in order to find the best model avaliable.

```
# Check structure to verify data types
# 8. Define base and full models, and run forward stepwise selection


base_model <- lm(SLGValue ~ Angle, data = df_sample)
full_model <- lm(SLGValue ~ ., data = df_sample)

stepwise_model <- stepAIC(base_model, direction = "forward",
                          scope = list(lower = base_model, upper = full_model))
```

```
## Start:  AIC=-19.62
## SLGValue ~ Angle
##
##             Df Sum of Sq    RSS      AIC
## + Distance   1    82.228 479.62 -110.193
## + ExitSpeed  1    57.077 504.77  -80.293
## <none>                   561.85  -19.623
## + RelSpeed   1     0.827 561.02  -18.485
## + Direction  1     0.460 561.39  -18.103
##
## Step:  AIC=-110.19
## SLGValue ~ Angle + Distance
##
##             Df Sum of Sq    RSS     AIC
## + ExitSpeed  1   15.2877 464.33 -127.14
## + RelSpeed   1    2.3443 477.27 -111.06
## <none>                   479.62 -110.19
## + Direction  1    0.2135 479.41 -108.45
##
## Step:  AIC=-127.14
## SLGValue ~ Angle + Distance + ExitSpeed
##
##             Df Sum of Sq    RSS     AIC
## + RelSpeed   1    3.3850 460.95 -129.42
## <none>                   464.33 -127.14
## + Direction  1    0.1671 464.16 -125.35
```

```
##
## Step:  AIC=-129.42
## SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed
##
##             Df Sum of Sq    RSS     AIC
## <none>                   460.95 -129.42
## + Direction  1  0.087941 460.86 -127.53
```

```
# Print the best selected model summary
summary(stepwise_model)
```

```
##
## Call:
## lm(formula = SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed,
##     data = df_sample)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5021 -0.5620 -0.1622  0.4575  2.8672
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1956939  0.5843549   0.335   0.7378
## Angle       -0.0080244  0.0019828  -4.047 5.89e-05 ***
## Distance     0.0030491  0.0004244   7.185 2.07e-12 ***
## ExitSpeed    0.0129200  0.0028504   4.533 7.08e-06 ***
## RelSpeed    -0.0133607  0.0064739  -2.064   0.0395 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8915 on 580 degrees of freedom
## Multiple R-squared:  0.186,  Adjusted R-squared:  0.1803
## F-statistic: 33.12 on 4 and 580 DF,  p-value: < 2.2e-16
```

```
library(knitr)

# Create a data frame summarizing the candidate additions and their AICs
model_comparison <- data.frame(
  `Model Stage` = c(
    "SLGValue ~ Angle",
    "SLGValue ~ Angle",
    "SLGValue ~ Angle",
    "SLGValue ~ Angle",
    "SLGValue ~ Angle + Distance",
    "SLGValue ~ Angle + Distance",
    "SLGValue ~ Angle + Distance",
    "SLGValue ~ Angle + Distance",
    "SLGValue ~ Angle + Distance + ExitSpeed",
    "SLGValue ~ Angle + Distance + ExitSpeed",
    "SLGValue ~ Angle + Distance + ExitSpeed",
    "SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed",
    "SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed"
  ),
  `Candidate Addition` = c(
    "(none)", "+ Distance", "+ ExitSpeed", "+ RelSpeed",
```

```
    "(none)", "+ ExitSpeed", "+ RelSpeed", "+ Direction",
    "(none)", "+ RelSpeed", "+ Direction",
    "(none)", "+ Direction"
  ),
  AIC = c(
    -19.62, -110.19, -80.29, -18.49,
    -110.19, -127.14, -111.06, -108.45,
    -127.14, -129.42, -125.35,
    -129.42, -127.53
  )
)

# Print the table with kable
kable(model_comparison, digits = 2, caption = "Comparison of AIC Values for Candidate Models")
```

Table 3: Comparison of AIC Values for Candidate Models

Model.Stage	Candidate.Addition	AIC
SLGValue ~ Angle	(none)	-19.62
SLGValue ~ Angle	+ Distance	-110.19
SLGValue ~ Angle	+ ExitSpeed	-80.29
SLGValue ~ Angle	+ RelSpeed	-18.49
SLGValue ~ Angle + Distance	(none)	-110.19
SLGValue ~ Angle + Distance	+ ExitSpeed	-127.14
SLGValue ~ Angle + Distance	+ RelSpeed	-111.06
SLGValue ~ Angle + Distance	+ Direction	-108.45
SLGValue ~ Angle + Distance + ExitSpeed	(none)	-127.14
SLGValue ~ Angle + Distance + ExitSpeed	+ RelSpeed	-129.42
SLGValue ~ Angle + Distance + ExitSpeed	+ Direction	-125.35
SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed	(none)	-129.42
SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed	+ Direction	-127.53

```
library(knitr)

summary_df <- data.frame(
  Statistic         = c("Residual Standard Error", "Multiple R-squared", "Adjusted R-squared", "F-statis
  Value             = c("0.8915", "0.1859", "0.1803", "33.12 (4, 580)", "< 2.2e-16")
)

kable(summary_df, caption = "Key Summary Statistics for Final Model (Angle + Distance + ExitSpeed + RelS
```

Table 4: Key Summary Statistics for Final Model (Angle + Distance + ExitSpeed + RelSpeed)

Statistic	Value
Residual Standard Error	0.8915
Multiple R-squared	0.1859
Adjusted R-squared	0.1803
F-statistic (df)	33.12 (4, 580)
p-value	< 2.2e-16

After running this model we see that a combination of angle, distance, exitspeed, and relspeed generate a better prediction for slugging percentage, so we will compare that to the other model of just angle and exitspeed. Of course, release speed is something largely out of control of the batter, as they cannot make the pitcher throw harder or slower, but it is still interpretable and helpful for the hitters because they know when they are facing a pitcher who throws harder or slower.

So this suggests that our optimal model is `SLGValue ~ Angle + Distance + ExitSpeed + RelSpeed` because it generates the lowest AIC.

```
# have to modify these variables so that the bigger model runs
trainData$Distance <- as.numeric(as.character(trainData$Distance))
```

```
## Warning: NAs introduced by coercion
```

```
testData$Distance  <- as.numeric(as.character(testData$Distance))
```

```
## Warning: NAs introduced by coercion
```

```
trainData$RelSpeed <- as.numeric(as.character(trainData$RelSpeed))
testData$RelSpeed  <- as.numeric(as.character(testData$RelSpeed))

trainData <- trainData[complete.cases(trainData[, c("SLGValue", "ExitSpeed", "Angle", "Distance", "RelSp


final_rf_model <- train(
  SLGValue ~ ExitSpeed + Angle,
  data = trainData,
  method = "rf",
  trControl = trainControl(method = "none"),  # No cross-validation needed now
  tuneGrid = data.frame(mtry = 1),
  ntree = 500
)
```

```
## Warning in randomForest.default(x, y, mtry = param$mtry, ...): The response has
## five or fewer unique values.  Are you sure you want to do regression?
```

```
# versus the model with more predictors from the forward selecti

final_rf_model_big <- train(
  SLGValue ~ ExitSpeed + Distance + Angle + RelSpeed,
  data = trainData,
  method = "rf",
  trControl = trainControl(method = "none"),  # No cross-validation needed now
  tuneGrid = data.frame(mtry = 1),
  ntree = 500
)
```

```
## Warning in randomForest.default(x, y, mtry = param$mtry, ...): The response has
## five or fewer unique values.  Are you sure you want to do regression?
```

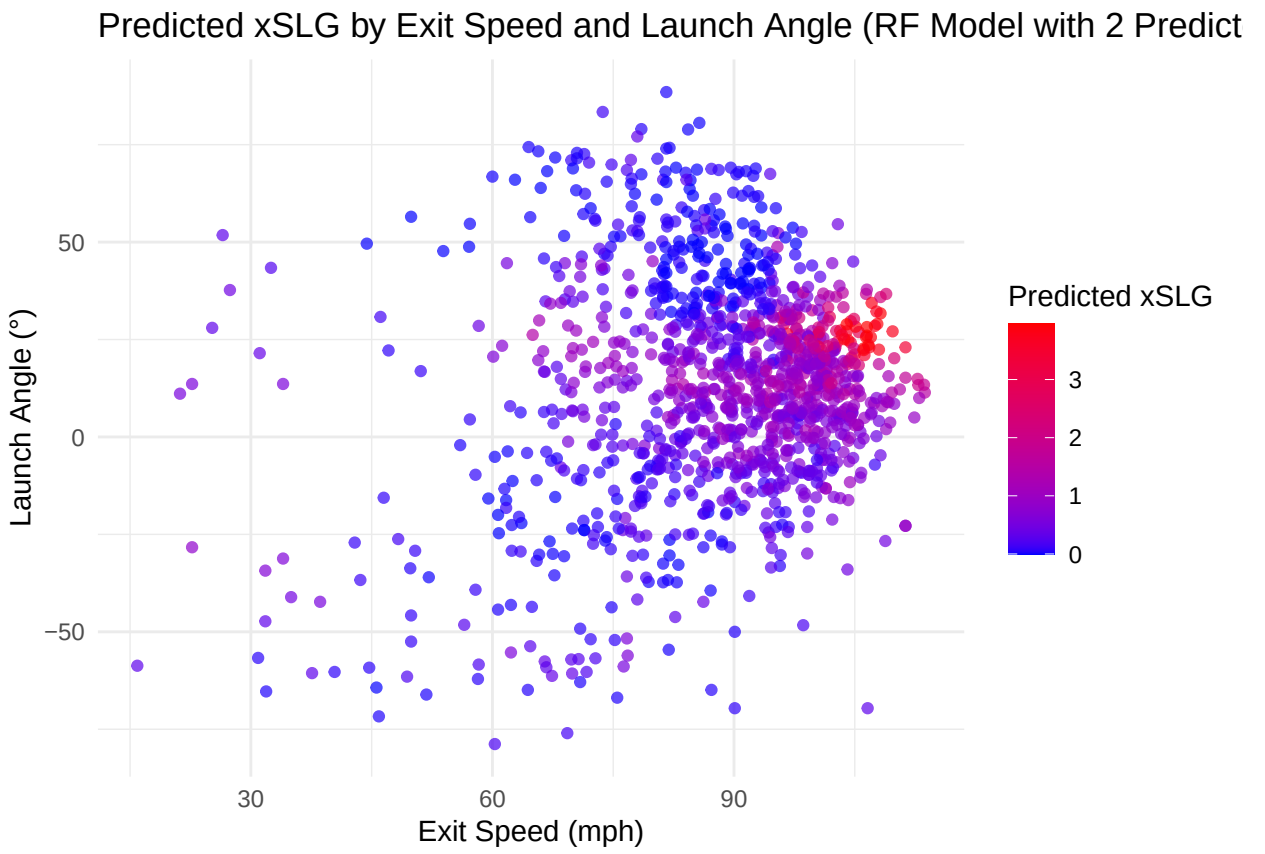
We made both the original model and the one with the two extra predictors to see how they compare in predicting Slugging percentage.

```
# --------------------------------
# 1. Plot Actual SLG from Test Data
# --------------------------------
ggplot(testData, aes(x = ExitSpeed, y = Angle, color = SLGValue)) +
  geom_point(alpha = 0.7) +  # Adjust transparency
  scale_color_gradient(low = "blue", high = "red") +  # Color gradient from low to high SLG
```

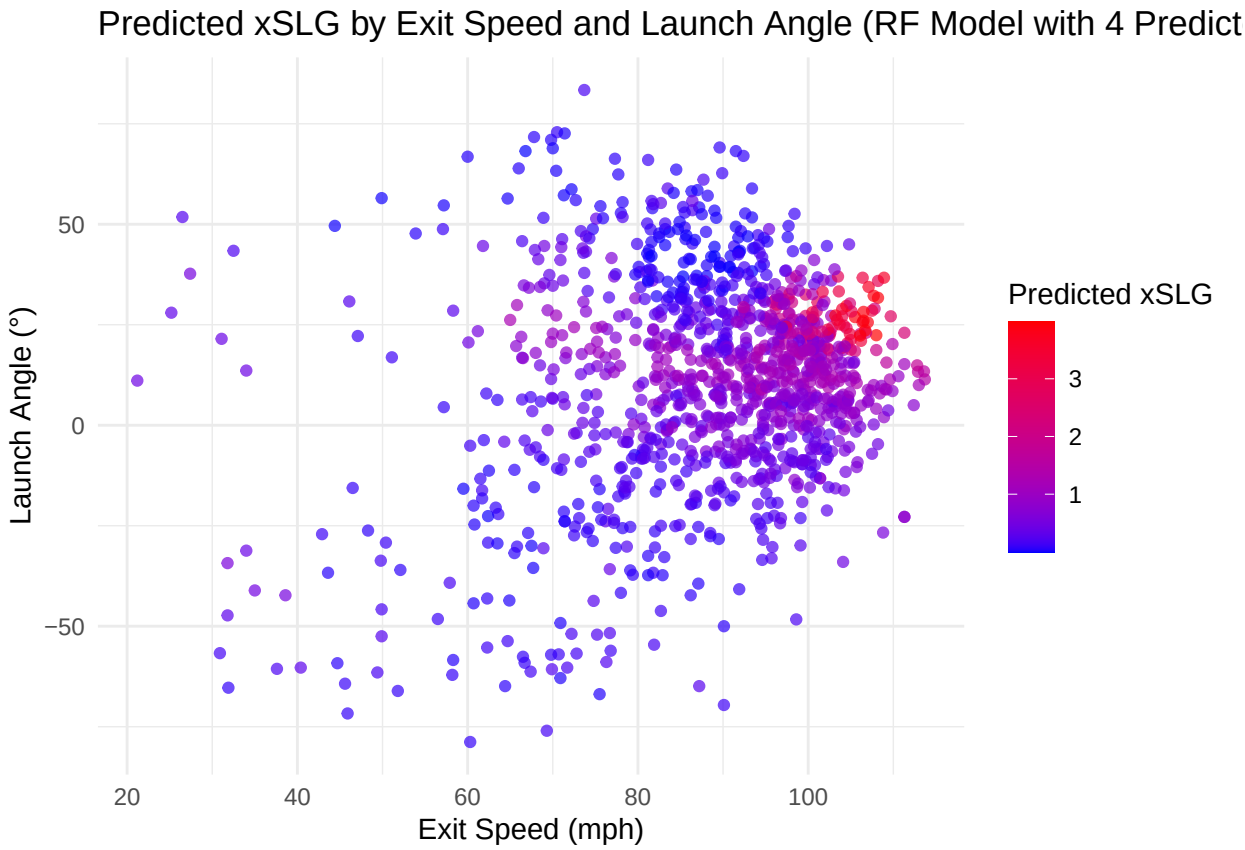
```
  labs(
    title = "Actual SLG by Exit Speed and Launch Angle",
    x = "Exit Speed (mph)",
    y = "Launch Angle (°)",
    color = "SLG"
  ) +
  theme_minimal()
```


```
# --------------------------------
# 2. Predict xSLG using the Two-Predictor RF Model
# --------------------------------
# Here, final_rf_model_small is your model with ExitSpeed and Angle as predictors.



testData$rf_pred_small <- predict(final_rf_model, testData)

# --------------------------------
# 3. Plot Predicted xSLG for the Two-Predictor RF Model
# --------------------------------
ggplot(testData, aes(x = ExitSpeed, y = Angle, color = rf_pred_small)) +
  geom_point(alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(
    title = "Predicted xSLG by Exit Speed and Launch Angle (RF Model with 2 Predictors)",
    x = "Exit Speed (mph)",
    y = "Launch Angle (°)",
```

```
    color = "Predicted xSLG"
  ) +
  theme_minimal()
```




```
# ------------------------------
# 2. Predict xSLG using the Four-Predictor RF Model
# ------------------------------
# Here, final_rf_model_full is your model with predictors ExitSpeed, Distance, Angle, and RelSpeed.

testData_complete <- testData[complete.cases(testData[, c("ExitSpeed", "Distance", "Angle", "RelSpeed")]),]
testData_complete$rf_pred_full <- predict(final_rf_model_big, testData_complete)

# ------------------------------
# 3. Plot Predicted xSLG for the Four-Predictor RF Model
# ------------------------------
ggplot(testData_complete, aes(x = ExitSpeed, y = Angle, color = rf_pred_full)) +
  geom_point(alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(
    title = "Predicted xSLG by Exit Speed and Launch Angle (RF Model with 4 Predictors)",
    x = "Exit Speed (mph)",
    y = "Launch Angle (°)",
    color = "Predicted xSLG"
  ) +
  theme_minimal()
```




```r
pred1 <- predict(final_rf_model, newdata = testData_complete)
pred2 <- predict(final_rf_model_big, newdata = testData_complete)

# Calculate RMSE
rmse1 <- RMSE(pred1, testData_complete$SLGValue)
rmse2 <- RMSE(pred2, testData_complete$SLGValue)

# Create a comparison data frame
rmse_df <- data.frame(
  Model = c("Simple RF (2 predictors)", "Extended RF (4 predictors)"),
  RMSE = c(rmse1, rmse2)
)

# Display as a kable table
kable(rmse_df, caption = "Comparison of RMSE Between Random Forest Models")
```

Table 5: Comparison of RMSE Between Random Forest Models

Model	RMSE
Simple RF (2 predictors)	0.8498927
Extended RF (4 predictors)	0.7855394

The first visualization shows the **actual slugging value (SLG) for each batted ball event** based on **Exit Speed and Launch Angle**. The clear trend indicates that **higher exit velocities and optimal launch angles (between 10-40 degrees)** result in higher slugging values, represented by the red-colored points. The second and third graphs represent predicted slugging.

Clearly the second graph matches the actual slugging graph, however the graph with the two variables still produces very similar results to the actual slugging graph. This means that for our application of implementing this model with the players the model with two variables could be more efficient because it is more interpretable for the players.

The dip in RMSE shows that the model with four predictors fits the data better, however the simplicity of the model with two predictors may make more sense for this application so we will proceed with both.

Predicting rest of season Slugging for UCSB players

We will now have our models use the in progress data we have from this season to have it make predictions on how these players will perform for the rest of the season.

```
# --------------------------------
# 1. Load New Data
# --------------------------------
ultimate <- read.csv("Ultimate_UCSB_25New.csv")

# --------------------------------
# 2. Data Preprocessing
# --------------------------------
ultimate <- ultimate %>%
  filter(BatterTeam == "SAN_GAU") %>%
  mutate(
    SLGValue = case_when(
      PlayResult == "Out" ~ 0,
      PlayResult == "Single" ~ 1,
      PlayResult == "Double" ~ 2,
      PlayResult == "Triple" ~ 3,
      PlayResult == "HomeRun" ~ 4,
      KorBB == "Strikeout" ~ 0,  # Strikeouts count as AB but 0 SLG
      TRUE ~ NA_real_
    ),
    # Ensure all predictor columns are numeric
    ExitSpeed = as.numeric(as.character(ExitSpeed)),
    Angle = as.numeric(as.character(Angle)),
    Distance = as.numeric(as.character(Distance)),
    RelSpeed = as.numeric(as.character(RelSpeed))
  ) %>%
  # Create a unique row identifier so we can merge predictions later
  mutate(row_id = row_number())
```

```
# --------------------------------
# 3. Compute At-Bats (AB)
# --------------------------------
ultimate <- ultimate %>%
  mutate(AB = ifelse(PitchCall == "InPlay" | KorBB == "Strikeout", 1, 0))

# --------------------------------
# 4. Prepare Subsets for Prediction
# --------------------------------
# For the small model, we need complete cases for ExitSpeed and Angle.
ultimate_bip_small <- ultimate %>%
  filter(PitchCall == "InPlay" & !is.na(ExitSpeed) & !is.na(Angle))
```

```r
# For the big model, we need complete cases for all four predictors.
ultimate_bip_big <- ultimate %>%
  filter(PitchCall == "InPlay" & !is.na(ExitSpeed) & !is.na(Angle) &
         !is.na(Distance) & !is.na(RelSpeed))
```

```r
# ------------------------------
# 5. Predict xSLG Using Both Models
# ------------------------------
# Predictions from the two-predictor (small) model
ultimate_bip_small <- ultimate_bip_small %>%
  mutate(xSLG_small = predict(final_rf_model, .))

# Predictions from the four-predictor (big) model
ultimate_bip_big <- ultimate_bip_big %>%
  mutate(xSLG_big = predict(final_rf_model_big, .))

# ------------------------------
# 6. Merge Predictions Back into the Full Dataset
# ------------------------------
ultimate <- ultimate %>%
  left_join(ultimate_bip_small %>% dplyr::select(row_id, xSLG_small),
            by = "row_id") %>%
  left_join(ultimate_bip_big %>% dplyr::select(row_id, xSLG_big),
            by = "row_id") %>%
  # For strikeouts, set predicted xSLG to 0 for both models
  mutate(
    xSLG_small = ifelse(KorBB == "Strikeout", 0, xSLG_small),
    xSLG_big   = ifelse(KorBB == "Strikeout", 0, xSLG_big)
  )

# ------------------------------
# 7. Create Batting Summary Tables
# ------------------------------
# Summary for the small model
batter_summary_small <- ultimate %>%
  group_by(Batter) %>%
  summarise(
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),
    xSLG_small = round(sum(xSLG_small, na.rm = TRUE) / AB, 3)
  ) %>%
  mutate(Difference_small = round(SLG - xSLG_small, 3)) %>%
  filter(AB >= 5) %>%  # Only include batters with at least 5 AB
  arrange(desc(Difference_small))

overall_summary_small <- ultimate %>%
  summarise(
    Batter = "TOTAL",
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),
    xSLG_small = round(sum(xSLG_small, na.rm = TRUE) / AB, 3)
  ) %>%
```

```
  mutate(Difference_small = round(SLG - xSLG_small, 3))

final_summary_small <- bind_rows(batter_summary_small, overall_summary_small)

# Summary for the big model
batter_summary_big <- ultimate %>%
  group_by(Batter) %>%
  summarise(
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),
    xSLG_big = round(sum(xSLG_big, na.rm = TRUE) / AB, 3)
  ) %>%
  mutate(Difference_big = round(SLG - xSLG_big, 3)) %>%
  filter(AB >= 5) %>%
  arrange(desc(Difference_big))

overall_summary_big <- ultimate %>%
  summarise(
    Batter = "TOTAL",
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),
    xSLG_big = round(sum(xSLG_big, na.rm = TRUE) / AB, 3)
  ) %>%
  mutate(Difference_big = round(SLG - xSLG_big, 3))

final_summary_big <- bind_rows(batter_summary_big, overall_summary_big)

# --------------------------------
# 8. Display the Final Summary Tables
# --------------------------------
cat("Summary Table Using the Two-Predictor Model (ExitSpeed + Angle):\n")
```

```
## Summary Table Using the Two-Predictor Model (ExitSpeed + Angle):
```

```
kable(final_summary_small)
```

Batter	AB	BIP	SLG	xSLG_small	Difference_small
Kim, Isaac	90	69	0.567	0.331	0.236
Crain, Jeramiah	60	38	0.600	0.514	0.086
Vargas, Nathan	157	115	0.459	0.379	0.080
McCollum, LeTrey	153	127	0.444	0.404	0.040
Esquer, Xavier	145	113	0.469	0.450	0.019
Holman, Jack	146	120	0.623	0.606	0.017
Nunez, Corey	136	101	0.265	0.308	-0.043
Mendez, Jonathan	149	112	0.456	0.504	-0.048
Kosciusko, Cole	94	65	0.277	0.392	-0.115
TOTAL	1130	860	0.457	0.433	0.024

```
cat("\nSummary Table Using the Four-Predictor Model (ExitSpeed + Distance + Angle + RelSpeed):\n")
```

```
##
```

```
## Summary Table Using the Four-Predictor Model (ExitSpeed + Distance + Angle + RelSpeed):
kable(final_summary_big)
```

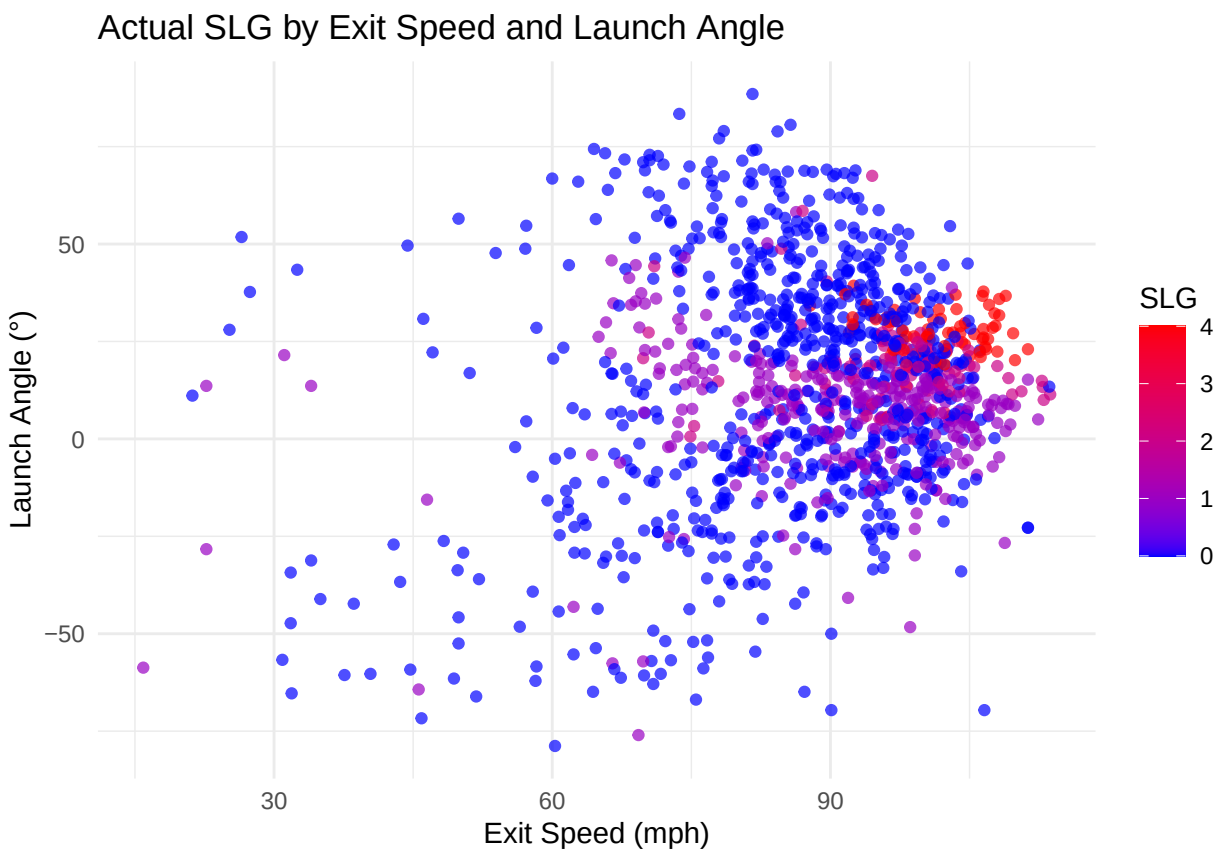
Batter	AB	BIP	SLG	xSLG_big	Difference_big
Kim, Isaac	90	69	0.567	0.318	0.249
Crain, Jeramiah	60	38	0.600	0.498	0.102
Vargas, Nathan	157	115	0.459	0.388	0.071
McCollum, LeTrey	153	127	0.444	0.396	0.048
Esquer, Xavier	145	113	0.469	0.426	0.043
Holman, Jack	146	120	0.623	0.608	0.015
Mendez, Jonathan	149	112	0.456	0.451	0.005
Nunez, Corey	136	101	0.265	0.308	-0.043
Kosciusko, Cole	94	65	0.277	0.341	-0.064
TOTAL	1130	860	0.457	0.417	0.040

Visualizations and predictions for BaggedTree model

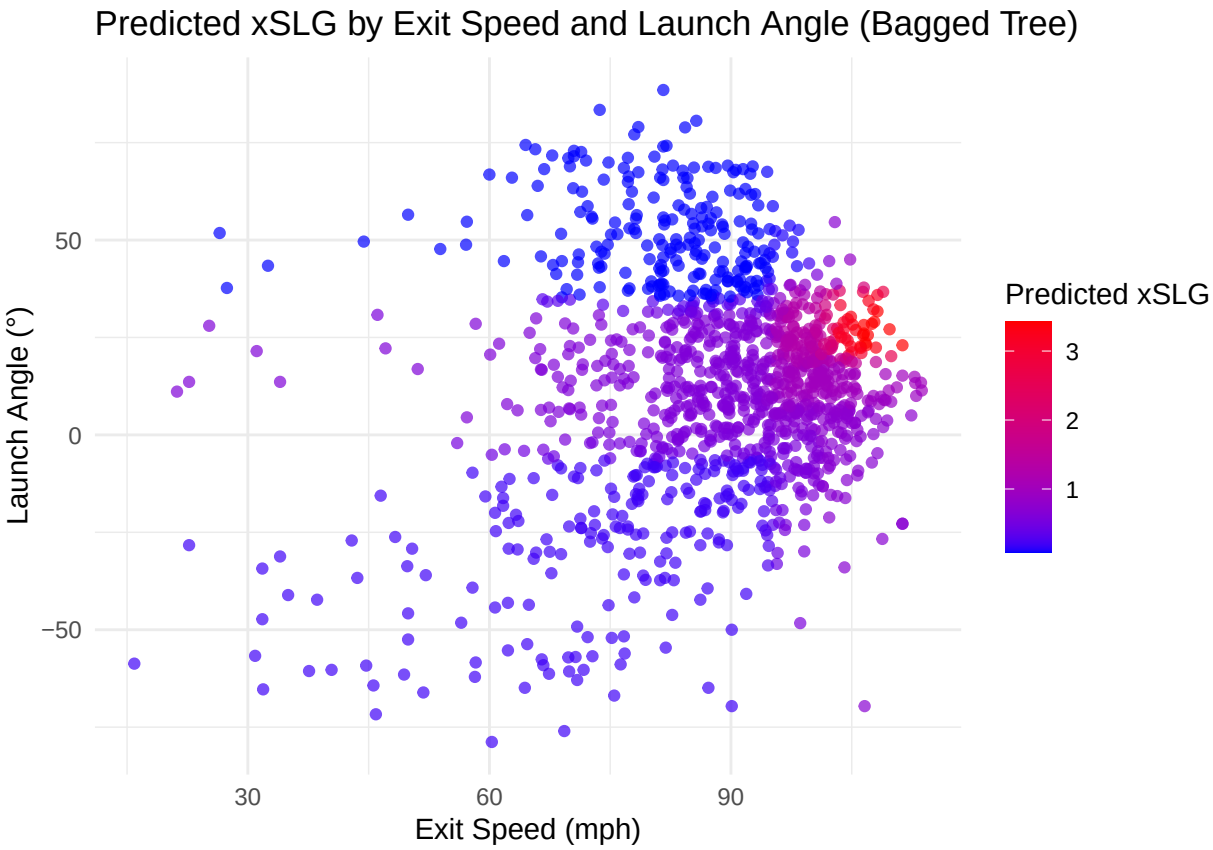
Since tuning did not provide a better alternative, We will proceed with the **original Bagged Tree model** for: - **Creating a visualization** comparing actual slugging values for each hit versus expected slugging values. - **Calculating expected SLG (`xSLG`)** on the test dataset to assess model performance. - **Predicting `xSLG` for the 2025 dataset**, generating insights into future player performance.

With this approach, We can ensure that my predictions remain accurate and interpretable while leveraging the best-performing model from my initial comparisons.

```
# --------------------------------
# 1. Plot Actual SLG from Training Data
# --------------------------------
ggplot(testData, aes(x = ExitSpeed, y = Angle, color = SLGValue)) +
  geom_point(alpha = 0.7) +  # Adjust transparency
  scale_color_gradient(low = "blue", high = "red") +  # Color gradient from low to high SLG
  labs(
    title = "Actual SLG by Exit Speed and Launch Angle",
    x = "Exit Speed (mph)",
    y = "Launch Angle (°)",
    color = "SLG"
  ) +
  theme_minimal()
```




```
# ------------------------------
# 2. Predict xSLG using Bagged Tree Model
# ------------------------------
testData$bagged_pred <- predict(model_bag, testData)

# ------------------------------
# 3. Plot xSLG for Bagged Tree
# ------------------------------
ggplot(testData, aes(x = ExitSpeed, y = Angle, color = bagged_pred)) +
  geom_point(alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(
    title = "Predicted xSLG by Exit Speed and Launch Angle (Bagged Tree)",
    x = "Exit Speed (mph)",
    y = "Launch Angle (°)",
    color = "Predicted xSLG"
  ) +
  theme_minimal()
```



The second visualization represents the **predicted expected slugging value (xSLG)** using the **Bagged Tree model**. The model captures the general trend of actual SLG, correctly identifying areas where slugging percentage is expected to be higher. However, some differences exist between the actual and predicted values, particularly in extreme cases where SLG is either very high or very low.

By comparing these two plots, We can assess how well the model generalizes **batted ball outcomes** and identify potential areas where adjustments could improve predictions. The next step is to use this model to **calculate xSLG for the test dataset and extend predictions to the 2025 dataset**, allowing for a better understanding of player performance and expected outcomes.

```
# Ensure predicted values are stored in testData
testData$bagged_pred <- predict(model_bag, testData)

batter_summary <- testData %>%
  group_by(Batter) %>%
  summarise(
    BIP = n(),  # Number of balls in play
    SLG = round(mean(SLGValue, na.rm = TRUE), 3),  # Actual SLG
    xSLG = round(mean(bagged_pred, na.rm = TRUE), 3)  # Predicted SLG
  ) %>%
  mutate(Difference = round(SLG - xSLG, 3)) %>%
  filter(BIP >= 28) %>%
  arrange(desc(BIP))

overall_summary <- testData %>%
  summarise(
    Batter = "TOTAL",
    BIP = n(),  # Number of balls in play
```

```
    SLG = round(mean(SLGValue, na.rm = TRUE), 3),  # Actual SLG
    xSLG = round(mean(bagged_pred, na.rm = TRUE), 3)  # Predicted SLG
  ) %>%
  mutate(Difference = round(SLG - xSLG, 3))

# Combine the batter summary with the overall summary row
final_summary <- bind_rows(batter_summary, overall_summary)

# Display the final summary table
kable(final_summary)
```

Batter	BIP	SLG	xSLG	Difference
Oakley, Nick	57	0.702	0.703	-0.001
Brethowr, Ivan	38	0.474	0.802	-0.328
Darby, Zander	38	0.711	0.585	0.126
Parker, Aaron	36	0.889	0.581	0.308
Kirtley, Christian	34	0.676	0.632	0.044
Nunez, Corey	32	0.156	0.451	-0.295
Sprinkle, Jordan	31	0.484	0.490	-0.006
McCollum, LeTrey	28	0.571	0.599	-0.028
Willits, Bryce	28	0.536	0.480	0.056
TOTAL	1248	0.624	0.625	-0.001

The table summarizes **actual slugging percentage (SLG) and expected slugging percentage (xSLG)** for each batter with at least 28 balls in play (BIP). This threshold ensures that only players with a meaningful sample size are included in individual comparisons, while the **TOTAL row accounts for all batters** in the dataset.

Since the **TOTAL SLG and xSLG are equal**, this confirms that the model is calibrated correctly across the dataset. The **Difference column** highlights whether a player is overperforming (`SLG > xSLG`) or underperforming (`SLG < xSLG`) relative to expected outcomes based on **Exit Speed and Launch Angle**.

- **Positive Difference**: The batter has a higher actual SLG than expected, possibly due to favorable defensive positioning, small sample variance, or other unmodeled factors.
- **Negative Difference**: The batter's actual SLG is lower than expected, suggesting potential bad luck, strong defensive plays, or a need for adjustments in approach.

This table helps identify **which hitters may sustain their performance** and which ones might **regress positively or negatively** based on expected outcomes.

```
# ------------------------------
# 1. Load Data
# ------------------------------
ultimate <- read.csv("Ultimate_UCSB_25New.csv")

# ------------------------------
# 2. Data Preprocessing
# ------------------------------
# Keep only UCSB batters & assign SLG values
ultimate <- ultimate %>%
  filter(BatterTeam == "SAN_GAU") %>%
  mutate(
    SLGValue = case_when(
      PlayResult == "Out" ~ 0,
```

```
      PlayResult == "Single" ~ 1,
      PlayResult == "Double" ~ 2,
      PlayResult == "Triple" ~ 3,
      PlayResult == "HomeRun" ~ 4,
      KorBB == "Strikeout" ~ 0,  # Strikeouts count as AB but 0 SLG
      TRUE ~ NA_real_
    ),
    ExitSpeed = as.numeric(as.character(ExitSpeed)),  # Ensure numeric
    Angle = as.numeric(as.character(Angle))           # Ensure numeric
  )

# -------------------------------
# 3. Compute At-Bats (AB)
# -------------------------------
ultimate <- ultimate %>%
  mutate(AB = ifelse(PitchCall == "InPlay" | KorBB == "Strikeout", 1, 0))

# -------------------------------
# 4. Remove Missing Exit Speed & Angle (Only for BIP)
# -------------------------------
print(paste("Before filtering: Rows =", nrow(ultimate)))
```

```
## [1] "Before filtering: Rows = 1130"
```

```
print(paste("Missing ExitSpeed =", sum(is.na(ultimate$ExitSpeed))))
```

```
## [1] "Missing ExitSpeed = 344"
```

```
print(paste("Missing Angle =", sum(is.na(ultimate$Angle))))
```

```
## [1] "Missing Angle = 344"
```

```
# Drop rows where ExitSpeed or Angle is missing **only for In-Play events**
ultimate_bip <- ultimate %>% filter(PitchCall == "InPlay") %>% drop_na(ExitSpeed, Angle)

print(paste("After filtering BIP: Rows =", nrow(ultimate_bip)))
```

```
## [1] "After filtering BIP: Rows = 786"
```

```
# -------------------------------
# 5. Convert BIP Data for Bagged Tree Prediction
# -------------------------------
# Predict xSLG using the Bagged Tree Model
ultimate_bip$xSLG <- predict(model_bag, ultimate_bip)

# -------------------------------
# 6. Check Column Names Before Merging
# -------------------------------
#print(colnames(ultimate_bip))  # Debugging step

# -------------------------------
# 7. Merge xSLG Back into Main Data (Including Strikeouts)
# -------------------------------
# Ensure strikeouts also have xSLG == 0
ultimate <- ultimate %>%
  left_join(
```

```
    ultimate_bip %>% dplyr::select(Batter, ExitSpeed, Angle, xSLG),
    by = c("Batter", "ExitSpeed", "Angle")
  ) %>%
  mutate(xSLG = ifelse(KorBB == "Strikeout", 0, xSLG))  # Assign 0 xSLG for strikeouts

# ------------------------------
# 8. Compute Batting Summary Table
# ------------------------------
batter_summary <- ultimate %>%
  group_by(Batter) %>%
  summarise(
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),  # Count only true BIP
    Strikeouts = sum(KorBB == "Strikeout"),  # Count strikeouts
    AvgEV = round(mean(ExitSpeed, na.rm = TRUE), 1),
    BABIP = round(sum(PlayResult %in% c("Single", "Double", "Triple", "Homerun")) / BIP,3),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),  # SLG = Total Bases / AB
    xSLG = round(sum(xSLG, na.rm = TRUE) / AB, 3) , # Predicted xSLG = Expected Total Bases / AB,
  ) %>%
  mutate(Difference = round(SLG - xSLG, 3)) %>%
  filter(AB >= 5) %>%  # Only include batters with at least 5 AB
  arrange(desc(Difference))

# ------------------------------
# 9. Compute Overall SLG Statistics
# ------------------------------
overall_summary <- ultimate %>%
  summarise(
    Batter = "TOTAL",
    AB = sum(AB),
    BIP = sum(PitchCall == "InPlay"),
    Strikeouts = sum(KorBB == "Strikeout"),
    AvgEV = round(mean(ExitSpeed, na.rm = TRUE), 1),
    BABIP = round(sum(PlayResult %in% c("Single", "Double", "Triple", "Homerun")) / BIP,3),
    SLG = round(sum(SLGValue, na.rm = TRUE) / AB, 3),
    xSLG = round(sum(xSLG, na.rm = TRUE) / AB, 3),
  ) %>%
  mutate(Difference = round(SLG - xSLG, 3))

# ------------------------------
# 10. Combine & Print Summary
# ------------------------------
final_summary <- bind_rows(batter_summary, overall_summary)
kable(final_summary)
```

Batter	AB	BIP	Strikeouts	AvgEV	BABIP	SLG	xSLG	Difference
Kim, Isaac	90	69	21	83.2	0.377	0.567	0.365	0.202
Crain, Jeramiah	60	38	22	96.8	0.421	0.600	0.483	0.117
Vargas, Nathan	157	115	42	89.0	0.339	0.459	0.414	0.045
Holman, Jack	146	120	26	90.4	0.342	0.623	0.586	0.037
McCollum, LeTrey	153	127	26	89.7	0.386	0.444	0.422	0.022
Esquer, Xavier	145	113	32	89.5	0.265	0.469	0.460	0.009
Mendez, Jonathan	149	112	37	88.2	0.321	0.456	0.502	-0.046

Batter	AB	BIP	Strikeouts	AvgEV	BABIP	SLG	xSLG	Difference
Nunez, Corey	136	101	35	86.1	0.307	0.265	0.325	-0.060
Kosciusko, Cole	94	65	29	88.4	0.277	0.277	0.364	-0.087
TOTAL	1130	860	270	88.8	0.333	0.457	0.440	0.017

This table provides a breakdown of **actual slugging percentage (SLG), expected slugging percentage (xSLG), and additional hitting metrics** for UCSB Baseball's main hitters across the **2024 Fall and 2025 season**. The purpose of this analysis is to **predict future performance trends** and identify which players may be overperforming or underperforming based on expected outcomes.

Strikeouts were included since they are accounted for in SLG but were **excluded from xSLG predictions model** because they always result in zero total bases. **BABIP (Batting Average on Balls in Play)** is also included, as it provides additional insight into whether a hitter has been particularly lucky or unlucky in their batted ball outcomes.

From the table, **Isaac Kim** has the highest positive difference between SLG and xSLG, indicating he may be overperforming. This suggests he has accumulated **a lot of weak base hits or BIP that are normally outs**, meaning he is **likely to regress** over the rest of the season. Similarly, **Jack Holman also has a positive difference**, likely influenced by his **six home runs in the first two weeks of the season**, an extremely rare feat that suggests he is **due for some regression** as well.

Conversely, the **unluckiest hitter is Cole Kosciusko**, who has a **mid-tier average exit velocity**, suggesting that **soft contact is not the issue**. Instead, he has had **many well-hit BIP that should have been hits but resulted in outs or fewer bases than expected**, meaning his performance may improve as the season progresses.

Future Considerations for Improving Expected SLG Models

While this model provides valuable insights into expected performance, **there are ways it can be improved** in the future. One key limitation is that **MLB has advanced tracking technology** that includes **baserunner speed data**, which plays a significant role in expected stats. A **slower runner is less likely to beat out throws or take extra bases**, meaning that **xSLG calculations in professional baseball are more refined**.

However, **this technology has not yet been implemented at the college level**. As tracking systems continue to evolve, **colleges could integrate baserunning metrics** into expected stat models, making projections more accurate. In future years, if this data becomes available, it could be incorporated into **college-level player evaluations** to better assess player strengths, weaknesses, and potential trends in performance.

For applying this model, the lowest RMSE was generated from the Random Forest model with four predictors, however between the models with two predictors the baggedTree was better than the Random Forest model with two predictors, so for simplicity it still may be worthwhile to present the players with the baggedTree model. We will also track these slugging predictions as the season progresses to see which model was more accurate.