2024 Cincinnati Reds Hackathon Submission

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Introduction

As noted in the prompt, pitcher's roles have been becoming more fluid in recent years. Many pitchers have successfully navigated going from the rotation to the bullpen, while others have excelled in a more "hybrid" style role with shorter starts.

This analysis explores differences between starting pitchers and relievers, identifies success-driving attributes for each role, builds predictive models for assessing pitcher performance upon role transition, and illustrates results using specific player examples.

Starting Pitchers vs Relief Pitchers and Important Attributes

The most important step to working with a new project is to understand what relationship is occurring for what is being studied. This first step aimed to differentiate the characteristics of starters and relievers.

Understanding what differentiates the two roles can help determine why players are more successful in specific roles. One interesting piece is included in Table 1.

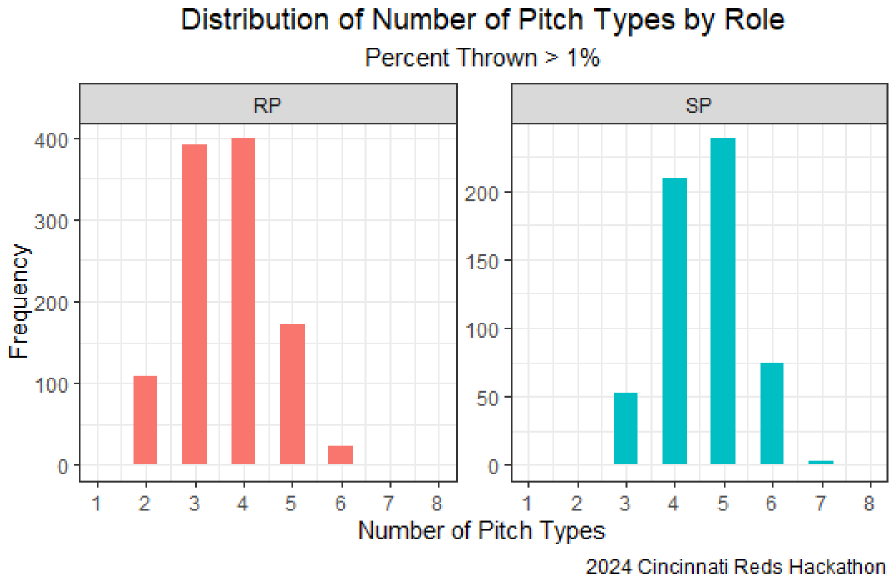
Table 1

Role	Stuff+	Location+	Pitching+
SP	97	101	100
RP	103	99	100

This table shows that starting pitchers generally have a little bit worse "stuff" than relievers, but they throw their pitches in better locations. This intuitively makes sense; starters have to pace themselves, so they can not necessarily throw as hard as they can on every pitch whereas relievers can.

Another conversation that is had between relievers and starters is the amount of unique pitch types that each roles have. The difference between starters and relievers is shown in Figure 1.

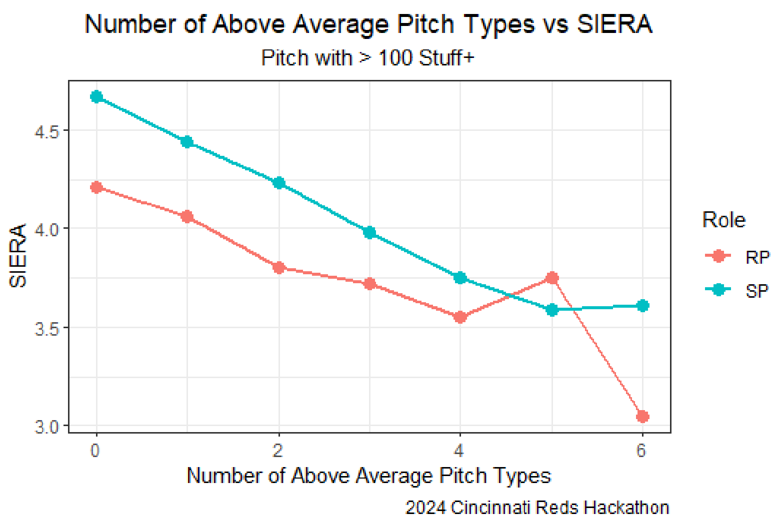
Figure 1



A pitch had to be thrown at least 1% of the time to be considered a distinct pitch type. What is generally thought is shown here. Most relievers have 3 or 4 pitch types whereas starters have 4 or 5.

We can also look at this in terms of number of quality of pitches. Instead, does the quantity of good pitches matter more? To quantify if a pitch was "good", it had to have a Stuff+ over 100. This relationship is shown in Figure 2.

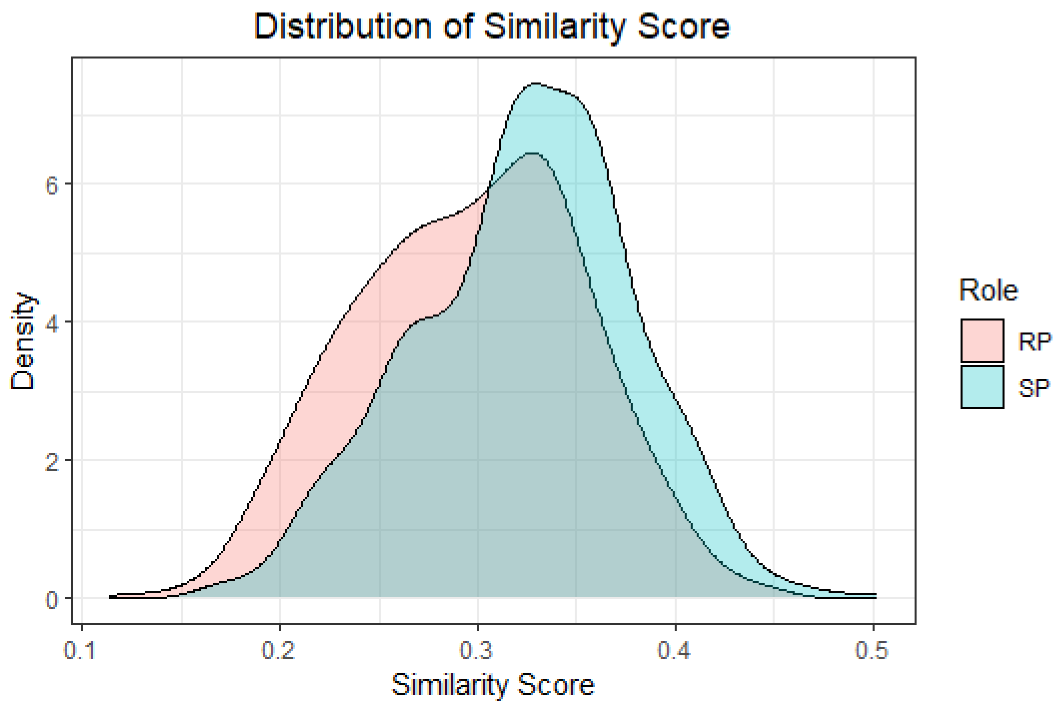
Figure 2



This makes a lot of sense: as a pitcher has more above-average pitch types, their SIERA goes down for both relievers and starters.

The average distance between movement metrics for pitches in an arsenal was used for a “similarity” score. A higher number means more arsenal diversity.

Figure 3



The plot shows that starting pitchers have arsenals that are more varied than those of relievers. Again, this intuitively makes sense. Starting pitchers need to face more hitters and therefore, a very diversified arsenal may help them make it farther in a game.

Modeling Process

The model that I decided to build could predict SIERA from a pitcher’s statistics and arsenal information. There will be 2 predictive models in the end, one for starters and one for relievers. I will use starter stats to predict starter SIERA and reliever stats to predict reliever SIERA. This will then be used to predict a pitcher switching roles. EDA was done along with the feature engineering for similarity and pitch types in the prior paragraphs.

Role Feature Adjustments

To do this, I used 75 pitchers who were both a starter and a reliever in the same season and adjusted each of the 13 numerical features to what they would be if they were in a different role. That was done using linear regression as all of those relationships were, in fact, linear. An example model would be:

Projected SP K% = 0.1 + 0.42 x RP K%

This would scale down the relievers' K%. For example, if a reliever had a K% of 60%, it would be shrunk to 25.2% by its slope and then moved up to 35.2% by the intercept. The same process was done for the other features. A train and test set were used to make sure that they were accurate.

Model Building

A train and test set for each role was created with 70% of the data going into the training sets and 30% in the test sets. For starting pitchers, there are 400 observations in the training set and 176 in the test set, for relievers there are 762 in the training set and 328 in the test set. The data is the unadjusted data and they will predict player SIERA.

As the EDA was done, it seemed that the majority of the relationships were linear. This means that a linear regression model could be the best fit for this problem. That is one of the models that I attempted and I also looked at an XGBoost to see if it can do any better than the linear regression.

For the linear regression, I simply trained it and tested it on new data. With the XGBoost, I did a grid search on 100 different combinations and 7 parameters to find the optimal set of hyperparameters. The combinations of hyperparameters were chosen using a Latin hypercube and parallel processing was used to speed up the process. The best model was selected by using minimum RMSE.

Model Results

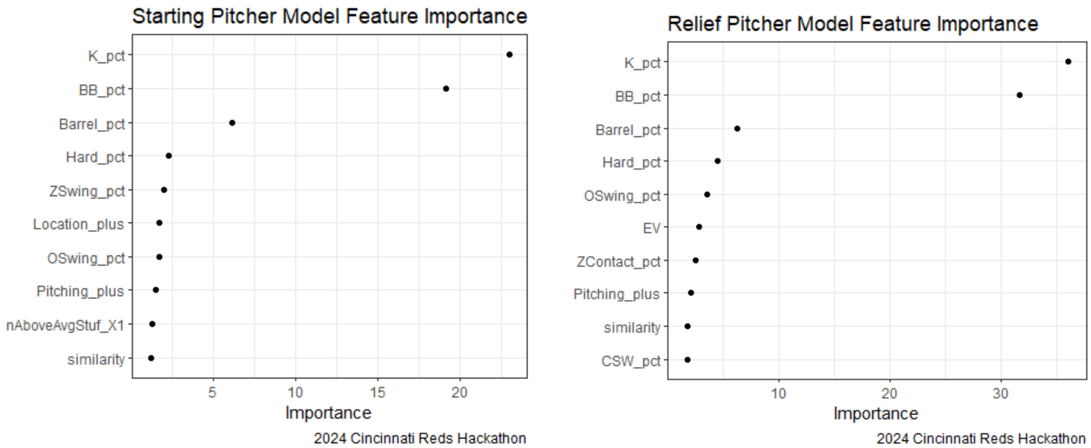
When comparing the two, the simple linear regression came out to be better. As stated earlier, the relationships between many variables and SIERA were linear, so this makes sense. Linear regression is also easier to interpret so that is good to use as well. Table 3 shows the results:

Table 2

Model	RMSE	R-Squared
SP Linear Regression	0.197	0.914
SP XGBoost	0.230	0.883
RP Linear Regression	0.258	0.890
RP XGBoost	0.289	0.863

Being able to interpret results is important as well; feature importance can do that for us. Figures 4 & 5 show us the 10 most important variables for both the starting pitcher and relief pitcher models. K% is the most important, followed by BB%, Barrel%, and Hard Hit%, which all make sense.

Figures 4 & 5



Player Analysis

These models can now be used to make projections on players that could add more value to a pitching staff by switching roles. In this section, there will be an example of a reliever changing to a starter and vice versa.

Felix Bautista

Bautista is already one of the most dominant relievers in the game, but he could add much more value with a switch to the rotation. Bautista still has a very high projected starter K% at 29.4%, would lower his walk rate to 8.7%, and his Location+ would go from 94 to 97. He also has 3 distinct and nasty pitch types that could play well when having to go for longer outings.

His predicted SIERA if he made the switch would be 3.67 which is extremely valuable for a starter. He would accumulate more WAR by pitching in longer outings as well.

The piece of this that is interesting to me would be to attempt to try other nasty relief pitchers in the rotation. Their stuff could carry them for longer innings even if they would have to hold back a little bit. The problem could be that they can not handle longer loads, but trying to have them start could have massive rewards.

Michael Kopech

Kopech has been in the bullpen in the past but has been starting the last two seasons with subpar results. His SIERA as a starter in 2022 and 2023 has been 4.72 and 5.44, respectively. His predicted SIERA in the bullpen would be 4.04, which is not great but is much better. He also only has 2 quality pitch types which matches more to the role of a reliever.

Something else to note is that in 2021, he dominated as a reliever with a 2.87 SIERA. He would strike out a good amount of hitters at 25.5% and help fix his walk issues from going to a BB% of 15.5% to about 10%.

Conclusion

This analysis shows what we can look for in terms of relievers changing to starters and vice-versa. One key takeaway is that if a reliever is very dominant, such as Felix Bautista, it may be worth attempting to start them as they could add more value that way. If they can not handle the workload, then a bullpen role would be best for them.

There are a few drawbacks to the methods presented in this paper. One is that there were not a ton of relievers that were also starters in the same season so it can be difficult to estimate the switchover. In terms of modeling, I would have also done regularization with my linear regression models and tried more advanced techniques such as splines and interaction terms to see if that would impact accuracy at all.

If I were to do further research on this, I would also add analysis on how much specific value a player would add by switching roles, whether that would be by something like WAR or dollars. I would also add more specific roles than relievers and starters as there are subsets of each type.