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1. Introduction

Context
The game of baseball is changing rapidly every decade. Since 2013, the average starting pitcher's innings dropped from 5.9 innings to 5.1 innings per appearance. Leading to an approximate 20% increase in relief appearances per team in 2023, jumping to 526 relief appearances from 478 relief appearances in 2013. Among these appearances, the additional innings these relievers had to cover - in 2013, were 3,048 multi-inning relief appearances (~102 per team); in 2023 this was up to 3,941 multi-inning appearances (~131 per team).

The aforementioned statistics illuminate a significant shift in the utilization of pitchers. The declining innings pitched by starters and the corresponding surge in relief appearances underscore a strategic metamorphosis within the game. This tactical shift brings to the fore the increased reliance on the bullpen, spotlighting the critical role of relievers in contemporary baseball.

Importance of Analysis
The analysis presented in this report is pivotal for several reasons. Foremost, it enables us to dissect the factors contributing to the increased burden on relievers. By understanding these factors, we can better prepare our pitching staff for the rigors of modern baseball, ensuring that they are equipped both physically and mentally to shoulder this load.

Additionally, this analysis is instrumental in assessing pitcher effectiveness. With the role of relievers becoming increasingly critical, evaluating their performance becomes a more complex and nuanced task. It is not simply a matter of innings pitched but the quality and strategic timing of those innings. By dissecting the data, we aim to distill the essence of what makes a reliever successful in this new era of baseball.

Data Sources
Fangraphs Overview: Fangraphs serves as the bedrock of our statistical analysis. Their comprehensive data on pitcher performance, including innings pitched, strikeout rates, walks, ERA, and much more, provide us with a quantitative backdrop for our qualitative assessments. This data is crucial for benchmarking our pitchers against league trends and understanding where they fit within the broader landscape of MLB pitching.

Baseball Savant Data: Baseball Savant enriches our analysis by offering pitch-by-pitch data that reveals the intricacies of each pitcher's game. From pitch velocity to spin rate, from exit velocity to launch angle on batted balls, Baseball Savant provides us with the tools to conduct a microscopic examination of pitcher effectiveness. This level of detail is vital for understanding how subtle changes in a pitcher's delivery or pitch selection can have outsized effects on their performance.

Baseball Reference: Finally, the historical data from Baseball Reference allows us to contextualize our analysis within the game's evolutionary timeline. By considering all position players who have pitched in official MLB games, we gain a holistic view of pitching trends and the changing role of player versatility. With the exclusion of the anomalous Shohei Ohtani, our focus remains sharp on traditional pitching roles, ensuring that our analysis is as targeted and relevant as possible.

In conclusion, the data from these sources, when synthesized, will not only provide us with a snapshot of the current state of pitching in MLB but also offer foresight into how the game might continue to evolve. This foresight will be instrumental in guiding our strategic decisions, ensuring that our team remains at the vanguard of baseball's unfolding narrative.

2. Methodology

Data Filtering
In our pursuit of clarity and precision, we meticulously filtered our dataset using the historical archives available at Baseball Reference. This repository served as our sieve, allowing us to separate position players from our primary subjects of study: the pitchers. In this filtration process, we consciously omitted the multifaceted Shohei Ohtani to maintain the purity of our pitcher-specific analysis.

Feature Engineering
Venturing deeper into the realm of Baseball Savant, we embarked on an expedition to engineer features that would best encapsulate pitcher performance across selected scenarios. We considered various situations that can significantly impact the outcome of a game:

- *Specific Scenario Metrics:* We quantified the frequency of 2-out walks, 0-2/1-2 walks, and lead-off walks per season. These scenarios are crucial as they often lead to high-leverage situations that can alter the course of an inning or the game itself.
- *Average Batters Faced and Innings Pitched:* We calculated the average batters faced per appearance and the average innings pitched per appearance to gauge the workload and staying power of a pitcher.
- *Inning-Specific Averages:* By examining the average inning a pitcher enters and exits the game, we gained insights into the strategic use of pitchers and their endurance.
- *Mode Inning Entry and Exit:* Identifying the most common inning for a pitcher's entry and exit allowed us to understand bullpen management trends and pitcher stamina.
- *Inning-Based Role Classification:* We classified pitchers into roles based on the innings they most frequently pitched: Innings [3,4] as Long Relievers, Innings [5,6] as Middle Relievers, Innings [7,8] as Setup Pitchers, and Inning [9] as Closers.

Analytical Techniques
Our analytical arsenal was equipped with sophisticated techniques designed to cut through the complexity of raw data and unearth underlying patterns:

- *Principal Component Analysis (PCA):* We implemented PCA across our feature set, including the newly engineered metrics. This dimensionality reduction technique allowed us to uncover the principal components accounting for at least 80% of the total variance.

More than a mere statistical exercise, PCA provided a lens through which we could discern the most impactful features, guiding our subsequent analysis.

- *Feature Loadings:* The loadings from our PCA became the cornerstones of our analysis, giving us a clear indication of which features were most significant in defining pitcher performance.

- *Z-Score Analysis:* Utilizing the feature loadings, we developed a Z-score framework to evaluate each pitcher. This scoring system categorized starting pitchers into Elite_SP, Strong_SP, Average_SP, and Suboptimal_SP, while relief pitchers were classified as Elite_RP, Strong_RP, Average_RP, and Suboptimal_RP. This stratification was anchored in our PCA findings and gave us a robust benchmark for assessing performance relative to a pitcher's role.

$$z = \frac{(X - \mu)}{\sigma}$$

X: A Specific Measured statistic for a pitcher, such as ERA, WHIP, and K/9. Mainly used from our feature loadings from the prior PCA Analysis.

μ (mu): The mean value of that specific statistic for the group of pitchers being considered, which could be all classified roles (Starting Pitcher, Middle Relief, and Setup/Closer)

σ (sigma): The standard deviation of that statistic for the group of pitchers.

- *Cosine Similarity*: We split the pitchers into two distinct cohorts: elite/strong and average/suboptimal. Within these groups, we analyzed the roles classified during the feature engineering phase to determine the pitchers' past performances. Employing Cosine Similarity, we ventured to align each average/suboptimal pitcher with a new role, predicated on their similarity to the performance metrics of their elite/strong counterparts

- *Elite Means*: After receiving our cosine similarity metrics we are then able to examine all pitching metrics across the elite level pitchers and compare them in our list of suboptimal pitchers (pitchers belonging to Average_SP, Average_RP, Suboptimal_SP, Suboptimal_RP). The Elite pitcher metrics we have aggregated belong to the Elite level pitching we categorized (Elite_SP, Elite_RP, Strong_SP, Strong_RP).

Player One: Luis L. Ortiz PIT

Current Role: Starting Pitcher
Common Inning Pitched:
Suggested Role: Setup/Closer
Throws: R
Age: 25
2023 Stats

Wins	5
Losses	5
ERA	4.78
G	18
IP	86.2
SO	59
WHIP	1.70

Analysis & Discussion:
Luis L. Ortiz has come off an average season as a starting pitcher. Our analysis proves he is suitable in a closing role since his statistical distributions are close to the mean of closers who meet our 'Elite Pitcher' criteria.

Swing Percentage (0.9% Above Elite Mean):

a. Analysis: Closers typically need to be able to induce swings, especially in high-leverage situations. A higher Swing% suggests that Ortiz is effective at making batters swing at his pitches. This could be due to his ability to deceive batters or to throw pitches that are challenging to lay off. In a closing role, this skill is crucial for quickly getting outs and preventing the opposition from gaining momentum.
b. Context: Being above the elite mean in Swing% indicates that Ortiz has a tendency to engage batters more effectively than many elite closers. This is

beneficial in a closing role, where the ability to generate swings (and ideally misses) can be the difference between a save and a blown opportunity.

2. LOB% (9.6 Percent Above Elite Mean):
    a. Analysis: A high LOB% is indicative of a pitcher's ability to work out of jams and strand runners on base. For a closer, who often enters the game in high-pressure situations with runners on base, a higher LOB% is particularly valuable. It suggests that Ortiz has a knack for maintaining control in critical moments and can prevent inherited runners from scoring.
    b. Context: Being significantly above the elite mean in this statistic implies that Ortiz excels in high-pressure situations, a hallmark of a successful closer. It's a skill that can have a direct impact on the outcome of games.

3. FAv (5.74 Percent Above Elite Mean):
    a. Analysis: A higher fastball velocity can be a significant advantage for a closer. It often correlates with higher strikeout rates and can be intimidating for hitters, especially in the late innings of a game.
    b. Context: Ortiz's fastball velocity being notably higher than the elite mean suggests that he has the raw power often sought in a closer. This ability to overpower hitters can be crucial in securing the final outs of a game.

In conclusion, Luis L. Ortiz's statistical profile, characterized by a higher than average Swing%, LOB%, and FAv compared to elite closers, supports the idea that he could excel in a closing role. His ability to induce swings, effectively strand runners, and deliver a powerful fastball align well with the key attributes of successful closers in high-pressure situations. These statistics, when taken together, provide a strong analytical basis for considering Ortiz for a closer position.

Player Two: Chase Silseth LAA

Current Role: Starting Pitcher
Common Inning Pitched:
Suggested Role: Setup/Closer
Throws: R
Age: 23
2023 Stats

Wins	4
Losses	1
ERA	3.96
G	16
IP	52.1
SO	56
WHIP	1.28

Analysis & Discussion:
Chase Silseth has come off an average season as a starting pitcher. Our analysis proves he is suitable in a setup pitcher closing role since his statistical distributions are close to the mean of closers who meet our 'Elite Pitcher' criteria.

1. Strikeouts (SO 1.82 percent below the Elite Mean):
   a. Analysis: Strikeouts are a critical measure of a pitcher's ability to control the game by directly eliminating hitters. For a setup man or closer, high strikeout rates are valuable because they reduce the chance of balls in play, which can lead to runs, especially in high-leverage situations.
   b. Context: Silseth being slightly below the elite mean in strikeouts indicates he's nearly on par with elite closers in terms of his ability to get batters out without relying on fielding. His strikeout capability, while marginally lower, still suggests effectiveness in situations where a strikeout is particularly crucial.

2. WAR (Wins Above Replacement) (1.8 percent below the Elite Mean):
    a. Analysis: WAR is a comprehensive statistic that estimates a player's overall contribution to their team in terms of wins. While traditionally used more for everyday players, WAR can still provide valuable insight into a pitcher's overall impact.
    b. Context: Silseth's WAR being slightly below the elite mean suggests that his overall contribution to his team is nearly at the level of elite closers. This indicates a solid all-around performance, taking into account not just his pitching but the overall impact of his appearances.

3. Pitchbot Fastball (<1 percent below the Elite Mean):
    a. Analysis: The fastball is a crucial pitch for any reliever, especially in a setup or closing role. Its effectiveness can be a major factor in a pitcher's success, as a dominant fastball can overpower hitters and set up other pitches.
    b. Context: Silseth's fastball quality being just below the elite mean indicates that he possesses a strong and effective fastball, nearly on par with those of elite closers. This can be a significant asset in high-pressure situations where fast, effective pitching is paramount.

In conclusion, Chase Silseth's profile, as indicated by his strikeout rate, WAR, and fastball quality, suggests he is well-suited for a role as a setup man in closing situations. His ability to generate strikeouts, overall contribution to team success, and the effectiveness of his fastball are all nearly at the level of elite closers. These attributes, combined with the role-specific demands of a setup pitcher in closing situations, make a strong case for his suitability in this role. His performance in these key areas, despite being slightly below the elite mean, shows he possesses the necessary skills and effectiveness for high-leverage late-game situations.key areas, despite being slightly below the elite mean, shows he possesses the necessary skills and effectiveness for high-leverage late-game situations.

Player Three: Jovani Moran MIN

Current Role: Middle Reliever
Suggested Role: Setup/Closer
Throws: L
Age: 26
2023 Stats

Wins	2
Losses	2
ERA	5.31
G	43
IP	42.1
SO	48
WHIP	1.46

Analysis & Discussion:

Jovani Moran has come off an average season as a starting pitcher. Our analysis proves he is suitable in a closing role since his statistical distributions are close to the mean of closers who meet our ‘Elite Pitcher’ criteria.

1. Swinging Strike Percentage (8.59 percent above the elite mean):
    a. Analysis: A high swinging strike percentage is a key indicator of a pitcher's ability to miss bats, which is crucial for a closer. The ability to generate swings and misses leads to strikeouts and reduces the chance of batters making contact, thereby lowering the risk of hits and runs.
    b. Context: Being significantly above the elite mean in swinging strike percentage suggests Moran has an exceptional ability to fool hitters and get

them to chase or miss pitches. This skill is especially valuable in high-pressure, late-inning situations where avoiding contact is often critical.

2. Pitch Bot Stuff Rating (2.72 percent above the elite mean):
    a. Analysis: A high 'stuff' rating indicates that Moran possesses an effective and perhaps diverse range of pitches. This is important for a closer, who needs to be able to reliably get outs in short, high-leverage appearances. Quality pitches are essential for keeping hitters off balance.
    b. Context: Being above the elite mean in this category implies Moran's pitches are not just effective, but potentially more deceptive or harder to hit compared to those of many elite closers. This could be a significant advantage in a closing role.

3. Opponent Batting Average (1.08 percent below the elite mean):
    a. Analysis: A low opponent batting average indicates that hitters generally struggle to make successful contact against Moran. For a closer, minimizing hits is essential, as every base runner represents a significant threat in the late innings of a close game.
    b. Context: Performing better than the elite mean in this metric shows Moran's effectiveness in limiting hits. This ability is crucial for a closer, who often faces the best hitters in high-pressure situations.

In summary, Jovani Moran's statistical profile — marked by a high swinging strike percentage, an above-average pitch bot stuff rating, and a lower-than-average opponent batting average compared to elite closers — strongly suggests he could be well-suited for a closing role. His ability to generate swings and misses, coupled with the quality of his pitches and effectiveness in limiting hits, aligns well with the key attributes of successful closers, particularly in critical game situations. These statistics collectively provide a compelling analytical basis for considering Moran as a potential closer.

Data Cleaning & Feature Engineering:

Approach:

In our effort to better understand defining and executing player transitions, we narrowed down our dataset to focus solely on players who have undergone transitions in the past three seasons. Our objective was to analyze and identify individuals who would be well-suited for a position change.

Within this subset, which specifically includes players who have transitioned, we assigned each pitcher a new position based on their performance as an SP or RP. For instance, if a player served as an RP in 2022 and transitioned to an SP role in 2023, their newly assigned position for both years would be SP. Subsequently, we applied a random forest classifier to this subset, using the assigned new role (y) and relevant variables from the Fangraph dataset (X). This approach allowed us to discern the distinctive traits associated with RP's and SP's. We selected the top 50 most important variables from the Fangraph dataset, which comprises over 300 variables.

To validate the suitability of the chosen variables for our project, we created a new dataset that included players performing above average as SP's and RP's, respectively. These players were likely in their correct positions, with no need for transition. We utilized models to predict the players' positions using the 50 most important variables, carefully addressing multicollinearity through Variable Inflation Factor (VIF) and correlation heatmap analysis. Additionally, we investigated variables that significantly changed after transition (refer to Form 1). Consequently, we utilized 11 variables in our models, achieving an accuracy of 79% in logistics regression and

85% in decision tree analysis. These results affirm that the selected variables serve as effective metrics for determining pitchers' positions.

	ERA	E_minus_F	GB_to_FB	pLI	wFA_per_c_sc	OContact_pct_sc	FStrike_pct	leadoff_walk_rate	bad_walk_rate	Barrel_pct
All_SP_Avg	4.534213	0.061179	1.179149	0.952886	-0.489675	0.586236	0.614569	0.000476	0.000031	0.084225
Before_transition_SP	5.749513	0.669446	1.202122	0.950705	-0.825691	0.600053	0.602877	0.000563	0.000016	0.091163
Afer_transition_RP	3.644171	-0.306446	1.386675	0.739022	0.271951	0.586410	0.602051	0.000563	0.000016	0.068489
All_RP_Avg	3.936045	-0.064161	1.282314	1.036468	-0.080993	0.549603	0.602536	0.000686	0.000110	0.072651

Form 1

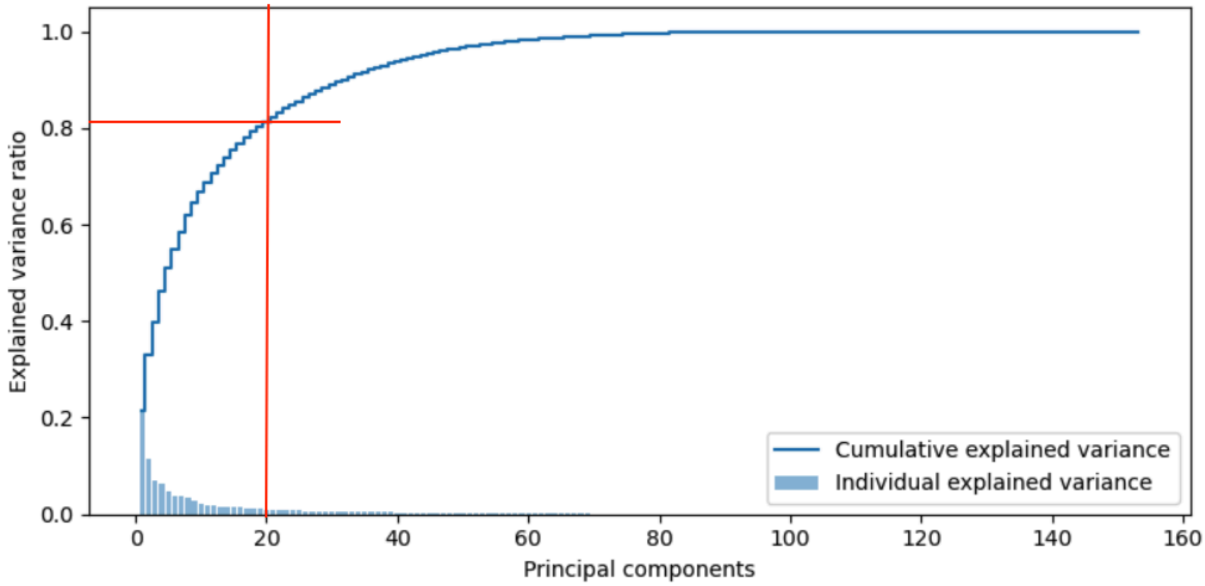
From[Eda’s PCA mismatch list approach, we XXXX and get this mismatch list].

Initial Clustering on the Original Dataset

The investigation commenced with a direct application of cluster analysis to the original dataset, comprising performance metrics for pitchers. This dataset contains over 300 variables that encapsulated various aspects of pitcher performance. The initial clustering aimed to categorize players into groups based on similarity in performance metrics, with a particular focus on distinguishing between starting pitchers (SPs) and relief pitchers (RPs). The outcome of this phase identified 613 players whose assigned roles did not match the cluster they were most aligned with, suggesting a potential mismatch.

Dimensionality Reduction with PCA

Given the high dimensionality of the dataset, there was a concern that the sheer number of variables could obfuscate meaningful patterns and hinder the clustering algorithm's effectiveness. To address this, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique.



By applying PCA, it was found that 20 principal components could explain approximately 85% of the variance in the original dataset. This significant reduction in dimensions, from over 300 variables to 20, while retaining most of the data's explanatory power, provided a more manageable and insightful dataset for subsequent analysis.

Improved Clustering with PCA-Reduced Data

Utilizing the PCA-reduced dataset, cluster analysis was performed again to categorize the players. This approach yielded a more refined understanding of role alignment, reducing the number of potential mismatches to 544 players. This improvement underscored the effectiveness of PCA in enhancing the clustering process by mitigating the "curse of dimensionality" and focusing on the most informative aspects of the data.

Identifying Mismatched Roles

The final step involved a detailed comparison of the actual roles of players against their roles as suggested by the cluster they belonged to in the PCA-reduced dataset. Players whose actual roles did not align with their clustered roles were flagged as potential mismatches. This process culminated in the identification of a subset of players for whom a role reassessment could be beneficial, based on the hypothesis that their performance metrics aligned more closely with a different pitching role than the one they were currently occupying.

We selected SP's who had relatively poor performance (ERA>3.5) yet possessed exceptional traits that could potentially position them as effective RP's, such as having a high pLI. One notable player meeting these criteria is Edward Cabrera, who has an outstanding track record over the past three seasons. This includes notable attributes like a high value in GB_to_FB, pLI, Stuff_plus, and more.

To predict Edward Cabrera's potential performance after transitioning to an RP role, we examined six players who made similar transitions and shared comparable records with Cabrera before the shift. Calculating the mean of their performance changes revealed that these players generally improved after transitioning (refer to Form 2). This indicates a high likelihood of Edward Cabrera succeeding in the RP role.

	avg_improvement
ERA	-0.979292
E_minus_F	-0.604825
LOB_Wins	0.108222
WHIP_plus	-4.962927
WPA	0.480157

Form 2

More about Edward Cabrera:

In the past three seasons, Edward has consistently averaged 4.7 innings per game, which is below the league-wide average for starting pitchers. Although he has maintained an average ERA of 4.42 during this period, which might seem a bit high, it's important to note that across 43 games, considering only the first three innings of each game, he allowed only 45 runs in a total of 129 innings pitched, averaging 0.34 runs per inning. This suggests that while Edward possesses notable skills, his endurance might lead to a decrease in pitching effectiveness beyond the third inning, resulting in a higher overall ERA.

Furthermore, Edward's performance metrics, such as pLI, indicate that he frequently pitches in high-pressure situations. His exceptional record in strikeout percentage and ground ball-to-fly ball ratio demonstrates his ability to thrive in situations with runners on base, a crucial attribute for relief pitchers who often enter the game in such scenarios.

Overall, considering Edward's impressive pitching skills and consistent performance within shorter innings, we believe he would be an excellent fit for the role of an RP, especially a closer. This transition could potentially provide him with enhanced career development opportunities.