1) **<u>Proposal:</u>** Action-Sequence RAA Decomposition method attributes a play's total RAA among fielders. Each play is segmented into four measurable defensive actions performed by fielders:

- **Approach Effort:** Movement from initial position towards the ball (sprints, dives).
- **Transfer:** Handling/passing the ball (flips, throws).
- **Reception/Putout:** Catching the ball or completing a tag/out.
- **Support:** Providing backup or cutoff.

For each DA, we train an XGBoost model to predict P(Success) (probability of successful execution), using XYZ coordinates of players and ball, their velocities (coordinate changes over timestamps derivation), ball characteristics (EV, LA, hang time, derived from XYZ and bat-ball contact timestamp), game state (outs, runners), distances to targets, and time-to-event metrics. P(Success) acts as our difficulty modifier.

A **Dynamic Responsibility Weight (DRW)** is calculated for each DA:
DRW = Base Weight × Effort Adjustment.

- **Base Weight:** Standard positional responsibility derived from historical play data and initial ball/fielder XYZ coordinates.
- **Effort Adjustment:** Quantifies required effort relative to average for similar plays. Calculated by comparing actual fielder movement (from XYZ traces) against optimal paths and incorporating factors such as speed, acceleration, and time pressure.

The total play RAA is then distributed based on an **Attribution Factor (AF)** for each DA:
Attributed RAA = Total Play RAA * (∑ Player's AFs for Play / Total Play AF for Play)
Where AF_action = Outcome_Score × Difficulty_Score × DRW.

- **Outcome_Score:** +1 for successful action, -1 for failed action relative to optimal.
- **Difficulty_Score:** Modifies RAA based on P(Success). Low P(Success) (hard plays) result in higher Difficulty_Score for successes and reduced negative Difficulty_Score for failures (e.g., 1 + (1 - P(Success))).
- **DRW:** Ensures fair attribution based on player responsibility.

This should ensure that total RAA is fully distributed with feedback.

**<u>Challenging Scenarios & Enhancements:</u>**

I expect this method would struggle the most with the outfield collision and wide flip situations given the more nuanced causal inference for multi-step failures.

***Wide Flip***: a first-baseman's error directly affecting the difficulty and success probability for the pitcher's reception of the ball needs to be accounted for in the model by tracking the cascade of events. It needs have the context to understand the poor throw quality based on the ball's XYZ and the pitcher's simultaneous movement to first. It must then re-evaluate the pitcher's probability of success due to the flip, and ensure the majority of the negative RAA attribution is given to the first baseman.

***Outfield Collision:*** This would be a major problem for a simple model that cannot account for event detection like collisions. The model would also need a method to understand call-offs and "whose ball that is." A function set to detect collisions based on XYZ player coordinates and their velocities could be used, and those results of determining which player is at fault would then need to be incorporated into the P(Success) calculations for the Approach and Reception/Putout DAs and the responsibility weights.

***Third Base Dive:*** The only major challenge model would face is sparsity of similar play data. In my experience watching baseball for my entire life, this specific action sequence and outcome is relatively rare. Synthetic data may need to be used for DRW calculations.

2) My calculation would be based on maximizing expected win probability (xWP). We want the point where xWP of pulling the SP and incurring a DH penalty exceeds the xWP of keeping the starter and DH such that if xWP_PullSP > xWP_KeepSP, you pull the pitcher. I'd create a pitcher performance tracker to estimate our starter's expected performance against the remainder of the opposing lineup. For starters, this is based on their baseline metrics taken from the matchup model for upcoming hitters (xwOBA allowed, xFIP), game state (pitches thrown, run differential), TTO penalty, and a context-based fatigue metric evaluating spin-rate/velocity deviations. This is factored into xWP_KeepSP.Our reliever(s) would be projected using their baseline metrics against likely hitters they'll face, and factored into xWP_PullSP. The DH penalty would be based on the xwOBA difference of the current DH and defensive replacement bench player for that spot, estimated against current and available opposing pitchers. The decision to pull is made when a Monte Carlo simulation of game states shows the xWP_PullSP offers higher win probability. An astute front office may opt for rotational utility DHs rather than big everyday hitters under this rule.

3a) The steal decision should be based on maximizing xWPA (expected win probability added):
$\mathbf{xWPA_{steal} = (P(success) * WPA_{success}) + ((1\text{-}P(success)) * WPA_{caught})}$
P(success) is based on baserunner sprint speed, catcher pop time, infielder fielding ability, and descriptive game state context through a mixed effects logistic regression model, such as a GLMM. I would like the following data collected and incorporated:

* **Runner**: acceleration from standstill, lead distance from first base, total distance to second base upon catcher receiving the pitch, binary indicator of 1st baseman holding the runner on
* **Pitcher**: time to plate from the stretch, pickoff success rate, most likely pitch velocity given batter handedness and count, pitcher handedness, pitcher statistics with men on base or in scoring position, binary indicator of the pitcher having a quick-pitch/slide-step delivery
* **Catcher**: throw strength, average throw location (1st or 3rd base side of 2nd base)
* **Defense:** Fielders positioning, caught stealing success rates of the opposing shortstop

b) Trailing by 1 in the 9th, the formula should not need to change, as $\mathbf{WPA_{success}}$ should account for the much larger changes in WP based on the potential baseout situations. Note: for this situation, according to historical win expectancies since 1990 (via gregstoll.com Win Expectancy Finder), the increase in win percentage for the home team from the failure state heavily outweighs the increase for the away team from the success state. This would be reflected in the final xWPA calculation.

4) Because the correlation is moderate, integration into existing models should be extremely conservative to start. This should not be a primary driver of model projections. This metric is much more useful as a supplement to player development, with core strength scores informing specialized training programs. Players in the Cubs' system displaying lower core strength and below-average power numbers could immediately be selected for core training to try and give their exit velocity a bump. An immediate action should be to begin collecting this data at all levels of the organization by making all coaches from rookie ball to the majors aware of this metric and it's value.

The main issues to consider with strictly looking at Cubs players centers around sample size. Results for correlation will be skewed by the team's organizational and development philosophies. If team scouts prefer a specific build, or the strength coaches have specific workouts, you will have an inherent selection bias. The sample should change drastically if we only consider amateur college players. The typical body composition of an 18-22 year old male athlete looks significantly different than that player who has developed long enough to break into the major leagues, Cubs or otherwise. I anticipate you would see a much higher variance in the correlation with EV assuming you also have these players' heights and weights. Also, the amount of strength training that college players commit to varies by player, team, and division (1,2,etc.). And college player success does not directly predict MLB success.