Exploring the New Coach Effect with Data

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Data Preparation

- Scraped all Bundesliga match data (2017–2025) using `worldfootballR`
- 30 teams, total 4876 matches (only `ForAgainst = For` rows kept)
- Matched coaches to each team
- Calculated Elo ratings for each team and opponent
- Computed key performance indicators (KPIs):
  - Match result points (3/1/0)
  - Efficiency: `eff = GF - xG_Expected`

Coach Change Events

- Identified coach change points and assigned `event_id`
- Created windows before/after the change
- Constructed:
  - `relative_time` (time index relative to change)
  - `post` (binary: pre/post change)
  - `time_post` (time since change)

Visualization

- Plotted average points over time by `relative_time`
- Compared pre- and post-change trends
- Goal: visually assess changes in team performance after coaching switches

Interrupted Time Series Model (ITS)

- Model structure:
  - Team fixed effect (baseline level)
  - Pre-change slope (trend before change)
  - Level jump after change (intervention effect)
  - Slope change after change (growth rate change)
  - Home advantage
  - Opponent strength
- Training/testing data split
- Interpretation:
  - Non-significant `C(Team)` $\rightarrow$ team aligns with average

Poisson Model

- Used for modeling count-type outcomes (e.g. goals, points)
- Key effects modeled:
  - Initial average team performance
  - Growth factor per match
  - One-time level shift after coach change
  - Slope change after coach change
  - Home field advantage
  - Opponent strength
  - Team fixed effects

Further Perspective: Tactical Efficiency

- Define `eff = GF - xG_Expected`
- If post-change `eff > 0` and significant → better tactical efficiency
- If `xG_Expected` ↑ but `eff     0` → chances created but not converted

Research Aim

To evaluate whether the change of coach has a statistically and practically significant effect on team performance, using model-based inference and standardized metrics.