Variance and Trajectory of Collective Performance Advancements across Track and Field Disciplines

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Abstract. This study explores the efficacy of machine learning algorithms in predicting the average top-100 performance of track and field athletes across different events, divisions, and sexes. Through comprehensive analysis, it was discovered that linear regression models tailored to individual event/division/sex combinations yielded the most accurate predictions. These models effectively captured the nuanced relationships between performance metrics and event-specific variables, demonstrating superior predictive capabilities compared to more generalized approaches, despite the small sample size of such tailored subsets. Conversely, attempts to uncover trends among events, divisions, and sexes using models incorporating additional subsets proved futile, as these models exhibited poorer performance and failed to identify meaningful correlations. These findings underscore the importance of considering event-specific and division-specific factors in predictive modeling for track and field performances, highlighting the need for tailored approaches that account for the unique characteristics of each variable. Ultimately, this study provides valuable insights into the predictive modeling of track and field performances, emphasizing the significance of granularity and specificity in algorithmic approaches to data analysis within the realm of sports analytics.
View this project on Github or Overleaf

Keywords: track and field · human performance · machine learning · sport progression

1 Introduction

As a sport, track and field has existed as long as any. The simplicity of performing basic athletic feats like running a predetermined distance or throwing a heavy object allowed it to start naturally with the idea of competition itself. As it grew in popularity, the need arose to standardize the rules and record performances for future reference. Today, this task falls upon organizations like USA Track and Field and World Athletics [7].

Over time, numerous athletes have set and reset various records across each discipline. Most notably, there are World Records, reserved for the overall top mark in recorded history. Like all others, these records have progressed with time [7].

Today, results are kept by multiple organizations across all levels of the sport, leading to a plethora of available data to utilize. MileSplit is the leader in recording high school marks, Track and Field Results Reporting System (TFRRS) is the college counterpart, and World Athletics handles the international leaderboards. With this data, not only are records available, but lists of the top hundreds of marks across all levels are generally available for the last 15 years. Adding depth beyond just the top performance should allow for more detailed analysis and a stronger resistance to anomalies at the top.

With the available data, it is now possible to analyze the progression (if any) of marks at various levels of competition across multiple disciplines. To date, no attempt has been made to compare the progression of performance quality across disciplines, whether it be to a depth of 1 (the annual leader) or 100 (the top 100 annually). Individual performances are each given a rating by the World Athletics scoring tables, which are scaled to each event to allow for comparison across disciplines [8].

2 Related Works

Research in the sport of track and field primarily focuses on the pursuit of performance, rather than the performances themselves. Because of this, research of this kind has not been done beyond anecdotal evidence. Some similar research, however, has been done in the sport of swimming. A 2019 analysis performed a similar examination of world record anomalies relating to equipment advancements, a topic briefly covered in this study as well [3].

On the topic of equipment, some studies have focused on finding event-specific improvements by measuring running economy improvements from emerging footwear technology [1]. However, this fails to show the resulting change in record progression in relation to history, which this study aims to do.

Furthermore, several attempts have been made to find the physical limits of human performance in specific disciplines [2] [5]. While these may be a potential factor that could influence further research, they are beyond the scope of this study.

3 Dataset Information

In this project, the primary source of data is results from Track and Field competitions. The athlete, their performance, the location, and the date are the main items being collected, though some of those are broken down further into several data attributes.

3.1 Background

The dataset utilized in this analysis comprises track and field results spanning from 2010 to 2023. It encompasses a diverse range of events sourced from reputable platforms such as MileSplit, TFRRS, and World Athletics. MileSplit is the primary site for recording high school results, while TFRRS handles the collegiate results, and World Athletics specializes in global professional rankings. Prior to 2010, record-keeping in the sport of track and field was sparse, incomplete, and unreliable. Therefore, results from before the 2010 season are omitted from this project.

3.2 Collection

The dataset was acquired through a systematic data scraping process executed via a custom Python program. This program, leveraging Selenium for dynamic webpage interaction, BeautifulSoup for HTML parsing, and OpenPyXL for Excel file manipulation, facilitated the extraction of track and field results from multiple online sources. The scraping process involved iteratively navigating through event pages, extracting relevant data elements such as athlete names, event details, and performance metrics, and storing them in a structured format. The program was executed on a local machine, with each iteration meticulously logged to monitor progress and identify potential errors.

The scraping process targeted prominent track and field platforms including MileSplit, TFRRS (Track and Field Results Reporting System), and World Athletics. These platforms host a vast array of competition results, ranging from local meets to international championships, providing a diverse and comprehensive dataset for analysis.

For each year, the top 100 results from 8 divisions were tracked: NCAA Divisions I, II, and III, NAIA, Kansas 1A, 3A, and 6A high schools, and the Global Leaderboard. Events tracked included the 100, 200, 400, 800, 1500/1600, 5000, and 10000-meter events, along with the long jump, triple jump, high jump, shot put, discus, javelin, and pole vault. Men's and women's events were tallied separately. In total, approximately 300,000 individual results spanning the period from 2010 to 2023 were gathered through the scraping process. The collected data was consolidated into an Excel spreadsheet format for further analysis and manipulation, facilitating seamless integration with popular data analytics tools and frameworks.

3.3 Limitations

Despite efforts to gather a comprehensive dataset, certain limitations were encountered during the collection process. Notably, the absence of weather data poses a constraint on the analysis, as weather conditions can significantly influence athletic performance. Particularly, wind speed during sprinting and jumping events was not taken into consideration. Additionally, the dataset may contain duplicate entries, necessitating careful preprocessing to ensure data integrity. Efforts were made to limit these instances during the cleaning process, but due to the large nature of the dataset, it cannot be guaranteed that every duplicate was removed. Furthermore, the presence of missing results, which could be attributed to incomplete submissions or other factors, introduces potential gaps

Table 1. Dataset Attributes

Column Name	Description	Data Type	Note
Rank	The overall ranking of the performance for that division and year	Integer	1 thru 100
Athlete	First and last name of the athlete	String	Varies
Sex	Distinguishes if the mark was recorded in Male or Female competition	String	Male or Female
Team	The team in which the athlete was competing for (typically school or country)	String	Ex. NW Missouri
Division	The level of competition in which the result was recorded.	String	Ex. NCAA D-II
Event	The track and field event in which the result was recorded	String	Ex. 100M
Mark	The mark that the athlete hit during competition. Recorded in minutes/seconds for timed events and meters for field events	Decimal	Ex. 9.58
Location	Details of the location of the competition. Can be a city, university, or meet name	String	Ex. New York, USA
Date	The date (MM/DD) in which the record was performed	Date	Ex. 10/31

in the dataset that may impact the analysis outcomes. These instances could be particularly more common in the first few years of the dataset, as the act of submitting the data was not required.

4 Data Cleaning and Preparation

Data cleaning is a critical phase in any data analysis project, aimed at ensuring the accuracy, consistency, and reliability of the dataset. This project is no different, as the data collected required standardization, adjustments, and unit conversions. Additionally, the needs of the project required some feature engineering, using calculations to create new fields.

4.1 Basic Cleaning and Transformations

The initial part of the data cleaning process involved addressing formatting inconsistencies, converting units, and standardizing data attributes for consistency across the dataset. The data retrieved from TFRRS and World Athletics contained symbols denoting conversions and special circumstances within the results. To ensure uniformity and accuracy, these symbols were systematically removed using Excel's text manipulation functions.

Another crucial aspect of data preprocessing involved standardizing units across various events. Time-based events were converted to seconds, while distance-based events were unified to meters. Converting distances from MileSplit, which originally utilized feet and inches (Ft-In), posed a particular challenge due to the non-standard format. However, through careful conversion algorithms implemented in Excel, distances were successfully transformed into meters, facilitating consistent analysis across all events.

Another inconsistency observed in the dataset pertained to the formatting of dates, with some entries ordered as Day/Month/Year while others followed the Month/Day/Year format. To ensure uniformity and facilitate chronological analysis, all dates were standardized to a single format using Excel's date manipulation functionalities, and the year was extracted to a separate field due to its significance in the data analysis that will be outlined below.

These basic cleaning and transformation steps laid the groundwork for subsequent analysis, ensuring the dataset's consistency and readiness for more advanced analytical techniques.

4.2 Feature Engineering

To enable meaningful comparisons across diverse track and field events, a new feature was engineered to incorporate the World Athletics performance score for each entry in the dataset. World Athletics utilizes a comprehensive scoring system ranging from 0 to 1400, designed to assess the relative performance levels across various events. Integrating this scoring mechanism into the dataset facilitates a standardized evaluation of athletes' performances, transcending event-specific metrics.

The implementation of the World Athletics performance score posed a unique challenge due to the format of the scoring tables, typically available in PDF format. To overcome this hurdle, a custom calculator was developed using Python scripting. Leveraging prior work by tontonsb on GitHub, which provided the necessary equations and coefficients for calculating the performance scores for each event, a Python script was tailored to automate the scoring process.[4] This script enabled seamless integration of the performance scores into the dataset, enhancing its analytical richness and utility. The final, cleaned dataset can be found on the GitHub Repository.

Table 2. Dataset Attributes Added During Cleaning

Column Name	Description	Data Type	Note
Year	The year (YYYY) in which the record was performed	Date	Ex. 2015
Score	The World Athletics rating of the performance according to the 2021 scoring tables	Decimal	Ex. 844.11

5 Exploratory Data Analysis

Once the data was prepared, the time came for exploratory data analysis (EDA). This data is almost exclusively focused on the outcome metric of performance, the data analysis is primarily univariate. Jupyter Notebooks for Python were used during the EDA process, and the notebook files are available on the Github Repository.

5.1 Progression of Events

The initial EDA was to conglomerate the data into an average top-100 mark (filtered to event, division, and sex) for each year, and plot it on a graph. Since that would amount to 208 graph lines, these filters were reasonably categorized for easier visualization. The first graph explored was arbitrarily filtered to Women's NCAA Division II performances. The following code and figure were produced:

```python
# Add the events to include
events = ['100m', '200m', '400m',
'800m', '1500m', '5000m', '10000m',
'Triple Jump', 'High Jump', 'Long Jump',
'Shot Put', 'Discus', 'Javelin']
plt.figure(figsize=(10, 6))

for event in events:
    # Filter the dataframe
    filtered_df_event = df[(df['Sex'] == 'Women') & (df['Division'] == 'NCAA D-II') & (df['Event'] == event)]
    # Calculate the average points
    average_points_event = filtered_df_event.groupby('Year')['Points'].mean()
    # Plot the value
    plt.plot(average_points_event.index, average_points_event.values, label=event)

plt.xlabel('Year')
plt.ylabel('Average Points')
plt.title('Average Points for Women, NCAA D-II, and Various Events')
plt.legend()
plt.show()
```

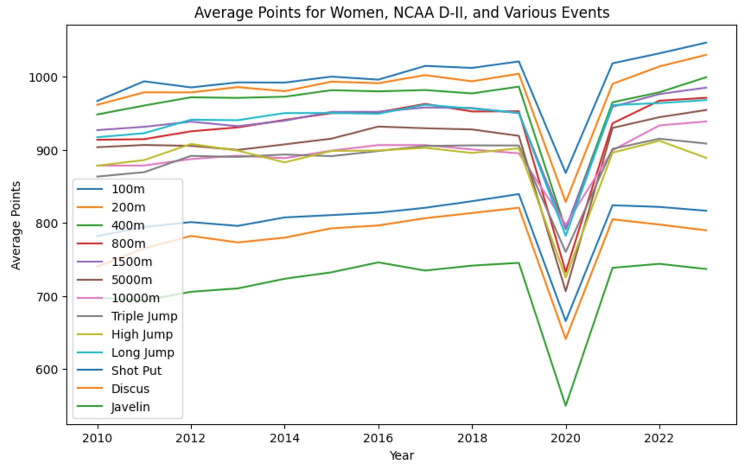

Fig. 1. Woman's D-II Performances over Time (M. Goeckel 2024)

At this point, it was immediately clear that the COVID-19 pandemic had severely skewed the results in 2020. With most competitions cancelled during that year, the lack of competition opportunities led to invalid results. In turn, the results recorded were not indicative of the overall state of the sport (which is the focus of this project). Because of this, the results from 2020 were removed from the dataframe, as such a significant dip would likely lead to inaccurate model predictions later in the project.

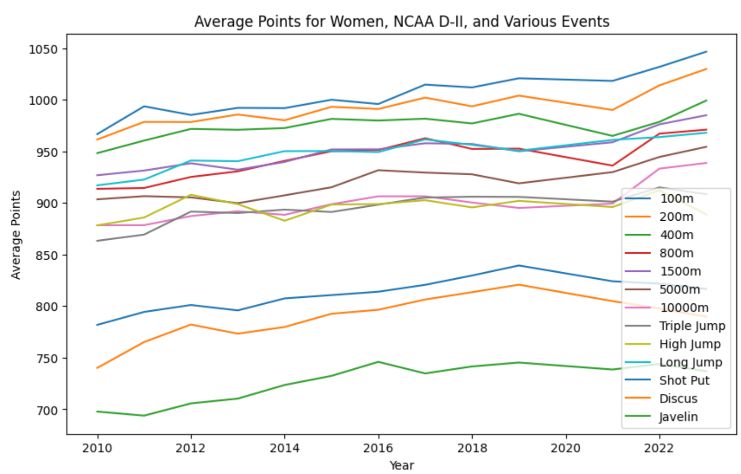

Fig. 2. Woman's D-II Performances after 2020 Removal (M. Goeckel 2024)

To further break down visualization, separate graphs were created to show trends among event groups. Figure 3 breaks down the Men's Worldwide performances (again, arbitrarily chosen) into distance, sprint, and field events. This revealed several hidden trends. The first of which is the affinity of the Worldwide leaderboard towards the Olympic cycle. Several events show peaks during Olympic years. The 10000m has the most obvious visualization of this.

Additionally, there was a noticeable increase in overall performances in the sprints from 2013 to 2016, and in the distance events from 2019-2023. Meanwhile, the field events, with the exception of the shot put, have remained stagnant. While it is beyond the scope of this project to speculate the reasoning behind these upward shifts, the release of "Super Shoes" has been a topic of discussion, even leading to World Athletics to place restrictions on legal footwear [6]. With this in mind, a reference line was added to the distance plot, indicating the release of Nike's ZoomX Dragonfly, the first widely-available track spike to fall into the "Super Shoe" category.

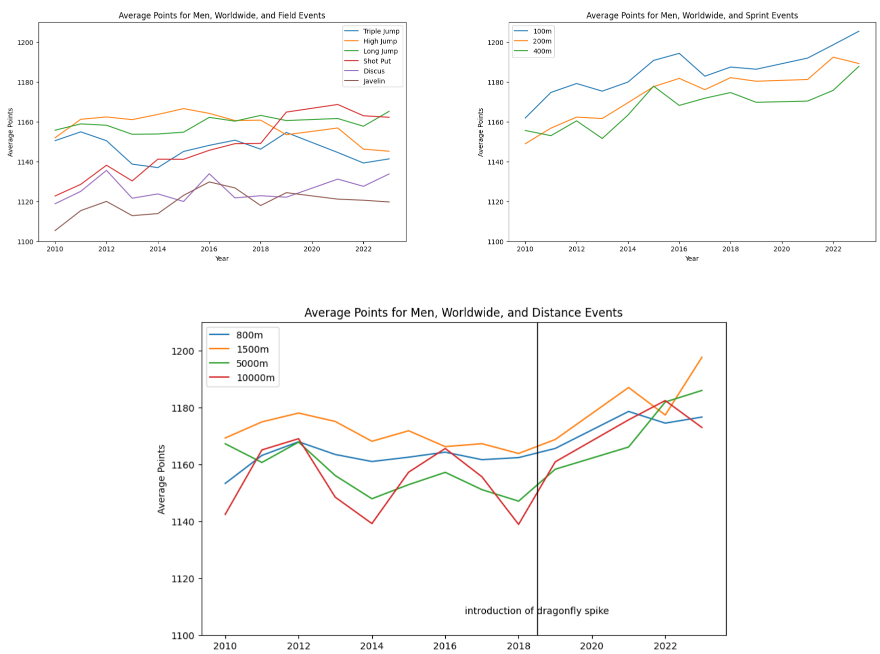

Fig. 3. Progression of Men's Professional Events, broken down by event group. (M. Goeckel 2024)

5.2 Validation of Top-100 Average as a Viable Metric

While it may seem like an arbitrarily-chosen standard, careful consideration was made to implement the top-100 average as the competitive standard. By averaging the performances of the top 100 athletes in each event, it effectively moderates the influence of outliers on the upper end while not oversaturating the dataset with inferior performances. This metric provides a quality representative snapshot of the competitive standard. Notably, as values approach the 100th rank, the density of performances increases, and outliers become less prevalent, resulting in a more stable and discernible average. Furthermore, the cap at 100 performances eliminates the possibility of bottom outliers, while also providing enough results to provide a comprehensive standard. Additionally, with the absence of bottom outliers, the upper outliers still have some influence over the average, which was intentional in the selection process. Champions often set the standard for future success, so it is rational to include upper outliers when considering a performance standard. Thus, the top-100 average emerges as a reliable and practical choice for evaluating track and field performances, providing a comprehensive yet focused perspective for exploratory data analysis.

Figure 4 provides context of what an entire dataset may look like for an event. Notice the average trending on the upper end of the high-density range. This provides a quality visualization of how the top-100 average uniquely provides a representative standard of that event's current competitive state.

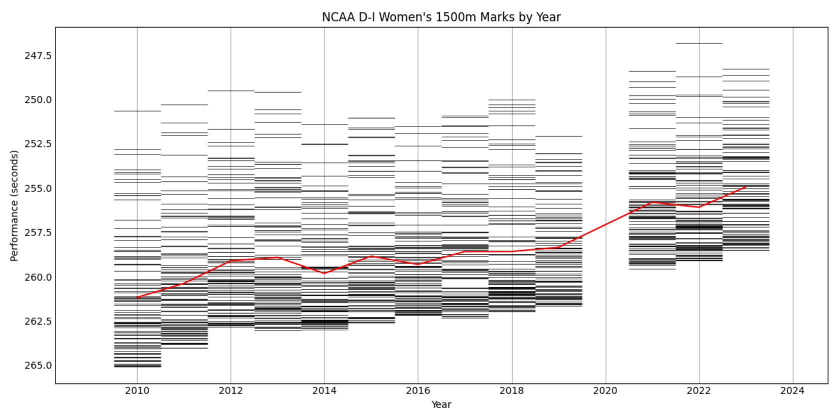

Fig. 4. Distribution of performances, showing upper outliers and increasing density on the lower end. (M. Goeckel 2024)

5.3 Newfound Limitations

Unfortunately, with any project will come unexpected adversity. During EDA, it was discovered that there was missing data among the collegiate entries. Figure 5 shows a heatmap distribution of top performances in NCAA Division I. While it would be expected to see a 'warmer' section surrounding the national championships in early June, no such trend was present. In fact, June (month 6) was not even present on the chart, indicating that zero top-100 marks were recorded in June. When compared to the global leaderboard in Figure 6, it was clear that this was not a mistake in programming the chart. After review, it was found that TFRRS does not include the national championships at any level in their annual lists. While this unfortunately leaves countless notable real-world results out of the set, the positive aspect is that it is uniform across all collegiate results. Thus, while the missing data may invalidate the collegiate results in comparison to the high school and professional marks, they are still comparable among themselves, and still valid year-by-year. This, fortunately, allows for the project to continue into the modeling phase.

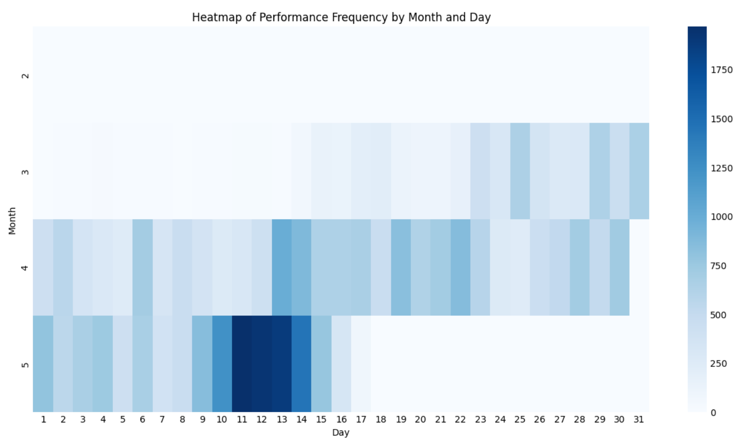

Fig. 5. The season best performances from NCAA D-I trending around conference meets instead of national championships shows a gap in the available data. (M. Goeckel 2024)

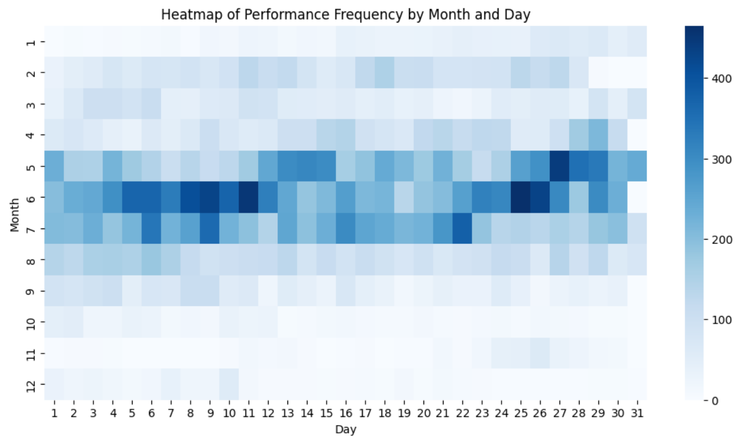

Fig. 6. The date heatmap for World Athletics shows a wider range of possibilities, since it does not have a set competition season. (M. Goeckel 2024)

6 Model Building

Modeling using machine learning is a critical aspect of this project, as one of the main goals is to forecast the future progression of the sport's events. In this section, various models were explored, including linear, tree, and time-series models.

6.1 Model Selection

As an exploratory method, a multitude of models were tried during the model building process. Initially, the basic SciKit-Learn models were tried, but it was discovered that the tree-based models, which performed best, were incapable of forecasting outside the training range. As a result, models from other packages that were time-series compatible were tried. The dependent variable (points) has multiple independent variables that affect it (sex, event, division, and year), so univariate analysis does not work. In the case of the ARIMA model, a multivariate adjustment was made, but ultimately was unsuccessful in satisfying the algorithm, leading to a LinAlg error. This was quite unfortunate, since ARIMA models are a common standard for time-series forecasting. Table 3 is a list of all models chosen and their respective python package.

In addition to a standard linear fit, which simply aggregates all data into a single model, there were two alternate approaches made using a linear regression: one with feature scaling, and one fit to each subset of data (filtered to division/-sex/event). The feature scaling method (found in the "model-scaling" notebook on GitHub) performed the linear regressions on filtered subsets of each trait (Division, Sex, and Event) and added them to the overall linear regression of the entire set, creating a linear equation that takes into account all three variables across the entire dataset, rather than a single subset. Ultimately, the success or failure of this method would indicate a relationship or lack thereof across divisions/sexes/events. Conversely, the single subset method takes only the 13 data points from each subset (filtered to a specific division, sex, and event) and creates a linear regression from those points.

Table 3. Selected Models

Model Name	Description	Package
Linear Regression	best fit liner	SciKit-Learn
Ridge Regression	Prevents overfitting by shrinking coefficients	SciKit-Learn
Lasso Regression	Shrinks coefficients and encourages sparsity	SciKit-Learn
Decision Tree Regression	Predicts using tree-based structure	SciKit-Learn
Random Forest Regression	Ensemble of decision trees for regression with bootstrapping and averaging	SciKit-Learn
Support Vector Regression	Finding optimal hyperplane for data separation	SciKit-Learn
Gradient Boosting Regression	Iteratively improves model by minimizing errors	SciKit-Learn
Prophet	Time-Series forecasting model from Meta	prophet
ARIMA	Time series forecasting using autoregression, differencing, and moving averages	Statsmodels
VAR	Time series model capturing interdependencies among variables	Statsmodels

6.2 Model Training

Each SciKit-Learn model used an 80/20 train/test split, meaning it was trained on 80 percent of the data and tested on the remaining 20 percent. The split was random, using the default random state of 42. The time-series models, however, were trained on the 2010-2021 data (78 percent), and tested on the final two years. Additional parameters were adjusted on several models (particularly the poor-performing ones), but the default parameters always produced the best results, so no parameter adjustments were necessary in the end.

6.3 Model Performance and Evaluation

Of the SciKit-Learn models, the tree-based models performed best. Notably, the Random Forest Regression produced the best performance metrics of all models, with a 0.994 R squared value, and a mean average error of 10, meaning that on average, it was only miscalculating by 10 points. The root mean squared error was also the lowest at 17. Of the three time-series models, none seemed to fit the set well or show correlation. This is unfortunate, as the time-series models are capable of recognizing the sequentiality of the data, a requirement for forecasting.

The tree models do not have such capability and are unable to forecast outside of the training range. Table 4 shows a comparison of each performance metric for the selected models.

Table 4. Performance Comparison of Different Regression Models

Model	RMSE	MAE	R^2
Individual Subset Linear Regression	16.0445	12.1210	0.9945
Random Forest Regression	17.06535	10.74354	0.99399
Decision Tree Regression	22.18599	13.01396	0.98984
Gradient Boosting Regression	39.44551	28.18553	0.96787
Linear Regression (All Data)	117.72177	95.72364	0.71382
Ridge Regression	117.72402	95.72757	0.71381
Lasso Regression	117.89145	96.06475	0.71299
Linear Regression with Feature Scaling	121.16606	88.08427	0.70197
VAR (Time Series)	215.25424	182.99602	-0.00654
Support Vector Regression	221.39544	184.32384	-0.01220
Prophet (Time Series)	285.64590	235.14233	-0.77249
ARIMA (Time Series)	LinAlg Error		

7 Results

With the Individual Subset Linear Regression model performing best with the training and testing data, that model was selected to project the 2024 point values. The choice was not difficult, as the only models that emerged with similar performance metrics were the tree-based models, which are incapable of making projections such as these. With this study being conducted in April 2024, the actual values for most divisions will be available within a few weeks of the project's completion. The indications of the training, however, suggest most of the projections will be within 20 points.

7.1 Model Forecast

While the process for achieving the most accurate forecasts is quite complex, the results themselves are rather straightforward. Table 5 includes the projections for the average top-100 point value for the global leaderboard. Projections were also made for other divisions, but were omitted from this report to eliminate repetitiveness. Such values can be found in the Github repository. The model projects several events (exactly half in Table 5) to see a decline in top-100 average point values. These events saw stronger rises in recent year(s), and the projection is suggesting a regression to the mean. It is important to understand that these are still following an upward linear trend, and the decline is due to the 2023 value being above the trendline. With 2024 being an Olympic year, these projections of decline may be more accurate for high school and college divisions, and the global division may see inaccuracies due to the Olympic Games. This is further explained in the 'Challenges' section below.

Table 5. 2023 Values and 2024 Projections for Worldwide Division (Top 100 Average)

Event	2023 Points	2024 Projection
Women 100m	1189	1192
Women 200m	1182	1182
Women 400m	1172	1168
Women 800m	1173	1168
Women 1500m	1187	1183
Women 5000m	1177	1173
Women 10000m	1166	1172
Women Triple Jump	1120	1116
Women High Jump	1131	1131
Women Long Jump	1155	1149
Women Shot Put	1084	1090
Women Discus	1075	1078
Women Javelin	1076	1084
Men 100m	1205	1204
Men 200m	1189	1196
Men 400m	1188	1184
Men 800m	1177	1176
Men 1500m	1198	1183
Men 5000m	1186	1171
Men 10000m	1173	1174
Men Triple Jump	1141	1143
Men High Jump	1145	1151
Men Long Jump	1165	1163
Men Shot Put	1162	1172
Men Discus	1134	1130
Men Javelin	1120	1126

7.2 Comparative Analysis

Each discipline in track and field appears to be on its own trajectory, with enough underlying factors for each one, making it distinct from the others. To better understand which events are advancing at faster rates, the charts like those shown in figures 2 and 3 were zero-shifted from 2010. This illustrates the change since 2010 without any initial bias. With a common starting point, Figure 7 makes it easier to view which events have seen the most growth since 2010, without the initial bias of some events starting higher than others. Figure 7 only shows values for the Global Women's leaderboard, but other divisions show similar results. In most divisions, the high jump is revealed to be the most stagnant over the time period, while the 100 meter is generally among the top growing events. Some events, like the shot put, vary widely between divisions. Overall, however, very few events, regardless of division, have seen notable decline. Of the ones that have seen a lower value in 2023 than 2010, all of them come from field events. The uniform growth of the running events raises questions, since both running and field events share a long history of maximal human performance. That characteristic should provide similar growth trajectories, so it appears that there may be an underlying force, unique to the running events, that is impacting these statistics. Early speculation would suggest 'super spikes' as this force, but research has yet to confirm this claim.

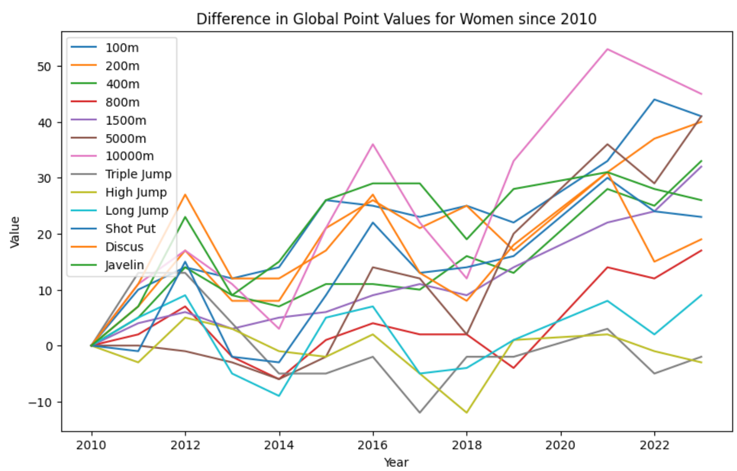

Fig. 7. The change in point values over time for each event, with the 2010 value set to zero. (M. Goeckel 2024)

8 Challenges

As the predictive models and analysis are applied, several challenges should be considered. First, the observed linear trends within the dataset may not accurately represent the broader context of track and field performance. Human performance tends to approach asymptotic limits as it reaches the pinnacle, deviating from the linear patterns observed in smaller samples. Understanding and accommodating this non-linear behavior is essential for ensuring accurate long-term predictions. In the larger picture, a linear regression of a small sample may merely be a tangent line to the greater curve. While short-term predictions may closely follow the performance metrics of the model training, long-term predictions are not likely to have the same accuracy.

Additionally, performance trends in track and field exhibit a cyclical nature, particularly evident in professional ranks. Athletes synchronize their training and peak performances with the Olympic Games, which occur every four years. These cyclical patterns introduce temporal dependencies and fluctuations in performance data, posing challenges for modeling efforts. Incorporating strategies to account for these fluctuations, such as seasonal adjustments or event-specific analyses, is crucial for enhancing the robustness and reliability of predictions. While these trends currently appear to be exclusive to the global leaderboard (rather than high school or college divisions), it may be necessary to apply an entirely separate, more complex model for the professional division.

9 Conclusion

Given the results of this project, it does not appear that there is a meaningful relationship between events (within or outside the same division and/or sex), division (within or outside the same event and/or sex), or sex (within or outside the same division and/or event). There may be similarities between series with one or more common traits (same division, sex, or event), but external series data should not be used in projections, as it was shown to be a detriment to model performance. Models are best suited to be trained on their own individual subset, even if the sample size is small. Additionally, the relationship among the 13-year timeframe studied was shown to be linear across all subsets. Projections beyond a few years is not recommended with this model, as the sample size is relatively small. Expanding the dataset to several decades may reveal a different shaped curve, and the linear nature may only be relevant to this small time period.

10 Future Work

Further research is suggested on this topic to further examine the human performance trends in the sport of track and field. Results from this study suggest a deeper view should be taken at individual subsets (ie. event/sex/division combinations) over a longer period of time, rather than multiple subsets over a short period of time. World Athletics, known in this project as the 'World' division, contains the largest backlog of performances, so it is the prime prospect for this kind of investigation. With the noted alignment of this division with the Olympic cycle, it may be worth investigating this with Olympiads as the time feature, rather than years.

Additionally, given the amount of data collected during this project, it would be advantageous to create a tool for readers to easily view filtered subsets of the data, rather than be limited to the figures shown in this report. A web app has been proposed, made with Shiny for Python, to reactively build graphs based on user-input filters. This way, readers can conduct their own exploratory analysis of the data, and stimulate new ideas for additional research.

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