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FITTING SPEEDRUN WORLD RECORD DATA TO A TRIPLE EXPONENTIAL DECAY MODEL FOR DATA ANALYSIS, PREDICTION AND VIDEO GAME GENRE COMPARISON

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ABSTRACT

Speedrunning is a gaming practice where players attempt to finish a game as quickly as possible. This paper models and fits world record speedrun data from 206 games using single, double, and triple exponential decay functions. Different data fitting performance metrics were applied to evaluate our data against the fitting functions, including R^2, L^2, MAE, MAPE, MSE, and RMSE. The results display the strongest fit with double and triple exponential decay, with values exhibiting between 35% and 93% better performance when compared to single exponential decay for L^2, MAE, MAPE, MSE, and RMSE. Triple exponential decay fits the speedrun world record data with the best performance metrics. The average R^2 for the triple exponential fit applied to the dataset was ~ 0.94. The triple exponential fit can be used to extrapolate predictions forward in time, allowing prediction of the next world record time. This is established through models built on reduced datasets with the last five data points removed (n-5). Extrapolating the fit forward in time demonstrates that the actual data falls within 95% confidence intervals of the model fit. This shows there is good agreement between the actual data and the predicted data. The nature of the triple exponential fit is also discussed, with each exponential term displaying unique initial quantities and values. The properties of these terms, such as the decay constant k and half-life λ, may be used to directly compare different video games' speedrun data. The model fitting metrics were applied to the whole dataset to produce a quantitative comparison of different game genres. This comparison displayed distinct decay rates and half-lives for game genres, with *Stealth* being the fastest and *Metroidvania* being amongst the slowest. Speedrunners, the speedrunning community, and video game developers would greatly benefit from this research by using the triple-exponential fit as a basis for evaluating new speedrun record submissions against the predicted fit, as a method for comparing multiple video game speedrun data, as an indication that a new mechanic or glitch has been discovered, or as an evaluation of video game code quality.

KEYWORDS

Speedrunning, Modelling, Exponential Decay, Prediction, Data Analysis

1. INTRODUCTION

Speedrunning is a gaming practice wherein players attempt to complete games in the shortest possible time. Over the past decade, this phenomenon has exploded in popularity, evolving not only as a mode of gameplay but also as a form of spectator entertainment (Brewer et al., 2023). The latter element is epitomised by the marathon gaming event Games Done Quick (GDQ). The competition is one of the most popular speedrunning events, in which speedrunners live-stream their gameplay on platforms such as Twitch to fundraise for a nominated charity. In 2010, the event's inaugural year, participants raised $10,000, rising to over $2 million in 2018 (Lafond, 2018). Over 124 million hours of speedrunning content were watched on Twitch in the first half of 2024, turning it into the 17th most popular tag on Twitch (Rowland, 2024). Although speedrunning is not new, with examples of speedrunning video games appearing in the 1990s (Kelfer 2022), its widespread coverage and popular adoption in modern gaming culture are relatively recent.

A speedrun attempt or 'run' represents an individual attempt to complete a video game in a given category under those category conditions as fast as possible. Popular speedrunning categories include the '100%' category and the so-called 'Any%' category. The '100% category entails beating a video game with total completion, by collecting all optional upgrades and items, etc. The 'Any%' category has the fewest restrictions, with the goal being simply to beat the game in as short a time as possible (Snyder, 2017). This can include the exploitation of in-game glitches, game code, or mechanics to reach the end state faster.

While Lafond (2018) has previously suggested that speedrunning strategies reflect complex mathematical problems, the field is relatively new, with the opportunity for academic study and data modelling. A study by Erdil and Sevilla (2023) reported that speedrunning world records could be represented by a 'power law pattern' with some approximations. They attempt to fit speedrun record data and forecast their model forward four to eight weeks. This work proposes that double and triple exponential decay models provide a better representation of speedrunning world records and enable much greater record forecasting.

Exponential decay fits are commonly used to evaluate experimental data on semiconductor physics, biophysics, nuclear physics (Rutherford and Sodd, 1903), chemistry and medical imaging (Istratov and Vyvenko, 1999). An example of multiexponential decay is found in phosphorescent measurements where Sasaki and Masuhara (1991) proposed that the resulting fluorescence dynamics, resulting from the excitation and fluorescence process of many atomic and molecular systems, is characterised by multiexponential decay. An example of triple-exponential decay can be found in Zachariasse et al. (1985), where an intramolecular excimer formation of an organic fluorescent compound could be fitted to a sum of three exponentials. In this study, we treat the speedrunning record data as part of a multiexponential decay system. As seen in Tju et al. (2021), R^2, MAE, and RMSE can be used as a model evaluation of a prediction with exponential regression. In Moradi, Hossei, and Kefayat (2025), five equations across three distinct case studies were evaluated using R^2 and RMSE, with some of their data following a fractional exponential equation.

Accurate speedrunning data modelling can predict the evolution of the next record through time and help identify potentially flawed or outlier speedrun record submissions, serving as a potential cheating detection mechanism. This research establishes a framework for analysing and studying speedrun record data. There is an opportunity to extract individual game metrics for comparison with other games with the purpose of understanding game mechanics, deriving

insights into player behaviour, and potentially establishing code quality assurance (QA) values. These metrics can be applied in game design, further study within speedrunning or code optimisation, allowing game developers to understand the player experience of a video game speedrun in depth. Significantly, this study aims to identify trends across speedrunning different game genres by examining the relationship between the exponential decay rate and half-life across multiple genres. This information could potentially be utilised by speedrunners to plan and understand how speedrun records vary by genre. In addition, this may aid game developers in identifying which genres best suit a popular speedrunning experience.

2. METHODOLOGY

2.1 Dataset

All speedrun record data was obtained directly from speedrun.com records as of August 2026. The data was downloaded directly from the 'stats' page of each game manually. The available API for speedrun.com is not officially supported, which makes it challenging to obtain large data sets consistently, as discussed later in the paper. Additional information on individual video game details, such as genre, developer, publisher, release year and release date, was obtained from the games' Wikipedia.org page.

The selected dataset consisted of games belonging to the 'Any%' category where possible, as this category generally has the most data. This sample comprised 206 individual games across various video game genres, gaming systems and release years. The full game list, containing the game's international name, speedrun.com short URL name, game ID, category description and speedrun.com category variables ID, is provided in supplementary information table S1. All popular game types dating back to 1985 were included in the dataset. Category, developer and publisher were acquired from Wikipedia.

2.2 Data Fitting and Analysis

To analyse the data, single, double, and triple exponential decay fitting equations were used. For fitting optimisation and minimisation, commonly used Python data science libraries were employed, namely scipy, scipy optimiser, pandas, and numpy. The multi-exponential decay formula is provided below.

$$S_{rec} = S_{wr} + \sum_{i=1}^{n} S_{n\ int}\, e^{-k_n t} \quad (1)$$

Where S_{rec} is the speedrunning record prediction, S_{wr} is the current speedrunning world record, $S_{n\ int}$ is the initial quantity of the decay element, k_n is the decay constant (also reported as λ) of the speedrun element, and t is time. The format is consistent with multiexponential systems (Sasaki and Masuhara, 1991).

2.3 Data Analysis Methodology

Python-based code was used to fit and extract metrics from the speedrun data individually before combining and comparing them. The initial data point in each dataset was set to t=0, with each subsequent data point timed relative to it. Each speedrun game's data was individually fit with single, double, and triple exponential decay models. To optimise the exponential fitting for convergence, the curve fit module from the library scipy.optimize was used. With this, it is possible to define the initial guess parameters (p0), the *bounds* of the optimisation minimisation and the maximum number of function evaluations (max_fev = 100000). The initial guess and bounds were dependent on the grade of the exponential fit for single, double, or triple. They are provided below and were produced following trial and error. The conditions allow all the datasets to converge; in some instances, the upper or lower limits are hit, however.

Single exponential, p0_single =[y.max() - y.min(), 1.0 / (np.ptp(x) or 1.0), y.min()], *bounds*=default (no bounds).

Double exponential , p0 =[(y.max() - y.min()) * 0.6, _p0_single[1] * 2, (y.max() - y.min()) * 0.3, p0_single[1], y.min()], *bounds*=[0, 1e-7, 0, 1e-7, 0], [y.max() * 10, 1, y.max() * 10, 1, y.max()].

Triple exponential, p0 =[(y.max() - y.min()) * 0.6, p0_single[1] * 4, (y.max() - y.min()) * 0.3, p0_single[1] * 2, y.max() - y.min() * 0.2, p0_single[1], y.min()], *bounds*=[0, 1e-7, 0, 1e-7, 0, 1e-7 , 0], [y.max() * 10, 1, y.max() * 10, 1, y.max() * 10, 1, y.max()].

This code enabled modelling the speedrun record data and comparing the fitting function data vs the real data. Having obtained the fitting residuals, several commonly reported accuracy performance metrics such as R^2 (Coefficient of determination), L^2 (Regularisation/Norm), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) are used to evaluate the fit. For L^2, MAE, MAPE, MSE and RMSE results can vary from 0 to $+\infty$, where the closer the result is to 0, the better; for R^2, results can vary from $-\infty$ to 1, where the closer the result is to 1, the better (Chicco, Warrens, and Jurman, 2021).

To test the triple exponential fit prediction capability, models were built using speedrun game data with the 5 most recent world records removed (n-5). Once the triple exponential model was fit, the model parameters were used to extrapolate the model forward in time to the original n time (most recent world record time) to compare the model prediction against the actual values. Confidence intervals of 95% were calculated using scipy.stats the "t" module and residuals in the model prediction against the actual real values.

Two data quality and model fitting algorithms were produced for this study. Both were checked and performed on each game dataset to improve the model fitting or evaluate which decay rank model fit the data best. The first check was to evaluate if there was a significant time difference between the first data point and the second. This check was necessary to improve the overall fitting on the 206 games, as having an initial data point with a large time difference to the second lowered the model fitting metrics. The check was performed programmatically by computing the time delta between the initial data point and the next subsequent point ($t_{ni+1} - t_{ni}$). This time delta was then compared to the total time span over the entire dataset (t_0 to t_{max}), if the time delta from the initial point to the next point was > 10% of the overall time span of the dataset, the first point was deleted and the second point became the new initial point for modelling. This analysis was performed recursively on each game dataset with the new initial point being set to t_0. In total, of the 206 games, 175 games had 0 first data points removed, 25

games had 1 point removed, 4 games had 2 points removed, 1 game (Tony Hawk's Pro Skater 4) had 3 points removed and 1 game (Castlevania - NES) had 5 points removed via this method.

The second check was performed on the model fitting to provide an estimate of which exponential model rank fit the data best. This 'Best Fit' parameter was determined by checking if either the upper or lower bounds (1 and 1e-7 respectively) of the fitting optimiser were hit in the proposed model fit for any of the exponential terms' decay rates k. The code logic was as follows: check the three decay rate terms for the triple exponential decay model fit and compare against the upper and lower bounds; if either bound was hit, the model fit was determined to be an 'overfit' and then the next lower rank model was checked. A similar logic was applied for the double exponential fit model, with the single exponential fit being the default fit if the double and triple exponential models hit the bounding fitting limits. Of the 206 games in the analysis, the triple exponential models were 'Best fit' for 144 games, double exponential models accounted for 51, with 11 single exponential best fit models.

Video game category analysis was performed using the best-fit determination for a game dataset combined with the genre description provided by Wikipedia. Each game's best model fit provided the major decay constant (k_major), which is the highest decay rate for the model fit; for example, the game *A Hat in Time,* which has a best fit of a triple exponential decay model with decay constant values of $[k_1 = 0.280770, k_2 = 0.002592, k_3 = 3.208478e\text{-}05]$, 'k_major' is taken as k_1. To extract the statistics for each game genre, the top 20 genres that appear with the highest frequency in the dataset were determined in a list. This list was then used to filter the main collected fitting dataset containing the fitting metrics of all games. K_major for each game matching the genre was then used to calculate the statistics. It is worth noting that many games have more than one genre. A game's fitting metrics can contribute to more than one genre type as a result. The number of games contributing to the calculated statistics for a genre is listed as n. To display each genre category median k major relative to each other, a normalised single exponential decay of the median k major with an initial value of 1 and a time span of 100 was produced. This was done to identify the fastest speedrun game category.

3. RESULTS AND DISCUSSION

3.1 Data Fitting and Metrics

Single, double, and triple exponential decay fits were applied to each of the speedrun game data. The individual accuracy metrics for the fits were collected, with the average values shown in Table 1. Chicco, Warrens, and Jurman (2021) reported the use of R^2, MSE, RMSE, MAE, and MAPE methods to evaluate the performance of regression analysis. Table 1 demonstrates an improvement in accuracy observed in all metrics by applying a triple exponential fit to speedrunning data, with the exception of triple exponential decay MSE, which has a higher result compared to the double exponential decay model. MSE heavily penalises large residuals. Both single and double exponential models are more flexible in fitting data with outliers. Due to the wide scope and amount of data from different genres and release dates, the outliers can cause the triple exponential model fits to have the largest residuals. For individual games in almost all cases, a triple exponential fit displayed better fitting metrics when compared to a double exponential fit. These fitting metrics for triple exponential data modelling provide a foundation for further analysis and insight. Based on these metrics, it is possible to perform

forward extrapolation of the speedrunning record data. One outcome of this would be to allow the speedrunning community to anticipate or predict the next speedrun record before it is achieved. It may also provide an understanding of how long it would take to achieve the new speedrun record for a given video game and category.

Table 1. Accuracy metrics averaged over the 206 games of fitted data in this study. Triple exponential decay metrics are shown to be the most performant on average across this dataset.'Best Fit' represents the exponential decay model fit which did not hit any of the upper or lower bounds when applied to an individual game's data. 144 games in this dataset were 'best fit' by a triple exponential decay model

	R2	RMSE	MAE	MSE	MAPE	L2	Best Fit
Single	0.887	182.681	131.074	128083.934	5.779	1213.93	11
Double	0.936	137.822	94.805	89433.357	3.315	918.373	51
Triple	0.942	134.390	88.536	101739.214	2.980	897.785	144

Figure 1 shows triple exponential fits for 4 games: *Getting Over It, Ghostrunner, Breath of the Wild*, and *Celeste*. These four games show accurate fitting metrics for triple exponential models applied to the data. These graphs are presented to demonstrate the fitting accuracy of the triple exponential model, in particular in Figure 1 (a). Figure 1 (c) shows that while the accuracy metrics are high, the observed data can still deviate from the proposed fit. There are many potential reasons for this, including a new speedrunning strategy or tactic being used or an updated rule change in a category. In Figure 1 (d), the accuracy metrics for the fit are good, but the ability of the fit to predict the next speedrun record data is not exact, given that the fit does not pass through the most recent record data. The observed data also implies an offset began at around 2000 days after the initial speedrun data.

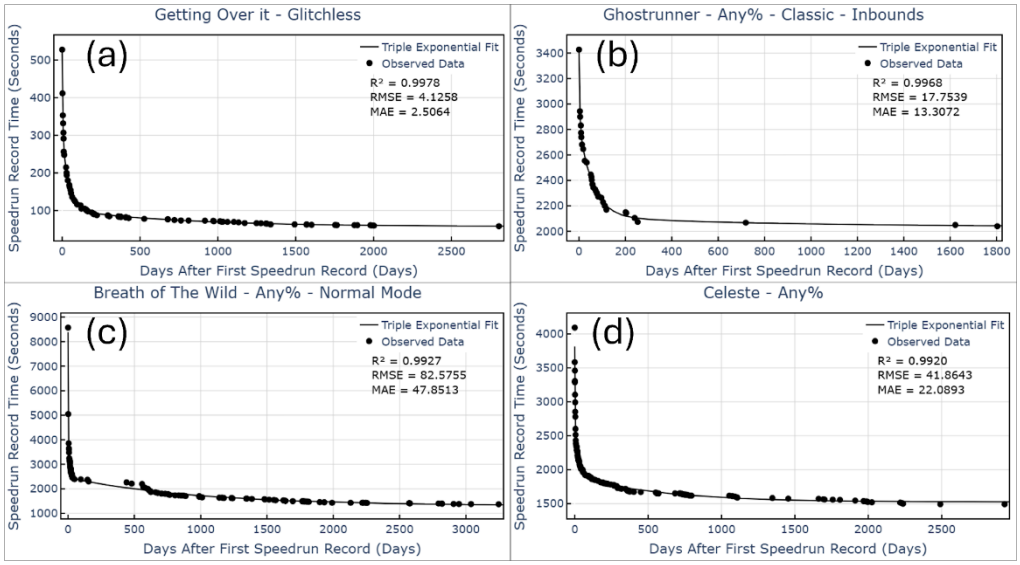

Figure 1. Triple exponential decay data fitting for 4 games: (a) *Getting Over It*, (b) *Ghostrunner*, (c) *Breath of the Wild* and (d) *Celeste*. (a) Demonstrates both good fit metrics and good overlap of the fit and the observed data. (b) – (d) Also show accurate fit metrics, but some deviation between the fit and the observed data

In Table 2, the triple exponential fitting parameters are provided for the four games reported in Figure 1. The parameters of an exponential fit produce the decay constant k_n. We can use the decay constant to directly compare different video games and perhaps determine which game is speedrunned the fastest. A larger decay constant implies a faster decay rate, or in this instance, the fastest improvement in speedrunning record times. *Breath of the Wild* has a k_1 decay constant of 1, meaning it hit the maximum upper bound of the fitting limit; it is therefore a fitting artefact as opposed to the real decay constant for k_1 of the fitting. Another feature of exponential decay is half-life ($t_{HL} = \ln 2 / k$), the time taken to reduce by half the initial amount. A common metric in the natural sciences, here it can be interpreted as the time taken for the speedrunning record time to reduce by half the initial speedrun record time. This is another metric that can be used to compare speedrunning data across games.

Table 2. Triple exponential fitting parameters for the four games seen in Figure 1. S_n represents the initial time quantity of the speedrun exponential element, k_n is the decay constant, with a higher number implying faster decay, and S_{wr} is the current speedrun world record

Game Name	S_1	S_2	S_3	k_1	k_2	k_3	S_{wr}
Getting Over It With Bennett Foddy	1.99E+02	2.21E+02	4.45E+01	2.44E-02	2.64E-01	1.33E-03	5.76E+01
Ghostrunner	5.91E+02	7.24E+02	7.81E+01	3.10E-01	1.68E-02	1.08E-03	2.03E+03
The Legend of Zelda: Breath of the Wild	4.29E+03	1.64E+03	1.15E+03	1.00E+00	7.45E-02	1.04E-03	1.31E+03
Celeste	1.32E+03	5.82E+02	3.91E+02	3.68E-01	3.21E-02	1.77E-03	1.52E+03

In speedrunning, there are several common behaviours and strategies used by speedrunners to obtain world record times. These include game mechanic glitches/exploits, game engine glitches/exploits and game mechanics mastery or routing optimisation. Each strategy is employed as a video game speedrun becomes more competitive through time, with each component impacting the final speedrun time. This observation maps to another feature of multiexponential decay - all components of the multiexponential model contribute at all times to the fitting (Sasaki and Masuhara, 1991). Mapping these individual speedrun strategies to the exponential components of the model will be explored further in future work

To test the predictive power of the model, triple exponential fits on individual game data were produced with five of the most recent world record data (n-5) removed. This fit was then extrapolated forward in time and tested against the five most recent world record times. The results of the extrapolation are shown in Figure 2, the extrapolated models are shown for the same 4 games displayed in Figure 1. In Figure 2 (a), (b) and (d), the extrapolated speedrun world record times predicted overlap with the actual world record times. Additionally, the 95% confidence intervals are overlaid on the plots for the model fit; this demonstrates that the model fit and extrapolation perform well, mapping to the actual data. From Figure 2 (b) and (d), we can infer that the prediction accuracy drops significantly when the model tries to extrapolate far into the future or if the time intervals between new world records are large.

A note on data quality and data access. There is a public API available to obtain speedrun record data, ManicJamie (2026), through code. Speedrun data, however, can be highly fragmented for a video game, with categories broken out into ever smaller subcategories, resulting in smaller datasets. It is also difficult to analyse speedrunning data holistically. There are many rule changes to speedrunning categories that can affect speedrun record data; these may also allow for new exploits in a certain category that were previously banned. It is difficult to extract these types of rule change data from the API. Historic speedrun record data is also hard to model in combination with newer data, given the change in quality of moderation and scrutiny in contemporary speedruns. There are some common features that appear consistently across speedrun world record data. The three features which have the greatest impact on accurate model fitting in this work can be described as (i) a large time delta between the first world record time and the next subsequent record, (ii) rapid decreases in world record time at some point throughout the dataset and (iii) lack of extra data to correlate or attribute to features (i) and (ii). As part of future work, further understanding of the observed features (ii) and (iii) will be undertaken, as it may provide deeper cross-game analysis. The impact of observed feature (i) on model fitting was minimised by implementing an iterative data quality check for each game dataset. The exact details are described in the methodology section. If the time difference between the first data point and the second was greater than 10% of the overall time sequence of all data, then the first point was removed. Implementing this check for feature (i) in the individual game data provided more accurate modelling results.

Fitting each game's speedrun record data produces a best-fit exponential decay model. Each game data converged to an optimised solution for single, double and triple exponential decay models within the boundary of 1 and 1e-7 decay constant limits. The fitting metrics for each exponential degree (single, double and triple exponential) are calculated individually. To identify the best exponential degree fit for each game, an algorithm was implemented to evaluate the decay constants in the triple exponential model fit, then the double, with the single exponential model remaining the default. The algorithm checked if either of the boundary limits were hit in any of the exponential terms; if they were, then the best-fit exponential degree or rank was decreased. Using this method, the breakdown of ‘Best fit’ for all games in the full 206-game list was: 144 games triple exponential model best fit, double exponential models accounted for 51 with 11 single exponential best fit models.

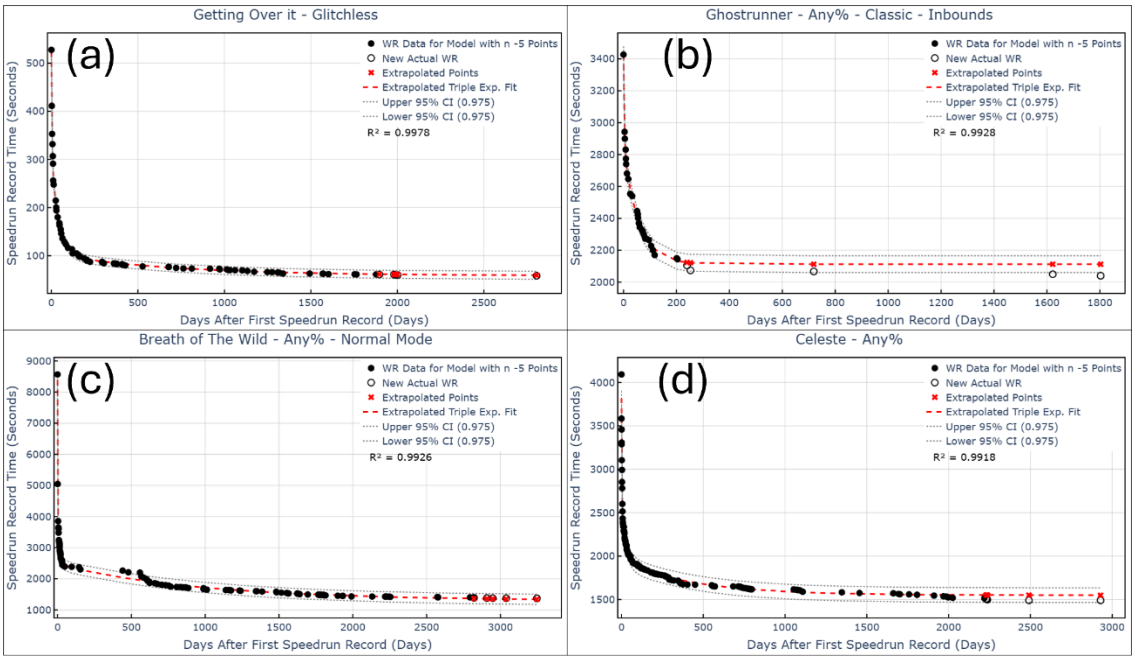

Figure 2. Extrapolation of triple-exponential decay data fitting for 4 games: (a) *Getting Over It*, (b) *Ghostrunner*, (c) *Breath of the Wild*, and (d) *Celeste*. The model is built by removing the five most recent WR (world records) in each game, fitting the reduced dataset and then extrapolating the model forward in time. (a) - (d) Show the model-predicted world record times depicted with a red cross, along with the actual world record times overlaid with a circle. Upper and lower 95% confidence intervals of the model fit are also shown. (a) and (c) demonstrate both a good approximation of the New Actual WR to the extrapolated points. (b) and (d) show a slight deviation, but the New Actual WR is still within the 95% CI. The actual data aligns with the model predictions and, in most cases, falls within the 95% confidence intervals, demonstrating the predictive power of the triple exponential model fit

The fastest decay rate term, 'k_major ', for each game's best-fit model was used to evaluate and compare model metrics across genres. Figure 3 (a) shows a box plot comparison of k_major statistics for each video game genre in the dataset. There is a clear distinction between game genres and their associated median k_major. The dispersion of the k_major values is large between 0 and 0.6, this is observed in both the interquartile range (IQR) and the minimum-to-maximum range of each genre. The distribution of values within the genre categories also appears right-skewed in most cases, with the median k_major values closer to the first quartile. These observations may be due to the fact that many games can have one or more genres associated with it, for example, "*Banjo-Kazooie*" has "*Platform*" and "*Action-Adventure*" as its listed genres. For clarity, the count of each game in each genre category is included in Fig. 3 (a). *Platform*, *Action* and *Adventure* are the most common genres in games captured in this study, with 90, 75 and 56 games, respectively, containing the genre. There is a clear distinction between these popular genres in their median k_major metric: *Platform* = 0.254, *Action* = 0.065 and *Action-Adventure* = 0.072. *Stealth* and *Puzzle-Platform* game genres have the fastest k_major decay rate of 0.44 and 0.43, respectively, indicating these game genres have the fastest improvement in speedrun record time relative to other game genres.

Figure 3 (b) is a visual representation of each game genre's median k_major applied to a normalised single exponential decay so each genre can be directly compared (*Sports, Strategy and Metroidvania* genres omitted for clarity). These data imply games in these genres will have the most rapid decrease in speedrun world record times relative to speedrunning other video game genres. The observed differences in the decay rate for the individual genres may be explained by the difference in the way speedrunners complete the game versus the game developer intended player experience. Further work will be required to attribute the observed speedrunning differences across genres quantitatively.

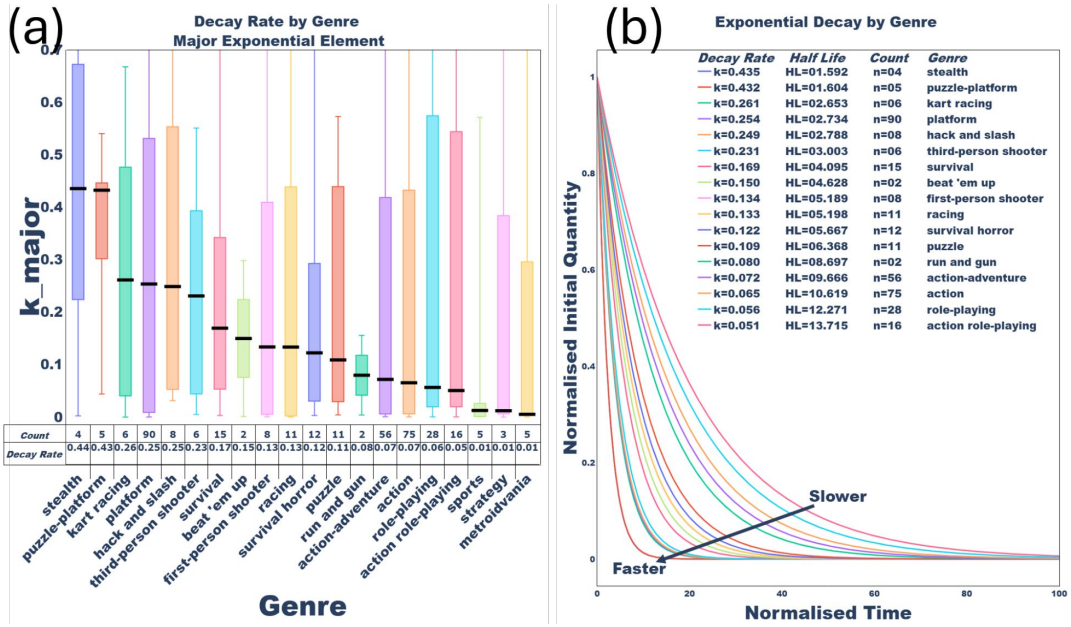

Figure 3. Grouping speedrun model metrics by game genre with the fastest decay rate k_major term from each game. (a) Box plots composed of the k_major from each game in the genre category. The count of games that fell within the genre and the median decay rate are embedded in the graph. (b) The median k_major decay rate for each game genre plotted on a normalised exponential decay function (*Sports, Strategy and Metroidvania* omitted for table clarity). The table lists decay rate, half-life, count and the genre label for reference

There are many applications of the triple exponential fitting of speedrunning record data. For speedrunners, the most relevant would be the ability to predict future speedrun record times and how long it would take to obtain them. Another aspect of the work presented in this paper is how video game playthrough data records could be analysed for educational and research purposes, such as data fitting or regression analysis. From an educational and research perspective, speedrun data analysis and modelling is relatively new; there is an opportunity for students and academics to apply established data analysis techniques to speedrunning data using the methods established in this paper as a basis. When a new world record diverges greatly from the triple-exponential decay curve, speedrunners could use this as an indication that a new mechanic or glitch was found in a specific game. For speedrun moderators, the fit may provide some scientific basis to identify outlier speedrun submissions or speedrun record data that

requires investigation. The triple exponential fit may be used to identify cheating since it would allow speedrun moderators to have new indicators for unexpected speedrun records. There is significant potential for game developers to quantify the quality of their game mechanics or game engine code using these fitting metrics. This could impact QA practices in gaming companies, for example. The findings of this paper, regarding prediction, could also be used by game developers to better plan patches and game updates. For example, when speedruns start to have diminishing returns in time, a new code update could increase the life cycles of games, offering a better overall experience for gamers and speedrunners. Game developers may also find value in understanding which game genres represent a better experience for speedrun players.

4. CONCLUSION

The objective of this study was to evaluate 206 different speedrunning world record data fit to multiexponential decay functions. A mathematical model was identified through a regression analysis. Various performance metrics were used to verify that the observed data were a good fit compared to the triple-exponential decay model fit. The performance metric R^2 exhibited an average result of 0.887 for single exponential, 0.936 for double exponential, and 0.942 for triple exponential decay. Speedrun data is difficult to analyse holistically due to the difficulty of generating large datasets from all the subcategories of a game, the self-reporting nature of speedrunning, rule changes, and historical speedrun data. Triple exponential decay models were shown to predict new future world record times when extrapolating forward in time. In addition, the actual data was consistently within the upper and lower bounds of the 95% confidence intervals. Each game's fastest decay component, k_major, was used to categorise the dataset by genre. Differences between game genres' model metrics were observed in the data. *Platform* genres had a median k_major of 0.254 (n=90), while *Action* genre games had a k_major of 0.065 (n=75). Further study may reveal consistent player behaviour observed in speedrunning regardless of the game type or category, methods to compare games directly through their exponential terms, and potentially some metrics for evaluating code quality. This will form the basis of future work.

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