Adil Khan

Data Science, Bellevue University

DSC 680: Applied Data Science

Dr. Catie Williams

NOV 11, 2022

Contents

ABSTRACT 3

INTRODUCTION 3

LITERATURE REVIEW 4

DATA 5

METHODS 6

Data Preparation 6

Analysis and Modeling 8

ANALYSIS 9

RESULTS 18

CONCLUSION 19

REFERENCES 21

APPENDIX A: PELOTON METRICS GLOSSARY [11] 23

APPENDIX B: CORRELATION COEFFICIENTS AND P-VALUES 24

ABSTRACT

Peloton® is a digital workout provider that sells fitness equipment along with a streaming subscription for cycling, strength, running, and other floor workouts. Motivation is a requirement for sticking to any routine. Knowing your motivating factors and using them strategically can lead to success in achieving your goals. The online fitness community provides many avenues of motivation including community, convenience, competition, and data. Developing a reproducible method to identify the factors that can improve performance and results can allow users to benefit even more from their investment. This project examined the Peloton® workout history for an individual user to determine the factors that influence their performance, correlation between workouts and weight, and improvement in overall fitness over time. The relationships between performance metrics were identified during correlation analysis. Visualization confirmed consistent activity overall was associated with weight loss; however, exercise was not the biggest contributing factor. Modeling using a blended regression algorithm was able to successfully rate each workout based on the average metrics during the cycling workout.

INTRODUCTION

The earliest form of at home workouts began with VHS tapes in 1979 and exploded with Jane Fonda's workout series in the 1980's. [3] As technology evolved, the workout video format moved to DVDs, then streaming from computers and tablets. [3] The home fitness equipment industry was booming in the 1990s with sales of traditional workout equipment like weights and treadmills as well as novelty items like the Thighmaster and Shake Weight. [6] In current times, we have seen a combination of digital fitness and equipment where a customer can get the instructor led coaching on gym quality equipment in the comfort of their home. Peloton® was founded in 2012 with a mission to "use technology and design to connect the world through fitness, empowering people to be the best version of themselves anywhere, anytime." [8] Founder John Foley wanted to provide an in-home high end boutique workout experience for people with busy schedules. [4] By 2019, they sold over 400,000 indoor spinning bikes

and had introduced their treadmill in 2018. [4] From January to March of 2020, sales of fitness equipment shot up 55% during lockdown. [6] Even though having the equipment at home can reduce the amount of time needed to fit a workout into a routine, a 2016 study found that motivation to exercise comes from incentives and rewards to sustain the habit long enough for health to be a motivator. [9] For some people, data can be a motivating factor.

LITERATURE REVIEW

Besides bringing the instructor led coaching experience into the comfort of your home, the connected apps generate data points about the exerciser and their workout. In 1985, the effect of percentile-based feedback on intrinsic motivation was evaluated on seventh and eighth grade children. Perceived interest-enjoyment, competence, effort, and pressure-tension were evaluated on the subjects after they were given positive-biased feedback, negative-biased feedback, or no biased feedback. The positive feedback group received scores above the 80th percentile and the negative feedback group received scores below the 20th percentile. The intrinsic motivators increased for the group that were told they were in the 80th percentile, indicating that data point had a positive effect on their performance. [12]

Along with home workout equipment, wearable trackers have become more popular to record

steps, activity, and calories burned. These devices not only collect the data but offer insights to users on how to improve the numbers. Some also incrementally increase goals as the user achieves different fitness levels. A questionnaire based 4-week study of 34 users of the fitness trackers JawBone and FitBit observed three key areas of the user interface that affected performance: data, gamification, and content.

The most impactful data refers to statistics on movement and sleep, goals, and visualizations.

Gamification motivates users by offering challenges or competitions for which the user can earn badges.

Content refers to the tracker and app's ability to support the wearer's goals. [1]

DATA

The workout metrics were downloaded using Peloton®'s unofficial API in JSON format in four separate files for one specific user.

- Workouts - The workouts file contained general information about each workout performed by the user such as date and time, type of workout, and other descriptors.
- Workout Summary - The workouts summary file contained the same data in the workouts file along with metrics about the ride in general, such as the difficulty rating and duration.
- Workout Performance - The workout performance file contained metrics about the workout specific to the user such as output, heart rate, cadence, resistance and more.
- Instructors - The instructor's data was downloaded to retrieve the name of each instructor referenced in the workout data.

After the relevant variables were parsed from the individual files and the remaining data was combined, the initial dataset contained 630 observations and 39 variables. The unit of observation for this analysis is a workout and no duplication existed among the observations. Most variables were numerical (27) with two Boolean, and ten categorical. Variables with a high level of cardinality and missing values were removed. Some metrics are only available for cycling workout types and had approximately 48% missing values. These variables were kept for analysis of cycling only workouts.

In addition to workout data, weight data was downloaded from the Apple Health Kit for the same user through the export to XML feature in the Health app. The xml file was filtered to only include data points from the RENPHO scale app and two measurements: body mass and lean body mass.

METHODS

Data Preparation

The data was wrangled, prepared, and profiled using Python 3 through Jupyter Notebook. A

Peloton® user account was used to connect to the API using the requests library. The Apple Health Kit data was loaded to a dataset using the xmltodict library. Pandas, numpy, and json libraries were used to manipulate data.

Each workout data file was first evaluated to determine irrelevant and redundant data that could be dropped. Any variables that contained JSON data in string format were parsed and relevant metrics were extracted. Once this process was complete for all the data files, the respective data frames were joined together. All date/time values were in epoch time format, represented as a ten-digit number. The pytz library was used to convert them to a readable date/time format. Once they were converted, some were GMT-5:00 and some were GMT-6:00. It appeared that initially the times were saved in Central time

(my local time zone) and then were switched Eastern time zone, which is where the Peloton® headquarters are located. When creating variables for the hour of the ride, they were all converted to Central Time. Workouts that were completed without a heart rate monitor contained a 0 for average and total heart rate metrics. Mean values were imputed from the average values for other workouts with the same duration of activity.

The weight data was loaded into a data frame, column names were tidied, and observations evaluated for duplicates. Fourteen dates (excluding times) were found to have multiple body mass measurements with different values. Rather than removing the duplicate observations, the mean of the weight values was calculated for each day. The weight data was merged with the main dataset based on date. The final dataset used in exploratory data analysis contained 28 variables, listed in Table 1.

Column	Description	Datatype
fitness_discipline	Type of workout. One of cycling, strength, stretching, cardio, meditation, or yoga.	string
is_total_work_personal_record	Indicates if this workout set a personal record	boolean
start_time	Date and time of the workout	Date and time
difficulty_estimate	Difficulty rating for the workout from the other users	float
Duration	Length of the workout in minutes	string
Name	Instructor name	string
avg_output	Average output of the ride in watts. Available for cycling workout only.	integer
avg_cadence	Average cadence of the ride in rpm. Available for cycling workout only.	integer
avg_resistance	Average resistance of the ride in %. Available for cycling workouts only	integer
avg_speed	Average speed of the ride in mph. Available for cycling workouts only.	float
total_output	Total output of the ride in watts. Available for cycling workout only.	Integer
total_distance	Total distance equivalent for the ride in miles. Available for cycling workout only.	float
total_calories	Total estimated calories burned during the ride in watts. Available for cycling workout only.	integer
max_heart	Maximum heart rate measured at any point during the workout in bpm. Available for workouts completed while wearing a heart rate monitor	integer
avg_heart	Average heart rate for the entire workout in bpm. Available for workouts completed while wearing a heart rate monitor	integer

max_output	Maximum output measured at any point during the workout in watts. Available for cycling workouts only.	integer
max_resist	Maximum resistance measured at any point during the workout in %. Available for cycling workouts only.	integer
max_cadence	Maximum cadence measured during the workout in rpm. Available for cycling workouts only.	integer
max_speed	Maximum speed recorded during the workout in mph. Available for cycling workouts only.	float
Power.Zone	Indicates whether the ride is a power zone ride. Available for cycling workouts only.	boolean
Month	Month when the workout was completed.	integer
Year	Year when the workout was completed.	integer
Weekday	Weekday when the workout was completed.	integer
Hour	Hour when the workout was completed.	integer
date_only	Date value for the workout	date
percent_leaderboard_rank	Percentile rank for where theparticipant finished on the leaderboard	float
lean_body_mass	Body mass of lean muscular tissue at the time of the workout	float
body_mass	Total body mass including fat at the time of the workout.	float

Table 1 Variables used in Exploratory Data Analysis

Analysis and Modeling

Exploratory Data Analysis was performed using R in a Jupyter notebook with the tidyverse library for data manipulation and ggplot2 for visualization. Univariate and multivariate analysis was performed with visualizations to further investigate interesting variables identified in data profiling for cycling workouts. The correlation coefficients were calculated and visualized in R using Pearson's correlation coefficient and a significance level of p-value < .05.

The pycaret library in Python 3 was used to predict the difficulty level for the ride based on the participants metrics. Missing values for heart rate were imputed based on the average heart rate for rides with the same duration. When setting up the models, the date_only and body_mass data was ignored. Duration and average resistance had to be explicitly specified as numeric because the method inferred them as categorical. The data was normalized using the minmax method. Because correlations were observed between variables, the collinear features were removed for correlations at a threshold of .75 and above. Missing values remaining in the dataset were imputed with the mean value. The features used in the model can be found in Table 2.

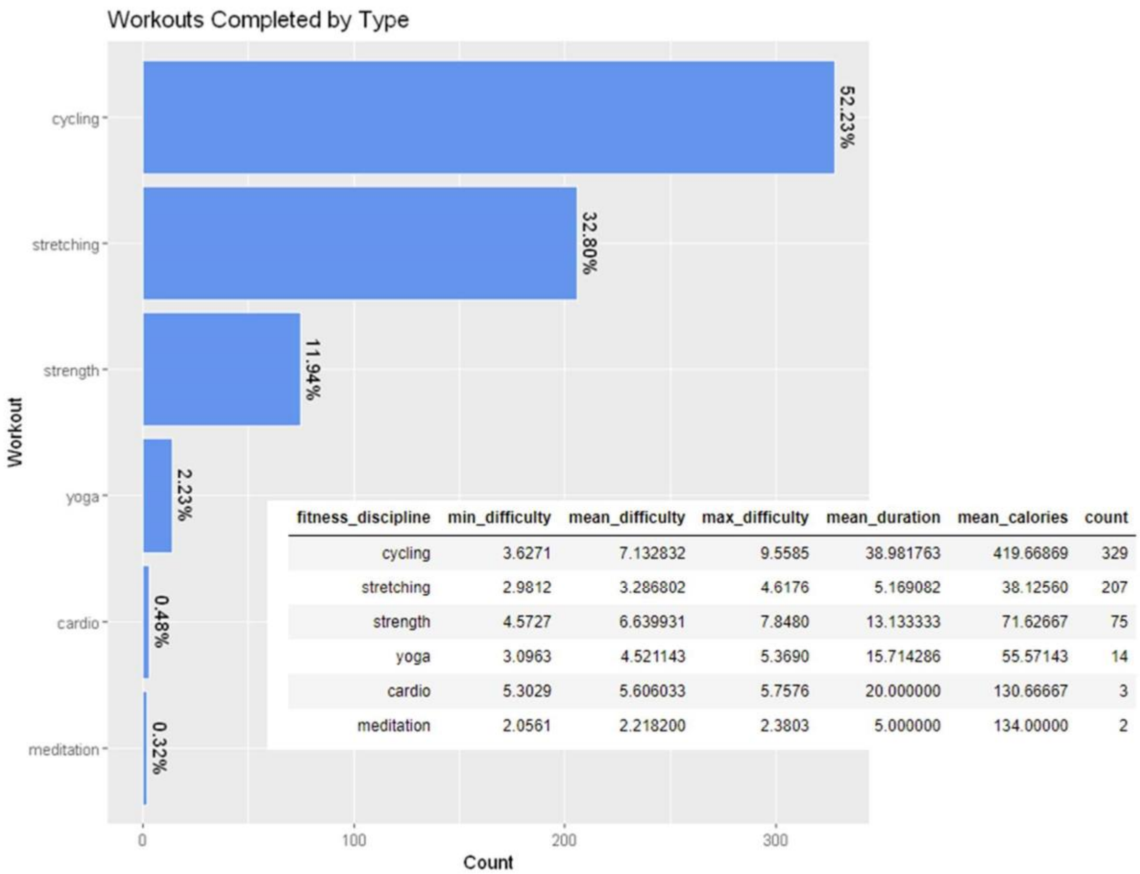
Features
duration
avg_output
avg_cadence
avg_resistance
avg_speed
total_calories
avg_heart
percent_leaderboard_rank

Table 2 Features used to Predict Ride Difficulty

ANALYSIS

Univariate and multivariate graph analysis was performed on each variable to identify trends and anomalies in the data. Cycling workouts represented 52.23% of the total workouts performed between 2017 and 2021, followed by stretching workouts at 32.80%. After most cycling workouts, the participant stretches. Almost 12% of the workouts completed were strength workouts. Figure 1 shows the distribution in workout types along with a table summarizing the general metrics for each type. The number of workouts for cardio, meditation, and yoga are too low to get an accurate representation of their overall difficulty, duration or calories burned. The difficulty of cycling workouts ranges from 3.6 to 9.5 with a mean of 7.1. As expected, stretching workouts have a lower min, mean, and max difficulty with a range from

2.9-4.6 and a mean of 3.2. Strength workouts were the most consistent in difficulty with the smallest range between the min of 4.5 and max of 7.8 and a mean difficulty of 6.6.



fitness_discipline	min_difficulty	mean_difficulty	max_difficulty	mean_duration	mean_calories	count
cycling	3.6271	7.132832	9.5585	38.981763	419.66869	329
stretching	2.9812	3.286802	4.6176	5.169082	38.12560	207
strength	4.5727	6.639931	7.8480	13.133333	71.62667	75
yoga	3.0963	4.521143	5.3690	15.714286	55.57143	14
cardio	5.3029	5.606033	5.7576	20.000000	130.66667	3
meditation	2.0561	2.218200	2.3803	5.000000	134.00000	2

Figure 1 Statistical Summary of all Completed Workouts

The duration for cycling workouts were typically larger with a mean of 38.98 minutes. When viewing the duration of workouts by type, cycling was the only workouts taken with a length of 45, 60 and 90 minutes. The mean calories burned for cycling was also the largest with 419.67 kcal. Again, the additional length of these types of workouts likely contributed to the higher caloric burn.

Cycling workouts offer additional metrics including output, cadence, resistance, distance, and speed, defined in Appendix A. When plotting these metrics for the entire dataset, outliers skewed the distributions because stretching, strength, and other workouts have 0 values for these metrics. The data was drilled down into cycling workouts only to view trends. Three periods of consistent cycling activity were evident when average output was plotted from 2017 through 2021, as shown in Figure 2. Gradually increasing average output was observed within each cluster. The longest time period of consistent activity was from end of year 2018 through the end of 2019. A gap in activity and a drop in average output was observed between 2019 and 2020. This coincided with a period of time in which the participant had multiple surgeries for treatment of a health issue. Even though the average output was lower when resuming cycling activity, the average output continued to increase as

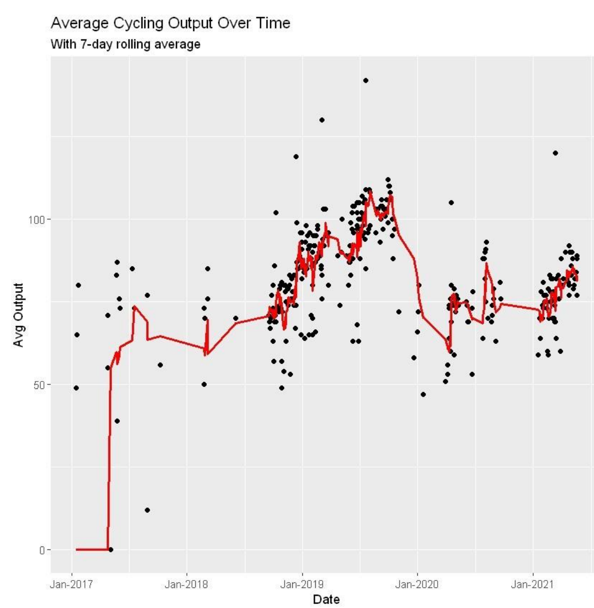


Figure 2 Average Output with 7 Day Rolling Mean

long as the workouts were consistent. The participant had another surgery in late 2020 but the average

output stayed consistent when activity resumed.

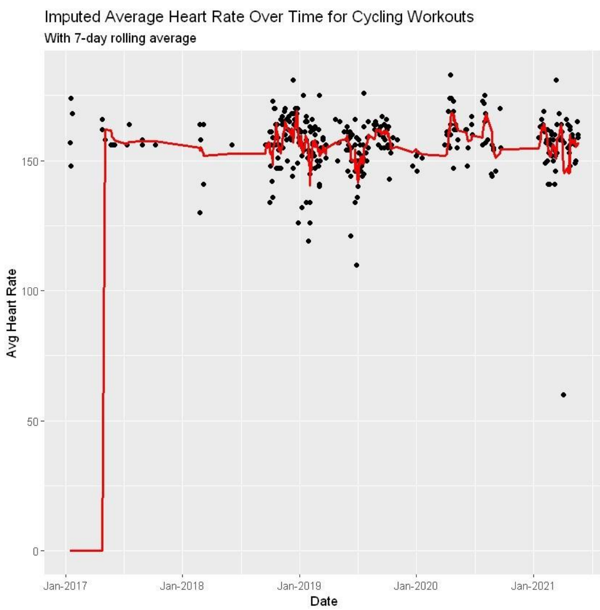


Figure 3 Imputed Average Heart Rate with 7 Day Rolling Mean

The average heart rate within the clusters of consistent activity indicates that heart rate gradually reduces with the consistent workouts, as shown in Figure 3. After the lapse of activity due to surgeries, heart rate was consistency higher than before which makes sense due the time off from working out and the events the body endured through the break. With the most recent cluster of consistent exercise, the average heart rate is observed to be gradually decreasing again.

Despite the break in workout consistency, average cadence continued to rise. Resistance, however, follows the same pattern as average output in that it increases with consistency of activity. High resistance fatigues the leg muscles faster while higher cadence is taxing on the cardiovascular system. If someone has not been consistently working the muscles needed for high resistance cycling, their average resistance would be lower. With the increase in activity, the leg muscles are being strengthened which increases the average resistance that can be sustained during efforts. Average speed surprisingly followed the same pattern of average output and resistance in that it increases with consistent cycling activity. Prior to plotting this data, it was assumed to be more related cadence than resistance.

Seventy percent of cycling workouts completed by the participant were Power Zone rides. Power Zone training is a method in cycling that focuses on 7 zones of power intentionally combined during workouts to achieve specific fitness results. [7] The output metric is the cue to indicate the desired effort to exert. [7] The overall metrics for cycling workouts were compared for Power Zone and non-Power Zone (regular) rides. Initially, most metrics for Power Zone rides were higher; however, the duration for regular rides was much lower causing a bias in the total output, distance, and calories comparisons. The data for average metrics was plotted for a more equitable comparison. The Power Zone rides still had higher averages for output, cadence, heart rate and speed. The average resistance for both types of rides was almost the same.

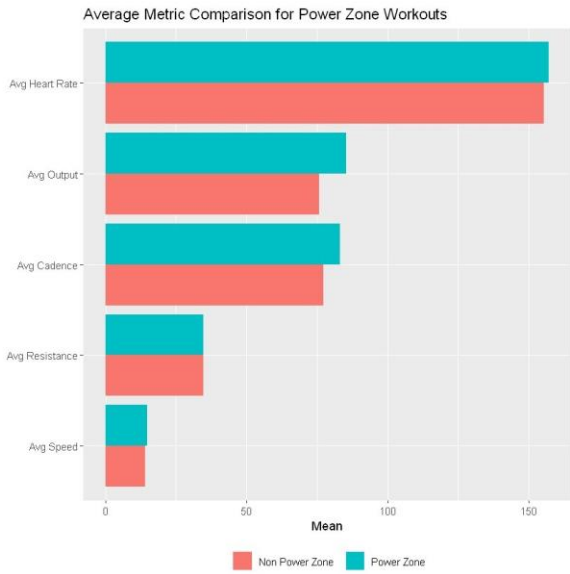
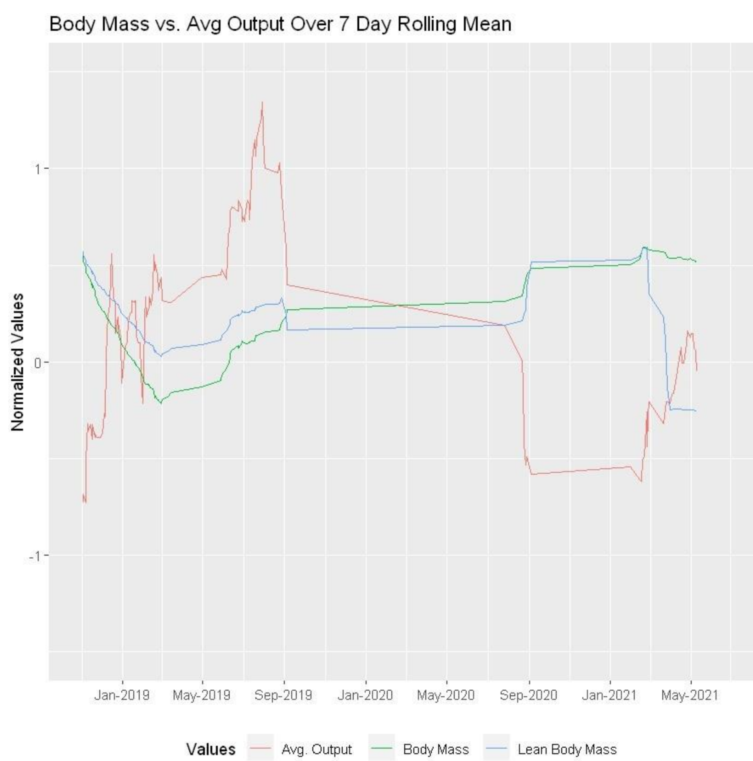


Figure 4 Power Zone Average Metric Comparison

Figure 5 Average Duration of Cycling Workouts

To explore the effect of cycling workout intensity on weight, the body mass and lean body mass were plotted over time with the average output. Three interesting trends were observed. From early 2018 through April of 2019, the body mass (both lean and overall) plummeted as the output increased; however, during another period of increased output in mid-2019, the body masses increased. Because the average output saw a large jump, the participant was likely pedaling at a higher resistance and possibly was building more muscle as demonstrated by the lean body mass climbing. During periods of low activity, the lean body mass dropped, and



the overall body mass rose. As the participant began to workout consistently again, the overall body mass began to drop again. A concerning note is that the lean body mass plummeted disproportionately around

February 2021. The explanation is the RENPHO weight monitoring app was switched from athletic mode to regular mode, which calculates the lean body mass as a lower percentage of total weight.

Because of this and the low correlation of

Figure 6 Body Mass and Average Output Comparison Over Time

lean body mass to the other variables, it was

excluded from modeling.

The correlation coefficient and p-values were calculated for each of the numeric variables using the Pearson method. Multiple strong significant correlations were found between the variables as seen in Figure 7. Correlation coefficients and p-values can be found in Appendix B. Interesting observations made from the correlation data include:

- Body mass has a moderately negative relationship with leaderboard rank (r = -.34), average resistance (r = -.57), average output (r = -.43), and average speed (r = -.42). Body mass is slightly positively correlated with average cadence (r = .26) indicating at higher weights, the participant rides at higher cadences. When the participant’s mass is higher, their performance suffers, and they tend to ride at higher cadence which requires more cardiovascular energy and less muscle energy. Lean Body Mass and the change in weight over 1 day did not have any significant relationships to the rest of the data.

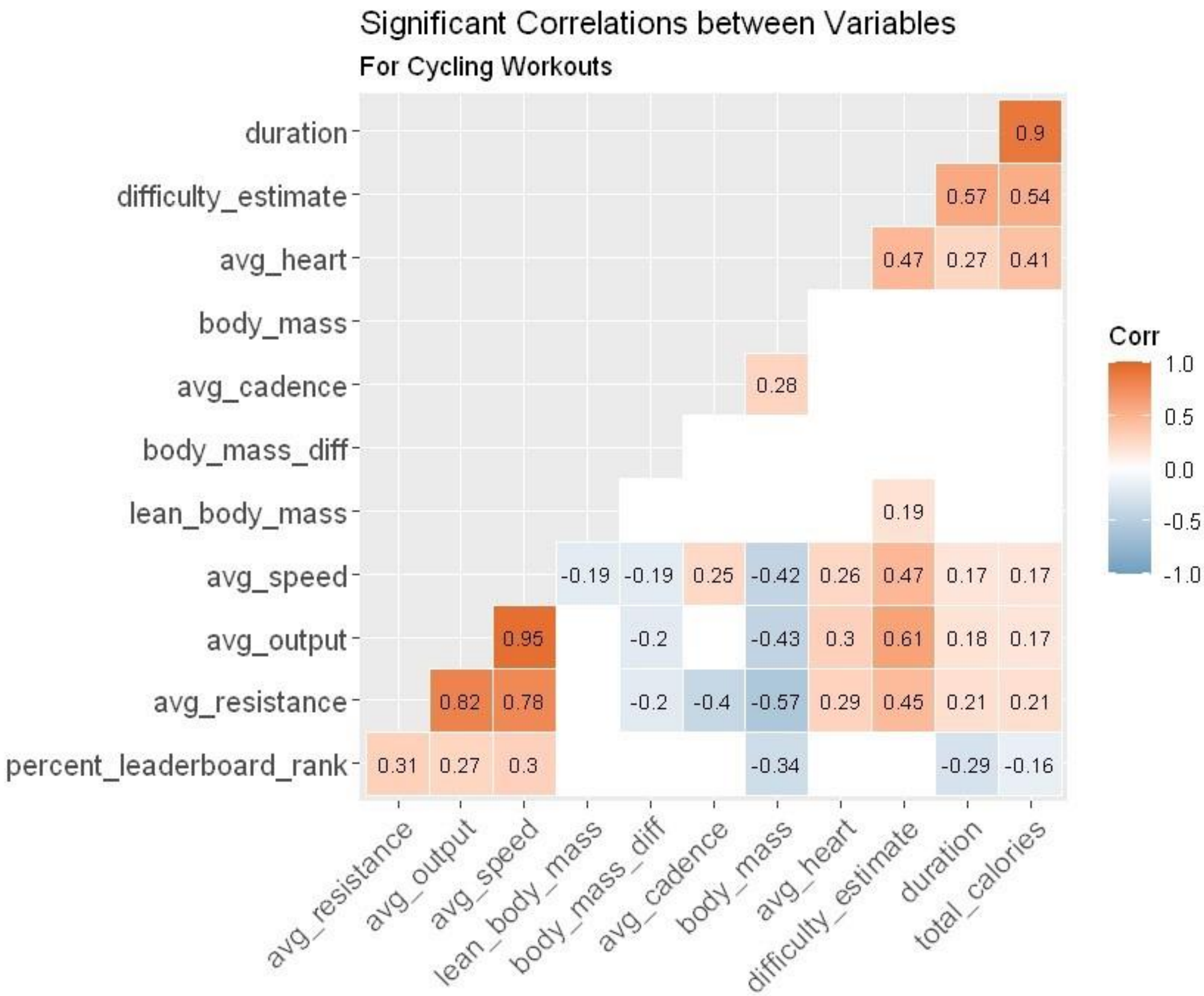


Figure 7 Significant Correlations between Variables

- Percentile rank on the leaderboard slightly influenced upward by average resistance (r = .31), average output (r = .27) and average speed (r = .3). It is slightly influenced downward by body mass (r = -.34), duration (r = -.29), and total calories (r = -.16).

- Average heart rate has a moderately positive relationship with the difficulty of the ride (r = .47) and the total calories burned (r = .41), and a slightly positive relationship with the averages of speed (r = .26), output (r = .3), and resistance (r = .29).

- Duration of the ride has the biggest influence on total calories burned (r = .90), followed by the difficulty estimate (r = .54) and average heart rate (r = 41).
- Positive relationships between average speed, average resistance, and average output were expected; however, the magnitude of those relationships was not. Average output is more correlated with average speed (r = .95) followed by average resistance (r = .82). Surprisingly, the relationship between average output and average cadence was not significant indicating cadence does not have an impact on raising ride output.
- Initially, cadence was thought to have a higher impact on the perceived speed on a ride since cadence is measured through pedaling. Based on the correlation values, average cadence influences speed (r = .25) only slightly. Average speed is primarily affected by the average resistance (r = .78).
- Average cadence and average resistance have a moderate negative relationship (r = .4) which was expected. Maintaining high cadence at a high resistance is difficult.
- Statistically significant strong positive relationships for difficulty estimate include duration, average output, average resistance, average speed, total calories, and average heart rate. This indicates that these metrics are good predictors for the difficulty of a ride. This led to the decision to create a model to rate the difficulty of a ride based on the participant’s metrics.

RESULTS

Based on findings in exploratory data analysis, difficulty estimate was determined to be the best target variable for the modeling component of this project. It had the most amount of significantly correlated features and can be used to assign a rating to new rides completed. The initial model was based on the best performing algorithm, Extra Trees Regressor. The extra trees regressor algorithm fits randomized decision trees on different samples of the data and averages them to improve accuracy and reduce the risk of overfitting. [10] After the model was tuned, the residuals were plotted and appeared to exhibit heteroscedasticity because the higher difficulty ratings were predicted more accurately than the lower difficulty ratings. The overall R^2 value for the training set was .70 and the R^2 value for the test dataset was .64. These are good results; however, the plots of the residuals and prediction error (Figures 8 and 9) indicate that improvements can be made to achieve a better fit.

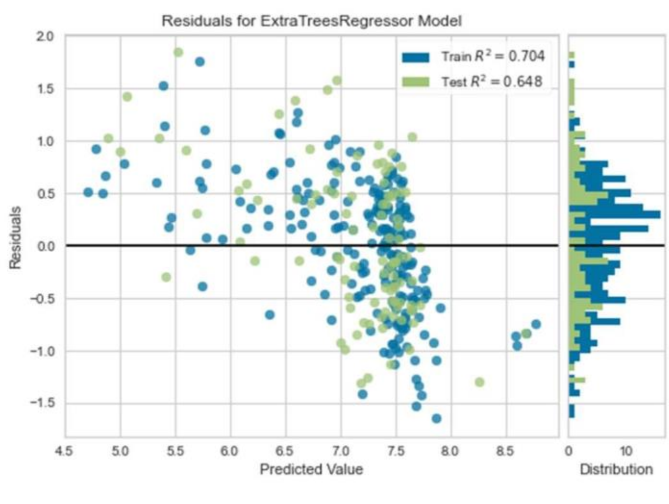


Figure 8 Initial Model Residuals

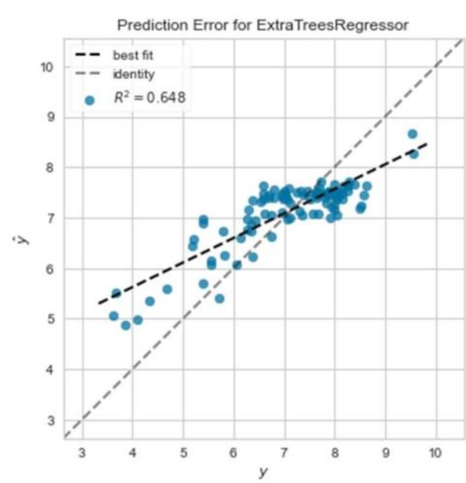


Figure 9 Prediction Errors

The multicollinearity threshold was lowered from .9 to .75 because of the many strong correlations observed between the variables. The top performing models were the K Neighbors Regressor and the Extra Trees Regressor. The K Neighbors regressor algorithm predicts numerical values by a similarity score among the closest data. [5] These algorithms were blended to a Voting Regressor model and trained on the data. The performance improved as noted in the training dataset R^2 score increasing to .94. The test dataset R^2 increased to .71, meaning the model accounted for 71% of the variation in the test data. When looking at the prediction error plot, the line of best fit is closer to the identity line.

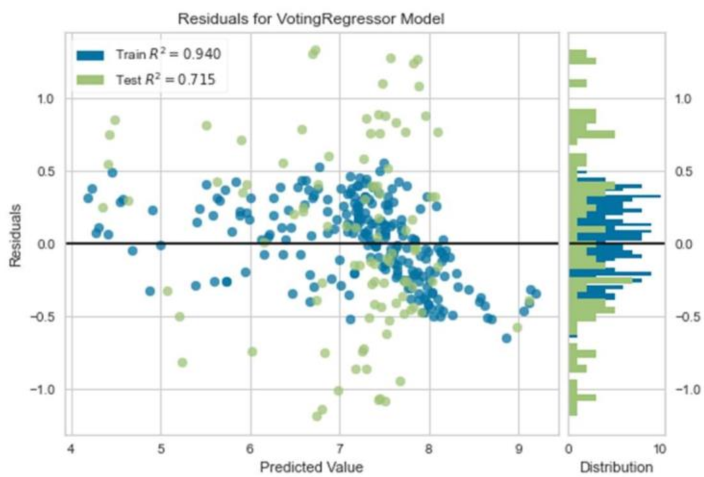


Figure 5 Voting Regressor Residuals

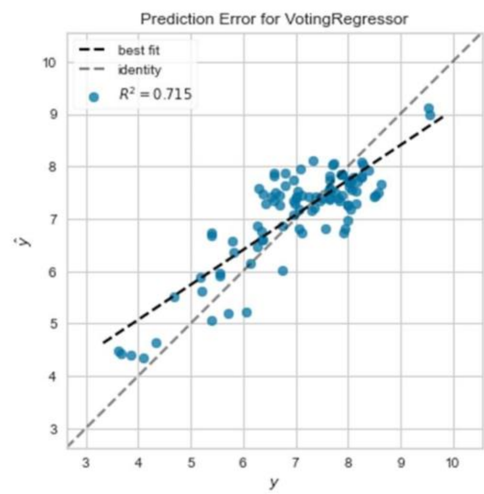


Figure 4 Voting Regressor Prediction Error

CONCLUSION

Based on this participant's metrics, cycling workouts offer the most variety in difficulty while strength workouts are the most consistent with moderate difficulty. When activity stops for long periods of time, weight loss stalls or increases, resistance decreases, and cadence is not affected. The participant's body mass at the time of the workout was a factor in the amount of energy they could expend during a ride. At a higher body mass, the participant tends to rely on cadence to complete rides rather than resistance. Higher cadence efforts depend on the cardiovascular system more so than the muscular system. [2] In order to build strength, the participant should lower the cadence and increase resistance, leading to increased performance and strength. Surprisingly, resistance played a large factor in increasing the speed and output during a cycling workout while cadence had little to no effect. Speed, output, and resistance cause the heart rate to rise more so than cadence which leads to more calories burned. The participant enjoys endurance rides that typically have a longer duration and a higher caloric burn. These variables are negatively associated with the percentile rank on the leaderboard. If the leaderboard is a motivating factor for cycling workouts, then the participant should consider varying their activity with shorter and higher intensity rides.

Overall, this project aimed to connect metrics measured during a specific Peloton® user's workout history and their weight loss. Consistency in general is key in both improving athletic performance and affecting weight loss more so than specific metrics within the workout.

REFERENCES

[1] Asimakopoulos, S., Asimakopoulos, G., & Spillers, F. (2017). Motivation and User Engagement in

Fitness Tracking: Heuristics for Mobile Healthcare Wearables. Informatics, 4(1), 5.

https://doi.org/10.3390/informatics4010005

[2] Is there a fitness difference between a high cadence and a low one? (2007, August 29). Outside Online. https://www.outsideonline.com/1768471/there-fitness-difference-between-high-cadence-and-lowone

[3] Jane Fonda's Workout. (2021). In Wikipedia. https://en.wikipedia.org/w/index.php?title=Jane_Fonda%27s_Workout&oldid=1008398255

[4] Jr, T. H. (2019, February 12). How Peloton exercise bikes became a $4 billion fitness start-up with a cult following. CNBC. https://www.cnbc.com/2019/02/12/how-peloton-exercise-bikes-and-streaminggained-a-cult-following.html

[5] K-Neighbors Regression Analysis in Python | by Imam Muhajir | Analytics Vidhya | Medium. (n.d.). Retrieved June 3, 2021, from https://medium.com/analytics-vidhya/k-neighbors-regression-analysis-inpython-61532d56d8e4

[6] Lufkin, B. (n.d.). The evolution of home fitness. Retrieved May 15, 2021, from https://www.bbc.com/worklife/article/20200504-covid-19-update-quarantine-home-workouts-duringcoronavirus

[7] Maximize Your Workouts: Power Zone Training FAQs. (2020, December 31). The Output. https://blog.onepeloton.com/power-zone-training-faqs-with-matt-wilpers-and-denis-morton/

[8] Peloton® | About Us. (n.d.). Retrieved May 15, 2021, from https://www.onepeloton.com/company

[9] Shephard, R. J. (1985). Motivation: The Key to Fitness Compliance. The Physician and

Sportsmedicine, 13(7), 88–101. https://doi.org/10.1080/00913847.1985.11708835

[10] sklearn.ensemble.ExtraTreesRegressor—Scikit-learn 0.24.2 documentation. (n.d.). Retrieved June 3,

2021, from https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.ExtraTreesRegressor.html

[11] Understanding your metrics. (n.d.). Peloton Support. Retrieved May 29, 2021, from https://support.onepeloton.com/hc/en-us/articles/203325985-Understanding-your-metrics

[12] Whitehead, J. R., & Corbin, C. B. (1991). Youth Fitness Testing: The Effect of Percentile-Based

Evaluative Feedback on Intrinsic Motivation. Research Quarterly for Exercise and Sport, 62(2),

225– 231. https://doi.org/10.1080/02701367.1991.10608714

APPENDIX A: PELOTON METRICS GLOSSARY [11]

- Cadence – how fast the rider is pedaling during the ride, measured in rotations per minute (rpm).
- Output – the amount of power/energy being exerted at any time, measured in watts.
- Resistance – the amount of weight applied to the flywheel to create friction, measured as a percent of the total possible.
- Total Output - the amount of work completed over the entire ride, measured in kilojoules (kj).

  This is calculated by dividing the average output in watts throughout the ride by 1000.

APPENDIX B: CORRELATION COEFFICIENTS AND P-VALUES

row	column	cor	p
difficulty_estimate	duration	0.569705007	3.40E-14
difficulty_estimate	avg_output	0.613670117	0.00E+00
duration	avg_output	0.181910143	2.64E-02
difficulty_estimate	avg_cadence	-0.02269383	7.84E-01
duration	avg_cadence	-0.06408306	4.37E-01
avg_output	avg_cadence	0.114250224	1.65E-01
difficulty_estimate	avg_resistance	0.449129064	9.18E-09
duration	avg_resistance	0.213715502	8.87E-03
avg_output	avg_resistance	0.816798685	0.00E+00
avg_cadence	avg_resistance	-0.40109997	3.99E-07
difficulty_estimate	avg_speed	0.469420187	1.55E-09
duration	avg_speed	0.174144429	3.37E-02
avg_output	avg_speed	0.951056479	0.00E+00
avg_cadence	avg_speed	0.246823732	2.41E-03
avg_resistance	avg_speed	0.7772143	0.00E+00
difficulty_estimate	total_calories	0.541579312	9.90E-13
duration	total_calories	0.897755167	0.00E+00
avg_output	total_calories	0.169163434	3.92E-02
avg_cadence	total_calories	-0.08040842	3.30E-01
avg_resistance	total_calories	0.212900529	9.14E-03
avg_speed	total_calories	0.169820878	3.84E-02
difficulty_estimate	avg_heart	0.466962154	1.94E-09
duration	avg_heart	0.266231703	1.03E-03
avg_output	avg_heart	0.304031165	1.64E-04
avg_cadence	avg_heart	-0.08593733	2.97E-01
avg_resistance	avg_heart	0.286226852	4.02E-04
avg_speed	avg_heart	0.261271633	1.29E-03
total_calories	avg_heart	0.413364442	1.61E-07
difficulty_estimate	percent_leaderboard_rank	-0.15317393	6.31E-02
duration	percent_leaderboard_rank	-0.28598534	4.26E-04

avg_output	percent_leaderboard_rank	0.27041343	8.87E-04
avg_cadence	percent_leaderboard_rank	-0.06244473	4.51E-01
avg_resistance	percent_leaderboard_rank	0.310712579	1.21E-04
avg_speed	percent_leaderboard_rank	0.295753057	2.63E-04
total_calories	percent_leaderboard_rank	-0.15822697	5.48E-02
avg_heart	percent_leaderboard_rank	-0.08004844	3.33E-01
difficulty_estimate	body_mass	-0.07946372	3.35E-01
duration	body_mass	0.016285073	8.44E-01
avg_output	body_mass	-0.4286826	4.92E-08
avg_cadence	body_mass	0.278251053	5.90E-04
avg_resistance	body_mass	-0.57448006	1.87E-14
avg_speed	body_mass	-0.42292082	7.73E-08
total_calories	body_mass	-0.00258322	9.75E-01
avg_heart	body_mass	0.063727184	4.40E-01
percent_leaderboard_rank	body_mass	-0.33828605	2.61E-05
difficulty_estimate	lean_body_mass	0.18965644	2.10E-02
duration	lean_body_mass	0.040270077	6.27E-01
avg_output	lean_body_mass	-0.11440516	1.66E-01
avg_cadence	lean_body_mass	-0.13756018	9.55E-02
avg_resistance	lean_body_mass	-0.10153265	2.19E-01
avg_speed	lean_body_mass	-0.18795109	2.22E-02
total_calories	lean_body_mass	0.146585753	7.54E-02
avg_heart	lean_body_mass	0.134153318	1.04E-01
percent_leaderboard_rank	lean_body_mass	-0.0265622	7.49E-01
body_mass	lean_body_mass	0.071279035	3.89E-01