A Data-Driven Approach to Optimizing Non-EBike Acceleration through Gear Ratio Optimization

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Abstract

Bikes with derailleurs use a complex mechanism to convert pedaling into acceleration. While it's commonly believed that higher gears accelerate bikes faster, the best gear-switching strategy for maximum acceleration remains debated. Many products claim to optimize gear shifting for acceleration, but their functioning and data aren't publicly available. We developed an automated system [1]interacting with derailleurs to investigate this. Our system significantly increased acceleration by 221.9% compared to using the highest gear as a control. However, our system underperformed manual transmission due to limited resources. Despite this, our findings indicate that optimal automated bike gear shifting significantly impacts acceleration. Although our system isn't as efficient as manual transmission, we've shed light on this opaque area with our model, methodology, and significant results.

Keywords: Robotics and Intelligent Machines; Cognitive Systems; Engineering Mechanics; Ground Vehicle Engineering

Introduction

We hypothesize that due to biking's similar variable power curve to internal combustion vehicles (Figure 1), a similar concept of gear-switching to cars can be to improve power efficiency in bicycles.

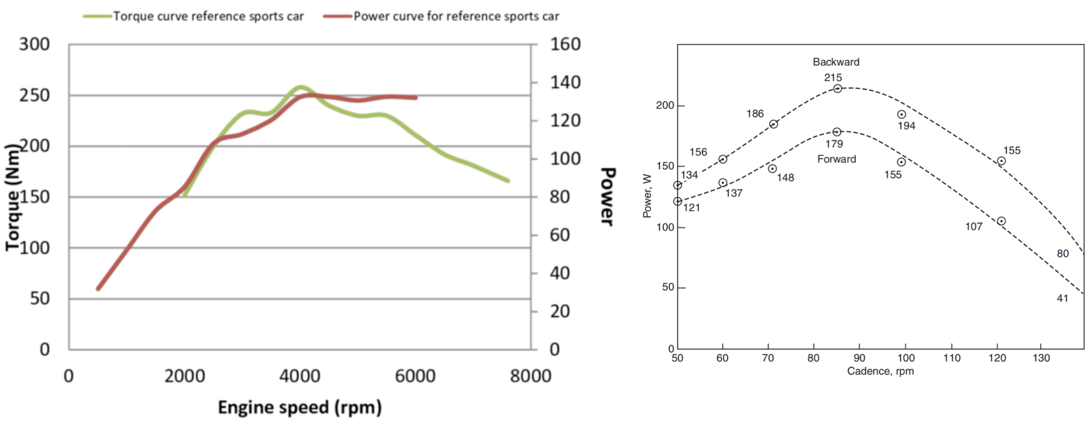


Figure 1: Torque comparison between sports cars[1] (left) and bikes[2] (page 98) (right).

Background Research

In exploring existing solutions to the problem of efficient gear-switching for bicycles, we found many: Shimano, Cambridge Consultant, and Peyman, among many others. The Shimano Di2 SyncroShift is an electronic shifting system that allows bikers to shift without pedaling by utilizing a chainring coupled to a drive unit to power the shifting of the gears. It is available on bikes with the EP600 and EP801 drivetrain.[3] Cambridge Consultant's Connected Bike uses Bluetooth to connect a mobile device to the bike, enabling features such as automatic gear shifting.[4] Peyman's fully automatic mechanical continuous variable transmission (CVT) variation system enables smooth acceleration and higher speeds and is lightweight and durable.[5]

Despite the numerous existing commercial products, no data was available on the efficiency improvement of their product. Thus, we set out to explore the effects of efficient gear-shifting on bicycles. We asked, "How does an automated gear-shifting system improve biking efficiency?" Our goal is to improve the transparency of data regarding our question, which as aforementioned, is often undisclosed by companies.

Continuation of Previous Project

This project is a continuation of our ISEF project earlier this year. Within this project, we substantially improved the efficiency of our system by making our code more efficient (reduced calculations and reduced motor spin times), improving upon our physical model (added correction system for gear lever pulling mechanism and using stronger materials for greater physical integrity).

[1]Github page: https://github.com/tario-you/isef_bike

Methods

To explore the potential impact of an automated gear-shifting system on bikes, we first had to gauge the effects that manual shifting had on acceleration to obtain a point of comparison.

Initial Testing

To prove the significance of the similar power curves and our hypothesis, we conducted an experiment in which we compared the acceleration with and without gear-shifting. Through the test, we found that shifting gears increased acceleration by 221.9 percent, a statistically significant result.

Therefore, optimal gear shifting patterns could similarly aid in the acceleration and cruising speed of biking.

Iteration 1: Environment Predictor

Model

At this stage in our project, we had not made a physical model yet.

Data Collection for Input Data

We screen-recorded the Giant connect app, which showed cadence, power, and speed during a biking trip around Shanghai that lasted 23 minutes (Figure 2). We chose to screen-record the data from the app rather than directly extract the data because the Garmin app's exported data is inaccurate (e.g., showing the velocity as zero when the bike was moving).

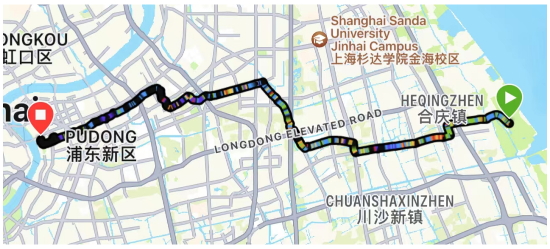
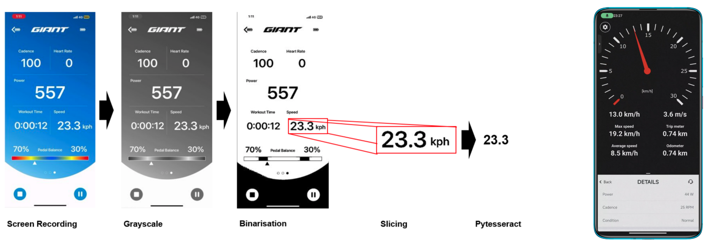


Figure 2: A map of the biking trip.

The bike trip included portions of acceleration, cruising, and deceleration, providing pertinent data to the neural network's goal.

Data Preprocessing

Each video frame was converted to grayscale, binarized, and then scaled to twice its original size (Figure 3).[6] We then sliced sections of the frame to match the location of the data points and converted the slices to text through PyTesseract.[6] We further preprocessed the data by configuring PyTesseract to recognize English, using a page segmentation mode (PSM) of 6 (assume a single uniform block of text), using OCR engine mode 3, and applying a character whitelist of "0123456789."[6] This preprocessing ensured that all our data points were numbers.



(a) Tesseract optimal character recognition (OCR) system.

(b) Phone view final model (for actual testing).

Figure 3: OCR process and phone view

Algorithm

This algorithm simulates an environment and predicts losses to find the best gear ratio. More specifically, we took the variables of speed and cadence to calculate the acceleration, which was then used to calculate environment loss variables such as air friction and rolling friction. A neural network (Figure 4) was then applied to learn patterns in our data to find gear ratios that minimized power lost to environmental losses and maximized acceleration.

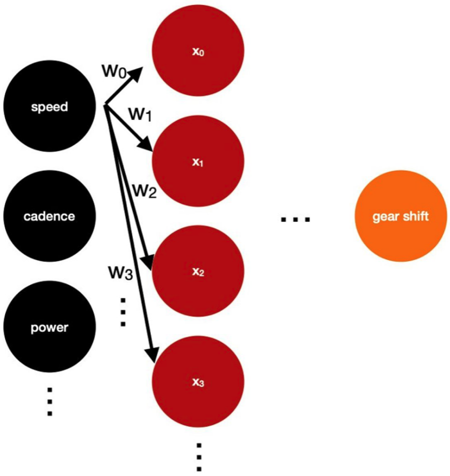


Figure 4: Neural network algorithm.

Shortcomings

The shortcomings of this system were that the neural network would learn and optimize the patterns in our biking styles, meaning it would automatically switch to the gears we would have switched to already; it would never find the best gear ratios to switch to.

Additionally, a significant factor that increases the margin of error in this system is that when predicting the power lost to the environment, we are using equations that apply to theoretical environments to estimate real-life situations, which also does not take into account other losses such as the wind direction and the material of the road. Below are some of the equations that we used.

Rolling resistance equation: $F = C_{rr}N$

Air resistance equation: $F_D = \frac{1}{2}pv^2C_dA$

Iteration 2: Ruleset Algorithm

Model

For our second solution, we added a Magene power meter to our bike so we could collect data on power as well. This data point of power eliminates much of the complexity and inaccuracy of predicting the wattage from the variables of speed and cadence, which is the method we used in iteration one; this single value can take into account many factors' impact on our system, from the user's weight to the aerodynamic drag they experience, which significantly simplifies the data points we previously had (Figure 4).

Figure 5: Virtual model 1.

We first made a virtual Blender model to plan our physical model's required materials and design (Figure 5).

We then built the virtual model onto a physical model with the Aimez SL1 bike from Giant. The motors connected to a 12-volt lithium-ion battery would pull the cables to different tensions to execute the algorithm's decisions (Figure 6). Additionally, an Arduino was used to carry out the algorithm for the bike to know which gear to switch to. Finally, the user would ride, and the bike would shift its gears.

The phone would have the appropriate apps to display the three data points and then broadcast its screen to the laptop to extract the numbers. The computer would then process the numbers with our algorithm and communicate to the Arduino to execute the gear shifts, ensuring the bike was on the optimal gear ratio.

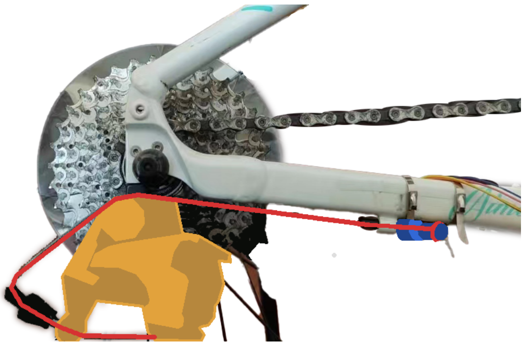


Figure 6: Physical model 1 (red = transmission cable; blue = 28byj48 stepper motor; orange = gear shifting system).

Data Collection for Input Data

We collected data using the Giant Connect app. We took five screen-recorded videos, each under 1 minute, of the app accelerating from a standstill. The 3 data points were speed, cadence (RPM), and power (measured in watts). We then used Tesseract OCR to read the datapoint inputs from our video data (Figure 3), as the raw exported .gpx and .tcx files from Garmin Connect were not as accurate as the on-screen display.[6]

Algorithm

The three data points are put through a ten-degree polynomial to obtain a torque curve (Figure 7).[7]

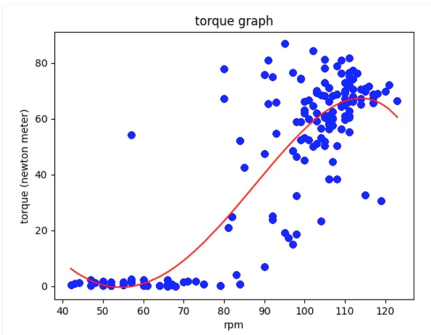


Figure 7: Our torque graph (blue: datapoints; red: best-fit polynomial regression).

These decisions for gear shifting are based on the decisions given by Physics for Gearheads by Randy Beikmann, which links the engine's torque output to the engine's rpm. Within the book, he introduces the idea that after shifting gears …

1. If the torque output of a car at a given speed is less than that of the engine's maximum rpm, then shifting at the engine's maximum rpm would be more efficient;
2. If the current and next torques are equal, or by shifting the gear up, the torque would increase, then shifting before the engine reaches maximum rpm would be more efficient.

Thus, by entering any speed and cadence into the algorithm, it would decide whether to upshift, downshift, or not shift based on …

1. If $|\text{current gear ratio} \times \text{current torque} - \text{upshift gear ratio} \times \text{upshift torque}| < 3$ (meaning the two products are around the same with a margin of error of three), then the decision is to upshift;
2. If downshift rpm < 150 (the maximum RPM we have measured from our data), then the decision is to downshift;

The computer then communicates with the Arduino via Pyfirmata to power the motors to shift the gears via the schematic in (Figure 8).[8]

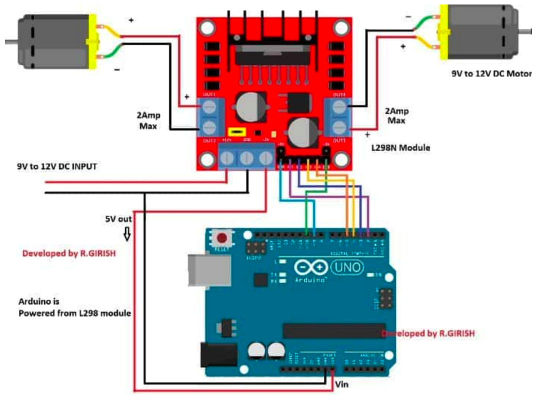


Figure 8: L298N DC motor driver schematic.[9]

The overall process is outlined in Figure 9. When fed the speed, cadence, and watts, this algorithm would output a decision for gear shifting.

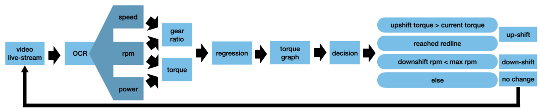


Figure 9: System block design.

Shortcomings

We realized there were issues regarding the lack of power of the motors, the need for sustained power output if the motor is directly pulling the wire, and the need for a method of directly sending the data from the sensors to the Arduino. We also found that controlling the transmission wire would require an expensive, high-torque motor and a nuanced control system for clutching the wire and pulling it to the appropriate lengths.

Iteration 3: Improved Bike Model

Model

Learning from the shortcomings of model 1, we designed a new virtual prototype in Blender (Figure 10) with the motors attached to the handlebar instead of near the rear derailleur. This system offers better control of the gears as all the motors have to do is pull the levers instead of calculating how much to pull and clutch the cable to shift gears and maintain gears.

We then built the physical model (Figure 11).

Figure 10: Virtual model 2 (blue: motor assembly, yellow: Arduino UNO, magenta: battery storage, red: power sensor, green: laptop).

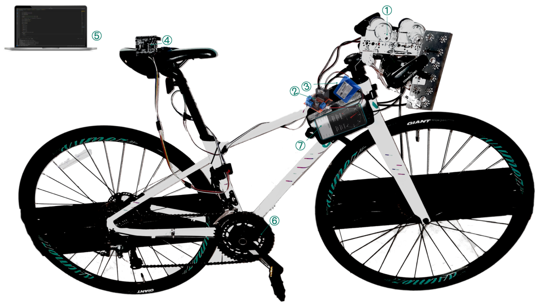


Figure 11: Physical model 2 (1. motor assembly, 2. motor driver, 3. battery, 4. Arduino UNO, 5. laptop, 6. power sensor, 7. phone).

Data Collection for Testing

We tested three conditions—accelerating on the maximum gear ratio of 4.73, accelerating with our algorithm, and accelerating with manual gear shifting —each with five trials to minimize the impacts of any trial that is an outlier — see Table 3.

Our control group is accelerating on the maximum gear ratio of 4.73.

The controlled variables were the person biking, the distance we timed, and the timing method. To ensure that the person biking did not tire over time, we allowed them ample time to rest between each trial. We biked over the same stretch of road of 159 meters. The timing method was the biker starting from a standstill and starting to pedal when the timer flashed the flashlight and began the stopwatch. When the biker crossed the 159-meter mark, the timer stopped the stopwatch.

After collecting the data, we used basic kinematic equations and the final speed reached to calculate the bike's acceleration between the two points, thereby showing the significance of the results. The significance of the results is then created by calculating the standard deviation of the data set we have collected. We calculated a range of two standard deviations, representing the 95 percent confidence interval. Once the two ranges, the assisted gear shifting and the acceleration on the maximum gear ratio, do not overlap, we can determine that the results are statistically significant. We also compared the percentage increase with the manual gear shifting we tested to determine the actual significance of our product in real-world applications.

Shortcomings

The model needs to be improved speed-wise as the gear switching time is around 0.9 seconds, much slower than manually doing so.

For the algorithm, we assumed that the ruleset from Physics for Gearheads is the best; however, there could be a better one out there that is more suited to our specific biking format.

Iteration 4: Reinforcement Learning Algorithm

Algorithm

For our current iteration of the solution, we incorporated the idea of artificial intelligence from our first iteration with the physical model we created.

However, this time, we propose reinforcement learning instead of a plain AI that can only recognize patterns in our biking style so we can genuinely achieve optimal gear-shifting patterns. Furthermore, this new model should avoid the problem of the previous model's ruleset's rigidity, potentially allowing it to find patterns not addressed by the ruleset.

For our model architecture — see Table 1, we use a long short term memory (LSTM) layer with 128 internal units, then dense layers to reduce the shape of the output down to eventually 3, which is the action size containing the three actions of upshift, downshift, and maintain.[10] We gradually reduced the shape of the output to avoid potential problems with the massive jump from a shape size of 128 to 3. Furthermore, we used an LSTM instead of a gated recurrent unit (GRU) or a simple recurrent neural network (simpleRNN) because the LSTM has more tunable parameters, which would make our algorithm better fitted.[11,12]

Table 1: Reinforcement learning model structure overview
(Total and trainable parameters: 77587).

Layer (type)	Output Shape	Param #
Model: "sequential"		
lstm (LSTM)	(None, 128)	66560
dense (Dense)	(None, 64)	8256
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 16)	528
dense_3 (Dense)	(None, 8)	136
dense_4 (Dense)	(None, 3)	27

For the environment of our reinforcement learning model, the state set is obtained not through random generation but through the extracted data points from the screen broadcast. The environment's step function takes an action, executes it, and calculates the reward, which is the change in speed due to the gear change action it executes.

For the agent of our model, we use a learning rate of 0.001, a gamma value of 0.99 which puts more weight on long-term rewards, an epsilon value of 1.0, and an epsilon decay value of 0.9995, which works to control the balance between the algorithm's exploration rate and exploitation of knowledge it already has (stored in the q values).[13] The agent's actions are based on the epsilon values, and the agent chooses between the three aforementioned possible actions. The agent also uses replay buffers to further train on the agent's memories and learn from its past.[14]

Shortcomings

As this has not been tested, the shortcomings are unknown, and common reinforcement learning flaws can be adjusted for during the testing phase of this iteration.

Benchmark Proposal for Automated Gear Shifting Systems (AGSS)

Since the market of bike acceleration optimization through gear switching for nonelectronic bikes is fairly unestablished (although there are many papers and products with concepts, none of them have implemented their solutions and come out with significant results), we have established a benchmark that assesses the effectiveness of not only our solution but also other people's and future solutions so that the solutions in this realm can be adequately compared.

The benchmark is the percentage increase in acceleration of the proposed solution based on acceleration at the bike's maximum gear ratio, which in our case was 4.73 — see Table 2.

Table 2: Proposed benchmark.

AGSS	Benchmark Max Gear Ratio	AGSS Improvement Bounds (% - %)
Our Solution	4.73 (52 : 11)	77.90% - 154.71%

Results and Discussion

Results

Raw Data

We have collected the in Table 3.

Table 3: Acceleration testing acceleration data.

	Acceleration (ms^{-2}) With...		
Trial No.	4.73 Gear Ratio (Control)	Our Solution	Manual Shifting
1	0.442	0.990	1.239
2	0.449	0.870	1.192
3	0.446	0.979	1.111
4	0.411	0.909	1.172
5	0.447	0.938	1.138

Data Processing

With our raw data, we then calculated the mean, standard deviation, and the 95% confidence intervals to determine statistical significance.

Table 4: Acceleration testing: means, standard deviations, and 95% confidence intervals.

	Acceleration (ms^{-2}) With...		
Trial No.	4.73 Gear Ratio (Control)	Our Solution	Manual Shifting
Mean	0.439	0.937	1.170
STD	0.0160	0.0497	0.0496
95% Confidence Intervals	0.407 - 0.471	0.838 - 1.037	1.071 - 1.270

The statistical significance compares as follows.

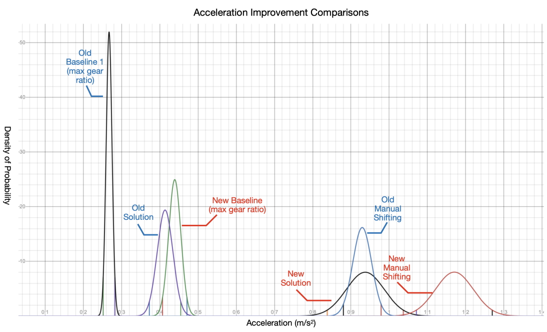


Figure 12: Graph comparing acceleration with no gear shift, automatic gear shift, and manual gear shift (red: Genius Olympiad results, blue: ISEF results)

Interpretation

Our data shows that our system is around 2.13 times better than accelerating on the maximum gear ratio, while manual shifting is 2.67 times better than accelerating on the maximum gear ratio (Table 4).

Our solution was ultimately successful because the project had significantly improved over the past iteration. In our ISEF research project (marked by the blue labels in Figure 12), our solution had a 111% acceleration increase over baseline 1. However, now, our solution has a 154.71% increase over the baseline (marked by the red labels in Figure 12). Most importantly, while our previous iteration was not statistically significant, as seen through the overlapping 95%-confidence intervals, our current model is, as seen through the separate 95%-confidence intervals of our solution and the baseline (the leftmost two red-labeled curves in Figure 12).

Of course, between the testing for the two iterations, the difference between the manual and no gear shifting is much greater on the second one than the first. On our second iteration, the acceleration is nearly 211.8% instead of 104.7%. Even when taking the different maximum percentages into account, our old results only utilize up to 54% of the available potential with manual gear shifting while our current model utilizes up to 73% of the available efficiency gains. As a result, we have substantially improved upon our old model.

Discussion

Reinforcement Learning

We can add more dimensions to our data for our reinforcement learning model as we currently only have one dimension with three input data types. If we incorporate the torque and past data points, the algorithm could produce better results with more input data.

Torque Graph Regression

For our torque graph, we can try different regression models and assess the accuracy of each model with a variety of loss functions, such as mean squared error, to have a more comprehensive understanding of which regression model best fits our data. This can make our algorithm more effective as a more accurate torque graph will represent a more accurate understanding of how the RPM affects the torque.

Model Gear Switching Speed

We can utilize a gearbox to compensate for the motors' slow gear switching times to improve our model's effectiveness. This will also improve the accuracy of the reinforcement learning model as the effects of each action will be reflected faster, and the model can better interpret which actions led to which results instead of having to interpret long-term results, which results in a higher noise level.

Compactness

We can improve the compactness and safety of our solution to progress our project into a more finalized product. Currently, the user would need to wear an extra backpack to contain a laptop to communicate with the Arduino, contributing to an overall irritating user experience. We can resolve this issue by using a Raspberry Pi to drive the whole system instead of a laptop.

Cost

Another step we can take towards a more finalized product is to reduce the project's cost. We can assess the effects of removing the input variable of wattage, which would reduce the cost by the cost of the power meter—the main contributor (around 1700 RMB) to our high price of around 3000 RMB right now, by comparing its accuracy with our current accuracy. If there is no significant impact on the accuracy, we can remove the power meter and significantly reduce the cost of our product.

Model Gear Switching Physical Integrity

Although we already used a stiffer method of pulling the gear levers—metal cables as opposed to our previous plastic string, there is a significant amount of elasticity in those metal cables, which often absorbs some of the slack by coiling up, leading to difficulty executing multiple gear changes consecutively without having to adjust the tension of the cable. A cable with less elasticity can be used to increase the physical integrity of our system and the duration our system can function without maintenance.

Improve Baseline Comparison

We are currently testing our product on ourselves, which may lead to results influenced by researcher bias; additionally, as we are more experienced in biking, we may not be the best test subjects. Thus, in the future, we should test our product on people who do not know how to bike and see the improvement between accelerating with and without it.

Implementing Our Reinforcement Learning

We can polish and implement the proposed reinforcement learning model into our physical model. For finetuning, we can tune our variables and network configurations to the most optimal ones for the resulting acceleration.[13] For implementation, we need to train our model to a point where it exceeds our current algorithm's acceleration improvement, and then we would have to conduct testing.

Conclusion

Within the relevant literature we have looked at, very little has discussed the potential impacts and implications of their solutions. We have explored our research question on the effect of automated bike gear shifting on acceleration, which was previously a black box with large corporations not disclosing their data and findings. Even though our system is worse than manual transmission because we do not have a corporate-level team working on this, we have added transparency to this black box through our model, methodology, and statistically significant results.

One possible application of our findings is that it could be commercialized to increase the general public's gear-shifting speeds, making biking a more efficient commute option.

Acknowledgements

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