Preliminary study on Rosemary, a personalized cycling assistant app

SIXIAN ZUO*, Technical University of Denmark, Denmark

This is the project report on a preliminary study of making a one-for-all cycling assistant app. Within the project, a small dataset of 11 students each cycling for around 20 minutes was collected via a demo app implemented under CARP framework, and analyzed to find key features that influence cycling behaviors. Speed, slope and cycling duration are proved to have significant influence on heart rate. Predicting heart rate with machine learning models inspires personalized exploiting of data in such app, and two models, random forest and LSTM were built and evaluated. Random forest has a better performance in this setting, while LSTM catered to time series has better potential in personalized study.

Additional Key Words and Phrases: cycling, mobile sensing, datasets, machine learning

1 INTRODUCTION

Cycling, as a fast and sustainable way of transportation tailored for urban citizens, draws significant attention in recent years. For instance, Copenhagen, one leading bike-friendly city, has now 62% of its people commuting to work or school on pedals [5]. Cycling is also embraced for health purposes, as it combines exercise and high mobility and fit well into the fast-paced modern lifestyle.

People's willingness of cycling and their real usage of bikes are encouraged and discouraged by many external or internal conditions, and the physical feedback or performances within the process that makes up the exercise part in their daily life shall vary among people. A study [4] has shown that environmental benefits, health benefits, economy and feeling of independence are four main aspects that encourage people to choose cycling to commute, while factors like infrastructure and safety, speed and effort, exposure to sun and rain and prestige often hinder people on this decision. Among all deterrent factors, lack of adequate cycling infrastructure, lack of safety (which is associated with the absence of infrastructure) and slopes are the most prominent barriers for people to choose to cycle. Another study based on roughly 7000 participants in UK reported inverse relationship between reported cycling volume and resting heart rate and in general higher resting heart rate of women than men[8]. This implies that with a same exercise goal such as a 400-calorie consumption session, different people require plans of different time length and intensity, and this usually applies to not only cycling, but all other kinds of exercises.

Therefore, for individuals, access to accurate and comprehensive road, traffic and weather information, and knowledge of their own physiological patterns could in principal aid them to better incorporate cycling into daily routines, and gain an utmost reward in improving health from cycling. Mobile applications installed on small portable devices, especially smartphones, together with small and portable physiological monitors such as smartwatches, are a shortcut to serve such purposes, as people can always use them "on-the-go".

Two mainstreams of current cycling mobile app market have covered the fore-mentioned concerns on different focus. One is **Route Planners** that take weather or traffic congestion into account, and visualize achievements or personal data reflection on geographical features. This type of apps usually puts aside physical features and data-driven encouragement of cycling, but offers accurate or exploratory routes with smart time planing and robust navigators. The other mainstream type, **Training Assistants**, is on the contrary very focused on health and performances, give guidance and record people's training data for self-promotion. However, they appear to be more attractive to people who are already obtained awareness and willingness to monitor and improve their physical features and performances,

Author's address: Sixian Zuo, s210365@student.dtu.dk, Technical University of Denmark, Anker Engelunds Vej 1, Kongens Lyngby, , Denmark, 2800.

and therefore seldom spread to an ordinary scenario where people cycle for work, school, shopping or just leisure, but also want to gain physical benefits from small snippets of cycling.

With a holistic aim to promote cycling and health in a wider range of cyclist personas with a mobile application, an application combines the above two mainstreams is needed. There also lies the need of support analysis to determine in cycling behaviors which features are important as indicators of physiological status, and how they can be used to provide informative assistance for users to ride faster, smoother or healthier. This project carried out the preliminary work of development such app approaching following research questions:

- How to collect cycling data through mobile sensing devices?
- What data shall be collected and used to provide exercise guidance?
- What models shall be used for learning personal physical features or patterns?

To investigate these questions, this project did a small demo app that acts as a data collector, a small real-life dataset collected from local students, and analysis on the dataset comparing two machine learning models' performances on heart rate prediction. The demo app is introduced in Chapt.3 and 4, and data collection and basic analysis is in Chapt.5. Comparison of heart rate prediction models is in Chapt.6.

2 RELATED WORK

2.1 Commercialized apps

2.1.1 Route Planners. *Komoot* [11] is a popular route planning application in which cyclists can gain inspirations from community posts. Especially suitable for outdoor exploration, *Komoot* allows users to either choose from other users' routes, or design their own start and destination based on the highlights for scenery in the community. *Komoot* takes cycling path types, surface types and granular elevation into account, providing 5 levels of time and average speed estimation based on the user's fitness level. It collects user's real-time heart rate, but doesn't provide any supporting functionality utilizing this feature. *Ride with GPS* [16], another popular route planning app, utilizes similar parameters for time estimation as Komoot, but fits in a broader condition from commute to adventure with detailed plan customization. *Google Maps*[6] provides route planning and navigation for cyclists with predicted time based on personal and crowd-sourced average speed, and the speed limits on specific roads, and it keeps track of the travels in a timeline. These two applications also don't probe into health purposes very much.

2.1.2 Training Assistants. *Strava* [9] is currently the most prevalent bike app in the market. On top of a sound tracking system (GPS, real-time speed and heart rate, etc.) to achieve monthly/yearly goals, *Strava* largely expands towards the athletes' community where sharing routes, joining and competing in events are possible. It is designed for serious exercising purposes, as its slogan suggests – *Features for athletes, made by athletes*, so anyone who wishes to gain more exercise can benefit with various training intensity. *TrainingPeaks* [14] approaches the cyclists having even more professional purposes. Customized training plan and one-on-one coach services enable users to prepare scientifically for the race. *TrainingPeaks* also includes more professional performance analysis to indicate one's fatigue, form and fitness out of the speed, distance, elevation and heart rate. These two applications, as mentioned in Introduction, are highly physiological related, and therefore face limits in commute settings.

2.2 Factors contributing to cycling behaviors

2.2.1 Cycling speed. Since the key to a good navigator is the time accuracy, knowing how fast the user can cycle under different circumstances becomes very essential. Many studies [3, 10, 19] have investigated the relationship between physiologic factors and the cycling performance among professional cyclists, and offered very technical advice on improving racing performances such as stretching back or arms to a specific height or angle. However, these studies have limited usage in daily settings. Study of Clarrya, et al. [1]. examined in detail how road conditions affect cycling speed. It shows that the speed decrease against unit uphill grade increase is larger than the speed increase against unit downhill grade; Being within a 35-meter proximity of a signalized intersection decreases cyclists' speed by 1.00 m/s on average, and being within 20 meters of a stop sign decreases cyclists' expected speed by 0.45 m/s; Larger roads tend to generate higher cycling speeds than smaller ones. They also proved that the speed varies in different time of day, and in different quarters of one trip. All of these road features can be used in a speed/time prediction model to navigate people to arrive on time. A fairly large study done by Gustavo Romanillost and Javier Gutiérrez [17] applied Ordinary Least Square regression with Finite Distributed Lag to decode the impact of 16 possible factors on cyclists' speeds, including static attributes like slope, intersections, age, gender, road type, bike type, trip time and distance, weather and time serial inputs like real-time traffic(cars) speed and cyclists' previous segment speeds, and confirmed their impacts by multiple models. They found out that apart from the positive correlation with the speed generated in the very last segment, *Street intersections/km* and *Slope* have biggest (negative) impact on current speed; *Purpose of the trip* also affects the speed, where people in general ride faster when riding to work than for leisure; Cloudy, especially rainy days decrease the speed.

2.2.2 Decision on bike usage. To encourage people to choose cycling instead of other transportation, it is also very important to know what matters the most to their decision. [12] tried to find the correlation between cyclists' age, gender and cycling frequency and 7 variables including low temperature endurance, safety concerns and infrastructure concerns via pure statistical methods. With a relatively small survey taken in a typical cold city, it shows that cyclists who still often cycle on such cold days didn't find it uncomfortable cycling in such a low temperature, and they share a common concern over iced or snowed roads.

A more generalized research done by Saneinejad, et al. [18] investigated the common factors' influence on choices among multiple types of transportation. With respect to bike, *low temperature under 15 °C*, *wind speed*, *rain* are leading impeding factors, and *well connected street networks* encourage more bike usage. They also proved that the influences differ across different age and gender groups, suggesting potential of individualized applications.

2.2.3 Cyclists' heart rate prediction models. Heart rate has long been used as a key indicator of exercise intensity, and a moderate-intensity physical activity requires a person's heart rate to be 50% to 70% of their maximum heart rate. There have been extensive portable heart rate monitors that allow software development, and many studies have been carried out on heart rate prediction. Although traditional machine learning models can be used for this task, neural networks tuned for time series are often discussed, as heart rate has continuity in time domain. Mutijarsa, et al. [13] built a FFNN(Feed Forward Neural Network) with cycling cadence and heart rate, and obtained MAE of around 3. Govers [7] discussed machine learning methods from regression models to RNN(Recurrent Neural Network) and LSTM(Long Short-Term Memory). Random forest in his case performed fairly well, with MAE around 0.8 and LSTM around 15.

Qiu's study [15] compared performances in predicting heart rate between models with 4 architecture – random forest, FFNN, simple RNN and LSTM on one cyclist's 10-mile training data. 4 architecture all showed drawbacks on this small dataset. Random forest suffered from severe overfitting, RNNs are too deep to train, and FFNN naturally lost time dependency.

3 DESIGN

The demo app is designed with three user personas depicting three types of main targeting users whose cycling purpose is **leisure**, **commute**, or **exercise**. The exercise volume or intensity they each seek and find adequate increases one by one, and as a result lead to different functionalities design workflow. The leisure purpose requires a workflow that is easy and simple, stimulates fun and enjoyment of cycling, and encourages to build a decent exercising habit through a rewarding/achievement system. People cycle to commute often have higher standards on the smart commute route planning and scheduling, so that they can avoid being lost, jammed or late. There also lies a common fact that each cycling commute trip usually does not exceed 40 minutes, and commute cyclists usually ride at their medium to high speed. The exercise goal during this trip is sometimes already fulfilled without any extra guidance, but commute cyclists might still gain enjoyment by having a nice data reflection where they review the days when they cycled. The exercise cyclists shall pay more attention to their real-time and historical physiological data, and requires better free route planning that reaches the wanted amount of exercise while giving nice scenery or other enjoyments along the way, so exercise gets more rewarding.

To cover these three personas, the demo app is designed to have (part of) following functionalities:

- *Navigator*: Used similar to existed Google Maps, where users can enter origin and destination to find a designed route to follow. They also get to see their own real-time location on the map.
- *Start and go*: The easiest entry to begin cycling activities at once.
- *Data collector*: Collects all kinds of (possibly) relevant data during cycling, including: duration, location, speed, heart rate, slope, weather.
- *In-time data viewer*: Allow users to check current and accumulated physiological data from the data collector so they can adjust to reach the goal.
- *Data reviewer*: Allow users to review all historical data, and gain certain achievements by visualization.
- *Personal information collector*: Show and store the basic personal information, so the application has an "individualized" setting, and people get to see their changes on body weight.

The demo app also includes auxiliary features such as the *data privacy consent sign-up page*, and a *device manager* to connect to heart rate monitors.

The low to high fidelity UI designs of the features were done in Figma, with microinteractions defined between states or pages. The main pages are shown in Fig.1.

4 IMPLEMENTATION

The demo app was built with CARP Mobile Sensing Framework [2], where back-end architecture is already defined, and many mobile sensing packages are incorporated. On top of CARP's own demonstration app, this project implemented components seen in Fig.2.

The app is deployed to local smartphone. First four functionalities described in the previous chapter are implemented in the *navigator page*, where a map package utilizing Google Maps web services is integrated, and real-time data collected from sensors or web services are shown. These functionalities were the main functionalities used for later dataset collection, and other functionalities are made with limited implementation mainly for demonstration purposes.

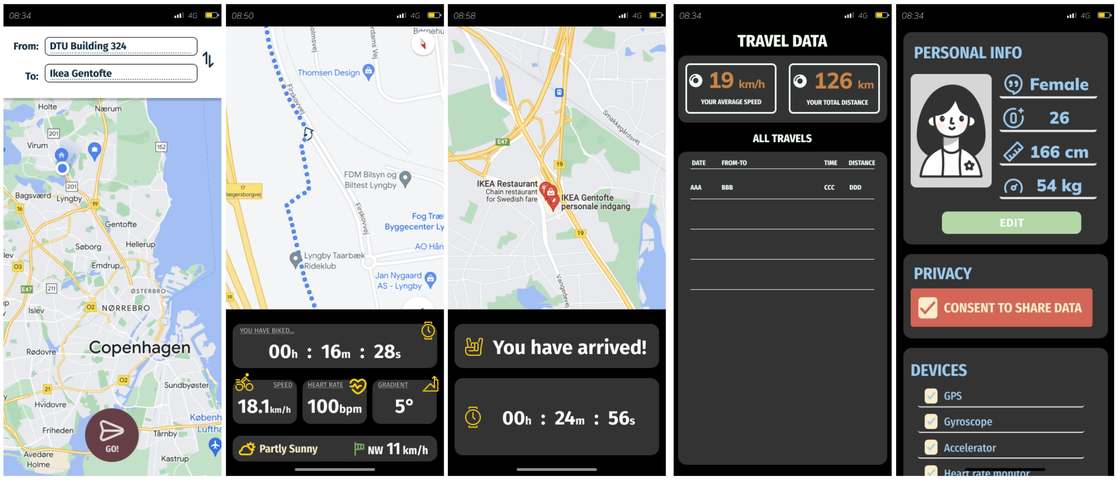

Fig. 1. Main pages of the high fidelity UI design.

Table 1. Sampling settings

Measure	Trigger type	Task type	Other settings
Pedometer	ImmediateTrigger	BackgroundTask	
Light	ImmediateTrigger	BackgroundTask	
Mobility	ImmediateTrigger	BackgroundTask	
Screen	ImmediateTrigger	BackgroundTask	
Memory	ImmediateTrigger	BackgroundTask	
Battery	ImmediateTrigger	BackgroundTask	
Device	RandomRecurrentTrigger	BackgroundTask	3 to 8 times during 8:00-20:00 in day
Location	ImmediateTrigger	BackgroundTask	Accuracy: high,; Distance: 5m; Interval: 1 second
Weather	ImmediateTrigger	BackgroundTask	
Polar	ImmediateTrigger	BackgroundTask	Polar Varity Sense

The needed real-time data is registered in the *Local Study Protocol Manager* under sampling settings specified in Table.1:

5 STUDY

5.1 Dataset collection

5.1.1 Real-person data. The project collected data of 11 DTU students cycling about 20 minutes from January 5,2023 to January 9, 2023. The time length of 20 minutes is mostly equivalant to their typical commute trip. The dataset of these people contains two subsets: a sensor dataset collected from the demo app and a Polar heart rate device, and a survey dataset collected from pre- and post-cycling interview. Unfortunately 2 participants wore the heart rate monitor switched-off during cycling, so the dataset contains 11 recordings of location information but only 9 recordings of heart rate.

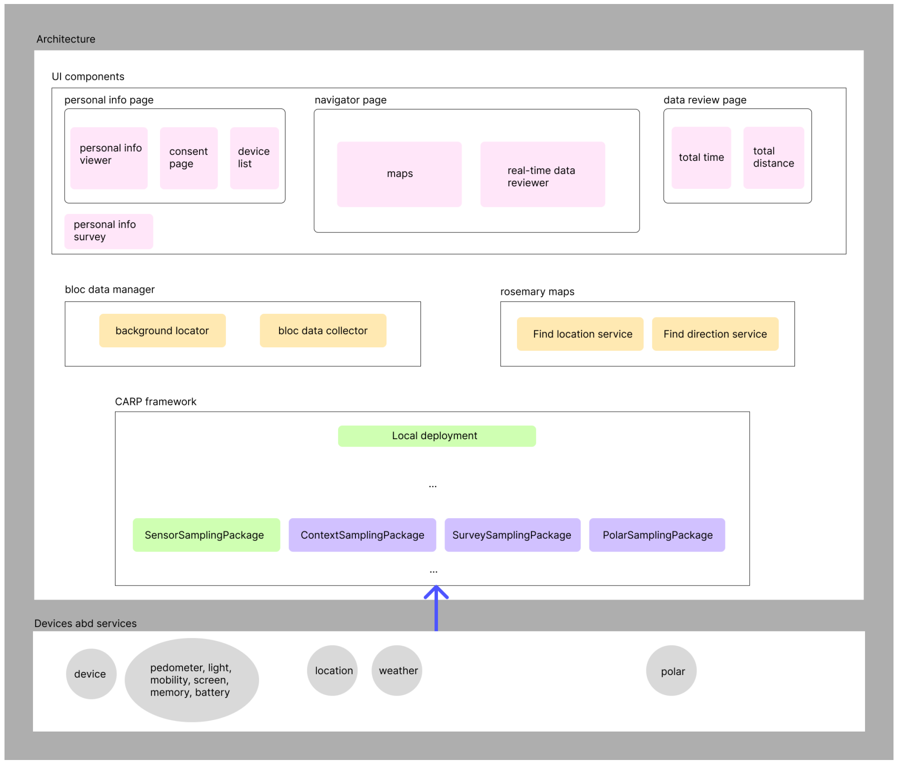

Fig. 2. Software architecture

5.1.2 Road information data. Considering slope significantly affects cycling speed and willingness, this project also collected data of the road information along the participants' trip. Utilizing *Nearest Roads*, *Place Details* and *Elevation* web services in the Google Maps API, each coordinates can be snapped to its nearest road segment in Google Maps, and details of this segment are extracted to get elevation along the road.

Google Maps by default divides roads into small grids with roughly 344m diagonals. The road segments are identified with specific ID, and coordinates on grid southeast-northwest borders are specified. The elevation within each segment is approximated by the elevation between southeast-northwest borders. An example of two consecutive segments in one collected trip is seen in Fig.3. Red dots correspond to centers of grids which lie on the road, and yellow lines are the real road segments. The diagonals in blue and green are used to approximate the segments, and elevation between southeast and northwest borders is used as an indicator of the slope.

5.1.3 Weather. Although the demo app has registered real-time weather request from web services, the development phone was run offline without SIM card. The small amount of weather information was only generated at the beginning or the end of a trip when WIFI was available inside buildings. To make up for the missing weather datapoints during the trip, the weather information is fetched from *openweathermaps* api's historical weather data. Following attributes are added for later analysis: weather main, weather description, temperature, feels-like temperature, pressure, humidity, visibility, wind speed, wind degree, wind gust.

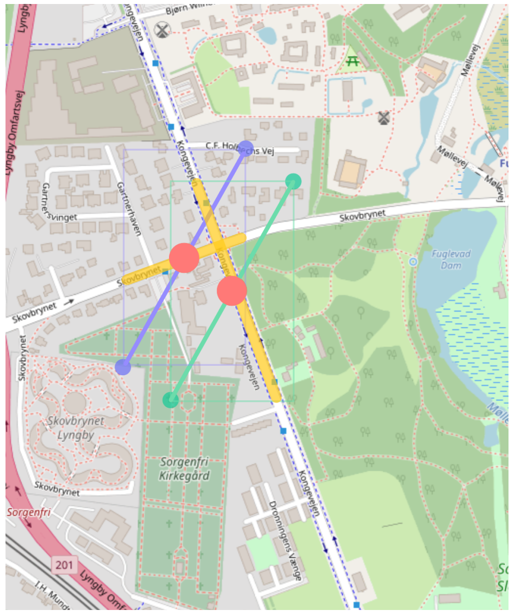

Fig. 3. Road Segement example

5.2 Raw dataset overview and preprocessing

The raw sensor dataset has 32086 datapoints in total, in which 10893 are heart rate datapoints, and 8350 are location datapoints. There are also 12305 pedometer datapoints if the participants cycled without heart rate monitor on. The pedometer datapoints are dropped due to irrelevance to a cycling data study. Amount of each type of the datapoints is recorded in the Appendix A.

The raw dataset is then divided and trimmed one by one based on the timestamps in the survey dataset marking the start of the pre-interview session. Besides, GPS tends to drift in each recording's beginning especially in the building where altitude reaches up to about 80m, and these datapoints are discarded given the fact that Copenhagen mostly lies under a 60m altitude.

After preprocessing, each participant's data overview is illustrated in Fig.4. Heart rate counts are usually slightly over a half of one's total datapoint counts, and proportional to the participant's sampling duration. Participant 5 and 9 have no heart rate data recorded.

However, participant #3 actually made two separate trips between which he had to stop to run some errands. The blank in-between is therefore deleted so his true cycling duration is decreased to 34 minutes.

As CARP collects only one type of data at a time, and heart rate sampling is in general called more frequently than location due to the 5-meter precision setting, the location points appear to be more sparse in time domain, leaving many heart rate datapoints redundant. Therefore, each location datapoint is assigned with the closest heart rate value in time. This left the dataset with 8093 valid datapoints.

The weather information is assigned to each corresponding road segment that each recorded coordinates lies in, and individual survey results are attached to each participants' location datapoints. After encoding the text features to numerical or 1-of-k labels, the main dataset used for analysis contains 43 attributes.

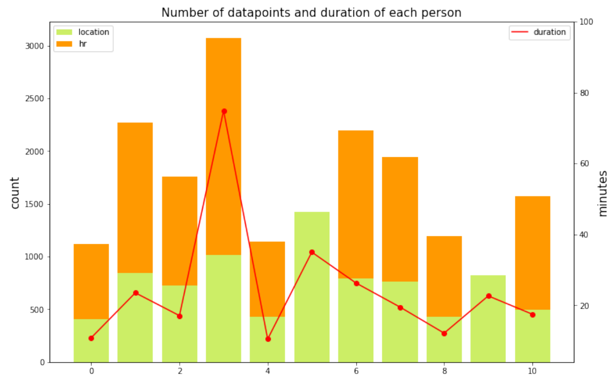

Fig. 4. Raw sensor dataset overview

5.3 Dataset statistics

5.3.1 Basic individual statistics. Out of 11 participants, 4 are female and 7 are male. The two genders contributes to the dataset respectively with 2446 and 5647 datapoints. The age ranges from 23 to 29 years old, with each datapoint count illustrated in Fig.5. The individual weight-height is also plotted, with colors specifying the self reported exercise level compared to the peers. With a major age group of around 25 years old, the participants' weights are roughly linearly proportional to their heights, since most points are aligned in a straight line, indicating no overweight or underweight participants are included. Although 3 participants' weights deviate to higher level, it does not imply possible causes in exercise habits, as they reported all kinds of exercise levels.

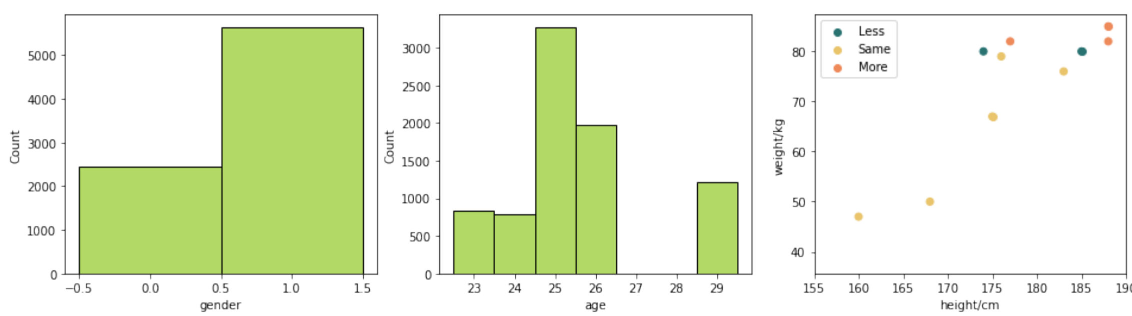

Fig. 5. Datapoints number of each participants.

5.3.2 Sensor dataset statistics. As mentioned, the participants were asked to ride under normal speed for roughly 20 minutes, and the recorded duration of their rides is demonstrated in Fig.6. The longest two trips spanned over 30 minutes, and three shorter trips lasted about 12 minutes. The mean duration of all participants lies as expected on the 21 minutes level.

The distribution of speed, heart rate and altitude is seen in Fig.7 The boxplot of individual speed shows an average speed of 14.82 km/h. It also shows that participant #0 rides significantly faster than all participants' average, and participant #10 rides significantly slower. Participant #1 has a wider range of speed variation; Participant #3, #6, #9 have

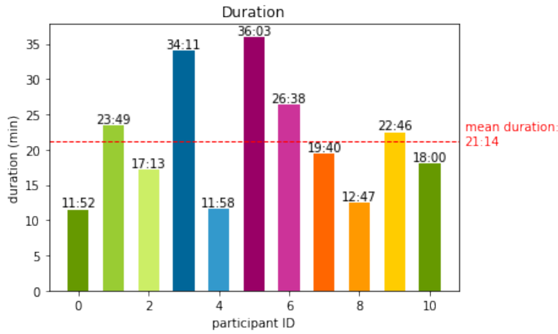

Fig. 6. Cycling duration of each participant.

a steadier speed. Participant #3 has many outliers datapoints where he ride up to more than 35km/h, but his datapoints also contain more outliers with lower speed, which might be originated from the two separated rides. In heart rate boxplot, people appear to have very different distribution. In general participants cycled for shorter duration (participant #4, #7, #10) have recorded lower heart rate, indicating lower intensity of exercise from shorter trips. But one exception exists in participant #0, who has quite high heart rate on a higher speed regardless of the short duration. The altitude boxplot helps to indicate slope's impacts on the exercise intensity participants might have gained. However, although participant #1 has very obvious span in altitude, which implies he cycled over many uphill or downhill segments, his heart rate distribution doesn't differ from the rest significantly.

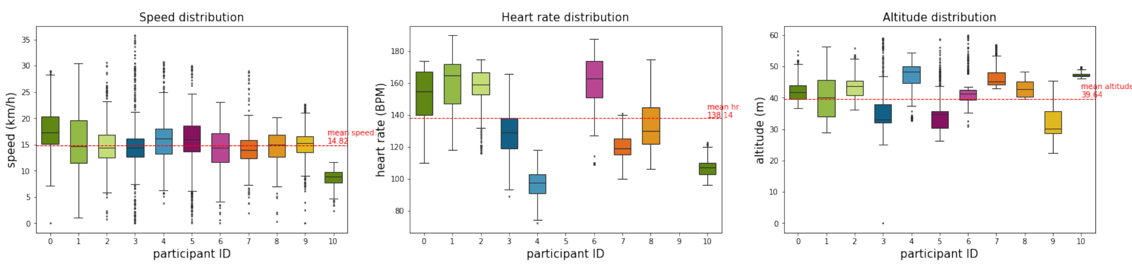

Fig. 7. Speed, heart rate and altitude distribution.

In Fig.8 all datapoints are plotted on a real map, where speeds in different areas can be seen. As many previous studies have found, many intersections meet with lower speeds, and the long, straight smooth road with few intersections facilitates cyclists to ride faster significantly. Routes within the range of the campus were also slower as expected.

Fig.9 juxtaposes the speed and road segment elevation on the map. The circled areas show clear correspondence in speed variation against uphills or downhills. The colors sometimes appear in reverse correspondence as the same route might be travelled with reverse direction. One thing to notice is the lag of "peak speed" revealed during long downhills in the yellow ellipse, as the instant speed is the result of both current slope and the speed gain accumulated from previous downhills.

5.3.3 Weather overview. The weather varied on the data collection dates in terms of temperature, wind speed and weather. The weathers through days can be seen in the Appendix B, while the temperature and wind speed changes

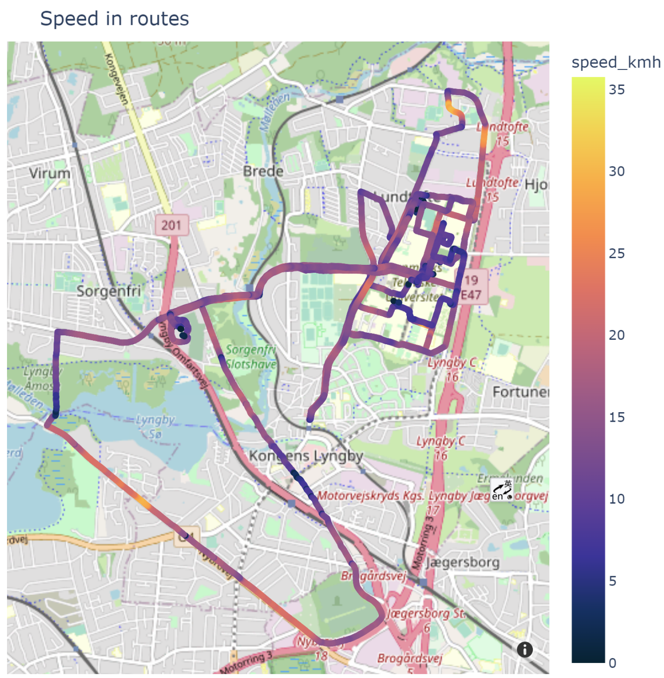

Fig. 8. Speed in routes.

along timeline with respect to each participant is shown in Fig.10. January 5 was colder with heavier wind, while the rest of the days had a milder weather for outdoor exercises.

5.3.4 Attributes correlation. To find the underlying interrelationships between features and to decode the important features that affect heart rate or other variables that worth further analysis, Pearson correlation is calculated between the 43 digitized feature columns. The complete correlation heatmap can be seen in Appendix C, and the following items are the excerpt from the 43 by 43 matrix that could be meaningful in attributes selection.

- *Participant ID*: feels_like: 0.710779, temp: 0.583231, moderate rain: 0.552072, pressure: -0.931783, wind_speed: -0.602769, light rain: -0.500655, purpose_leisure: -0.464115, hr: -0.443902
- *Speed*: wind_speed: 0.303743, willingness: 0.295598, pressure:0.289905, bike:0.205237, purpose_leisure: 0.202600, participant_ID:-0.349752, age: -0.217962, feels_like: -0.202254, longitude: -0.193066, deltaElevation:-0.151208
- *hr*: bike: 0.503103, light rain: 0.282393, pressure: 0.240841, deltaElevation: 0.161284, duration_seconds: 0.157784, feedback: -0.474375, purpose_exercise: -0.449789, overcast clouds: -0.449789, participant_ID: -0.443902, exercise_time: -0.441921,
- *feedback*: exercise_time: 0.747379, ex_level: 0.743966, willingness: 0.644407, latitude: 0.432960, height: 0.407114, age: -0.541603, hr: -0.474375, purpose_leisure: -0.427119, tire: -0.394319, altitude: 0.216186,

The participant ID is mainly correlated with weather, as the weather has quite unique signature each day and is assigned to the participants cycled on the corresponding days. It is also correlated with heart rate with quite high coefficient, indicating there is significant individual differences between heart rate level.

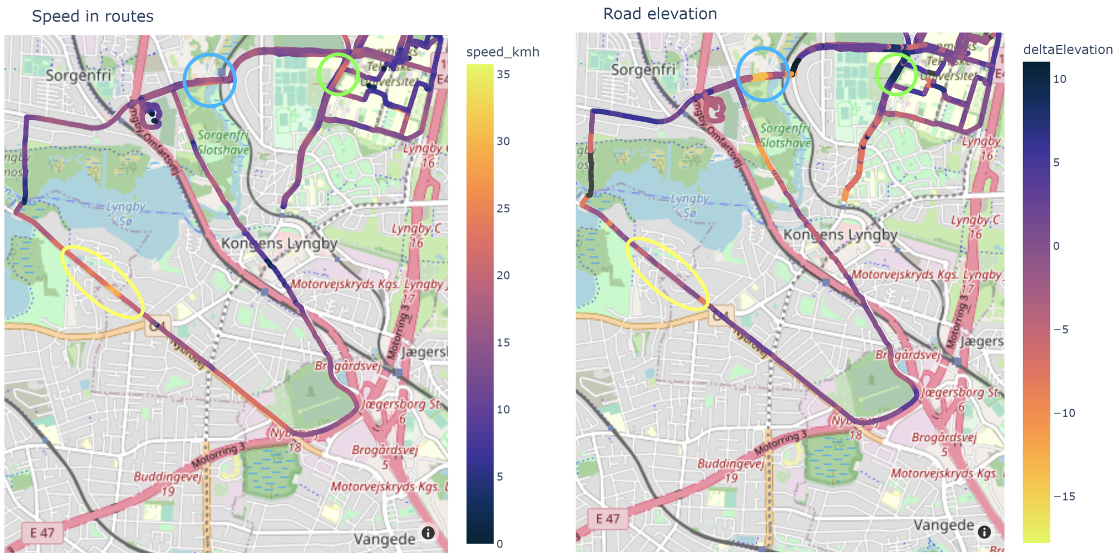

Fig. 9. Comparison between speed and road segment elevation

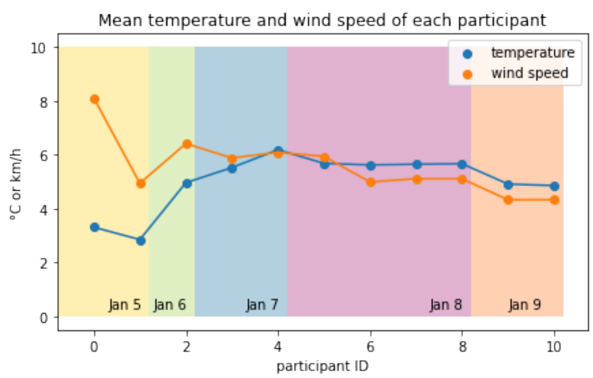

Fig. 10. Weather timeline

The speed's correlation with weather, although seemingly high, also lack evidence due to the same reason mentioned above. But there is comparatively significant correlation between speed and participant ID, meaning the cyclists have different average speeds or speed patterns in the recordings. The sign doesn't mean anything since the participant ID 0 to 10 are just nominal numbers. But the minus significant correlation between speed and age or delta elevation is meaningful, proving that older students, even still young at their middle to later twenties, might have to exercise at lower intensity and cycle slower. The positive elevation, i.e. uphills, negatively contributes to the speed.

Heart rate, apart from showing significant differences across participants with a high coefficient, is also positively correlated with elevation and duration. In most cases, the steeper an uphill slope is, the longer one cycle, the higher heart rate the participant will have.

In the post-interview, participants were also asked about the feedback on the app itself. The feedback is strongly positively correlated with athletic level features such as exercise time, exercise level and willingness to cycle for health. This implies with existed functionalities, the app might be easier to be promoted among students who already has a exercising habit or routine, and will need more attractiveness to reach less active students.

The correlation is used for feature selection in following machine learning model sections. Weather seems to offer insufficient information due to small variance through the days, and therefore are not preferable input in this study; Personal differences do exist in cycling performances, so it requires effort to keep adequate identity features; Elevation and duration might be essential in cycling behaviors such as heart rate and speed, and thus should be considered among the most important features in the app's future functionalities.

5.4 Heart rate prediction models

Based on previous studies on activity heart rate prediction, this project chose two models to train and compare: random forest and LSTM. The purpose of building such models is to first check if there is any individual heart rate pattern in the collected dataset, and to evaluate their performances including potential to be used in future work, for instance, a model-based real-time audio coach that instructs users to ride raster or slower according to the current heart rate and road/weather conditions.

The dataset collected is composed of time series from 9 participants. In the most ideal case, a well generalized model should cater to all people's data pattern, in other words, to be able to predict correctly not knowing which person the input comes from. This is also the goal this project's models partly aim at. Under this premise, 9 participants' each recording should be considered as a whole, as if they are different patterns of each (type of) person under different conditions, so the participant ID and other features highly correlated with identity should be left out in training; What's more, in the collected dataset, weather features in combination can be used to identify the exact date, and then as a key indicator of which person a datapoint belongs to. An individual-mingled dataset with weak identity information is made according to these requirements, and is used to train a random forest model which in principal has no capability of handling features' time continuity, but can still recognize the "relay" from one participant to next, since the duration(timestamp) feature is kept in it.

On the other hand, to train and evaluate models on an individual basis is still necessary. Models like LSTM naturally require time continuity in the input series, and as a result can only be trained on one person's data at a time. Therefore in this project, in each training epoch of the LSTM model, the model was optimized on participants one by one, but tested on the mingled dataset. In this way the model can still be seen as a generalized model evaluated on all people.

The dataset for trainning models only kept 9 out 11 participants' data who has valid heart rate recorded, and because of this the person numbers in this session are not the same with the original participant ID.

5.4.1 Random forest regressor. The project trained and tested models with 7 optional numbers of estimators ranging from 2 to 100, and 5 optional maximum depths from 2 to 20. The complete results with each set of parameters are kept in Appendix D. The criteria of performances used here are mean square error (MSE) and mean absolute error (MAE) on the test set.

Results show that as maximum depth goes over 10, the performances become steady, regardless of the number of estimators, where MSE mostly stays within 18-22 and MAE within 3.0-3.3. Among all parameter sets, the best model has 100 estimators and 20 maximum depth, where its MSE drops to 17.95 and MAE to 3.04.

The predictions of the best regressor from all datapoints compared with true targets are plotted on Fig.11 The RF model performed fairly well on this dataset, in which most of the peaks and valleys are well depicted, such as in person 1, 2, 4, 6 and 8. However, a sparse heart rate recording in time result in larger error, such as in person 5 and person 9, in which both higher and lower values are lost. This might also be caused by the lower average heart rate of these two participants, as the model is biased towards higher output by the rest of participants.

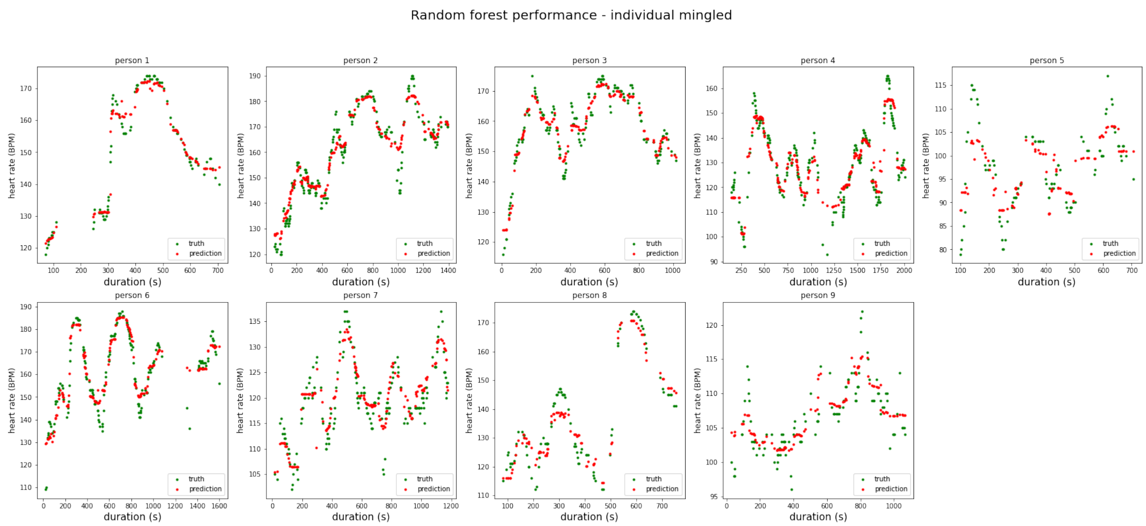

Fig. 11. Random forest prediction results on individuals-mingled dataset

The trees inside a random forest are "grown" with greedy split choices maximizing the purity gain, and therefore offer insights on the importance of features. The feature with higher purity gain is considered to contain more characteristics of the dataset, and can better differentiate underlying patterns. The GINI importances, i.e. the mean impurity decreases of the features in the mingled dataset are illustrated below in Fig.12 It is not surprising that height and weight still remain high importance, as they inform part of the personal identity. The weekly exercise time, less informative but still could be a major source of personal identity, also has high importance. Besides these, the duration in seconds is found to be the most important feature, implying that the heart rate is significantly dependent to the time one has cycled.

In spite of the satisfying performances shown above, this random forest model still raises concern in its generalization ability. Now that it's considered by default irrelevant to weathers, in the long run, however, any cyclist will face heart rate or speed fluctuations when it's raining heavily or extremely hot. The limited amount of the dataset has put limits to further investigate this issue.

5.4.2 LSTM. The long short-term memory (LSTM) model, a revised RNN model equipped with memory gates to keep and forget historical data, is especially suitable for time series study. In this small session, the normalized dataset with all attributes except the exact participant ID is used for training and testing. The parameters was tuned repeatedly. Considering that the heart rate data is extracted every 5 meters moving in location, the sequence length kept in memory is set to be 3, meaning the heart rate has high continuity in 15-meter road segments. This echoes with the definition of "proximity" to intersections or signal lights in Clarrya, et al. [1] study.

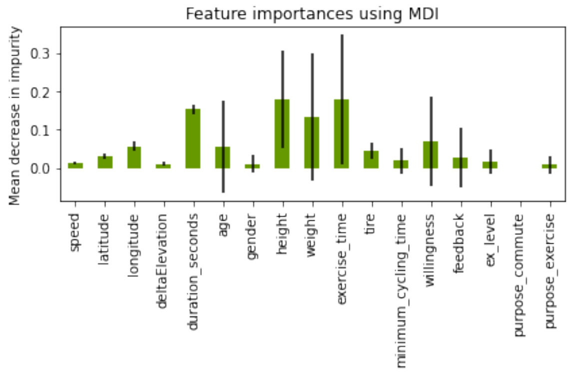

Fig. 12. Feature importance in the random forest model.

The number of hidden layers and the number of hidden units in each layer don't alter the performances greatly, so they are chosen to be 2 and 10, in order to lessen the computation amount in training. The learning rate has a great impact on reaching the optima. It is set to be 0.01 eventually, as bigger learning rates like 0.05 and 0.1 lead the model tramped around the saddle point back and forth. The model was trained for 600-800 epochs, because sometimes the performance worsen after the 700th epoch.

Another phenomenon worth noticing during training is how the model escaped one local optima to a better optima. This sometimes happens after the 300th epoch, and currently the best performance this LSTM model obtained is around 60 MSE at some point between 500th to 600th epoch. The performances in the 300th epoch and 600th epoch are plotted in Fig.13 and Fig.14. The losses of person 1 and 9 are usually lowest, at less than 20, and person 2, 3, 6, 7 at slightly higher, around 40-50. Person 5 in general has 60. The person 4 and 8 represent the local optima, as the MSE of these two are always higher: one at around 80, and another around 100.

The model is able to capture main shapes and trends in most of the participants, such as in person 1, 2, 3, 4, 6, and 9, but details are mostly lost. Person 5, 7, 8 are, on the contrary, predicted to have lots of static values. However, after reviewing the prediction changes through epochs, the shape of person 7 and 8 were gradually lost, which seems to be "sacrificed" to improvements of other participants. The person 4's prediction is again dominated by system bias, as its lower values become insignificant compared to the majority of the dataset having a higher output.

Compared to random forest, LSTM does not outperform on the dataset this project managed to collect. This has also proved how small dataset face limits when used in a complex model like neural networks. However, it also suggests greater potential in individualized learning of LSTM, since it grasped the main patterns of most participants, and the internal representations allow deeper insights used in later researches.

6 DISCUSSION

This project was run as a complete and structured small preliminary study, and ended with abundant findings eligible as grounding evidence for a potentially larger project. The demo app design received an average score of 6.45 out of 10 on its helpfulness in health or cycling performances, but the willingness to cycle more to exercise is very low for people who lack exercise habits, which calls for more user study to motivate this type of people to get involved before all other concerns.

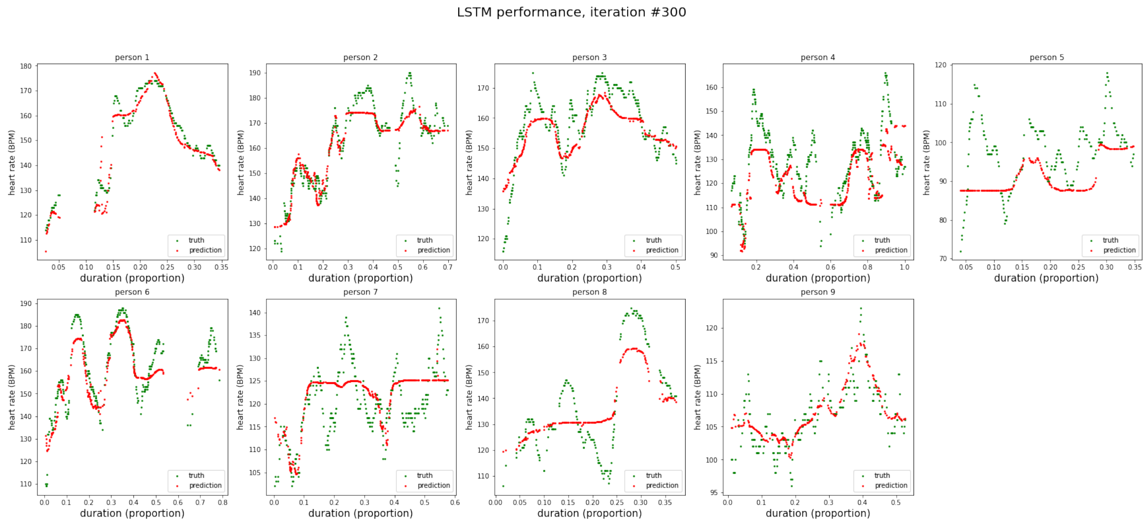

Fig. 13. Prediction of LSTM model at epoch 300

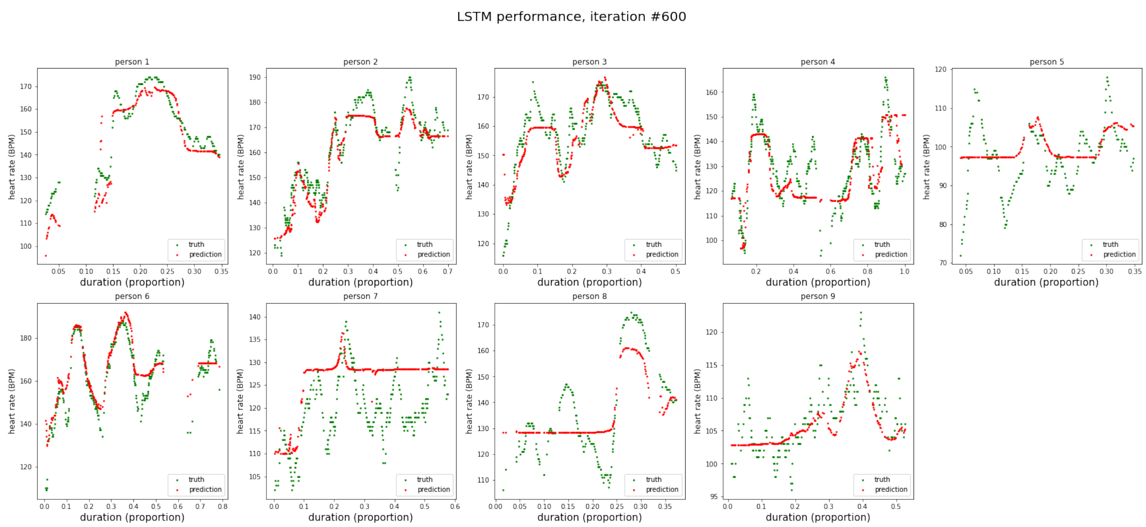

Fig. 14. Prediction of LSTM model at epoch 600

The data collection runs mostly as expected, in which data is correctly collected from 9 out of 11 participants. This small dataset has diverse usage and potential, that reveals a very vivid tip of student personas at DTU. However, the missing heart rate part emphasized on the need to have better process control during collection, which can also be a major improvement.

The data analysis, together with the two heart rate prediction models composed the main contribution in this study. It is proved that elevation (slope) significantly influences speed with certain time lag, and heart rate is very often under the influence of speed, slope and duration. These information is needed, either to make an accurate route planner, or an exercise assistant. Both models worked with acceptable performances, with random forest having lower prediction error due to the small size of the dataset. The cycling patterns, especially heart rate patterns, have a very strong individual bias, and as a consequence often alter the predictions of machine learning models in community learning, but there is still good potential in utilizing complex network such as LSTM in individualized exercise apps to learn and benefit from a single user's personal data.

7 CONCLUSION

The project and report has covered and answered all proposed research questions. The demo app worked under CARP framework provides efficient ways to collect location, weather and heart rate data,and speed, slope and duration should be taken as most important features in a cycling app aiming to all kinds of cyclists. Predicting heart rate is possible way for such an app to participate in people's exercise, and it could be done via different machine learning models that depends on the size of the dataset, or the scale of the model, either for community or individuals.

REFERENCES

[1] Andrew Clarrya, Ahmadreza Faghih Imanib, Eric J.Mille. 2019. Where we ride faster? Examining cycling speed using smartphone GPS data. *Sustainable Cities and Society* 49 (2019), 101594. https://doi.org/10.1016/j.scs.2019.101594

[2] CACHET. 2022. CARP. https://carp.cachet.dk/cams/

[3] Chapman AR, Vicenzino B, Blanch P, Knox JJ, Dowlan S, Hodges PW . 2008. The influence of body position on leg kinematics and muscle recruitment during cycling. *J Sci Med Sport* 11(6) (2008), 519–26. https://doi.org/10.1016/j.jsams.2007.04.010

[4] Adriana A. de Sousa, Suely P. Sanches, and Marcos A.G. Ferreira. 2014. Perception of Barriers for the Use of Bicycles. *Procedia - Social and Behavioral Sciences* 160 (2014), 304–313. https://doi.org/10.1016/j.sbspro.2014.12.142 XI Congreso de Ingenieria del Transporte (CIT 2014).

[5] Sean Fleming. 2018. What makes Copenhagen the world's most bike-friendly city? https://www.weforum.org/agenda/2018/10/what-makes-copenhagen-the-worlds-most-bike-friendly-city/#:~:text=There%20are%20675%2C000%20bicycles%20and,in%201970%20%E2%80%93%20a%20real%20milestone

[6] Google LLC. 2022. Google Maps. https://www.google.com/maps

[7] Ruben Govers. 2021. Predicting Heart Rates Of Sport Activities Using Machine Learning. http://essay.utwente.nl/85685/

[8] Milo Hollingworth, A Harper, and Mark Hamer. 2014. Dose–response associations between cycling activity and risk of hypertension in regular cyclists: The UK Cycling for Health Study. *Journal of human hypertension* 29 (10 2014). https://doi.org/10.1038/jhh.2014.89

[9] Strava Inc. 2022. Strava. https://www.strava.com/features

[10] Jeukendrup, A.E., Martin, J. . 2001. Improving Cycling Performance. *Sports Med* 31 (2001), 559–56. https://doi.org/10.2165/00007256-200131070-00009

[11] komoot GmbH. 2022. Komoot. https://www.komoot.com/

[12] M.Amiri, F.Sadeghpour. 2015. Cycling characteristics in cities with cold weather. *Sustainable Cities and Society* 14 (2015), 397–403. https://doi.org/10.1016/j.scs.2013.11.009

[13] Kusprasapta Mutijarsa, Muhammad Ichwan, and Dina Budhi Utami. 2016. Heart rate prediction based on cycling cadence using feedforward neural network. In *2016 International Conference on Computer, Control, Informatics and its Applications (IC3INA)*. 72–76. https://doi.org/10.1109/IC3INA.2016.7863026

[14] Peaksware, LLC. 2022. Training Peaks. https://www.trainingpeaks.com

[15] Xiaoxing Qiu, Jules White, and Douglas Schmidt. 2021. A Study of Machine Learning Models for Personalized Heart Rate Forecasting in Mountain Biking. 87–94. https://doi.org/10.5220/0010630600003059

[16] Ride with GPS. 2022. Ride With GPS. https://ridewithgps.com/app

[17] Gustavo Romanillos and Javier Gutiérrez. 2020. Cyclists do better. Analyzing urban cycling operating speeds and accessibility. *International Journal of Sustainable Transportation* 14, 6 (2020), 448–464. https://doi.org/10.1080/15568318.2019.1575493 arXiv:https://doi.org/10.1080/15568318.2019.1575493

[18] Sheyda Saneinejad, Matthew J.Roorda, Christopher Kennedy. 2012. Modelling the impact of weather conditions on active transportation travel behaviour. *Transportation Research Part D: Transport and Environment* 17(2) (2012), 129–137. https://doi.org/10.1016/j.trd.2011.09.005

[19] Skovereng K, Aasvold LO, Ettema G. 2020. On the effect of changing handgrip position on joint specific power and cycling kinematics in recreational and professional cyclists. *PLoS One* 15(8) (2020), e0237768. https://doi.org/10.1371/journal.pone.0237768

A TYPE OF THE DATAPOINTS

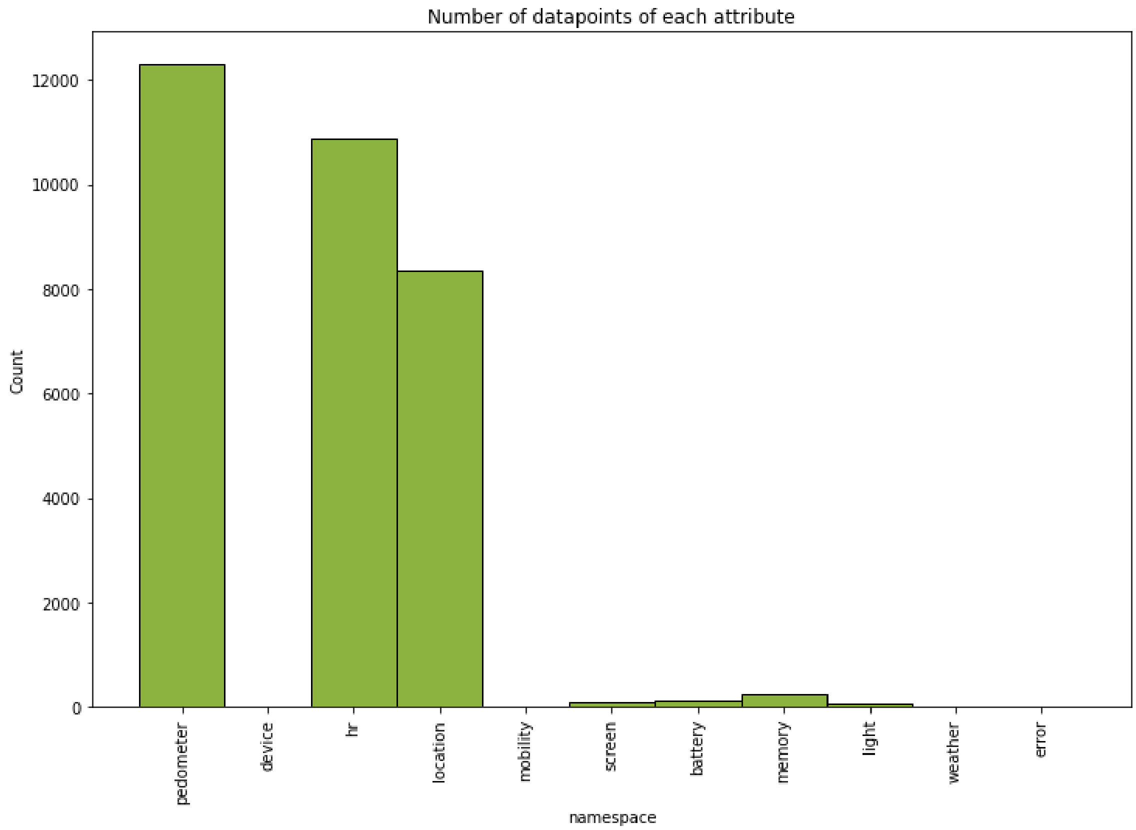

Fig. 15

B WEATHERS THROUGH DAYS

Table 2. Weather

Date	Weather
Jan. 05	light rain
Jan. 06	light rain
Jan. 07	light rain, overcast clouds
Jan. 08	light rain, moderate rain
Jan. 08	light rain

C CORRELATION HEATMAP

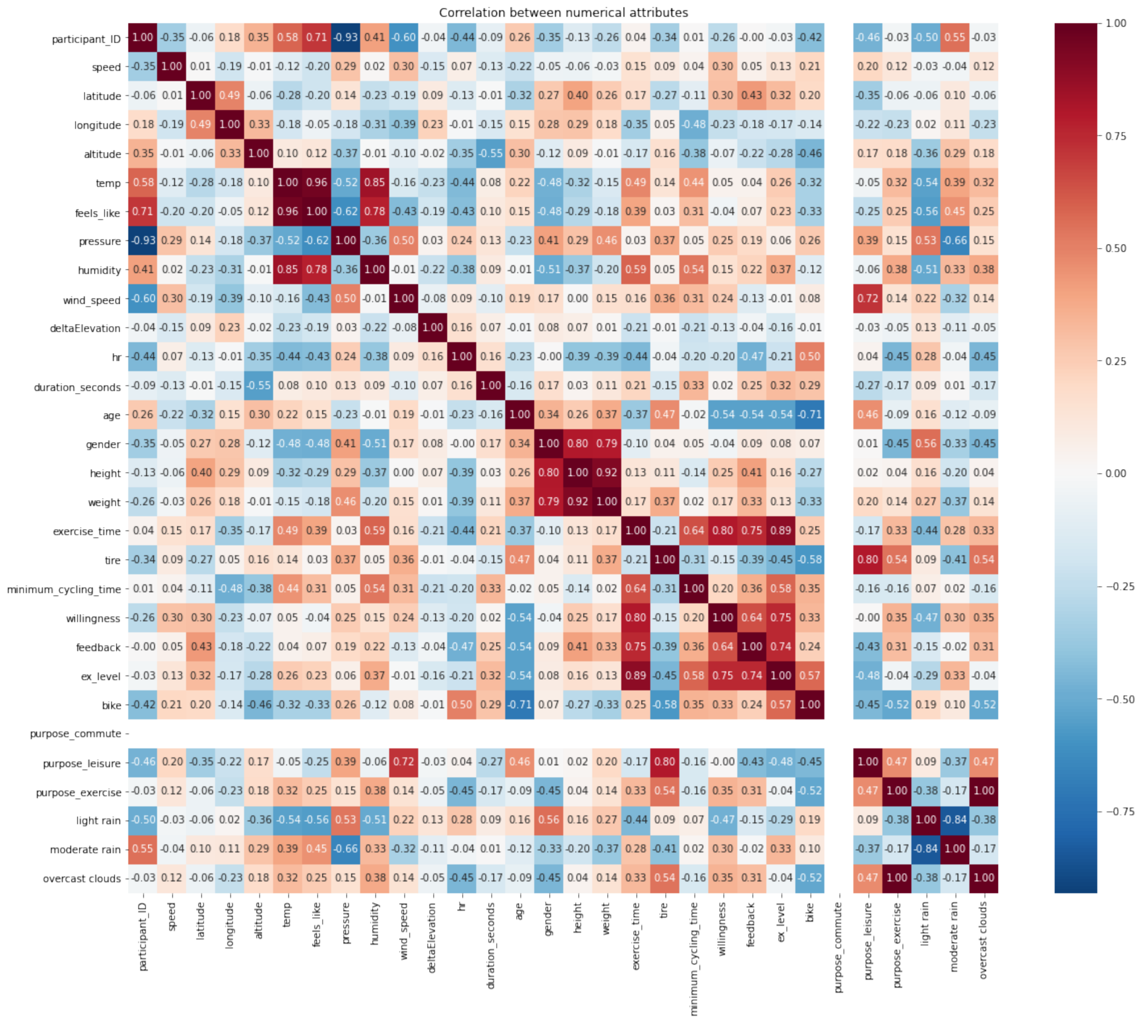

Fig. 16

D COMPLETE RESULTS

——— 2 trees, 2 depth———

trainning set: Mean Absolute Error: 11.117141783333876 Mean Squared Error: 202.22007166099147 Root Mean Squared Error: 14.220410390034159 test set: Mean Absolute Error: 11.56912085510349 Mean Squared Error: 215.26534736002085 Root Mean Squared Error: 14.671923778428678

——— 2 trees, 5 depth———

trainning set: Mean Absolute Error: 6.360418699301915 Mean Squared Error: 69.89171624362508 Root Mean Squared Error: 8.36012656863669

test set: Mean Absolute Error: 6.822753894299119 Mean Squared Error: 79.99740777777384 Root Mean Squared Error: 8.94412699919751

——— 2 trees, 8 depth——— trainning set: Mean Absolute Error: 3.915702102115839 Mean Squared Error: 28.67979031765326 Root Mean Squared Error: 5.355351558735735

test set: Mean Absolute Error: 4.302976680403018 Mean Squared Error: 34.88658877346717 Root Mean Squared Error: 5.906487007813288

——— 2 trees, 10 depth——— trainning set: Mean Absolute Error: 3.2811677997935225 Mean Squared Error: 22.34918115808256 Root Mean Squared Error: 4.727492057960813

test set: Mean Absolute Error: 3.762602303416009 Mean Squared Error: 29.537152927020987 Root Mean Squared Error: 5.434809373567852

——— 2 trees, 20 depth——— trainning set: Mean Absolute Error: 3.2223047194087746 Mean Squared Error: 21.08180051741022 Root Mean Squared Error: 4.591492188538517

test set: Mean Absolute Error: 3.6020579140131104 Mean Squared Error: 26.658266172105307 Root Mean Squared Error: 5.163164356487726

——— 5 trees, 2 depth——— trainning set: Mean Absolute Error: 11.12349816343404 Mean Squared Error: 203.7802470744001 Root Mean Squared Error: 14.275161893106505

test set: Mean Absolute Error: 11.535033845672675 Mean Squared Error: 216.92223725265137 Root Mean Squared Error: 14.728280186520466

——— 5 trees, 5 depth——— trainning set: Mean Absolute Error: 5.992329222443308 Mean Squared Error: 62.255352114515176 Root Mean Squared Error: 7.890206088215642

test set: Mean Absolute Error: 6.494057465700381 Mean Squared Error: 72.47153942024667 Root Mean Squared Error: 8.51302175612436

——— 5 trees, 8 depth——— trainning set: Mean Absolute Error: 3.5836489284496182 Mean Squared Error: 24.71427832133972 Root Mean Squared Error: 4.9713457253886215

test set: Mean Absolute Error: 3.9797551840171304 Mean Squared Error: 30.811408160031444 Root Mean Squared Error: 5.550802478924236

——— 5 trees, 10 depth——— trainning set: Mean Absolute Error: 3.041786902418272 Mean Squared Error: 18.166129456306006 Root Mean Squared Error: 4.262174263953318

test set: Mean Absolute Error: 3.405062787667054 Mean Squared Error: 23.32832086178393 Root Mean Squared Error: 4.829940047431638

——— 5 trees, 20 depth——— trainning set: Mean Absolute Error: 2.891151721008188 Mean Squared Error: 16.894615741790467 Root Mean Squared Error: 4.110306039918496

test set: Mean Absolute Error: 3.2093895963339296 Mean Squared Error: 20.70950053711056 Root Mean Squared Error: 4.55076922476965

——— 10 trees, 2 depth——— trainning set: Mean Absolute Error: 11.090169879850238 Mean Squared Error: 204.57444932318185 Root Mean Squared Error: 14.30295246874511

test set: Mean Absolute Error: 11.511240570740839 Mean Squared Error: 217.81402602840987 Root Mean Squared Error: 14.758523843135867

——— 10 trees, 5 depth——— trainning set: Mean Absolute Error: 6.218310804841449 Mean Squared Error: 67.64566432763003 Root Mean Squared Error: 8.224698433841208

test set: Mean Absolute Error: 6.743142902072732 Mean Squared Error: 79.0420143782309 Root Mean Squared Error: 8.890557596587005

——— 10 trees, 8 depth——— trainning set: Mean Absolute Error: 3.4579715292575326 Mean Squared Error: 22.635546782358595 Root Mean Squared Error: 4.757682921586788

test set: Mean Absolute Error: 3.934584438683832 Mean Squared Error: 29.643513968040526 Root Mean Squared Error: 5.444585748065736

——— 10 trees, 10 depth——— trainning set: Mean Absolute Error: 3.007323260918116 Mean Squared Error: 17.260345198408306 Root Mean Squared Error: 4.154557160325069

test set: Mean Absolute Error: 3.4586700542374813 Mean Squared Error: 24.49237389247351 Root Mean Squared Error: 4.948977055157309

——— 10 trees, 20 depth——— trainning set: Mean Absolute Error: 2.8203760745811564 Mean Squared Error: 16.009483595923868 Root Mean Squared Error: 4.0011852738812115

test set: Mean Absolute Error: 3.2572157241203947 Mean Squared Error: 21.577374682167342 Root Mean Squared Error: 4.6451452810614375

——— 15 trees, 2 depth——— trainning set: Mean Absolute Error: 11.088444655875215 Mean Squared Error: 203.94585642598986 Root Mean Squared Error: 14.280961327095241

test set: Mean Absolute Error: 11.507374285288586 Mean Squared Error: 216.57873228316345 Root Mean Squared Error: 14.7166141582622

——— 15 trees, 5 depth——— trainning set: Mean Absolute Error: 6.101575012988296 Mean Squared Error: 64.47914063495075 Root Mean Squared Error: 8.02989044974779

test set: Mean Absolute Error: 6.561560929998248 Mean Squared Error: 74.17396719469245 Root Mean Squared Error: 8.612430968936264

——— 15 trees, 8 depth——— trainning set: Mean Absolute Error: 3.4048487570536636 Mean Squared Error: 22.325099321936914 Root Mean Squared Error: 4.724944372364283

test set: Mean Absolute Error: 3.881648719336694 Mean Squared Error: 28.789884283392862 Root Mean Squared Error: 5.365620586977136

——— 15 trees, 10 depth——— trainning set: Mean Absolute Error: 2.934401874295898 Mean Squared Error: 16.972013186866228 Root Mean Squared Error: 4.119710328028686

test set: Mean Absolute Error: 3.367528343026295 Mean Squared Error: 22.7129559606649 Root Mean Squared Error: 4.765811154532343

——— 15 trees, 20 depth——— trainning set: Mean Absolute Error: 2.733960696808435 Mean Squared Error: 15.132581177906602 Root Mean Squared Error: 3.8900618475683135

test set: Mean Absolute Error: 3.080797680392708 Mean Squared Error: 19.80733516562508 Root Mean Squared Error: 4.450543243877659

——— 20 trees, 2 depth——— trainning set: Mean Absolute Error: 11.31565752083866 Mean Squared Error: 208.38091616625576 Root Mean Squared Error: 14.435404953317235

test set: Mean Absolute Error: 11.867788944104921 Mean Squared Error: 225.02347759463072 Root Mean Squared Error: 15.000782566074035

——— 20 trees, 5 depth——— trainning set: Mean Absolute Error: 6.024797764430291 Mean Squared Error: 61.794645956426514 Root Mean Squared Error: 7.86095706364222

test set: Mean Absolute Error: 6.520389919735286 Mean Squared Error: 71.8070231941374 Root Mean Squared Error: 8.47390247726143

——— 20 trees, 8 depth——— trainning set: Mean Absolute Error: 3.4890764326950907 Mean Squared Error: 23.25519991687628 Root Mean Squared Error: 4.822364556612895

test set: Mean Absolute Error: 3.894104643615034 Mean Squared Error: 29.45523386181185 Root Mean Squared Error: 5.427267623934888

——— 20 trees, 10 depth——— trainning set: Mean Absolute Error: 2.924555474150815 Mean Squared Error: 16.809132305330415 Root Mean Squared Error: 4.099894182211343

test set: Mean Absolute Error: 3.3488561112186632 Mean Squared Error: 22.491299645930418 Root Mean Squared Error: 4.742499303735364

——— 20 trees, 20 depth——— trainning set: Mean Absolute Error: 2.7430906189512934 Mean Squared Error: 14.849391752251515 Root Mean Squared Error: 3.8534908527530614

test set: Mean Absolute Error: 3.1407617151803424 Mean Squared Error: 20.158220467675772 Root Mean Squared Error: 4.489790693080889

——— 50 trees, 2 depth——— trainning set: Mean Absolute Error: 11.086892197771583 Mean Squared Error: 202.62071902374902 Root Mean Squared Error: 14.23449047292347

test set: Mean Absolute Error: 11.539795655278915 Mean Squared Error: 216.30614796885115 Root Mean Squared Error: 14.70735013416255

——— 50 trees, 5 depth——— trainning set: Mean Absolute Error: 5.849315103784557 Mean Squared Error: 58.558233239490036 Root Mean Squared Error: 7.652335149448829

test set: Mean Absolute Error: 6.320873925795824 Mean Squared Error: 68.1444266567978 Root Mean Squared Error: 8.254963758660471

——— 50 trees, 8 depth——— trainning set: Mean Absolute Error: 3.3977111287886794 Mean Squared Error: 22.273635055317545 Root Mean Squared Error: 4.7194952119180655

test set: Mean Absolute Error: 3.8838858374221794 Mean Squared Error: 29.128162914384337 Root Mean Squared Error: 5.397051316634328

——— 50 trees, 10 depth——— trainning set: Mean Absolute Error: 2.860200229429682 Mean Squared Error: 15.841992910025398 Root Mean Squared Error: 3.9802001092941794

test set: Mean Absolute Error: 3.262857297873901 Mean Squared Error: 21.25059450754635 Root Mean Squared Error: 4.609836711592543

——— 50 trees, 20 depth——— trainning set: Mean Absolute Error: 2.724250311807407 Mean Squared Error: 14.786550657347199 Root Mean Squared Error: 3.8453284199593667

test set: Mean Absolute Error: 3.1028023514656713 Mean Squared Error: 20.0330987130522283 Root Mean Squared Error: 4.475834973840332

——— 100 trees, 2 depth——— trainning set: Mean Absolute Error: 11.09329455226466 Mean Squared Error: 202.805736290015 Root Mean Squared Error: 14.240987897263834

test set: Mean Absolute Error: 11.547095894709535 Mean Squared Error: 217.14273617202946 Root Mean Squared Error: 14.73576384759302

——— 100 trees, 5 depth——— trainning set: Mean Absolute Error: 5.967066174656692 Mean Squared Error: 61.69496366980841 Root Mean Squared Error: 7.854614164286391

test set: Mean Absolute Error: 6.459633903449936 Mean Squared Error: 71.82526064743826 Root Mean Squared Error: 8.474978504246383

——— 100 trees, 8 depth——— trainning set: Mean Absolute Error: 3.3781072889040837 Mean Squared Error: 22.046839902757473 Root Mean Squared Error: 4.695406255347611

test set: Mean Absolute Error: 3.8287121876953054 Mean Squared Error: 28.5291515131776 Root Mean Squared Error: 5.341268717559303

——— 100 trees, 10 depth——— trainning set: Mean Absolute Error: 2.860607850400107 Mean Squared Error: 16.063316303827406 Root Mean Squared Error: 4.007906723443973

test set: Mean Absolute Error: 3.2702811664299496 Mean Squared Error: 21.431667074186663 Root Mean Squared Error: 4.62943485472975

——— 100 trees, 20 depth——— trainning set: Mean Absolute Error: 2.7084382887767617 Mean Squared Error: 14.790672539693343 Root Mean Squared Error: 3.845864342341438

test set: Mean Absolute Error: 3.1033050224602485 Mean Squared Error: 19.96697710351832 Root Mean Squared Error: 4.468442357636308

E UI ARTIFECTS

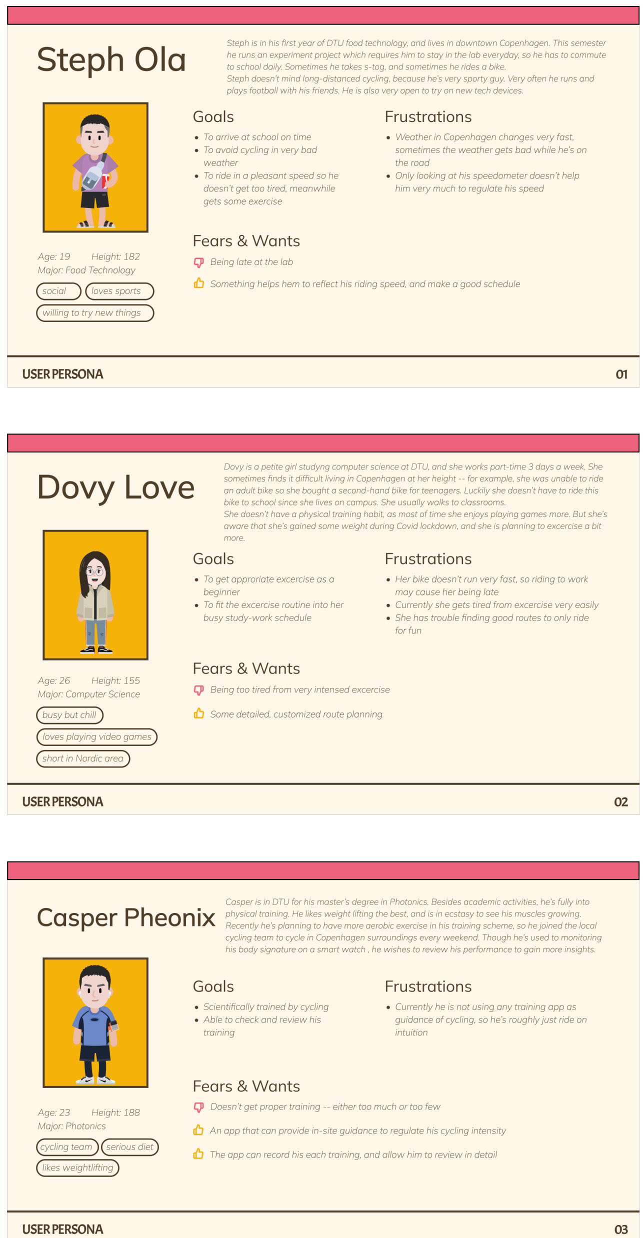

Fig. 17

Fig. 18

F DATASET COLLECTION PROCESS

- Greeting

  - Introduction of app: what is its inspiration, functionalities

  - Introduction of data:

  a. location, speed, heart rate

  b. age, gender, weight, height, exercise level

  c. general biking habit information

  d. feedback

  e. anonymous

  - Click Consent

  - Filling personal info survey

  - Install device

- click on play, ride, exit
- Post-survey:

a. type of bike, purpose of biking, frequency of biking

b. willingness to cycle for health

c. helpfulness of this app on improving health or performances

- Thank you gift