Empirical analysis of pacing in road cycling

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ABSTRACT

The pacing profile adopted throughout a competitive time trial may be decisive in the overall outcomes of the event. Riders distribute their energy resources based on a range of factors including prior experience, perception of effort, knowledge of distance to cover and potential motivation. Some athletes and professional cycling teams may also quantify individual pacing strategies derived from computational scientific methods. In this work we collect and analyze data of self-selected individual pacing profiles from approximately 12,000 competitive riders on a well-known hill climbing road segment in the Adelaide Hills, South Australia. We found that riders chose from a variety of very different pacing profiles, including some opposing profiles. For the classification of pacing this paper describes the pipeline of collection GPS-based and time stamped performance data, data filtering, augmentation of road gradient and power values, and the classification procedure.

KEYWORDS

datasets, data driven performance analysis

Figure 1: In competitive road cycling, the pacing strategy for a time trial may be decisive. Riders distribute their energy resources based on a range of factors including prior experience, perception of effort, knowledge of distance to cover and potential motivation. In this work, we collect and analyze individual pacing profiles from approximately 12,000 competitive riders on a very popular hill climbing road segment in the Adelaide Hills, South Australia, shown above. The segment starts at the marker (upper right), and ascends 270.3 m over a distance of 5.54 km to the finish at the upper left.

1 INTRODUCTION

With recent decades, the deployment of new technologies, including power meters and GPS-based tracking, have had a significant impact on how athletes train and compete within road cycling. Power meters have become more affordable and ubiquitous, complementing heart rate based assessments of training load and performance. Of course, these new types of sensor data have also boosted method development in sport and exercise science. Moreover, in the last 10–20 years, sporting social networks have emerged and offer athletes mechanisms to collect, share, compare, and discuss their cycling performance data online. The huge volume of data available from personal devices and from online platforms offers new challenges and opportunities within sports analytics, that cannot be tackled by sport and exercise researchers alone. To harness the full potential of the new data sources in sports such as road cycling, expertise from computer science and engineering can be beneficial. This has led to a rapidly expanding area of research in data analysis and mathematical modeling in sport and exercise science with the aim to improve the technique and performance of athletes. In this contribution we present a case study, analyzing the best performance of approximately 12,000 ambitious road cyclists on a popular uphill time trial track in Adelaide, South Australia (see Figure 1).
In road cycling, an athlete’s pacing profile may be incredibly decisive in the overall outcome of a race, especially within individual cycling time trials. An optimal pacing profile allows athletes to distribute their energy resources appropriately in order to maximize performance and avoid excessive fatigue prior to the completion of the exercise task. Such a strategy may therefore indicate, for example, where to sprint or increase power output and where to ride with a moderate, constant power output. Therefore, a pacing profile can be defined in either power in Watts (W) or speed in kilometers/hour (km/h) as a function of distance along the race track.

The literature review paper [1] presents an overview of pacing profiles generally observed in endurance sports and proposes six basic profiles, known as positive, negative, all-out, even, parabolic-shaped, and variable pacing. These different pacing profiles have been proposed based on observations by a number of researchers in laboratory and field studies. However, the number of cases observed in these studies is typically small (n in the range of 1–20). We analyze a very large dataset of comparable personal best performances in order to classify each attempt according to the above proposed pacing profiles. With this study we are able to see how well the actual pacing profile matches with those that were previously observed or derived and which pacing strategies have been the most successful in the scenario of the selected uphill cycling task. The six basic types of pacing strategies are outlined based upon previous research [1] and are sketched in Fig. 2.

- **A negative pacing** profile is identified by a relatively slow start, followed by a gradual increase in speed, resulting in the first half of the event performed slower than the second.
- **Positive pacing** profile is the opposite to a negative profile and characterized by a decline in speed throughout an exercise task.
- A positive pacing profile is similar to an all-out pacing profile where athletes produce the highest possible power output from commencement of an event which gradually declines. It is important to note that this decline in power output may differ to speed when commencing from a standing start.
- **An even pacing** profile is often suggested to be optimal to performance in endurance tasks (> 2 min duration).
- Despite the suggestion that an even pacing strategy is optimal, a relatively high speed is often observed at the start and end of endurance tasks, resulting in a parabolic profile.
- **Variable pacing** refers to the variable distribution in power output which is often observed during outdoor exercise tasks. This pacing profile is aligned with an even profile since the variation in power output is adopted presumably to account for varying external conditions (i.e., gradient and wind) and in attempt to maintain an even distribution of speed.

Since the road that we selected for this study has varying gradient and the achievable speed depends on the gradient, we favor the classification of pacing profiles observed based on the spatial distribution of power rather than speed.

A similar empirical study of pacing for the case of long distance running has recently been carried out by de Leeuw et al. [3]. They analyzed about 120,000 race results over three distances (10 km, half and full marathon). Each record for the full marathon contained nine split times and the finish time together with gender and age. For the full marathon distance the authors reported only one characteristic class of pacing, namely positive pacing that was further subdivided into three subgroups corresponding to differing rates of decrease of speed during the race. This was obtained by an unsupervised clustering method. For the shorter distances also even and negative pacing was found, and the class of positive pacing was more dominant among the athletes that performed above average in their peer groups with respect to age and gender.

Our study differs in that it considers cycling, not running, and the duration of the rides is much shorter (11 to 25 minutes) than for the running events from 10 to 42 km. The data for cycling is richer, providing speed and allowing for estimation of power at all points along the track. Based on the findings in [3], we expect a larger variety of pacing profiles for cycling with shorter duration.

In this paper we contribute an application of data analytics to classify cyclists’ pacing profiles on a hill climbing time trial segment. Appropriate data mining techniques, although quite straightforward, confirm and extend previous findings of the literature that had been derived from case studies at much smaller scales. In summary, the contributions are the following:

1. We have compiled a large-scale dataset of best effort performances of a large sample of cyclists on a popular and competitive hill climbing road segment. Using a physical model of cycling we reconstructed and validated power profiles from the given speed values. The data series were processed into a uniform and aligned format making the estimated power comparable between all riders.
2. We devised and applied standard regression methods to classify the data records according to the pacing profiles that had been self-selected by the athletes.
3. Our results have confirmed that riders choose to follow a pacing profile from one of those previously described in the literature. All of the known patterns were observed except the all-out profile which, however, was replaced by a new, similar profile, called parabolic negative.
4. The results also reveal trends showing which pacing profiles were more performant, being preferred by the more experienced and successful riders.

![Figure 2: Six basic types of pacing profiles, shown by power as a function of distance along the race track. Top row: Positive, even, and negative pacing. Bottom row: parabolic (positive), parabolic negative, and variable pacing.](image-url)
2 DATA ACQUISITION, CLEANSING, AND PREPROCESSING

2.1 Data Selection

For our study we have selected an uphill cycling track on Norton Summit Rd in Adelaide, South Australia. The East side of the city is bounded by a mountain range, called Adelaide Hills, and the Norton Summit Rd starts at the border of the urban part of the city, going up the hill until a small settlement, called Norton Summit. Adelaide is a metropolitan city of about 1.4 million inhabitants and has a very large cycling community. Moreover, the city hosts the professional international cycling event, the Tour Down Under, every January since 1999, attracting thousands of cyclists from Australia and around the world. Norton Summit Rd is close to the city, easily accessible, and offers a climb of 270.3 m over a distance of 5.54 km (4.9 % average slope) on a well surfaced road with little traffic.

Therefore, over the years, this climb has become a very popular benchmark for cyclists to test and compare their performance level. At the time of writing this manuscript, the social media platform Strava has listed approximately 330,000 uploads of GPS-based activities for rides on the corresponding Strava segment, called “Norton Summit” [6]). These rides were performed by almost 20,000 cyclists, over a period of 12 years. Given that some cyclists have attempted this segment many times, we expect that their personal best performance corresponds to their individual optimal pacing strategy.

These personal best performances are listed in a online leaderboard, from where also the corresponding individual performance records can be loaded into a browser for visual inspection. This includes the track, speed, power, heart rate, cadence, and temperature. Depending on the measurement devices and sensors used, some of these may not be available for all of the rides.

The best recorded performance on the Norton Summit segment was achieved by a professional cyclist on January 22, 2016, during the Stage 4 of the Tour Down Under from Norwood to Victor Harbor. With an average power of 427 Watt he reached an average speed of 29.6 km/h and the climb took 11:06 min. Presumably, the pacing of this athlete was close to optimal on this record ride. See Fig. 5 for an illustration of a similar ride.

2.2 Filtering: Outliers and Slow Riders

Since we aimed to retrieve data showing the personal best self-selected pacing profiles, we disregarded data records with a large
Within the data available, it is likely that not all performances were maximal and that some of the listed cyclists intentionally rode slowly, possibly even stopping, or turning around, presumably to rejoin some fellow riders that had fallen behind. Furthermore, some data recording devices deliver only sparsely spaced track points. Such records would not be useful to study qualities of pacing profiles. Altogether, we pruned the dataset according to the following criteria.

- The total riding time is restricted to 25 minutes, amounting to a minimal average speed of 13.3 km/h. For a rider with a total mass of 87.7 kg (body mass, bicycle, equipment), this requires an average power of about 205 W over 25 minutes.
- The minimal speed at any point on the whole segment was required to be at least 8 km/h.
- The total distance covered on the segment must be within one standard deviation from the mean distance for all rides. The number of recorded distances that are too large, was 802. There were 405 that were too small.
- The average sampling distance between any two consecutive track points must be at most 22 m. For 757 records the average sampling distance was too large.
- The maximal sampling distance between any two consecutive track points must be at most 70 m. For 180 records the maximal sampling distance was too large.

These conditions for filtering outliers and too slow riders reduced the dataset from 16,068 to 12,202 records. See Fig. 6 and Table 1.

**Table 1: Overview of the collected and filtered dataset.** All of the records contain date, GPS longitude and latitude, time stamps, distance, and elevation. Some of the records also contain other data as listed in the table.

<table>
<thead>
<tr>
<th>Records with</th>
<th>Complete dataset</th>
<th>Filtered dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professional riders</td>
<td>16,068 records</td>
<td>12,202 records</td>
</tr>
<tr>
<td>Power data</td>
<td>2,893</td>
<td>2,554</td>
</tr>
<tr>
<td>Heart rate data</td>
<td>7,658</td>
<td>6,319</td>
</tr>
<tr>
<td>Cadence data</td>
<td>7,705</td>
<td>6,498</td>
</tr>
<tr>
<td>Temperature data</td>
<td>10,183</td>
<td>8,748</td>
</tr>
</tbody>
</table>

Figure 6: Filtering outliers and slow riders. Top left: Histogram of recorded total segment lengths. Records outside of the mean 5,542.99 m (red line) plus/minus 1 standard deviation 84.97 m (blue lines) are considered as outliers (1,207 records). Top right: Histogram of minimal speed. Records with minimal speed less than 8 km/h are considered as outliers (2,337 records). The leftmost histogram bar shows 303 records of riders that had completely stopped during the ascend for a few seconds. Bottom left: Histogram of average spatial sampling distance. Records with average sampling distance greater than 22 m (red line) are considered as outliers (757 records). Bottom right: Histogram of maximal spatial sampling distance. Records with maximal sampling distance greater than 70 m (red line) are considered as outliers (180 records).
2.3 Data Alignment and Resampling

In order to compare speed and power profiles as pacing profiles for the chosen road segment, these data series need to be aligned on a common reference scale of distance or time. For the purpose of spatial mapping, we first estimate the total distance \( s_{\text{total}} \) and then map the recorded distances linearly onto the interval \([0, s_{\text{total}}]\) for all the track points of all data records.

For the estimation of the total distance \( s_{\text{total}} \), we considered rides of the filtered dataset that had a mean sampling distance up to 6 m. This gave 5,213 measurement values for the total distance. We applied bootstrapping, resampling this set of distance values with replacement 1,000 times, computing the mean distance each time. The mean value of these results gave \( s_{\text{total}} = 5,545.54 \) m with a 95% confidence interval of 1.96 m.

We chose to work with resampled data, on a uniform grid of 512 grid points. Thus, the spacing between consecutive data points is 5,545.54/511 = 10.85 m. For the resampling we applied a Gaussian filter with a standard deviation of \( \sigma = 40 \) m. This way, we achieved a (spatially) uniform resampling of speed and power measurements. Timestamps at the grid points were obtained by linear interpolation.

After filtering the speed data was no longer consistent with distance and times. We integrated speed and compared the obtained distance with 5,545.54 m. The difference divided by the finish time gave us a (very small) offset that we applied on the speed data. The distance with 5,545.54 m. The difference divided by the finish time gave us a (very small) offset that we applied on the speed data. The acceleration at each grid point was estimated, using central differences of the resampled speed values.

2.4 Elevation, Gradient, and Power

In this study we have considered pacing based upon power output over the distance of the event/climb. However, only 2,354 of the 12,202 records have power measurements. Moreover, these were obtained using different power meters that may not have been calibrated. Thus, we regard these power measurements as neither sufficient nor suitable for comparison across the whole dataset. Therefore, we propose to use an indirect approach by estimating power at the sample locations in each record by means of a physical model.

Any such model equation predicting power from speed measurements relies on given slope values for the entire race course. The road gradient along the track is a fixed parameter of the environment. Most of the energy required to ride the Norton Summit segment must be devoted to the work required for climbing the vertical distance. Therefore, an accurate gradient estimate is crucial for the quality of the power estimates. For estimating elevation, we considered the 3,448 rides of the filtered dataset that had a maximal sampling distance of 10 m. We resampled the given elevation data in the records with a Gaussian filter (\( \sigma = 10 \) m) on the uniform grid. The median elevation for the first sample point at distance 0.0 m was taken as the initial elevation, and likewise the median of the corresponding data for the last sample point gave the elevation at the end. Then we linearly aligned the elevation data of each record with these start and end elevations and finally averaged the results at each sample point. The road segment continuously gains altitude, starting at 140.4 m and reaching 410.7 m, climbing a total of 270.3 m. Central differences were used to estimate the gradient.

In 1998 Martin et al. [5] proposed a mathematical model for road cycling power based on Newtonian mechanics as an equilibrium of the rider’s pedaling power and resistance power induced by aerodynamic drag \( P_{\text{air}} \), rolling resistance \( P_{\text{roll}} \), bearing friction \( P_{\text{bear}} \), gravitation \( P_{\text{pot}} \) and inertia \( P_{\text{kin}} \), given by the following differential equation:

\[
\eta P = mgv + \mu mgv + \beta_0 v + \beta_1 v^2 + \left( \frac{I_v}{I_w} \right) + \frac{1}{2} c_d \rho A v^3 + \frac{1}{2}
\]

Dahmen et al. [2] validated this model under realistic conditions in 2011 with the parameters presented in Table 2. In order to verify our computer power profiles, we compared them with the power measurements contained in the raw data. However, for individual riders, we do not know the personal parameters, and therefore we adjusted only the dominating factor, namely the total mass of rider and bike. For each given power profile from measurements, we considered total masses from 50 kg to 100 kg in steps of 0.1 kg, computing for each one the power profile from the physical model and the corresponding root-mean-square error (RMSE) between estimated and measured power. The mass at which the minimum RMSE occurred was taken as an approximation of the actual (unknown) total mass.

We did this for all power profiles with an average power between 100 W and 500 W. Figure 7 shows the histogram of the resulting RMSE values. On average, the median of the errors is below 20 W, which we consider a very good result given that the true masses are unknown, all other parameters are from literature, and power measurements typically suffer from noise by nature of the sensors.

Since approximately 80% of our data records do not include power measurements, we chose to use the same fixed total mass for all of the riders. For this purpose, we selected the weight yielding the lowest average error for all records together that have power measurements. The minimum is at 87.7 kg with an RMSE of 39 W. In conclusion, for the analysis we computed power for all records using a mass of 87.7 kg and parameter values from Table 2.

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Unit</th>
<th>Default value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total mass</td>
<td>( m )</td>
<td>kg</td>
<td>87.7</td>
</tr>
<tr>
<td>Acceleration of gravity</td>
<td>( g )</td>
<td>m/s(^2)</td>
<td>9.81</td>
</tr>
<tr>
<td>Friction factor</td>
<td>( \mu )</td>
<td></td>
<td>0.004</td>
</tr>
<tr>
<td>Bearing factor</td>
<td>( \beta_0 )</td>
<td>N</td>
<td>0.091</td>
</tr>
<tr>
<td>Bearing factor</td>
<td>( \beta_1 )</td>
<td>N s</td>
<td>0.0087</td>
</tr>
<tr>
<td>Wheel inertia</td>
<td>( I_w )</td>
<td>kg m(^2)</td>
<td>0.14</td>
</tr>
<tr>
<td>Wheel radius</td>
<td>( r_w )</td>
<td>m</td>
<td>0.33</td>
</tr>
<tr>
<td>Drag coefficient</td>
<td>( c_d )</td>
<td></td>
<td>0.7</td>
</tr>
<tr>
<td>Air density</td>
<td>( \rho )</td>
<td>kg/m(^3)</td>
<td>1.2</td>
</tr>
<tr>
<td>Cross-sectional area</td>
<td>( A )</td>
<td>m(^2)</td>
<td>0.4</td>
</tr>
<tr>
<td>Chain efficiency</td>
<td>( \eta )</td>
<td></td>
<td>0.975</td>
</tr>
</tbody>
</table>

Table 2: Parameters of the physical model.
we carry out a linear regression resulting in a power-distance relationship $P_1(x) = a_1x + a_0$ along with an RMS error $E_1$. For the parabolic pacing classes we perform a polynomial regression of degree 2, resulting in a quadratic model $P_2(x) = b_2x^2 + b_1x + b_0$ with RMS error $E_2$. In order to differentiate this from the linear case, the absolute value of the coefficient $b_2$ for the quadratic term is required to be at least $q_2$. The model with the smaller RMS error is accepted, if the error is sufficiently small (min($E_1$, $E_2$) ≤ $E_{\text{max}}$), otherwise the remaining class of variable pacing is assigned to the record. To differentiate between positive, even, and negative pacing, a threshold $q_1$ for the slope $a_1$ is introduced. By visual inspection, we found that $E_{\text{max}} = 0.15, q_1 = 0.1, q_2 = 1.4$ are suitable parameters.

Of all 12,202 records, 9,663 passed the test for the linear regression, and Fig. 9 shows the histogram of the slopes for these. The parameter $q_1$ determines the total width of the bars around slope 0, comprising the rides with even pacing.

Table 3 lists the classification results. Positive pacing is the most commonly observed profile, followed by even pacing. There are

\begin{table}[h]
\centering
\caption{Overview of the classification results.}
\label{table:classification}
\begin{tabular}{|c|c|}
\hline
Class & Records \\
\hline
Positive & 5,236 \\
Negative & 666 \\
Even & 3,761 \\
Parabolic positive & 545 \\
Parabolic negative & 395 \\
Variable & 1,599 \\
\hline
\end{tabular}
\end{table}

3 Classification of Pacing

Of the six pacing profiles proposed in the literature and outlined above in Section 1, we have observed most profiles apart from the all-out profile. However, this profile is only optimal in extremely short duration sport events of a few seconds up to a minute or two. Given that the Norton Summit segment requires at least 11 minutes to complete it is too long for the adoption of an all-out profile. However, we found in the data, that some riders chose a profile similar to all-out, starting with increasing power, but not as fast as in an all-out profile, followed by a middle part with high power output, and finishing with decreasing power. This profile may well be modelled by a parabolic function, however, with a negative second derivative. Therefore, our proposal for classification of pacing profiles has these six classes: Positive, Even, Negative, Parabolic Positive, Parabolic Negative, and Variable Pacing. The first three classes may be identified by linear regression, the parabolic classes by polynomial (quadratic) regression, leaving the remaining cases for the class of variable pacing.

The pacing profile classification for a data record is based on power estimates. There are large differences of power between riders with different performance potentials. In order to better classify riders of such different ranges of power, we normalize power by dividing by the average power in each record.\footnote{Not to be confused with the trademark Normalized Power® (NP) of Peaksware, LLC.} For convenience, we also rescale distance to the interval $x \in [0, 1]$. The classification then proceeds as follows (cmp. Alg. 1), where $q_1, q_2,$ and $E_{\text{max}}$ are parameters of the method. For each data record, we carry out a linear regression resulting in a power-distance relationship $P_1(x) = a_1x + a_0$ along with an RMS error $E_1$. For the parabolic pacing classes we perform a polynomial regression of degree 2, resulting in a quadratic model $P_2(x) = b_2x^2 + b_1x + b_0$ with RMS error $E_2$. In order to differentiate this from the linear case, the absolute value of the coefficient $b_2$ for the quadratic term is required.

\begin{algorithm}
\caption{Classification of pacing profile from power data.}
\label{alg:classification}
\textbf{Input:} Normalized power $P(x) \geq 0$, uniformly sampled at distances $x_k, k = 0, \ldots, K-1$, parameters $q_1, q_2, E_{\text{max}} > 0$
\textbf{Linear regression on power data}
Result: $P_1(x_k) = a_1 x_k + a_0$
RMS error $E_1 = \left( \frac{1}{K} \sum_{n=0}^{K-1} (P_1(x_k) - P(x_k))^2 \right)^{1/2}$
\textbf{Quadratic regression with constraint $|b_2| \geq q_2$}
Result: $P_2(x_k) = b_2 x_k^2 + b_1 x_k + b_0$
RMS error $E_2 = \left( \frac{1}{K} \sum_{n=0}^{K-1} (P_2(x_k) - P(x_k))^2 \right)^{1/2}$
if $E_1 \leq E_{\text{max}}$ and $E_2 \leq E_{\text{max}}$ then
  \begin{enumerate}
  \item \textbf{Linear Model}
  if $|a_1| < q_1$ then
    \textbf{return} Class Even
  else if $a_1 \leq -q_1$ then
    \textbf{return} Class Positive
  else if $a_1 \geq q_1$ then
    \textbf{return} Class Negative
  end if
  \item \textbf{Parabolic Model}
  if $b_2 \geq q_2$ then
    \textbf{return} Class Parabolic Positive
  else if $b_2 \leq -q_2$ then
    \textbf{return} Class Parabolic Negative
  end if
  \item else
    \textbf{return} Class Variable
  end if
end if
\end{enumerate}
\end{algorithm}

Figure 7: Histogram of root-mean-square errors of the power estimates for each record containing power measurements. The average error is 23 W (red line) and the median is at 19.7 W. Blue lines show average plus/minus one standard deviation. RMSEs greater than 100 W are grouped together at 100 W.
fewer but still many cases of negative and both kinds of parabolic pacing. Approximately 1,599 records (13 %) could not be identified by linear or quadratic regression and thus were assigned to the classification of variable pacing.

In Fig. 10 we highlight that the class distribution depends on the average speed of the riders. For each pacing class, an approximate smooth density function is computed using Kernel density estimation. Then the fractional parts for each class are visualized. This graph shows that

- riders with relatively slower performances, compared to the entire sample population (average speed up to 17 km/h), typically achieved their best results using a positive pacing strategy. Conversely,

- in riders with better performances (17–27 km/h) the positive pacing profile is still common, but less frequently used in favor of even and negative pacing profiles.

- An even profile was the most prevalent profile among the very best riders (27–30 km/h). This is important as it indicates that better performing athletes have faster performances times, not only because of greater average power output but also a greater capacity to minimize slowing when external load is high (i.e., high gradient), and therefore adopt a more even pacing profile.

Finally, we present the scatter plot of the standard deviation of the normalized speed (from speed resampled at 1 sec intervals) versus average speed in Fig. 11. In theory, disregarding any variability due to wind, the optimal pacing should be one of constant speed, except for an initial transitional period and just before the finish line [4]. Therefore, we expect a smaller variability of speed for the strongest and most successful riders. The regression line in the scatter plot confirms this, clearly having a negative slope.

Further along this reasoning, we have also compared the classification of pacing profiles according to normalized speed in place of power. Because the standard deviation of speed, averaged over all riders, was only 85 % of the average standard deviation of power, we also scaled the threshold $E_{\text{max}}$ by 85 %. As a result, we obtained 858 records that were classified as an even pacing profile according to speed. The majority of these (75 %) had been classified according to power as positive pacing, besides 13 % as variable pacing and 12 % as negative parabolic pacing. Fig. 12 presents the distribution of these constant speed pacings over the range of average speeds. It confirms our findings that better performing athletes tend to adopt a more even pacing profile of speed.

### 4 LIMITATIONS

The optimal pacing is influenced by wind conditions. For example, a tail wind may lead to a change in pacing, allowing the athlete to reduce the exerted power where the road gradient is small, while
increasing power output on the steeper sections, in order to keep the variance of speed as small as possible. Although hourly wind data is available for the region near Norton Summit from the Bureau of Meteorology, Australia, we would not be able to make good use of it since the time of day is not contained in the data records we collected.

We can compare performances only with respect to the whole sample of all rides, but not with respect to age and gender. Therefore, the findings could be made more specific, if such data were available.

5 CONCLUSIONS AND FUTURE WORK
In this article, we have compiled and studied a large-scale dataset of best effort performances of a sample of cyclists on an uphill time trial. In order to classify the rides according to pacing profiles, we provided and evaluated methods for data cleansing, resampling, registration, computational derivation of power profiles from speed, and a classification algorithm based on polynomial regression. Our results show that cyclists self-select all pacing profiles that have been described in the literature, and which of these are preferred by high performance riders.

Our classification procedure is based on previously described pacing profiles. Although we have discovered a new pacing profile (parabolic negative), there may be even more pacing profiles that may be found using unsupervised clustering methods. Furthermore, considering the way athletes self-regulate their pacing during exercise, it may be advantageous to segment a record into three parts, a initial phase, a part at the end that may contain a final spurt, and the remaining. Each part may be classified separately, offering a more structured approach than the current models. We also plan to analyze to what extent a performance record can be characterized by a profile of power versus road gradient, and whether such profiles differ between riders of differing performance levels. Finally, we will extend the data analytics work to study how the pacing profiles depend on age, gender, and weight of the athletes, as well as on wind conditions during the rides.

REFERENCES