# How to Deal with Sports Activity Datasets for Data Mining and Analysis:

## Some Tips and Future Challenges

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## ABSTRACT

The aim of this paper is to briefly present the fundamentals of sports training to computational intelligence community and present a short description on recently released sport activity datasets for data mining and data analysis. Training plan for professional mountainbiker is presented in details. Moreover, tools for parsing sport activities files are discussed. Finally, tips and open challenges are exposed that refer to the data analysis and data mining of the proposed sports activity datasets.

Keywords:Computational Intelligence, Data Mining, Dataset, Sport Training

## 1. INTRODUCTION

Nowadays, sport activities mean for people more than only a passive or active spending of their leisure time (Rauter, 2014). The sporty lifestyle of a human can be easily explained as motives for satisfaction and enjoyment, developing abilities, establishing friendships and overcoming the challenges inherent to the specific sport activity. Many people consider leisure activities like engaging in sports as very important (Rauter, 2014). Bryan (2000) explains that those people who engage in sport activities in their leisure time or practice a specific sport very seriously sooner or later become completely focused on their most popular sport. For these kind of people, everything connected with the training seems to be very important.

Over past years, mobile technology has made a big step forward. In line with this, these technologies allow us to obtain information from anywhere at any time (Novatchkov et al., 2011). The increased popularity of mobile smart-phones and tablet computers in developed economies determines how and where sports footage, highlights and information are accessed (Hutchins, 2014). These devices can also be used as sports trackers for tracking data during the athletes' workouts. These tracked workouts can also be exported as XML files and analyzed later. For instance, Garmin Connect web service developed a wonderful online training service, where users can analyze workout data after finishing their activities. For more and more serious cyclists, the using of such sport applications is unavoidable because they put the cycling world at the forefront of their life (Rauter et al., 2015a).

In other words, these applications offer an immense of different tasks for data analysis and data mining. Number ideas about using these methods were discussed in paper (Fister et al., 2015). The mentioned data should also be used for the automatic planning of sports training sessions as proposed in Fister et al. (2015). Unfortunately, when someone reviews an existing literature about the related research topics, he/she can realize that there is a lack of research tackling the data analysis and data mining of sport activities created by sport trackers (Fister et al., 2013).

Sports training is a dynamical process, where input parameters are changed on the basis of current training, personal characteristic, weather, time, well-being, etc. Although some sport applications allow users a certain kind of automatic planning for training sessions, this planning is based on a lot of input parameters, which cannot be changed during the process of training. Therefore, additional effort in developing the artificial sports trainer is expected that will be capable of dynamically planning sports sessions. We hope that this proposed data collection of sports activity datasets could help and accelerate this development process in the future. This was also the main reason to collect training data of different outdoor athletes and make these publicly available in order to enable potential researchers to discover new ways of training data analysis.

The structure of the paper is as follows. Section 2 refers to fundamentals of contemporary sports training. Section 3 focuses on the answer to the question how to analyze sports activity datasets. In line with this, two formats of these datasets, i.e., GPX and TCX are describes in detail. In section 4, future challenges for data analyzing and data mining of the proposed sports activity datasets are exposed in order to motivate the potential developers. The paper concludes with Section 5, where the directions for the future work is outlined.

## 2. FUNDAMENTALS OF CONTEMPORARY SPORTS TRAINING

As mentioned earlier, sports applications can analyze the data of our training sessions, organize virtual competitions or even help us in sports training advertising. However, the main question is how sport applications can contribute in the more effective process of sport training (Rauter, 2014).

The definition of sports training is based on the scientific and pedagogical principles of the planned systematic activities or processes in order to obtain the highest achievements of the trained in the particular sports discipline (Ušaj, 2003). The final effect of the systematic training process can be manifested as:

- Achieved sports form,
- Increased capacity of the athlete’s organisms,
- An over-training syndrome Faria et al. (2005), in the worst case.

While introducing his ground breaking theory of periodization in Romania in 1963, Bompa (1994) proposed revolutionary western training methods for the optimal designing training programs. Today, periodization is the basis of every serious athlete's training. This is a scientifically based method for structuring short-term and long-term training plans.

For smart training planning, a sport training quantification is the key for success. The sports training quantification has always been a goal to be achieved by researchers in sport sciences. There are a lot of publications (Banister, 1991; Foster et al., 2001; Lucia et al., 1999) with the purpose of validating or proposing methods for measuring and controlling the training load. For measuring the sport training intensity most athletes use heart rate frequency monitors, where the time duration of the exercise by the average heart rate serves as a measure of the intensity. This is the simple method for monitoring the difficulty of sport training (Anta and Esteve-Lanao, 2011).

Banister (1991) made a step forward in the smart training analysis of training sessions by using the method TRIMP. In order to quantify training load, this method used so-called training impulses that take into consideration the intensity of exercise as calculated by the heart rate (HR) and the duration of a training session. Beside the physiological parameters (HR) of the monitoring exercise intensity, some other parameters as for example power data (from power meter) can be used for monitoring the difficulty of sport training (Klika et al., 2007). Cyclists especially use these devices very often, where a measure Training Stress Score (TSS) is proposed as a way of expressing the workload from a training session. These measure is the product of the workouts intensity and duration.

Grounded within current research on exercise physiology, athletic psychology, and training methodology, periodization varies the intensity and volume of training in order to optimize the body's ability to recover and rebuild (Issurin, 2010). This results in better performance, i.e., improved sport form and less risk of injury.

The athlete in relation to the expected competitive performance can describe sport form as a phenomenon of short-term increased capacity and is also perceived on the subjective level. For instance, in such conditions, cyclist feels that a certain load of cycling can be overcome with little effort or the higher load at the maximum effort Anta and Esteve-Lanao (2011). In simple terms, it means that the athlete ”is in best shape at the right time.” Efficiency of the process of sports training also means that the athlete rationalizes the time devoted to the training.

## 2.1. Sample of Cycling Sports Training

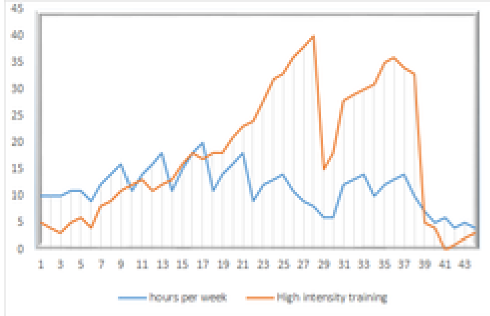
To illustrate how the sports training plan looks like in practice, a sample from cycling sport is presented in this section. This training was prescribed by cycling coach and it is devoted to a professional mountain cyclist. Table 1 present specific training process of this cyclist that used a different methods of training type. For long low intensity aerobic training they often used road cycles. Priority in the last few days before the main competition has specific short high intensity training sessions with the lot of rest periods in between. These type of training must be performed with the racing mountain bikes.

Table 1. Example of training for mouintainbike race (XCO) - tapering for last 14 days before the competition

| DAY | METHODS - Type of Training | DURATION | INTENSITY |
|---|---|---|---|
| 1 | RACE | | |
| 2 | Easy riding on the race track with some acceleration 3-4 times up to 2 minutes | 1h | Low intensity with short intensity blocks |
| 3 | Rest day, | | |
| 4 | Mountain bike interval training on the similar race profile for 2 x 20’ fast; between sets 5’-8’ of easy riding | 2h | Low & high intensity |
| 5 | Rest day | | |
| 6 | Mountain bike Hill climbing interval 4 x 4’ very fast; between sets 3’-4’ of easyriding (DH) | 2h | Low & high intensity |
| 7 | Mountain bike (interval training 2 sets of 3-5x 90” very fast acceleration;) | 1h30min | Low & high intensity |
| 8 | Rest day | | |
| 9 | Rest day | | |
| 10 | Endurance running with road bicycle(flat terraing) | 3h30min | Low intensity |
| 11 | Endurance running with road bicycle(up and down terrain) | 3h | Low intensity |
| 12 | Rest day | | |
| 13 | Endurance running with road bicycle(hilly terrain) | 3h | Low intensity |
| 14 | Mountain bike Hill climbing interval 2 sets of 4’x2’ very fast with 1 recovery; between sets 15’ of easy riding) | 2h | Low & high intensity |

Figure 1 presents the concept of yearly training periodization cycles according to two measures, i.e., duration (hour per week) and intensity (heart rate). As can be seen from this figure, the athlete had two main competitions in the year (i.e., in week 28 and 36). Interestingly, after these events an intensity of training (red line) decreases by decreasing the training duration. In summary, the athlete increased the intensity of training before and decreased it after the competitions. Duration of training sessions (blue line) follows a competitive trend, where the intensity of training session increases before the competition and contrary decreases after the competition. As matter of fact, the athlete finished with training after week 34, where the training intensity and duration fall under minimum values.

Figure 1. Concept of yearly training periodization for two main competitions




## 3. HOW TO ANALYZE SPORTS ACTIVITY DATASETS

Monitoring the progress of performances during sports training is the eternal desire of each professional as well as amateur athlete. The rapid development of mobile technology realizes this desire. Nowadays, you cannot imagine the athlete without tracking devices either sports watches (e.g., Garmin, Polar) or mobile devices (e.g., smart-phone) during its workout, on which data about sports activities are saved.

This means that producing sports training data does not represent problem anymore. However, difficulties have arisen when these big amount of data need to be analyzed. A lot of web applications offer their users some kind of sports activity data visualization, where usually the movement of the athlete is visualized on Google Maps together with some statistical measures like average heart rate during sports session, velocity, length of the performed course, etc. Unfortunately, this visualization typically encompasses only one sports session. However, these data are insufficient for monitoring an athlete's progress by coaches, where analysis covered activities during a longer period of time must be performed. In this way, a global analysis of sports activity datasets is needed, where beside an athlete coaches and experts from different domains, like anatomy, physiology, biomechanics, psychology, sociology, and didactics, must also be included.

In order to accelerate the progress of data mining and analysis of sports activity datasets, the activity datasets from nine professional cyclists during three years training period were assembled and made publicly available by Rauter et al. (2015b). Data were directly exported from their Strava or Garmin Connect accounts. Data format of sports activities could be written in GPX (Global Positioning System Exchange Format) or TCX (Training Center XML) format, which are basically the XML formats adapted to specific purposes. From each dataset, in depth information can be obtained: GPS location, elevation, duration, distance, average and maximal heart rate, while some workouts also include data obtained from power meters.

Let us notice that this suite is not the ultimate, because we have invited cyclists and athletes from other sports disciplines to help us to enrich this collection with their activity datasets in future. Thus, they will enable further development of the automatic sports trainer specifically in the case that developers will make their training software solutions opened.

Typically, treatment of the sports activity data consists of three steps:

- Data preprocessing,

- Data processing,
- Data visualization.

In data preprocessing, data from GPX and TCX datasets are parsed and filtered information is stored within a database. Statistical data analysis and/or data mining methods can be used during the data processing step. This step depends on the long-term (strategy) and short-term (tactics) demands of the sports training. The results of the data processing are presented to users usually in graphical forms, where some hidden information can also be discovered from the database and the depicted coaches.

While the data pre-processing step is already automatized, the development of the last two steps are left to the developers according to the strategy/tactics of sports training as outlined by different coaches. In the remainder of the paper, formats of GPX and TCX datasets are described in detail.

### 3.1. Format of TCX Datasets

The TCX dataset format was introduced by Garmin. According to the description in Wikipedia (2015), this format is similar to the GPX format since it exchanges GPS tracks but treats a track as an activity rather than simply a series of GPS points. Algorithm 1 and Algorithm 2 (Figure 2 and Figure 3) represent snippets from TCX dataset. The former represents overall summary of monitored training session, while the latter an example of trackpoint.

Figure 2. Algorithm 1

**Algorithm 1** Activity

```
⟨Activity Sport=”Biking”⟩
⟨Id⟩2015-02-02T14:24:24.000Z⟨/Id⟩
⟨Lap StartTime=”2015-02-02T14:24:24.000Z”⟩
 ⟨TotalTimeSeconds⟩5658.131⟨/TotalTimeSeconds⟩
 ⟨DistanceMeters⟩42645.58⟨/DistanceMeters⟩
⟨MaximumSpeed⟩16.74799919128418⟨/MaximumSpeed⟩
⟨Calories⟩591⟨/Calories⟩
⟨AverageHeartRateBpm⟩
 ⟨Value⟩142⟨/Value⟩
⟨/AverageHeartRateBpm⟩
⟨MaximumHeartRateBpm⟩
 ⟨Value⟩194⟨/Value⟩
⟨/MaximumHeartRateBpm⟩
⟨Intensity⟩Active⟨/Intensity⟩
⟨Cadence⟩82⟨/Cadence⟩
⟨TriggerMethod⟩Manual⟨/TriggerMethod⟩
⟨Track⟩
 ⟨Trackpoint⟩
...
...
⟨Activity⟩
```

Figure 3. Algorithm 2

**Algorithm 2** Trackpoint in TCX file

```
⟨Trackpoint⟩
    ⟨Time⟩2015-02-02T15:01:24.000Z⟨/Time⟩
    ⟨Position⟩
        ⟨LatitudeDegrees⟩46.24080430⟨/LatitudeDegrees⟩
      ⟨LongitudeDegrees⟩15.25768772⟨/LongitudeDegrees⟩
    ⟨/Position⟩
    ⟨AltitudeMeters⟩305.0⟨/AltitudeMeters⟩
    ⟨DistanceMeters⟩17035.140625⟨/DistanceMeters⟩
    ⟨HeartRateBpm⟩
        ⟨Value⟩157⟨/Value⟩
    ⟨/HeartRateBpm⟩
    ⟨Cadence⟩94⟨/Cadence⟩
    ⟨Extensions⟩
        ⟨TPX xmlns="http://www ... Extension/v2"⟩
        ⟨Speed⟩9.008000373840332⟨/Speed⟩
        ⟨/TPX⟩
    ⟨/Extensions⟩
⟨/Trackpoint⟩
```

There are many ways how to handle TCX datasets, since there are many parsers which allow their processing. For example, a very simple and efficient tool is the python-tcxparser which was written by Vinod Kurup (accessible at Github account: vkurup). The Python-tcxparser is a minimal parser for TCX dataset format (Kurup, 2015). This parser is able to extract the following data (Kurup, 2015):

- Latitude and longitude of the start point of the training activity,
- Type of the training activity (running, walking, etc),
- Time of completion of the training activity (in iso utc),
- Distance of the training activity (in meters),
- Duration of the training activity (in seconds),
- Calories burned during the training activity (as estimated by device),
- Average, maximum and minimum heart rate during the training activity and
- Average pace during the training activity.

Note that TCX forma is not static because the format of these datasets is adapted by emerging the new measuring devices in order to enable tracking the new indicators of athlete's readiness.

### 3.2. Format of GPX Datasets

GPX is a light-weight (TopoGrafix, 2015) XML format for the interchange of GPS data (waypoints, routes, and tracks) between applications and web services on the Internet. A snippet from the GPX dataset is presented in Algorithm 3 (Figure 4). A very robust tool for handling GPX datasets is gpxpy (Krajina, 2015) which is written in Python.

Figure 4. Algorithm 3

**Algorithm 3** Trackpoint in GPX file

```
⟨trkpt lat=”46.5167650” lon=”16.2472000”⟩
        ⟨ele⟩181.8⟨/ele⟩
        ⟨time⟩2014-08-10T08:55:46Z⟨/time⟩
        ⟨extensions⟩
          ⟨gpxtpx:TrackPointExtension⟩
            ⟨gpxtpx:atemp⟩25⟨/gpxtpx:atemp⟩
            ⟨gpxtpx:hr⟩147⟨/gpxtpx:hr⟩
          ⟨/gpxtpx:TrackPointExtension⟩
        ⟨/extensions⟩
⟨/trkpt⟩
```

## 4. FUTURE CHALLENGES

In sports theory, there are many indicators for identifying the athlete’s readiness, like lactate, oxygen consumption and respiratory exchange ratio (RER). Unfortunately, these indicators have been measured in the ambulance in the past. However, new researches the sports domain shows that these indicators could also be easily obtained by sports trackers briefly, similar to data about power meters. Increasing types of measuring data available by sports trackers however opens the new possibilities for analyzing the sports activity datasets.

On the other hand, the number of methods for data analyzing and data mining have been increasing rapidly. Let us list only a few of the more important ones that are appropriate for use in sports:

- Clustering,
- Classification,
- Sequential pattern mining,
- Association rule mining.

Clustering groups several objects into groups of similar attributes (Alazmi and Alazmi, 2012). Classification refers to a categorization of object and ideas, where these are recognized, differentiated and understood (Alazmi and Alazmi, 2012). Sequential pattern mining algorithms search for patterns in order to detect trends in sequential data (Alazmi and Alazmi, 2012). The task of association rule mining is to find hidden if-then rules within the dataset containing unrelated attributes (Alazmi and Alazmi, 2012).

Finally, there are some hints beyond the development and design of applications that could be interesting for trainers and the trained in the future (Fister Jr. et al., 2015):

- Optimization of sports’ equipment (e.g., bike frames, wetsuits and helmets),
- Optimization of different player positions on the field in team sport,
- Detection of doping in sport,
- Training course generation,

- Predictions of overall times in different competitions,
- Detection of the athlete's crisis during endurance competitions,
- Avoiding pain and over-training.

However, this list of challenges if far to be complete because of new coach's demands, emerging of the new sport disciplines and/or the new measuring devices, etc. In addition, a lot of current research work in sport domain Chl´ıbkov´a et al. (2014); Romer et al. (2014); Lin and Chen (2015); Baca et al. (2009); Novatchkov and Baca (2013); Baca (2014); Capozzi et al. (2015); Buttussi and Chittaro (2008); Petrovi´c et al. (2015); Cort´es et al. (2014) might also bring new ideas.

## 5. CONCLUSION

There is a growing number of people who are successfully using a variety of sport applications. Primary tasks of such sport applications is tracking and analyzing their workouts. These tracked workouts can also be exported as XML files and analyzed later. In order to enable potential researches to discover new ways of training and data analysis collected sports activity datasets of nine professional cyclists obtained by sports trackers which could help and also accelerate the development of artificial sports trainer that could replace the real trainer in the future. Thus, assistance of all potential developers will be welcome.

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