Applied Data Science: An Approach to Explain a Complex Team Ball Game

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Abstract: Team handball is a fast and complex game with a very traditional background and so far, almost no collection of digital information. Only a few attempts have been made to come up with models to explain the mechanisms of the game based on measured indicators. CoCoAnDa is a project located at the Baden-Wuerttemberg Cooperative State University that addresses this gap. While having started with the aim to introduce data mining technology into an almost non-digitalized team sport, the project has extended its scope by introducing mechanisms to collect digital information as well as by developing field specific models to interpret the collected data.

The work presented will show the design of specialized apps that have been implemented to manually collect a maximum of data during team handball matches by a single observer. This paper will also describe the analysis of available data collected as part of the match organization of 1,190 matches of the first and 1,559 matches of the second German team handball league, HBL. Furthermore, the data of more than 150 games of national teams, the first league, and the third league have been manually collected using the apps developed as part of the project.

1 INTRODUCTION

Since October 1917, when Max Heiser decided on the name "Handball" for the previously by himself invented game "Torball" (DHB, 2017), team handball has evolved tremendously, particularly in Europe. The complexity and trickiness of this team ball game, with its permanent game continuum in which two teams interfere with each other, exert a fascination on the involved people that can hardly be described by words or in terms of explanations.

What might be explainable to the outside, seems to be very hard to understand from the inside. Why does the "inner circle" of team handball struggle to decrypt the own sport? Other team sports have been subject to digitalization in the past already. For instance, nothing is left to chance in the professional leagues in North America having a multi-million-dollar budget, as at is the case in basketball, football, and baseball. In Europe, soccer, volleyball, and hockey have been digitally decoded to a vast extend. Team handball, however, seems to have not yet reached its digital maturity.

Coaches who talk publicly about their work, do have the basic problem to express verbally what they do, and they must also justify what they do. Frequently they struggle to find explanations for spectators and journalists which leads to (over-)simplifications. And if an explanation cannot be found they come up with hollow words like "team mentality" which cannot be directly observed and thus it cannot be refuted. According to Jack McCallum, the resulting platitudes and banalities are the "lingua franca" (McCallum, 2007) of sports and immune to falsification.

To replace the beloved folklore and customs by a non-guessing storytelling which is based on data and numbers, should be in the interest of all involved parties. For sure, there is still the "gut feeling", an intuition that cannot be explained, yet (Kahnemann, 2013). However, believe and knowledge cannot be maximized at the same time. To maximize one of the

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two, the other one needs to be pushed back in order to get the necessary additional space for optimization. Frequently, findings “eat up” intuitions in this situation.
Whether “big data” steals the romance of sport, as it was written by the NZZ in June 2019 (Berger, 2019), or whether the “DNA” of team handball (as well as ice hockey) can be decrypted completely, is still an open research question. We are working on an answer and we have some first results.

2 INDICATORS IN TEAM HANDBALL

2.1 Basics of Team Handball

Team handball is played indoors on a field of 20 x 40 meters (IHF- International Handball Federation, 2016) It is played by two teams consisting of 7 players out of which one player is the (optional) goalkeeper. There is a goal on each side of the field and a penalty area in front of the goal. Only the goalkeeper of the defending team is allowed inside the penalty area.

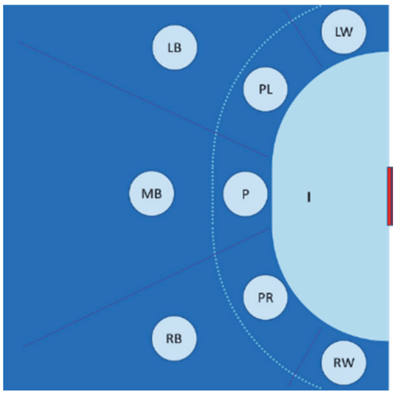

Figure 1 : Attacking zones.

An attack of a team might end with the following outcomes, which means that the attack ends, and the ball possession changes:

- The team throws the ball at the goal and scores a goal (*goal*).
- The team throws the ball and misses the goal (*miss*), or the goalkeeper saves the ball (*save*).
- During the attack the attacking team loses the ball due to a *ball handling error* of one of the players.
- During the attack the attacking team loses the ball due to a violation of the rules of the game (*rule violation*).

Attempts to score a goal, by throwing the ball at the goal, are differentiated based on the position of the player on the field from which the attempt is made. There are 8 attacking zones (plus the penalty line) per side which are distinguished (see Figure 1):

- Left Back, Mid Back, Right Back
- Pivot Left, Pivot, Pivot Right
- Left Wing, Right Wing

2.2 Attack Effectiveness and Attempt Effectiveness

The *attack effectiveness* is a key performance indicator of teams. It is the ratio of the number of successful attacks (attacks which ended with a goal) divided by the total number of attacks performed by the team.

The *attempt effectiveness* is a key performance indicator of teams as well as of players and exists in two variants:

- The overall attempt effectives (also called throw effectiveness), which is the number of successful attempts (which scored a goal) divided by the total number of attempts (of the team or player).
- The zone-specific attempt effectiveness, which focusses on attempts in a specific field zone only.

2.3 Technical Error Ratio

All attacks which do not result in an attempt to score a goal are considered to be technical errors. They consist of ball handling errors as well as rule violations. The ratio of technical errors is the number of attacks without an attempt divided by the total number of attacks.

2.4 Defence Effectiveness and Goalkeeper Effectiveness

Whenever the opponent attempts to score a goal and the attempt does not result in a goal due to a blocked ball by a defensive field player or due to a saved ball by the goalkeeper, it is considered a successful defence. Thus, the *defence effectiveness* is defined as the sum of saves plus the number of blocks divided by the total number of opponent attacks.

The *goalkeeper effectiveness* is an indicator of the goalkeepers only and defined as the number of saves divided by the total number of opponents’ attempts without considering the number of blocked or missed attempts. The goalkeeper effectiveness is a team performance indicator because only saves are recorded which lead to an end of an attack. There is also a variant of the indicator, the personal goalkeeper's effectiveness, which includes saves that did not end the attack of the opponent.

3 DATA COLLECTION

Team handball is a very traditional sport and the regulations have been very restrictive until recently. For instance, the first German league (Handball Bundesliga, HBL) waited until the season 2019/2020 to automatically collect data using sensors, and the International Handball Federation just recently decided to allow to use information from outside the field of play for coaching purposes during a match. Hence, there is not much data available about team handball matches. Even worse, the available data that has been collected in the past, like data that has been collected by Sportradar (Sportradar, 2015) for betting purposes, do not have the needed quality for in-depth analysis in the context of research projects. For instance, simple checks for the balanced number of attacks during a match reveal significant discrepancies. Furthermore, there are errors and missing data, e.g. due to network outages during the recording. As a consequence, the CoCoAnDa project (Schwenkreis F. , 2019) had to develop its own data gathering mechanisms first, in order to collect enough data with sufficient quality as a basis for applying analytics.

3.1 Specialized Mobile Apps for Data Collection

One of the major challenges to collect data in case of team handball are the limited budgets of the teams (even in the first league). When looking at options to collect data during matches, the teams usually need solutions that can be used when playing at home as well as abroad. Thus, fixed solutions in the arenas do only make sense if all teams of a league agree to equip their sports hall with that solution and to share the collected data. In general, we are still far from such a uniform infrastructure (and its use) in the halls. Thus, CoCoAnDa decided to build mobile apps that support the manual collection of information which can be digitally processed later. Currently, we use two apps to collect information and one app to provide a near real-time visualization to the coaches.

3.1.1 The Scouting App

The so-called Scouting App (see Figure 2) was developed to record the team handball specific events during a match. It has been developed with a main emphasis on the efficient recording of events with a minimum risk of errors. The app is based on the Ionic™ framework (ionic, 2019), runs on Android™ tablets, and allows to record the following events:

- Attempts to score with their location, involved players and outcome
- Scoring goals including the targeted area of the goal
- Technical errors including the involved players
- Sanctioned fouls and penalties including the involved players (as well as temporary suspensions)
- Saves including the targeted area of the goal and misses
- Blocked attempts including the involved player
- Replacing the goalkeeper by an additional field player

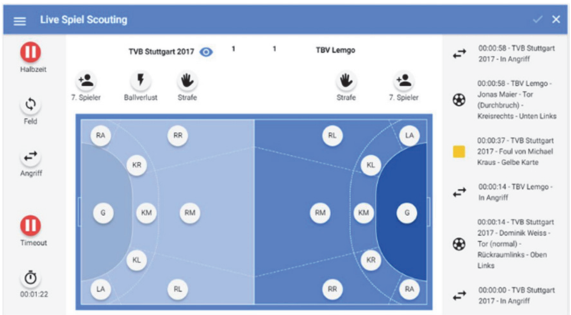

Figure 2 : The Scouting App.

The app generates events which are sent via a local wireless network to a so-called data backend which stores the events in a PostgreSQL™ (PostgreSQL, 2019) database. The data backend can also be run on the same Android tablet as the Scouting App itself. Hence, the Scouting tablet is a very lightweight and highly portable solution (Schwenkreis F. , 2018). It can be used without any support of the sport halls of a match, even when it is used in combination with the near real-time monitoring app: The Coaching App.

Using the Scouting App, we have recorded the game events of 89 first league matches and 52 matches of the 3rd and the 4th league, the national women's team, and the national junior teams.

3.1.2 The Passcounter App

The PassCounter App (Figure 3) is an additional stand-alone app that has been developed to "record" a team handball match based on passes rather than time and game events. Since more than 1500 passes happen during the 60 minutes of a team handball match, the PassCounter App has been particularly designed to support the efficient recording of passes and to cope with errors.

With the PassCounter App we record the number of passes, the number of fouls, and the number of technical errors during an attack as well as misses. Since the recording person needs to react very fast to events on the field, there is a high probability of errors. Two features help to minimize the number of errors in the result generated by the PassCounter App:

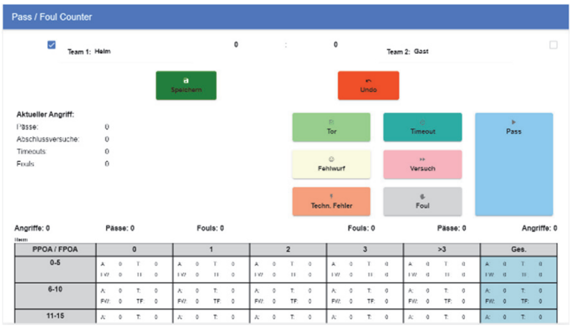

Figure 3 : The PassCounter App.

- A large button for recording passes.
- An Undo button to compensate for errors.

Up to this point we have recorded the information of 145 first league matches and of 22 matches of lower leagues, the women's national team and the EHF Champions League using the PassCounter App.

3.2 Sensor-based Data

With the introduction of sensor-based recording of the players' location in the first league, we have now access to the precise positions of players and their movement traces (with a time resolution of 20 positions per second). This will allow us to automatically detect tactics and trigger actions in the future (Schwenkreis F. , 2018), and by combining this information with the collected game events we will be able to analyse the success of certain tactics. Furthermore, we can calculate a sophisticated player contribution index based on the position data (Schwenkreis F. , 2019). However, this is just at its beginning and we cannot present results, yet.

3.3 Publicly Available Data

As mentioned before, there is some publicly available data, that is collected by the German Bundesliga (HBL, 2019). Although its overall quality is questionable (e.g., we detected huge differences in the number of attacks per team in a single match), some information can still be used, as for example the sequence of scored goals. Since the HBL cooperates with the CoCoAnDa project, we have received the collected data of almost four seasons of the first (1190 matches) and the second (1559 matches) German team handball leagues.

4 ANALYSIS AND INSIGHTS

The following results have been derived from the data that we have collected with our apps. We have used the publicly available data from the HBL to verify our findings and to check for differences between the leagues. Whenever the data from the HBL did not have the necessary quality, we have not included a comparison with the league's data.

4.1 Basic Observations

According to our observations, a match of the first German league consists in average of approximately 49 (between 40 and 60) attacks per team. Each team performs 40 attempts, out of which 14 (between 5 and 22) are misses or opponent saves and 26 (between 15 and 40) result in goals. Thus, the defence effectiveness is almost identical with the goalkeeper effectiveness. In average the goalkeepers have approximately 9 saves (between 3 and 19) per game, i.e. 5 of the 14 misses are attempts that effectively miss the goal. In average, 10 (between 3 and 16) attacks are finished with a technical error. Blocked attempts ending an attack are rare in matches and in average there is a single blocked ball in two games.

Regarding the performance indicators introduced in section 2 an average team of the HBL has:

- An attack effectiveness of approximately 53% and a zone independent attempt effectiveness of approximately 65%.
- A technical error rate of approximately 20%.
- A goalkeeper effectiveness of approximately 23%.

A comparison with lower level leagues shows a higher number of attacks, resulting in more goals, more misses, and more saves. The number of technical errors per match seems to be almost identical, which is also the case for the attempt effectiveness.

4.2 Data Science Approach

Data Science (Provost & Fawcett, 2013) focusses on the application of data mining technologies to answer "business-level" questions. In the context of the CoCoAnDa project we are targeting questions of team handball coaches and try to find answers using data mining as well as other data analytic approaches. The overall objective is to find patterns that allow to predict the final outcome, or the future development of matches, based on the indicators of players or the team that can be influenced by the coaches (and the players themselves). However, as a first step we focused on identifying "alerts" which indicate the need for a change in order to avoid a loss.

4.2.1 The Baseline

When applying predictive modelling there needs to be a baseline regarding probabilities in order to evaluate the quality of results. A very simple starting point is to look at the random case first. In case of matches that would correspond with throwing a coin to determine the winner of the match. I.e. the probability of winning a match is 50% in the pure random case (ignoring ties).

A typical question in case of team ball sports is whether there is a significant advantage of playing at home rather than playing abroad. In case of our observation there is an advantage of being the home team: In approximately 73% of the cases the home team does not lose.

Another question that came up was, whether the outcome of a match can be derived from the current rank of the teams in the league. It turned out that having a better or equal rank than the opponent team (before the match) results in a 71% "probability" of not losing the game.

The first three baseline "predictions" are completely independent from the actual match or any property of the players. Thus, they cannot be consciously influenced by the coaches or the players. Finally, we looked at the halftime results and whether the outcome of the match can be derived from them. We found, that in 72% the cases, a team does not lose, if the team was not behind at halftime. I.e. if your team is behind at halftime, there is only a 28% chance that your team will not be losing in the end.

4.2.2 Zone-specific Insights

Collecting match information using the Scouting App has increased the data quality and enhanced the information with additional data compared to the HBL data. Based on the attack information of 384 team specific views of matches (correspond with 192 matches), we were able to analyse 13,656 attempts.

According to our observations, an average team in the first German league has an attempt effectiveness of approximately 42% from the far distance (9 meters and beyond), a near-zone attempt effectiveness of approximately 75%, and an attempt effectiveness from the wing positions of approximately 66%, which adds up to an overall attempt effectiveness of 58%.

Overall, goalkeepers reach in average approximately an effectiveness of 49% from the far zone, 20% from the near zone and 28% from the wings (which adds up to 25% in total).

We have compared these numbers with indicators collected during 52 games of a team playing 3rd league in one season and 4th league in a second season. While the lower leagues have a 4% higher attempt effectiveness from the far zone, and similar effectiveness from the near zone, the attempt effectiveness from the wings is 6% lower. The overall effectiveness is 57%. The zone-specific goalkeeper effectiveness numbers in the lower leagues are 7% lower regarding the far zone, similar in the near zone and 12% better from the wings.

4.2.3 Goal Area Specific Insights

The Scouting App has been extended with the ability to record the goal area that has been targeted by an attempt which reaches the goal. The goal has been divided into nine areas for that purpose (see Figure 4). Three areas in the top section: top left, top mid, and top right

- Three areas in the middle section: mid left, mid mid, mid right
- Three areas in the bottom section: bottom left, bottom right, bottom right

Figure 4 : Goal Areas.

Whenever a goal is scored or a save happens, the targeted goal area is recorded from the attacker's point of view. I.e. from a goalkeeper's perspective the zones are mirrored. Furthermore, we do not actually record the goal area where the ball passes the goal line but rather the area where the ball passes the goalkeeper or where the goalkeeper saves the ball. Hence, the collected information is intended to answer questions like "Where are the strong/weak areas of a goalkeeper?", "Is there an area which should be better covered by the blocking players to help the goalkeeper?", or "Has an attacker a certain "sweet area" when attempting?".

The recording of the goal areas in case of saves by goalkeepers has been added rather recently. Thus, we have only data of 92 HBL games, and 7105 attempts at this time. Most attempts are targeted at the bottom section of the goal (approximately 52%). Less than a quarter of the attempts (22%) are targeted at the top section, even though the summarized attempt effectiveness numbers are very similar (77% at the bottom and 77% at the top respectively). Only about one fifth of the attempts are targeted at the middle section, which shows a significantly lower attempt effectiveness of only 44%. The goalkeeper's effectiveness can simply be calculated by subtracting the attempt effectiveness from 100%.

Again, the numbers have been compared to the data collected in the 4th league. We were able to use 23 matches) including 2,015 attempts. The distribution of the attempts across goal areas is almost the same as in case of the HBL (with a maximum difference of 2% in each section). However, in case of the lower league we have a lower attempt effectiveness of 74% in the top section, a significantly higher effectiveness of 59% in the middle section, and 74% in the bottom section.

4.2.4 Significance of the Sequence of Goals

While considering the question whether the outcome of a match can be predicted significantly before the end of a match based on the team's performance, we looked at the most prominent indicator: the number of goals. Several hypotheses have been investigated and one showed a surprising result: "The team that scores the nth goal first, will not lose the match".

With the collected data from the Scouting App, the complete sequence of match events is available and can be analysed. Thus, we compared the "predictability" of different numbers of goals (the n) ranging from 10 up to 28 based on 98 matches of the first league.

Below the investigated range, the accuracy decreases. Above the goal 24 the accuracy does also decrease because the number of matches in which less than the required number of goals are scored, increases (we have in average of approximately 25 goals per match and team in the set of observed matches).

Two results are particularly interesting. There is a peak (local maximum) around goal 16 (92.9%) after which the accuracy decreases. Furthermore, there is a second peak (the global maximum) around goal 20/21 (95.9%).

We have verified these patterns with the data from 52 matches of the lower leagues. We have found the same two peaks, the first one at goal 16 (85.4%) and the second one at goal 26 (100%). However, the average number of goals per match is significantly higher (approx. 29) compared to the matches of the first league.

Since the publicly available HBL data has sufficient quality regarding the sequence of goals, we also verified the "two peak finding" using long-term data (almost 4 seasons) of 1190 first league matches and of 1559 second league matches. The two peaks do not exist in long-term data. However, at goal 16 we find an accuracy of 86.6% in the first league and 83.2% in the second league. The maximum accuracy is at goal 21 in the first league (91.3%) and 22 in the second league (88.9%). If we just look at the 306 matches of the last season of the first league, we find the two peaks at 17 goals (89.5%) and at goal 20 (91.5%). Based on 379 second league matches of the last season we found the first peak at goal 16 (85%) and the maximum at goal 21 (91%).

4.2.5 Advanced Insights using Data Mining Techniques

The prediction of the winner of matches is a typical classification task (Provost & Fawcett, 2013). The business questions "behind" the classification is: "Which (minimal) combination of indicators that we measure can be used to predict the outcome of a match". Since we are measuring the indicators while the match is played, and we want to have an indication during the match whether we need to intervene, it is useless to train models using the absolute numbers of finished matches. We rather need to use relative indicators as introduced in section 2 that can be measured throughout the match.

Data Mining and its methods are completely new to team handball coaches. Thus, it is very important that the results can be explained in terms which can be understood by the coaches. That is why we started by using tree classification as the data mining method. Tree classification models can be explained as a set of rules over the measured indicators, which makes them understandable.

Regarding the computation parameters, we found that the information gain criterion was the best split criterion and using pruning and pre-pruning avoids overfitting of the model (while reducing the prediction accuracy a bit). The tree model we have found has a prediction accuracy (of the training data) of approximately 94% and seems to be a logical extension of the basic observation. Here is a summary of the rules:

- If the attempt effectiveness is 65% or better, and the defence effectiveness is 26% or better, and the penalty (seven meter) ratio is higher than 56% we will win the game. Even if the penalty ratio is lower, this can be compensated with faster attacks (average attack time less than 36 seconds).
- If our attempt effectiveness is 65% or better, but our defence effectiveness is less than 26%, the low defence effectiveness can be compensated by a very high attempt effectiveness (greater than 77%) in order to still win the game.
- If the attempt effectiveness is less than 65%, we can compensate for that by a defence effectiveness of 34% or more. Otherwise, it is likely that we will lose the game.

As an alternative to the tree classification method we have used the support vector machines (SVMs) technique (Steinwart & Christmann, 2008). Based on the radial kernel the resulting model reached a prediction accuracy (of the training data) of approximately 99%. Unfortunately, SVM models cannot be described by a simple set of rules as in case of the tree classifier. SVM models are partially described in terms of weights of the measured indicators. The basic insight is slightly different:

- The defence effectiveness is most important, then attempt effectiveness follows and the goalkeeper effectiveness is ranked third in terms of their weight.
- With a significant distance, the previous indicators are followed by the penalty success ratio and the fast break success ratio.
- Finally, it is beneficial to have a low average attack time.

Besides trying to find a combination of indicators that can be used to predict the outcome of matches, we also looked at further questions:

- "Can we predict the outcome of a game based on the zone-specific attempt effectiveness?" No significant patterns were found while analysing the zone-specific effectiveness. It seems that the zone-specific effectiveness of the teams varies too much.
- "Can we predict the final rank class of a team after a season based on the performance indicators of a team?"
  The rank class of a team splits the league table into multiple sections like "champions league", "EHF cup", "mid-range", and "declassification range".

Unfortunately, we do not have enough data with sufficient quality to derive accurate patterns for these questions at this point.

5 PASSES, FOULS, AND (NON-)SUCCESS

While the work presented in section 4 focusses on questions from a complete match perspective, we extended our work by a more attack-oriented view. Since a match consists of more than 100 attacks, the probability of attack-success (i.e. scoring a goal) is highly correlated with winning the game.

Thus, we investigated the properties of attacks by collecting the detail data using the PassCounter App in addition to the data collected by the Scouting App. Up to now, the pass data of 140 matches of the first league have been recorded (plus 20 other matches). This allows first insights based on 13,866 attacks consisting of approximately 183,000 passes and 7,950 sanctioned fouls of the first league, and 2,540 attacks of the other matches consisting of approximately 30,000 passes and 1,280 sanctioned fouls.

Since this is work that just has recently been started, the detailed results have not been verified yet, due to the relatively small amount of data (at the point in time this paper was written). However, we can derive from the collected data that a match in the HBL consists in average of approximately 1,300 passes and 56 sanctioned fouls (which is about 1 sanctioned foul every second attack).

As being mentioned before, we do not have enough data yet to verify some interesting patterns that have been discovered using data mining techniques, like association rules. The recently introduced sensors in the HBL (Kinexon, 2017) will help to collect pass data automatically if the match balls are equipped with the sensors in addition to the players. However, the quality of that recording needs to be proven first, for instance, based on the data that we collect using the PassCounter App.

6 CONCLUSIONS

This paper reflects the work of approximately 3 years. Since there was almost no detailed data of team handball of sufficient quality when we started, mobile apps had to be developed first to generate the data for the later analysis. We are still far from being able to "decrypt the DNA of a team handball match", but we found some first patterns and we can explain some characterizing properties of the game. Particularly, we can explain the differences to other games like soccer and why models that have been developed in the context of soccer cannot be applied in case of team handball.

Some coaches use the findings presented in this paper to evaluate the performance of their team. The Coaching App provides a feature that allows to use the numbers as thresholds which drive the colouring of the graphical representation of the collected data. For instance, if the goalkeeper's effectiveness is significantly below the average of the league, then the indicator is coloured in red. Furthermore, we do also provide team specific effectiveness numbers derived from the historical data of the team.

The actual challenge of team handball is the fact that the game is a multi-dimensional problem. All attempts to sufficiently explain the game based on a single dimension have proven to be inaccurate. With the availability of multi-dimensional data mining analytics, we now have a chance to bring the insights to the next level.

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