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Modeling the Badminton Stroke Pattern Through the Sequential Pattern Discovery Using Equivalent Classes (SPADE) Algorithm

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Abstract

Badminton is one of the most popular sports in the world, especially in Asia. It has a parent organization called Badminton World Federation (BWF). Discussion about player strategies in winning various championships held by BWF is an interesting topic to discuss. This paper aims to analyze the hitting patterns of badminton players by paying attention to the sequence of types of strokes made by the players, including lobs, netting, smashes, drives, and dropshots. Sequential pattern discovery using the equivalent class algorithm (SPADE) is the appropriate method to identify these problems because it can determine the rules and probabilities of player's hitting patterns based on the order of the types of strokes. In this paper, we analyze the stroke pattern of the two top-ranked badminton players in the men's singles sector at the Malaysia Open 2022 championship, where Viktor Axelsen and Kento Momota met in the final. Based on the results of this research, we analyze the strategies and recommended hitting patterns from the information on the two players' patterns. The results of this study, in general, can be used as information for players to understand and analyze the opponent's performance or strategy before competing.

Keywords: *Badminton, Kento Momota, Rules, SPADE, Stroke Pattern, Viktor Axelsen*

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1 Introduction

Badminton is one of the popular sports in the world, especially in Asia. This sport is played by hitting the shuttlecock using a racket across the net or the opponent's area. The sport is played one-on-one or two-on-two, with a score collected to win 21 points. Badminton has a parent organization called the Badminton World Federation (BWF). BWF aims to organize, promote, develop, and popularize badminton worldwide. BWF also organizes various kinds of international championships at the highest level that are routinely held every year, such as the BWF World Tour, BWF World Championship, Thomas Cup, Uber Cup, and many others.

Getting points at the badminton championships is certainly not easy. Careful preparation is needed both physically, mentally, and especially strategically. The strategy used must be neatly arranged so that the attacks carried out can produce points optimally. Most of the previous studies discussed the strategy of badminton players from the physical perspective. Sakurai and Ohtsuki (2000) studied the spatio-temporal relationship between muscle activity and the smash stroke to analyze player's performance [18]. Alcock and Cable (2009) compared the physiological demands such as heart rate response, player profile, and game characteristics to assist coaches in designing training programs [2]. Identification of player movements on the field is also an important aspect to learn in order to develop game strategies in badminton matches. Huang et al. (2019) studied the maximal right lunge movement of badminton players using the injury mechanism model [11]. Valldecabres et al. (2020) studied about player movement on the court in terms of play, round, and match state, and found that contextual variables modulate the movement of elite players on the court. This information can be used by players and coaches in understanding opponent behavior [20], [21]. Another study on player movement was done by Ramli et al. (2021) who studied the interaction between mechanical variables in the forehand shot technique and provided the related performance outcome [17]. The latest study on measuring the performance of badminton players from the physical aspect was carried out by Malwanage et al. (2022) who investigated the effectiveness of balance exercises on the footwork performance of badminton players [13].

Over time, apart from optimizing the physical performance of badminton players, many statistical studies have been conducted regarding the evaluation of badminton games which aim to provide information to both players and coaches in order to improve the performance of the athletes. Aydogmus et al. (2014) studied the physical characteristics of the 2012 Olympic players in the badminton sector, including average match, rally durations, and the highest rally strokes

[4]. The information obtained from the results of the analysis can be used by coaches to improve athlete performance related to technical and tactical aspects, as well as athlete training scheduling so that performance is more optimal. A similar study was conducted by Torres-Luque et al. (2019) who studied the statistical difference in the set analysis in the badminton sector at the 2019 Rio Olympic [19]. Along with the development of science, statistical analysis related to the performance of badminton players began to be developed using data science tools.

Many recent studies that analyze badminton games use these data science methods. Human action recognition of the player's movement is one of the keys to be done before conducting further performance analysis [14]. Some action recognition analyses have been done using data science methods such as the use Convolutional Neural Network (CNN) method with various developments for tracking badminton player positions from sports broadcast videos [16], [15], [14]. In general, these studies can be said to have only studied player movements on the field, but have not specifically studied the opponent's playing pattern. Throughout our literature search, research on the analysis of playing patterns of badminton players is still rare. We found two studies in 2020 that talk about this. First, Gomez et al. (2020) used Network Science to create a badminton stroke network (BSN) whose results are shown in the form of a graph visualization that depicts the player's stroke position on the court [9]. Second, Ardiantoro and Sunarmi (2020) analyze the striking patterns of badminton players using the frequent pattern (FP) algorithm. The results show changes in the pattern of a badminton player's stroke based on the type of stroke, including serve, netting, dropshot, lob, smash, backhand, and drive [3]. However, the two recent studies have not shown the hitting patterns of two players facing each other. Study on such matters is very important to conduct in order to determine the best strategy for dealing with an opponent's blows. Therefore, this study aims to examine the strategy of playing badminton based on the stroke patterns of two players facing each other.

In this study, we analyze the stroke patterns of two world's top-ranked men's singles players in one of the badminton championships held by BWF, i.e. Malaysia Open 2022. Malaysia Open 2022 is an example of the championship organized by the BWF, included in the BWF World Tour. Several parties are played at the match, including men's singles (MS), women's singles (WS), men's doubles (MD), women's doubles (WD), and mixed doubles (XD). There are many interesting matches in the Malaysia Open 2022, one of which is the match between Viktor Axelsen and Kento Momota. According to data from BWF, the two players were ranked 1st and 2nd in the world when the championship was held. However, the points difference between the two players is quite large. During the meeting, Viktor Axelsen defeated Kento Momota in the final with scores of 21-4 and 21-7. Kento Momota is a 28-year-old Japanese athlete. He is a former world number one in the MS sector and is currently ranked 23rd [5]. He has a record of 368 wins and 99 losses. Meanwhile, Viktor Axelsen is a 28-year-old Danish athlete currently ranked number one in the world in the MS sector [5]. He has a record of 480 wins and 142 losses. Based on the ranking and winning records, both players have and are currently dominating the MS sector. Therefore, the study of the two players' hitting strategies is an interesting matter to discuss.

One of the popular methods used to study the pattern between items in large dataset is Sequential Pattern Mining [10]. In the analysis of badminton stroke pattern, we need to consider the order of the strokes based on the time order of their occurrence. Therefore, the most appropriate method to use is the Sequential Pattern Discovery using Equivalent Classes (SPADE) algorithm which has advantages in analyzing patterns of events in sequential time [23]. Based on the results of the pattern analysis, we recommend the types of shots a player should make when facing certain types of shots from opponents based on its probability. This research will be very useful for coaches and players in determining strategies and shots that must be made based on the opponent's movements.

2 Methodology

2.1 Association rule

Association rule is a technique in data mining to find associative rules between combinations of events. The association rule is a form of "if antecedent (X), then consequent (Y)" or if "the event precedes (X)" then "the consequence (Y)" [8]. The association rule is used to determine the relationship between items. The set of items is defined as an itemset, for example, the itemset contains a k-item called a k-itemset. The tendency for the emergence of itemsets in the number of transactions is called frequency. The importance of an association rule can be determined by two parameters, namely support and confidence.

Support is the percentage of the combination of items in the database [6]. Support for the "$X \Rightarrow Y$" rule is a collection of attributes or probability of X and Y attributes that occur simultaneously. Thus, the support value of an item is obtained by the following formula [24].

$$Support(X) = P(X) = \frac{n(X)}{n(S)} \tag{1}$$

where

$P(X)$: probability of event X
$n(X)$: the number of occurrence of X
$n(S)$: total number of occurrence

For two items, the support value is defined as follows [24].

$$Support(X \Rightarrow Y) = P(X \cap Y) = \frac{n(X \cap Y)}{n(S)} \tag{2}$$

where

$P(X \cap Y)$: probability of event X and Y occurs simultaneously

$n(X \cap Y)$: the number of simultaneous occurrence of X and Y

Support in this study is defined as the probability of the occurrence of several items (shot type) made by the player from the overall hit made. In this analysis, minimum support will also be determined with the aim of generating items from the badminton strokes dataset.

The confidence rule "$X \Rightarrow Y$" is a set of attributes or the probability of occurrence of several items simultaneously where one item has occurred first. Thus, the confidence value of a combination of items is obtained by the following formula [24].

$$Confidence(X \Rightarrow Y) = P(Y|X) = \frac{P(Y \cap X)}{P(X)} \quad (3)$$

where

$P(Y|X)$: conditional probability of event Y given that event X has occured

$P(Y \cap X)$: probability of Y and X occurred simultaneously

In this study, confidence is defined as the probability of multiple items (multiple shot types) being performed by a player in a single rally. In this analysis, minimum confidence will also be determined, which is a parameter that defines the minimum level of confidence that must be met by quality rules [1].

In the association rule, there is also a formula called lift ratio. The value of the lift ratio ranges from 0 to infinity. The minimum value of the lift ratio is not determined as is support and confidence. The rule often appears simultaneously but independently if the value of the lift ratio is equal to 1. An independent rule is a rule that gets consequent independent of the antecedent [12]. A better rule is recommended if we have a lift ratio value of more than 1 because antecedents positively affect consequents. Vice versa, if the lift ratio value is less than 1, the antecedent negatively affects the consequent. It means that a rule with a lift ratio value of more than 1 is a strong rule. The formula of the lift ratio is as follows.

$$Lift\,ratio(X \Rightarrow Y) = \frac{P(Y \cap X)}{P(X)P(Y)} \quad (4)$$

In other words,

$$\begin{aligned} Lift\,ratio(X \Rightarrow Y) &= \frac{Confidence(X \Rightarrow Y)}{P(Y)} \\ &= \frac{Confidence(X \Rightarrow Y)}{Support(Y)} \quad (5) \end{aligned}$$

2.2 Sequential Pattern Discovery using Equivalent Classes (SPADE)

Sequential pattern is the occurrence of an event with a pattern that describes the sequence of time. This pattern will be successfully obtained by using large amounts of data by making transactions repeatedly. For example, a customer will have an identity that is recorded by making repeated shopping transactions at a shopping center [1]. Sequential pattern discovery using equivalent classes (SPADE) is a pattern mining algorithm that uses vertical data format in a database. In the vertical data format, the database sequence forms a collection of sequences with the format [itemset :(sequence_ID, eventID)] [23].

The steps of the SPADE algorithm in finding and determining the rules of the frequent sequence are as follows [23], [22].

1. Computing frequent 1-sequence
   To find the frequent 1-sequence database, all we have to do is scan each set of items in the sequence database. For each itemset, store its id-list (a pair of *sid* which is the sequenceID and *eid* which is the eventID). Then scan the id-list of each of these id-lists, every time an *sid* is found that did not exist before, the value of support is added. Sequences that are included in the frequent 1-sequence are those whose support is more than min_sup; the minimum support used as a limit on the frequency of occurrences that must be met by a group of data to be used as a rule.

2. Computing frequent 2-sequence
   In searching for frequent 2-sequence, the data used is data from frequent 1-sequence, so there is no need to search from the sequence database again. For each frequent 1-sequence, combine it with all other frequent 1-sequences. For example, if 1-sequence A is combined with 1-sequence B, then the probability of 2-sequence occurring is A, B where A and B appear simultaneously in the transaction, $A \rightarrow B$ where item B appears after item A, and $B \rightarrow A$ where item B appears after item A. For each frequent 1-sequence merger this is done checking whether the id-list has the same *sid*, if the same then checking whether the eid of 1-sequence A is equal to, less than or more than the *eid* of 1-sequence B. If the same then the id-list is included in 2-sequence A, B. If *eid* B is greater than A then the id-list is included in 2-sequence $A \rightarrow B$ and if *eid* A is greater than B then the id-list is included in the 2-sequence $B \rightarrow A$. Then, as in the frequent 1-sequence, add support for each previously unmet *sid*. From the 2-sequence then checked whether the support was more than min_sup. If eligible then it is included in the frequent 2-sequence.

3. Computing frequent k-sequence
   After obtaining frequent 2-sequences, the next process is to find frequent k-sequences. To get

Table 1: Operational definition of the variables

No.	Variable	Definition
1.	Rally	The match lasts from the player making the first shot until the shuttlecock falls and scores a point.
2.	Stroke types	The type of stroke made during the match, consists of:
	Smash (Sm)	A sharp, fast and hard shot towards the opponent's field.
	Dropshot (Ds)	The stroke made to drop the shuttlecock as close to the net as possible on the opponent's court.
	Drive (Dr)	Shots made horizontally in all directions.
	Netting (Nt)	A shot made smoothly or slowly and dropped as close to the net as possible.
	Lob (Lb)	The stroke is made by directing the shuttlecock as high as possible so that it will fall sharply into the opponent's field.
3.	Stroke sequence	Sequence of strokes made in one rally.

these frequent k-sequences, combine frequent $(k-1)$-sequences that have the same initial conditions. For example, to find frequent 3-sequences, combine frequent 2-sequences that have the same initial conditions. Then to find frequent 4-sequences, combine frequent 3-sequences that have the same initial conditions, and so on. To find the frequent $(k-1)$-sequence prefix, remove the last item from the sequence. For example, if there are frequent 4-sequences $A \rightarrow B \rightarrow C \rightarrow D$, then the prefix is $A \rightarrow B \rightarrow C$.

4. Formating the rule
   After finding all frequent sequences, the rules of those sequences are determined. 1-sequence is not used to form rules because it consists of only 1 item. For 2-sequences, the antecedent is the first item and the consequent is the second item. For example, for sequences $A \rightarrow B$, the rule formed is $A \Rightarrow B$. As for sequences that are more than 2, i.e. k-sequences,the consequent is the last item, while the antecedent is all items before the last item. For example, in the 4-sequences $A \rightarrow B \rightarrow C \rightarrow D$, the resulting rule is $A \rightarrow B \rightarrow C \Rightarrow D$. For each rule, the confidence value is calculated. If the rule meets the min_conf limit, then the rule is accepted. Furthermore, from the accepted rule, calculate the value of the lift ratio–the greater the better–with a limit of 1. If the rule has a lift ratio value greater than or equal to 1, then in that rule the antecedent has a positive influence on the consequent. Therefore, the rule is said to be a good rule. On the other hand, if the lift ratio value is less than 1, the rule is considered not good.

What is no less important is, based on the resulting rules, what strategy should be used by the opponent when facing Viktor Axelsen and Kento Momota. The strategy can be prepared in the following steps:

1. Check through what shots player $P_i, i = 1, 2$, where P_1 is Viktor Axelsen and P_2 is Kento Momota, will often get points. Note these strokes as S_{p_i} (point-scoring strokes). Let $S_{p_i} = \{$smash, dropshot, drive, netting, lob$\}$.
2. Based on the first step, check what strokes can anticipate S_{p_i} to not being scored. The trick is to check what shots can return player P_i's ball when the player uses a certain S_{p_i}. Write down this type of stroke in $S_{a_{ij}}$ (anticipated strokes), where i denote the point-scoring stroke and j denote the anticipated strokes for the corresponding point-scoring stroke i.
3. Sort $S_{a_{ij}}$ based on how often the strokes occur in the rules so that the opponent can anticipate S_{p_i} and provide a graphical term for easy reading.

3 Results and Discussion

In this work, we collected shot types data from the video of the match between Viktor Axelsen and Kento Momota at Malaysia Open 2022 from BWF TV youtube channel [7]. The data consist of rally sequence, as well as stroke types and sequence. Table 1 provides the operational definition of the variables used in this research.

Based on the collected data, we obtain information regarding percentage of types of strokes made by both Viktor Axelsen and Kento Momota which are provided in Fig. 1.

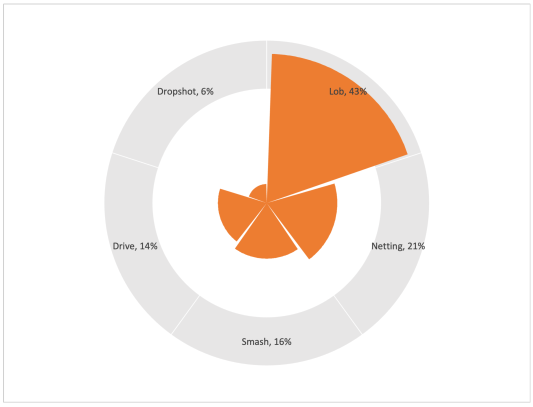
In general, in the Malaysia Open 2022 match, Kento Momota used all five types of strokes evenly compared to Viktor Axelsen who was more dominant in making lob shot. Contrary to Kento Momota, who often takes dropshots, Viktor Axelsen rarely uses this type of shot. However, both of them do drives with almost the same percentage and netting with the same percentage. The distribution of the use of the five types of strokes between Viktor Axelsen and Kento Momota in each rally during the match is presented in Fig. 2.

From Fig. 2, we can see that Viktor Axelsen uses lobs, smashes and netting more often in every rally than Kento Momota. Meanwhile, Kento Momota uses dropshot and drive more often than Viktor Axelsen. More specifically, the sequence of types of strokes made by Viktor Axelsen and Kento Momota at the Malaysia Open 2022 is presented in Table 2.

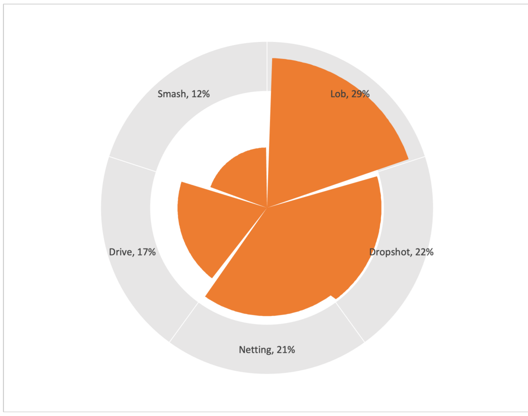
Table 2 provides the stroke sequence made by Viktor

Table 2: Stroke sequence by Viktor Axelsen and Kento Momota at Malaysia Open 2022

Player's name	Rally	Strokes type	Stroke sequence	Axelsen's Point	Momota's point
Momota	1	Lb	1		
Axelsen	1	Ds	2		
Momota	1	Nt	3		
Axelsen	1	Nt	4		
⋮	⋮	⋮	⋮	⋮	⋮
Momota	1	Lb	13		
Axelsen	1	Sm	14	1	0
⋮	⋮	⋮	⋮	⋮	⋮
Momota	53	Lb	11		
Axelsen	53	Sm	12	21	7



(a) Viktor Axelsen



(b) Kento Momota

Figure 1: Percentage of type of stroke made by Viktor Axelsen and Kento Momota

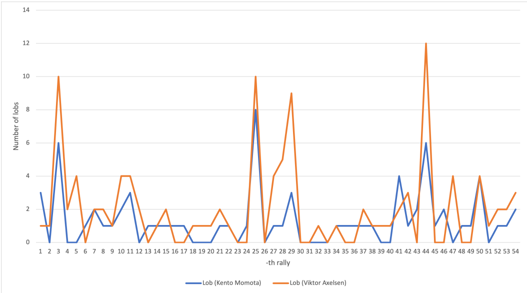
Axelsen and Kento Momota in each rally until Viktor Axelsen won over Kento Momota in two straight games with a final score of 21-7. In the first rally, Kento Momota served in a lob and was returned by Viktor Axelsen with a dropshot. Next, Kento Momota did a netting, which was also returned by Viktor Axelsen with a netting shot. And so on until the end of the first rally which was won by Viktor Axelsen with the last return being a smash. This sequence of shots was recorded in the same way until the game ended in the 53rd rally which was ended by Viktor Axelsen with a smash and made it 21-7 in the second game. The steps taken after recording the strokes sequence are data pre-processing and data selection which aims to remove unnecessary variables in the data. The results of the two steps are then be transformed into a vertical data format that conforms to the rules of the SPADE algorithm. We transform the rally variable into the sequence id *sid*, the stroke type into *items*, the stroke sequence into event id *eid*, and the number of each stroke type into the variable *size*. Those vertical data format is provided in Table 3.

Table 3: Vertical data format of the stroke sequence

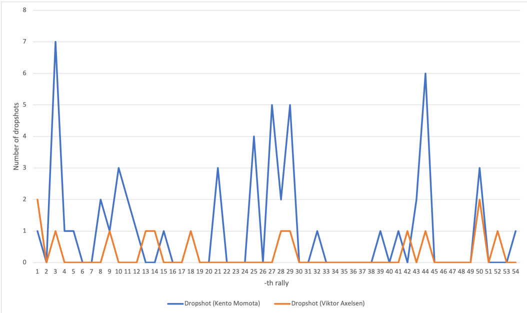
sid	*items*	*eid*	*size*
1	Lb(M)	1	1
1	Ds(A)	2	1
1	Nt(M)	3	1
⋮	⋮	⋮	⋮
1	Lb(M)	13	1
1	Sm(A)	14	1
⋮	⋮	⋮	⋮
53	Lb(M)	11	1
53	Sm(A)	12	1

By using the SPADE algorithm, we obtain rules that describe the sequence of shots made by Viktor Axelsen and Kento Momota along with its support, confidence, and lift ratio values. The results of the rules which have confidence value greater than one are presented in Table 4.

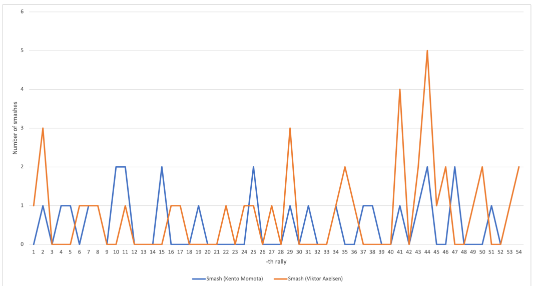
There are several rules formed as a result of the use of SPADE algorithm, however, we select the rules formed using a minimum support value of 0.2 and confidence value of 1, and found that the rules formed were 2 to 6 consecutive strokes patterns. The first rule $<\{\text{Netting(M)}\}> \Rightarrow <\{\text{Lob(A)}\}>$ is a frequent 2-sequences having the highest *support* value of 0.7143. It means that 71.43% of the total shots throughout the rally were netting shots taken by Kento Momota and followed by lobs made by Viktor Axelsen. The confidence value of 1 means that if Kento Momota make a netting shot, then with a confidence level of 100%, it will be returned by Viktor Axelsen with a lob shot. The



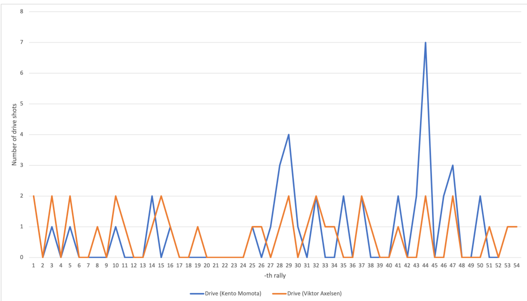
(a) Lob



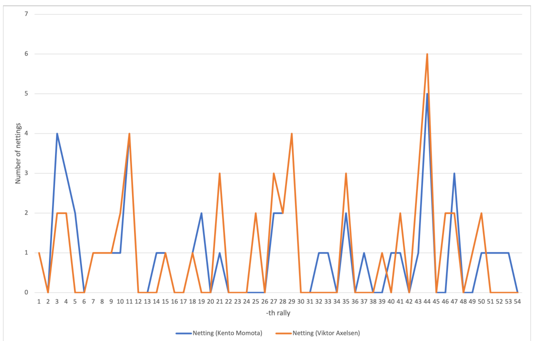
(b) Dropshot



(c) Smash



(d) Drive

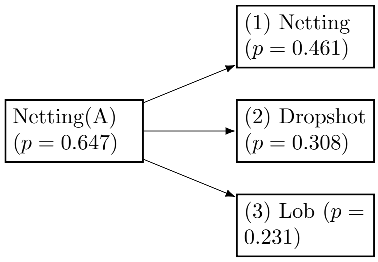


(e) Netting

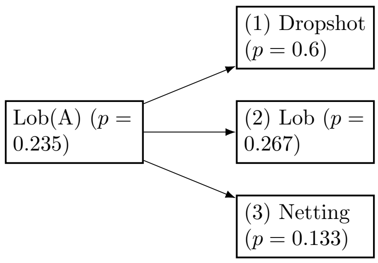
Figure 2: Distribution of the use of each strokes between Viktor Axelsen and Kento Momota in each rally

lift ratio value of 1.120 (greater than one) means that the relationship between the two types of strokes of both Kento Momota and Viktor Axelsen is strong. The second rule <{Netting(A)}, {Lob(M)}, {Lob(A)}> ⇒ <{Dropshot(M)}> with the support value of 0.4286 means that 42.86% of the total shots in the two game at Malaysia Open 2022 were, in sequence, netting made by Viktor Axelsen, lob by Kento Momota, lob by Viktor Axelsen, and ends with dropshot by Kento Momota. Likewise, a confidence value of 1 means that with a confidence level of 100%, if the previous sequence of shots was netting made by Viktor Axelsen, lob by Kento Momota, and lob by Viktor Axelsen, then points will be scored by Kento Momota after he returns Viktor Axelsen's shot using a drop shot. All other rules can be explained in the same way.

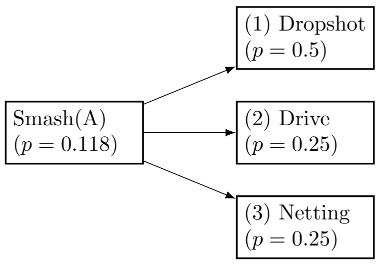
Based on the 21 rules obtained, it can be seen that Viktor Axelsen will get points from lobs, netting, and smashes. Meanwhile, Kento Momota gets points from dropshots and lobs. Therefore, based on the steps explained in subsection 2.2, we obtain the point-scoring strokes for the two players, i.e. $S_{p_1} = \{\text{lob, netting, smash}\}$ and $S_{p_2} = \{\text{dropshot, lob}\}$. By tracing the rules in Table 4, the sequence $S_{a_{ij}}$ is obtained. The order of recommendations $S_{a_{ij}}$ for opponents who will face Viktor Axelsen and Kento Momota's shots is provided in Fig. 3 and 4.



(a) Netting (A)



(b) Lob (A)



(c) Smash (A)

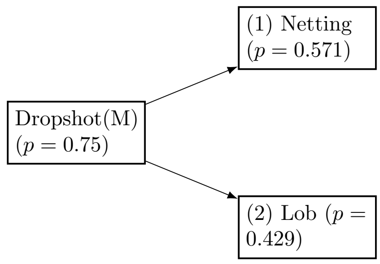
Figure 3: Strategies for dealing with Viktor Axelsen's point-scoring strokes

Table 4: Stroke patterns between Viktor Axelsen and Kento Momota in Malaysia Open 2022

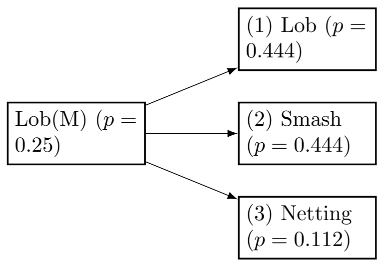
No.	Rules (stroke patterns)	support	confidence	lift ratio
1	<{Nt(M)}> ⇒ <{Lb(A)}>	0.7143	1	1.120
2	<{Nt(A)}, {Lb(M)}, {Lb(A)}> ⇒ <{Ds(M)}>	0.4286	1	1.474
3	<{Nt(A)}, {Ds(M)}, {Lb(A)}> ⇒ <{Ds(M)}>	0.3929	1	1.474
4	<{Ds(M)}, {Nt(A)}, {Ds(M)}> ⇒ <{Nt(A)}>	0.3571	1	1.556
5	<{Lb(M)}, {Lb(A)}, {Ds(M)}, {Lb(A)}, {Ds(M)}> ⇒ <{Nt(A)}>	0.3571	1	1.556
6	<{Nt(A)}, {Ds(M)}, {Lb(A)}, {Lb(M)}> ⇒ <{Sm(A)}>	0.3571	1	1.273
7	<{Sm(A)}, {Ds(M)}> ⇒ <{Lb(A)}>	0.3571	1	1.120
8	<{Lb(M)}, {Sm(A)}, {Ds(M)}> ⇒ <{Lb(A)}>	0.3571	1	1.120
9	<{Dr(M)}, {Nt(A)}, {Nt(M)}> ⇒ <{Nt(A)}>	0.3214	1	1.556
10	<{Lb(A)}, {Ds(M)}, {Nt(A)}, {Ds(M)}> ⇒ <{Nt(A)}>	0.3214	1	1.556
11	<{Nt(M)}, {Lb(A)}, {Lb(M)}, {Lb(A)}, {Ds(M)}> ⇒ <{Nt(A)}>	0.3214	1	1.556
12	<{Ds(M)}, {Nt(A)}, {Lb(M)}, {Lb(A)}, {Ds(M)}> ⇒ <{Nt(A)}>	0.3214	1	1.556
13	<{Nt(A)}, {Lb(M)}, {Sm(A)}, {Dr(M)} > ⇒ <{Nt(A)}>	0.3214	1	1.556
14	<{Nt(A)}, {Nt(M)}, {Lb(A)}> ⇒ <{Ds(M)}>	0.3214	1	1.474
15	<{Lb(A)}, {Nt(M)}, {Lb(A)}, {Lb(M)}> ⇒ <{Sm(A)}>	0.3214	1	1.273
16	<{Nt(A)}, {Nt(M)}, {Lb(A)}> ⇒ <{Lb(M)}>	0.3214	1	1.120
17	<{Nt(A)}, {Nt(M)}, {Lb(A)}, {Ds(M)}> ⇒ <{Lob(A)}>	0.3214	1	1.120
18	<{Sm(M)}, {Sm(A)}, {Nt(M)}> ⇒ <{Nt(A)}>	0.2857	1	1.556
19	<{Sm(M)}, {Lb(A)}, {Nt(M)}> ⇒ <{Nt(A)}>	0.2857	1	1.556
20	<{Lb(M)}, {Nt(A)}, {Nt(M)}> ⇒ <{Nt(A)}>	0.2857	1	1.556
21	<{Ds(M)}, {Nt(A)}, {Nt(M)}> ⇒ <{Nt(A)}>	0.2857	1	1.556

A: Viktor Axelsen and M: Kento Momota

Fig. 3 and 4 are strategies that can be developed to withstand opponent attacks against Viktor Axelsen and Kento Momota's strokes based on their performance at the Malaysia Open 2022. Of the 21 rules obtained with a confidence value greater than one, Viktor Axelsen's strokes that most often result in points are netting, with a percentage of 64.7%, followed by lobs of 23.5%, and smashes of 11.8%. Furthermore, based on the identification on the rules that are formed, the opponent can return Viktor Axelsen's netting stroke by also netting, dropshot, or lob to anticipate him from gaining point. If Viktor Axelsen's netting shot results in a thin ball in front of the net, then the opponent can return it by netting. If the netting results in the ball being lifted up, the opponent can return it with a dropshot or lob. Based on the second strategy, if Viktor Axelsen lobs the ball then the opponent can return it with a dropshot, lob or netting. Meanwhile, if Viktor Axelsen delivers a smash, then the opponent can return it with a dropshot, drive or netting ball. Somewhat different from Viktor Axelsen, Kento Momota's shots that often result in points are dropshot with percentage of 75% and lob with percentage of 25%. If Kento Momota takes a dropshot, the opponent can return it with a netting or lob ball. Meanwhile, if he lobs, the opponent can anticipate him from gaining points by lobbing, smashing, or netting.



(a) Dropshot (M)



(b) Lob (M)

Figure 4: Strategies for dealing with Kento Momota's point-scoring strokes

4 Conclusion

In order to optimize the performance of badminton players, in addition to physical preparation, both players and coaches also need to develop strategies to face opponents by looking at the opponent's playing patterns. From this study, at least based on the performance of the two top-ranked players in the MS sector at the Malaysia Open 2022, we get information about the stroke patterns of the two players. From the patterns formed, we can develop strategies that need to be carried out by other players if in a match they have to face Viktor Axelsen or Kento Momota. Viktor Axelsen earned points from netting, lobs and smashes. While Kento Momota getting points from dropshots and lobs. From these points-scoring strokes, we then analyze what strokes can be made to overcome the acquisition of these points.

The results of this analysis will be very useful for players and coaches in developing game strategies so that player performance becomes more optimal. Because data collection in this study was carried out conventionally by looking at the match on BWF youtube channel, in future research action recognition can be developed which can read the types of player strokes in each rally and then combine them with the association rules model that we offer so that the analysis of badminton stroke patterns can be carried out more efficiently.

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