The Importance of the Serve in Winning Points in Tennis: A Bayesian Analysis Using Data for the Two winners of the 2019 French Open Singles

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2022

The Importance of the Serve in Winning Points in Tennis: A Bayesian Analysis Using Data for the Two Winners of the 2019 French Open Singles

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March 2021

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Abstract

The Reverend Thomas Bayes, an 18^{th} century Presbyterian minister, proved what, arguably, is the most important theorem in statistics. Its importance stems from its capacity to transform the answer to a question relating to the likelihood that if a point is won, it will have been preceded by a first service (the probability that if the theory is true, the data will be observed) to an answer to a more interesting and relevant question: if the first serve is good, what is the probability that the point will be won (the probability that if the data is observed, the theory will be true)? Empirical flesh is put on Bayes' theorem by studying the performance of the winners of the men's and women's singles titles at the 2019 French Open: Rafael Nadal and Ashleigh Barty. Whatever the prior likelihood that they would win a point on their service game, this had to be revised upward for both players if the data showed that their first serve was 'good' and had to revised downward if the point required that they serve again. On the assumption that the prior probability was 60%, this then allows the analyst to deduce that the probability of winning a point on the first service was 65.9% for Barty and 73.8% for Nadal. Similarly, it could be deduced that the probability of winning a point on the second service was 34.1% for Barty and 26.2% for Nadal. The contribution of the paper lies in applying Bayes' Theorem to show how, in service games in tennis, evidence can be turned into insight.

1. Introduction

The Reverend Thomas Bayes, an 18th century Presbyterian minister, proved what, arguably, is the most important theorem in statistics.[1] Bayes' Theorem states that the probability of a hypothesis being true (event *T*), *given that the data have been observed* (event *A*), is the probability of the hypothesis being true, *before any data have been observed*, times an "updating factor". The theorem is encapsulated by the well-known equation: [2]

$$P(T \mid A) = \frac{P(A \mid T)}{P(A)} \times P(T) \tag{1}$$

where: $P(T)$ represents the *prior* belief that the hypothesis is true *before the data have been observed*; *P(A)* is the probability of observing the data, *regardless of whether the hypothesis is true or not*; *P(A|T)* is the probability of observing the data, given that the hypothesis is true, and $P(A \mid T) / P(A)$ is the Bayesian "updating factor" which translates one's *prior* (that is, *before* observing the data) belief about the hypothesis's validity into a *posterior* (that is, *after* observing the data) belief .[3]

Bayes' theorem has been extensively applied in law and in medicine. For example, in the area of law it has shed light on the so-called "prosecutor's fallacy" whereby a prosecutor argues that since the probability of observing a particular piece of evidence (say, blood type identical to that found at the scene of the crime), *under the assumed innocence of the defendant*, is very small (that is, $P(A \mid T)$ is low), the probability of the defendant being innocent, *given that his blood type matches that at the crime scene*, must also be very small (that is, $P(T \mid A)$ must also be low). This fallacious reasoning stems from assuming that the ratio $P(T) / P(A)$ in equation (1) is equal to unity (Thompson and Schumann, 1987; Aitken, 1996). If, however, the prior belief that the defendant is innocent (*P(T)*), relative to the probability of finding a blood type identical to that found at the scene of the crime, is high then $P(T \mid A)$ could be high even though $P(A \mid T)$ was low.

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[1] See *The Economist*, "In Praise of Bayes", 28 September 2000, https://www.economist.com/science-and-technology/2000/09/28/in-praise-of-bayes.

[2] *P* in this term represents probability and the symbol | denotes that the event following | has already occurred.

[3] The updating factor is the ratio of the probability of observing the data when the theory is true, to that of observing the data regardless of whether the theory is true or false: $P(A) = P(A \mid T)P(T) + P(A \mid \overline{T})P(\overline{T})$, $\overline{T}$ being the event that the theory is false.

In medicine the theorem has, for example, been used to analyse the efficacy of breast screening. Proponents of screening would argue, on the basis of the "screening fallacy", that because the probability of the screen returning a positive result, *given that the patient has cancer*, is large (that is, $P(A|T)$ is high), the probability of the patient having cancer, *given that the screen returns a positive result*, must also be large (that is, $P(T|A)$ must also be high). This fallacious reasoning again stems from assuming that the ratio $P(T)/P(A)$ in equation (1) is equal to unity. If, however, the proportion of persons with cancer in the population, relative to the proportion of positive screen results, is small (i.e. $P(T)/P(A)$ in equation (1) is low) then $P(T|A)$ could be appreciably smaller than $P(A|T)$. The size of this difference represents cancer "over diagnosis" and has recently been estimated at 10% (Zackrisson *et al.*, 2006). In effect, 1 in 10 women diagnosed with breast cancer would not require treatment.

In this paper we apply these ideas to examining the importance of the serve – specifically, the first serve (FS) and the second serve (SS) – in winning a point. Excluding double faults, we assume that for the player serving for a particular point there are two possible options: the FS was 'good' (event A) or the FS was 'bad' or a fault (event $\tilde{A}$). Because the possibility of double faults has been excluded, event $\tilde{A}$ is synonymous with the SS being good. In this paper we distinguish between the probabilities of two events: (i) the probability that a winning point was *preceded* by a good FS or, in other words, what is the probability that if the FS is good the point would be won? (ii) the probability that a good first service would be *succeeded* by a winning point or, in other words, what is the probability that a winning point would be result of a good first service?

However, the question of interest is not about the likelihood that, if a point was won, it would have been *preceded* by a good FS - that is, (i) above – but, rather, the likelihood that a 'good' FS will be *succeeded* by a winning point - that is point (ii) above. It is important to emphasise that conceptually these are separate questions in much the same way that the probability that a test for cancer will report positive, *if one has cancer*, is conceptually different from the probability that one has cancer *if the test for cancer is positive.*

Similarly, the question of interest is not about the likelihood that a losing point will have been *preceded* by a 'bad' FS, but, rather, it is the likelihood that a 'bad' FS would be *succeeded* by a losing point. Again, it is important to emphasise that these are two separate questions in much the same way that the probability that a test for cancer will report negative, *if one does not have cancer*, is conceptually different from the probability that one does not have has cancer *if the test for cancer is negative.* The strength of Bayes' Theorem is that it is able to provide an answer to the second set of questions by linking it, via equation (1) above, to the first set.

The performance of tennis players has been the subject of considerable statistical analysis (*inter alia* Cui *et. al.* 2018; Moss and O'Donoghue 2015; O'Donoghue (2012); Cross and Pollard 2009; O'Donoghue and Brown 2009, 2008) and, in particular, the importance of the serve has been extensively examined. Furlong (1995) found that serve was more important on grass than on clay and more important in men's than in women's singles while Hugh and Clarke (1995) found that serve was more important at Wimbledon than in the Australian Open. O'Donoghue and Ingram (2001) showed that the duration of a rally depended on service speed while O'Donoghue and Ballantyne (2004) and Unierzyski and Wieczorek (2004) showed, respectively, how service speed and placement could be used to improve the effectiveness of the service.

More recently, O'Donoghue and Brown (2008) studied the rate at which the service advantage decayed as the rally progessed: in men's tennis the advantage persisted for three to four shots after the first serve but, in women's, the advantage of the first serves was lost after two shots. Notwithstanding the richness of the literature on the importance of the serve in tennis, to the best of our knowledge, a Bayesian analysis of the type articulated in this paper has not, been attempted and that is this paper's raison d'être.

The data for this paper is from website www.rolandgarros.com. The existence of this data is due to analytics provided by Roland Garros's new technology partner, Infosys. According to the Infosys Press release, "the collaboration is aimed at enriching the game by providing fans, players and coaches with a new experience leveraging Infosys' expertise in digital technologies such as artificial intelligence, big data and analytics, mobility, virtual and augmented reality".[4]

2. Bayesian Analysis of the Outcomes of Service Points

The first question of interest is that if a player won a service point (event T occurred), what is the probability that it would have been *preceded* by a good FS, event A? To put it slightly differently, what is the probability that event A occurs, *conditional on event T having occurred*? This probability is written as $P(A|T)=\alpha$, for some real number $0\le\alpha\le1$. The *sensitivity* of the first serve is defined by α: the more sensitive the first serve, the greater the likelihood that a point won will have been *preceded* by a 'good' FS.

Similarly, the *specificity* of the first serve, β, is defined as the likelihood that a point *lost* will have been preceded by a 'bad' FS: $P(\tilde{A}|\tilde{T})=\beta$. Following from this, *1-specificity* = *1-β* = $1-P(\tilde{A}|\tilde{T})=P(A|\tilde{T})$ is the probability of a *false positive*: the probability that a point *lost* (false) will have been preceded by a 'good' FS (positive). Similarly, *1-sensitivity* = *1-α* = $1-P(A|T)=P(\tilde{A}|T)$ is the probability of a *true negative*: the probability that a point won (true) would have been preceded by a 'bad' FS (negative). These four possibilities are set out in Table 1.

<Table 1>

As discussed above, Bayes' Theorem states that the probability of a theory being true (event T: a player wins a point), *given that the data have been observed* (event A: her FS was 'good') is given by equation (1), above. After the data have been observed, the Bayesian "updating factor" in equation (1), $P(A|T)/P(A)$, translates one's *prior* belief about the theory's validity into a *posterior* belief which, in the context of tennis, translates one's *prior* belief about a player winning a service point into a *posterior* belief about winning the point after the data was observed.

The probability of a 'good' FS is the weighted sum of the probabilities of a "true positive" (a player wins the point [true] with a good FS [positive]) and a "false positive" (a player loses the point

[4] Infosys and Roland Garros Partner for Digital Innovation, Infosys Press Release 20 March 2019. https://www.infosys.com/newsroom/press-releases/Pages/digital-innovation-partner-roland-garros.aspx (accessed 25 June 2019)

[false] with a good FS [positive], the weights being the strength of one's prior belief, $P(T)$, where $P(\tilde{T}) = 1 - P(T)$:

$$P(A) = P(A \cap T) + P(A \cap \tilde{T}) = P(T) \times \overbrace{P(A|T)}^{\text{prob of a true positive}} + P(\tilde{T}) \times \overbrace{P(A|\tilde{T})}^{\text{prob of a false positive}} \tag{2}$$

where: $\tilde{T}$ is the event that the player loses the point and $P(\tilde{T}) = 1 - P(T)$.

By analogous reasoning:

$$P(\tilde{A}) = P(\tilde{A} \cap T) + P(\tilde{A} \cap \tilde{T}) = P(T) \times \overbrace{P(\tilde{A}|T)}^{\text{prob of a true negative}} + P(\tilde{T}) \times \overbrace{P(\tilde{A}|\tilde{T})}^{\text{prob of a false negative}} \tag{3}$$

Equation (3) says that the probability of a 'bad' FS is the weighted sum of the probabilities of a "true negative" (a player wins the point [true] with a bad FS [negative]) and a "false negative" (a player loses the point [false] with a 'bad' FS [negative], the weights being the strength of one's prior belief, *P(T)*.

Substituting the expression in (2) into equation (1) yields:

$$P(T \mid A) = \frac{P(T) \times P(A|T)}{P(T) \times P(A|T) + P(\tilde{T}) \times P(A|\tilde{T})} = P(T) \times \frac{P(A|T)}{P(A)} \tag{4}$$

In an analogous manner, one can also enquire about $P(T \mid \tilde{A})$, the probability of winning a point after a second serve, by substituting equation (3) into equation (1):[5]

$$P(T \mid \tilde{A}) = \frac{P(T) \times P(\tilde{A}|T)}{P(T) \times P(\tilde{A}|T) + P(\tilde{T}) \times P(\tilde{A}|\tilde{T})} = P(T) \times \frac{P(\tilde{A}|T)}{P(\tilde{A})} \tag{5}$$

Now suppose that *prior* to a match being played, a particular player is expected to win 60% of the points for which she is serving, that is $P(T) = 0.6$. Suppose also that if the serving player *wins* a point, the chances are 70% that it will be on a first serve: in other words, using the terminology developed earlier, the player's serve has a sensitivity, $\alpha = P(A \mid T) = 0.70$. Similarly, suppose that if the serving player *loses* the point, the chances are 85% that it will be on her second serve: in other words, again using the earlier terminology, the player's serve has a specificity, $\beta = P(\tilde{A} \mid \tilde{T}) = 0.85$;

[5] Note that $\tilde{A}$ is the event that the FS was 'bad' and, since double faults are excluded, it is the event that the SS was 'good'.

this implies that the probability of a false positive – the probability of the serving player's losing point being *preceded* by a 'good' first serve - is $1-\beta = P(A\,|\,\tilde{T}) = 0.15$.

Substituting these assumed values into equation (4) yields:

$$P(T\,|\,A) = \frac{0.6\times 0.7}{0.6\times 0.7 + 0.4\times 0.15} = 0.88 \tag{6}$$

or, in other words, there is a 88% chance that a good first serve would be *succeeded* by a winning point.. Similarly, substituting these assumed values into equation (5) yields:

$$P(T\,|\,\tilde{A}) = \frac{0.6\times 0.3}{0.6\times 0.3 + 0.4\times 0.85} = 0.35 \tag{7}$$

or, in other words, there is a 35% chance of that the second serve would be *succeeded* by a winning point.

3. Estimates using Data for Barty and Nadal from the 2019 French Open

This paper puts empirical flesh on the analysis set out in the previous section by considering the aggregate performance of Ashleigh Barty and Rafael Nadal, respectively,the French Open women's and men's champions in 2019, against successive opponents from Round 1 of the tournament to the final. The performance data for Barty and Nadal, against their various opponents, is set out in Tables 2 and 3, respectively.

Table 2 shows that in the eight matches Barty played for her title, excluding 15 double faults, she served 450 times of which 268 first serves were good and the remaining 182 first serves were 'bad' (that is, resulted in a second serve). Consequently, in the notation adopted in this paper, $P(A) = 268/450 = 59.6\%$ and $P(\tilde{A}) = 40.4\%$ for Barty. Table 3 shows that in the eight matches Nadal played for his title, excluding 15 double faults, he served 575 times of which 403 first serves were good and the remaining 172 first serves were 'bad' (that is, resulted in a second serve). Consequently, in the notation adopted in this paper, $P(A) = 403/575 = 70.1\%$ and $P(\tilde{A}) = 29.9\%$ for Nadal. One difference between Nadal and Barty is that, compared to Barty, a greater proportion of his first serves were good: 70.1% versus 59.6%.

<Tables 2 and 3>

First Serve Analysis

Barty won 191 points from the 268 first serves and she won 99 points from her 182 second serves and so, over the eight matches she played, she won a total 290 points from her service games. In addition to these points won on her service, Barty also won 220 of the 453 points on which she received service. Consequently, Barty won a total of 510 points in the singles of the 2019 French Open: 191 on her first serve, 99 on her second serve, and 220 points when she was the receiver.

Nadal, on the other hand, won 301 points from the 403 first serves and he won 107 points from his 172 second serves and so, over the eight matches he played, he won a total 408 points from his service games. In addition to these points won on his service, Nadal also won 289 of the 604 points on which he received service. Consequently, Nadal won a total of 697 points in the 2019 French Open: 301 on his first serve, 107 on his second serve, and 289 points when he was the receiver.[6]

In other words, 191 and 99 of Barty's points were preceded, respectively, by first and second serves so that, in terms of the notation used earlier, $P(A\,|\,T) = 191/290 = 0.659$ and $P(\tilde{A}\,|\,T) = 99/290 = 0.341$ where *T* is the event that Barty won a point in a service game. The *prior* belief was that 60% of these 450 services would result in a point being won: *P(T)=0.6*; in fact, 64.4% of these services (290 out of 450) resulted in a winning point.

In contrast, 301 and 107 of Nadal's points were preceded, respectively, by first and second serves so that, in terms of the notation used earlier, $P(A\,|\,T) = 301/408 = 0.738$ and $P(\tilde{A}\,|\,T) = 107/408 = 0.262$ where *T* is the event that Nadal won a point in a service game. The *prior* belief was that 60% of Nadal's 575 services would result in a point being won: *P(T)=0.6*; in fact, 70.1% of these services (408 out of 575) resulted in a winning point.

Substituting the values detailed above for Barty into equation (4) yields the probability that a 'good' first serve by her would be *succeeded* by a winning point as:

[6] Nadal played a total of 1,179 points (697 won and 482 lost) over 985 minutes of play implying that the average point lasted 50 seconds. Barty, on the other hand, played 903 points (510 won and 393 lost) over 540 minutes of play implying that the average point lasted 39 seconds.

$$P(T \mid A) = 0.6 \times \frac{P(A/T)}{P(A)} = 0.6 \times \frac{0.659}{0.596} = 0.6 \times 1.11 \tag{8}$$

In other words, the *Bayesian updating factor* in respect of the prior belief that Barty would win a point on her service (in this case, 60%) was $0.659/0.596 = 1.11$. *Whatever the prior belief* that Barty would win a point in a service game (*P(T)*), it would have been raised after the data had been observed (which is that Barty's first serve was 'good').

Similarly, substituting Nadal's values detailed into equation (4) yields the probability that a 'good' first serve by him would be *succeeded* by a winning point as:

$$P(T \mid A) = 0.6 \times \frac{P(A/T)}{P(A)} = 0.6 \times \frac{0.738}{0.711} = 0.6 \times 1.04 \tag{9}$$

In other words, the *updating factor* in respect of the prior belief that Nadal would win a point on her service (in this case, 60%) was $0.738/0.711 = 1.04$. *Whatever the prior belief* that Nadal would win a point in a service game (*P(T)*), it would also have been raised after the data had been observed (which is that his first serve was 'good').

The upper panel of Table 4 sets out the calculations discussed above in tabular format.

It is important to note that the Bayesian updating factor for Nadal was *lower* than that for Barty: 1.04 versus 1.11. The Bayesian updating factor is computed as the ratio of the likelihood of the data being observed when the theory is true ((*P(A|T):* the probability that a winning point is preceded by a 'good' first serve) to the likelihood of the data being observed (*P(A):* the first serve was 'good'). Although for Nadal the likelihood of a winning point being preceded by a 'good' first serve was greater than for Barty (73.8% versus 65.9%), the likelihood that Nadal put in a 'good' first serve was also higher (71.1% versus 59.6%): a greater disproportionality between these two values for Barty meant that her Bayesian updating factor was higher than Nadal's.

Second Serve Analysis

Of the 290 points that Barty won on her service games, 99 points were won on her second serve. Consequently, $P(\tilde{A} \mid T) = 99/290 = 0.341$. At the same time, the probability of a second serve was $P(\tilde{A}) = 182/450 = 0.404$ so that, after substituting these values in equation (5), the probability that a second serve by Barty would be *succeeded* by a winning point is:

$$P(T \mid \tilde{A}) = 0.6 \times \frac{P(\tilde{A} / T)}{P(\tilde{A})} = 0.6 \times \frac{0.341}{0.404} = 0.844 \qquad (10)$$

In other words, the *updating factor* in respect of the prior belief that Barty would win a point on her service (in this case, 60%) was $0.341 / 0.404 = 0.844$. *Whatever the prior belief* that Barty would win a point in a service game (*P(T)*), it would have been lowered after the data had been observed (which is that Barty's first serve was 'bad').

Of the 408 points that Nadal won on his service games, 107 points were won on his second serve. Consequently, $P(\tilde{A} | T) = 107 / 408 = 0.262$. At the same time, the probability of a second serve was $P(\tilde{A}) = 172 / 575 = 0.299$ so that, after substituting these values in equation (5), the probability that a second serve by Barty would be *succeeded* by a winning point is:

$$P(T \mid \tilde{A}) = 0.6 \times \frac{P(\tilde{A} / T)}{P(\tilde{A})} = 0.6 \times \frac{0.262}{0.299} = 0.876 \qquad (11)$$

In other words, the *updating factor* in respect of the prior belief that Nadal would win a point on his service (in this case, 60%) was $0.262 / 0.299 = 0.876$. *Whatever the prior belief* that Nadal would win a point in a service game (*P(T)*), it would have been lowered after the data had been observed (which is that his first serve was 'bad').

The lower panel of Table 4 sets out the calculations discussed above in tabular format.

Now it is important to note that the Bayesian updating factor for Nadal was *higher* than Barty's: 0.876 versus 0.844. As mentioned earlier, the Bayesian updating factor is computed as the ratio of the likelihood of the data being observed when the theory is true ($P(\tilde{A} | T)$) (the probability that a winning point is preceded by a 'bad' first serve) to the likelihood of the data being observed (*P(A):* the first serve was 'bad'). Although for Nadal the likelihood of a winning point being preceded by a 'bad' first serve was lower than for Barty (26.2% versus 34.1%), the likelihood that Nadal put in a bad first serve was also lower (29.9% versus 40.4 %): a greater disproportionality between these two values for Nadal meant that his Bayesian updating factor was higher than Barty's.

<Table 4>

4. Conclusions

Matthews (2005) lists Bayes' Theorem as one of the 25 big ideas of science. It is a way of turning evidence into insight and "is now being recognised as the most reliable way of making sense of evidence. From scientists, to jury members, to code-breakers, to consumers, everyone can benefit from its powers" (p. 86). This paper represents an attempt to enable tennis analysts to benefit from its powers. It is does so by transforming the answer to question what is the likelihood that if a point is won, it will have been preceded by a first service (the probability that if the theory is true, the data will be observed) to a more interesting and relevant question: if the first serve is good, what is the probability that the point will be won (the probability that if the data is observed, the theory will be true).

Empirical flesh was put on Bayes' theorem by studying the performance of the winners of the men's and singles titles at the 2019 French Open: Rafael Nadal and Ashleigh Barty. Whatever the prior likelihood that they would win a point on their service game, this had to be revised upward for both players if the data showed that their first serve was 'good' and had to revised downward if the point required that they serve again. On the assumption that the prior probability was 60%, this then allows the analyst to deduce that the probabilities of winning a point on the first service were 65.9% for Barty and 73.8% for Nadal. Similarly, it could be deduced that the probabilities of winning a point on the second service were 34.1% for Barty and 26.2% for Nadal. The contribution of the paper lies in showing how in tennis evidence can be turned into insight for service games.

Table 1: The Reliability of the Service in Winning a Point

True Positive (Sensitivity): $P(A\,|\,T)=\alpha$	True Negative (1-Sensitivity) $P(\tilde{A}\,|\,T)=1-\alpha$
False Positive (1-Specificity): $P(A\,|\,\tilde{T})=1-\beta$	False Negative (Specificity): $P(\tilde{A}\,|\,\tilde{T})=\beta$

T is the event that the first serve was good while $\tilde{T}$ is the event that the first serve was a fault (but the second serve was good).

A is the event that the point was won, while $\tilde{A}$ is the event that the point was lost.

Table 2: Performance Statistics of Ashleigh Barty vis-à-vis Successive Opponents: Women's Singles French Open 2019

Name	Round	Aces	Double Faults	Serves	First Serves	Win on First Serve	Second Serves	Win on Second Serve	Receiving Points	Win on Receiving	Total Points Won	Total Points Lost	Duration (Minutes)
Barty Vondrousova	Final	3	1	54	37	23	17	13	64	33	69	49	70
Barty Anisimova	SF	5	3	93	49	34	44	20	97	49	103	87	113
Barty Keys	QF	4	1	60	36	29	24	15	60	24	68	52	69
Barty Kenin	4R	11	3	73	47	36	26	13	82	37	86	69	90
Barty Petkovic	3R	8	3	50	29	23	21	12	49	23	58	41	60
Barty Collins	2R	4	2	65	34	25	31	17	54	26	68	51	78
Barty Pegula	1R	3	2	55	36	21	19	9	47	28	58	44	60
Barty	All	38	15	450	268	191	182	99	453	220	510	393	540

Source: Stats+ from rolandgarros.com

Table 3: Performance Statistics of Rafael Nadal vis-à-vis Successive Opponents: Men's Singles French Open 2019

Name	Round	Aces	Double Faults	Serves	First Serves	Win on First Serve	Second Serves	Win on Second Serve	Receiving Points	Win on Receiving	Total Points Won	Total Points Lost	Duration (Minutes)
Nadal Thiem	Final	3	0	106	78	57	28	18	92	41	116	82	111
Nadal Federer	SF	3	1	88	72	49	16	9	93	44	102	79	104
Nadal Nishikori	QF	3	3	69	50	38	19	10	74	40	88	55	111
Nadal Londero	4R	6	1	76	54	40	22	13	82	39	92	66	110
Nadal Goffin	3R	5	5	96	56	44	40	28	105	43	115	86	115
Nadal Maden	2R	3	3	72	46	34	26	16	74	40	90	56	112
Nadal Hanfmann	1R	5	2	68	47	39	21	13	84	42	94	58	112
Nadal	All	28	15	575	403	301	172	107	604	289	697	482	985

Source: Stats+ from rolandgarros.com

Table 4:
Bayesian Calculations for Barty and Nadal in the 2019 French Open Singles Championship

First Serve Analysis (%)		
	Barty	**Nadal**
Prior probability that a point will be won on a service game: *P(T)*	60	60
Probability of a good first serve: *P(A)*	59.6	70.1
Probability that a winning point would be preceded by a first serve: *P(A/T)*	65.9	73.8
Updating factor computed from equations (8) and (9)	1.11	1.04
Ex-post probability that a good first serve would be succeeded by a winning point: *P(T/A)*	66.6	62.4
Second Serve Analysis (%)		
Prior probability that a point will be won on a service game: *P(T)*	60	60
Probability of a second serve: $P(\tilde{A})$	40.4	29.9
Probability that a winning point would be preceded by a second serve: $P(\tilde{A}\|T)$	34.1	26.2
Updating factor computed from equations (10) and (11)	0.844	0.876
Ex-post probability that a good second serve would be succeeded by a winning point: $P(T\|\tilde{A})$	50.6	52.6

Source Own calculations using data from rolandgarros.com

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