A New Metric to Analyze Viewer Experience in Pro Tennis

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Recently, organizations such as the NCAA have been attempting to increase viewership of tennis by implementing rule changes to reduce the length of the individual matches. The logic behind these changes is to increase the relative importance of each point making the overall experience more exciting. I think this is a particularly interesting problem for the sport of tennis, which is currently fighting falling ratings (losing 1.4 million viewers this year for the men's U.S. Open finals) but is increasing the uncertainty of games the best way to gain viewership or increase the excitement of the sport? The process for determining which rule changes lead to more viewers can be a complicated question; however, I would say that by statistically examining the shot selection across a variety of tournaments and players, we can get an alternate and useful metric to determine how exciting or interesting a match is, which could provide some insight into the issue.

The metric I am introducing is intuitively a measure of how different the shot selection distribution is from the expected distribution. The metric that other models use is linked to the effect that each point has on the overall game. The latter is a legitimate metric that tries to describes the excitement associated with the increase in uncertainty as to who the winner will be, but it fails to capture the excitement that comes from the creativity and diverse performance of the players. Excitement derived from unorthodox plays and unexpected moves plays a role in how interesting one deems the game. Such events are often replayed as highlights afterwards and shared and circulated on social media (incidentally which can help to draw in new fans of the sport). We can define the following simple model:

f = forehand groundstroke (excluding slices, chips, etc.) b = backhand groundstroke (excluding slices, chips, etc.) r = forehand slice (including defensive chips, but not drop shots) s = backhand slice (including defensive chips, but not drop shots) v = forehand volley z = backhand volley o = standard overhead/smash	p = "backhand" overhead/smash u = forehand drop shot y = backhand drop shot l = forehand lob m = backhand lob h = forehand half-volley i = backhand half-volley j = forehand swinging volley k = backhand swinging volley t = all trick shots, including behind-the-back, between-the-legs, and "tweeners." q = any unknown shot

$$G \text{ is a random variable that takes on vectors in the form } \hat{g} \in (\mathbb{N} \cup \{0\})^{18} \text{ such that}$$

$$\hat{g} = [f, b, r, s, v, z, o, p, u, y, l, m, h, i, j, k, t, q]$$

$$Intuitively\ G\ can\ be\ thought\ of\ as\ a\ numerical\ representation\ of\ a\ match.$$

$$Lets\ define\ a\ useful\ transformation\ T: \mathbb{R}^{18} \rightarrow \mathbb{R}^{18}\ that\ is\ defined\ as$$

$$T(\hat{a}) = \frac{100(\hat{a})}{\sum_{i \in D} a_i}\ where\ D\ is\ \{1, 2, \ldots, 18\}\ and\ a_i\ is\ the\ element\ in\ the\ ith\ column$$

The transformation T simply changes the vector of numbers to the vector of percentages.

A new statistic φ will be defined as the following:

$$\varphi = \sqrt{\sum_{i=1}^{18} (T(\mathbb{E}(G))_i - T(\widehat{g^*})_i)^2}\ \ where\ \widehat{g^*}\ is\ an\ observed\ instance\ of\ G$$

Higher φ values will indicate a more interesting match (Note that we only require a rough estimate of the center of the data as our metric gives us only ordinal information. In fact, any measure of the center will do.).

Implementing the model:

$T(\mathbb{E}(G)) =$ [*45.69, 36.16, 2.08, 9.529, 1.384, 1.52, 0.842, 0.057, 0.456, 0.614, 0.403, 0.745, 0.15072, 0.152674, 0.171139, 0.026, 0.015, 0*]

$$\mathbb{E}(G)\ is\ estimated\ from\ our\ data\ set\ as\ \bar{G} = \frac{1}{n}\sum_j G_j\ which\ is\ the\ MLE\ for\ \mu\ of\ G,$$

$$and\ G_j\ are\ i.i.d\ R.V's \sim G$$

And choosing a game vector based on real data give the following sample values

$$\varphi_{1978-01-25\ Borg\ vs\ Gottfried} = 41.5$$

$$\varphi_{1990-09-09\ Agassi\ vs\ Sampras} = 11.21$$

$$\varphi_{2014\ Austrailian\ Open\ Wawrinka\ vs\ Nadal} = 9.34$$

Borg vs Gottfriend deviated from the standard shot selection distribution, having more backhand slices than any other shot. Agassi vs Sampras was closer to our expected vector, however the match still deviated due to both players choosing to hit topspin backhand groundstrokes rather than slices. The Wawrinka/Nadal match was close to what was expected, just with a higher percentage of forehand topspin groundstrokes.

So what is the significance of φ? Mathematically, φ calculates the distance between the two vector representations of distributions by finding the norm of the difference vector (difference between the transformed expected and transformed observed vector), but what insights can this give us into a specific game? First of all, this metric can be a useful tool to identify games that stand out due to the prevalence of a specific shot. High φ values can signal that the style or pace of gameplay was atypical (prevalence of volleys for example could indicate a faster pace of game). For closer analysis, one can examine the specific vectors involved in the calculations. The transformed observed game vector gives the distribution of the shot selection during the match. Each component-wise squared deviation can help to indicate where the major differences between the expected vector and the observed vector are. These can all help draw quantitative conclusions about the types of shots that the players took and the overall style of the game.

Now this metric gives some information, but φ doesn't directly account for shot placement or shot speed. Placement and speed do affect the style and pace of the game, however understanding the types of shots that were taken give a robust base statistic from which information about speed and placement can be inferred. Slice shots are on average slower than overheads for example, and lobs are deeper shots on average than volleys. The φ value can flag which games may have interesting speed or placement characteristics that can be investigated further using different methods.

Another concern that was raised was whether some high φ games were in fact more boring than low φ games. This would raise an argument against the ability of φ to find interesting games. Such an example, raised by a friend of mine, was that a game of all forehands might be more boring than a game with the expected distributions of shots. The point of φ is not to implement subjective definitions of how interesting a game is. Such an approach would require an identification of an ideal distribution that leads to the "most interesting game" which is infeasible to derive or choose in a truly logical manner. φ consistently determines objectively how different the gameplay is from the norm. The more unexpected the gameplay is, the more surprising it is. And this element of surprise is something that could attract viewers to the game and can be an objective value that can be interpreted to find how relatively interesting a game is. Many times this can be an indicator of how exciting each point is (simply because it isn't what we expect). It is worth noting that the only thing the value of $\varphi(G)$ ensures is that G is more irregular than some G* s.t. $\varphi(G^*) < \varphi(G)$. For me personally, a game with just forehands would be worth watching, but to those who are concerned with penalizing such games for their homogenity they can introduce a new metric:

$$\vartheta = 10000 - \sum_i (T(\widehat{g^*})_i)^2$$

ϑ is maximized when all the components of the observed game vector are equal, which would be the game with the most equal balance of the shots.

Our initial proposal however, has yet to be answered. Does this φ metric in any way reflect how exciting or interesting a game is? In some ways yes. Traditional metrics as to how exciting or interesting a game is only factor in how close the match is. The idea is that by removing some of the "win-by-two" rules in tennis, officials can increase the chances of upsets, making each game effectively closer. This could make the game more fast paced which could appeal to a new audience. On the other hand, games with a high φ value could have creative, 'unorthodox' points that would lend themselves well to replays and other short clips that could appear on social media and reach out to a larger fan base (much in the way that clips of cool plays in the NBA have broadened the NBA fan base as people watch Steph Curry make ridiculous shots). Games that have less predictable point patterns can be more interesting to watch, and can be more exciting. Both these metrics are important, and consideration to both of them is vital to improving the sport in the long run.

Just as officials have suggested getting rid of a win-by-two structure in deuce points, is there a similar way to incentivize patterns of play that increase the φ of a game? One potential way would be to implement time restrictions of some sort on points, such as forcing the service player to try and finish the point off before a certain time else the receiver gets the point (a sort of offense/defense structure). This would reduce the amounts of forehand and backhand rallies, and increase attempts at net points and approach shots. This decrease in groundstrokes would increase the φ value of a match.

This would be a very radical change, and is unlikely to occur, but I think that in order to truly make the sport more exciting and reach out to a larger fan base, the φ metric or a similar statistic should be evaluated alongside other measures of excitement.