
Random Walker Ranking for NCAA Division I-A Football

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1. INTRODUCTION. The Bowl Championship Series (BCS) agreement was created in 1998 to match the top two NCAA Division I-A college football teams in a National Championship game at the end of each season. As part of the agreement, the official BCS Standings are used to pick which two teams most deserve to play in the championship game and which teams should play in the other major bowl games. The BCS Standings have significant financial ramifications, as the National Championship Game and major bowl games yield financial payouts to the conferences of the appearing teams projected to be \$14–\$17 million per team in 2007 [1]. In addition to this direct financial benefit, BCS bowl appearances likely generate indirect gains from increases in both alumni contributions and student applications. Before the BCS, the matchups in many bowl games were determined according to conference traditions, so matches between the #1 and #2 teams in the nation rarely occurred. At times, this yielded multiple undefeated teams and co-National Champions (most recently, Nebraska and Michigan in 1997). On other occasions, a single team with an arguably easy schedule could go undefeated and be declared National Champion by polls without ever having played a “major” opponent (e.g., BYU in 1984).

The BCS system endeavors to address these problems while maintaining the tradition of finishing the season with bowl games. Prior to 2004, BCS Standings were determined by a combination of two polls (coaches and sportswriters), selected algorithmic rankings, strength of schedule, losses, and bonus points awarded for defeating highly-ranked teams. This system double-counted key contributions, because reasonable polls and rankings already took losses and strength of schedule into account (see, for example, [4]). In 2004, the BCS instituted a formula that simply averages polls and computer rankings, but the system continues to vary from year to year as specific polls and computer systems are added and removed.

The fundamental difficulty in accurately ranking or even agreeing on a ranking methodology for college football lies in two factors—the dearth of games played by each team and the large disparities in types and difficulties of individual schedules. For instance, should an undefeated team from a purportedly weaker conference with few tough nonconference opponents be ranked ahead of a “major conference” team that lost a game or two while playing difficult opposition both in its conference and in its nonconference matchups? While each game outcome is an imperfect paired comparison between two teams, the schedule of 10–13 regular season games (including conference championships) played by each of the 119 Division I-A football teams severely limits the quantity of information relative to, for example, college and professional basketball and baseball schedules. Moreover, most of the Division I-A football teams play the majority of their games within their conferences, and there are significant variations in the level of play across different conferences that further complicate attempts to select the top two teams from the available information. To make matters worse, it is not even clear what the phrase “top two” should mean: does it refer to the two teams with the best overall seasons or the two playing the best at the end of the season?

Despite the obvious difficulties, many systems for ranking college football teams have been promoted by mathematically and computationally inclined fans (see, for example, those listed by Massey [15]). Many of these schemes are relatively complicated mathematically, making it virtually impossible for the lay sports enthusiast to understand the ranking methodology and its underlying assumptions. Worse still, essential details of many of the algorithms currently used by the BCS are not even openly declared (the only one completely declared in the public domain is the system by Colley [6], though some others are at least partially explained). Of those that are at least partially public, some include seemingly arbitrary parameters whose effects are difficult to interpret, and others are tweaked periodically to obtain the purportedly most reasonable ranking based on previous results.

In this article, we demonstrate that a simply-explained algorithm constructed by crudely mimicking the behavior of voters can provide reasonable rankings. We define a collection of voting automatons (random walkers) each of which declares its preference for a single team. Each automaton repeatedly selects a game at random from its preferred team's schedule and decides whether to change its preference to the opponent as biased by the game outcome, preferring but not absolutely certain to go with the winner, repeating this process indefinitely. In the simplest implementation of this process, the probability p of choosing the winner is kept constant across voters and games played, with $p > 1/2$ because on average the winner should be recognized as the better team and $p < 1$ to allow a given voter to argue that the losing team is still the better team (moreover, the $p = 1$ limit can be mathematically more complicated in certain scenarios, as discussed in section 3). The voting automatons are nothing more than independent, biased random walkers on a graph connecting the teams (vertices) by their head-to-head games (edges). These "voters" thereby obey idealized behavioral rules dictated by one of the most natural arguments relating the relative ranking of two teams: "my team beat your team." Indeed, the statistics of such biased random walkers can be presented as nothing more than the logical extension of this argument repeated *ad infinitum*.

This algorithm is easy to explain in terms of the "microscopic" behavior of individual walkers who randomly change their opinion about which team is best (biased by the outcomes of individual games). Of course, this behavior is grossly simplistic compared with real-world poll voters. In fact, under the specified range of p , a single walker will never reach a definitive conclusion about which team is the best; rather, it will forever change its allegiance from one team to another, ultimately traversing the entire graph. However, the "macroscopic" total number of votes cast for each team by an aggregate of random-walking voters quickly reaches a statistically-steady ranking.

The advantage of the algorithm discussed here is that it can be easily understood in terms of single-voter behavior. Additionally, it has a single explicit, precisely-defined parameter with a meaningful interpretation at the single-voter level. We do not claim that this ranking is superior to other algorithms, nor do we review the vast number of ranking systems available, as numerous reviews are already available (see, for example, [11], [20], [7], [14] for reviews of different ranking methodologies and the list of algorithms and "Bibliography on College Football Ranking Systems" maintained by [22]). We do not even claim that this ranking algorithm is wholly novel; indeed, the resulting linear algebra problem is in the class of "direct methods" discussed by Keener [11] and has many similarities to the linear algebra problem solved by Colley [6]. Rather, we propose this random-walker ranking on the strength of its simple interpretation: our intent is to show that this simply-defined ranking yields reasonable results.

The remainder of this article is organized as follows: In section 2, we give the mathematical definition of the ranking algorithm and examine its statistical properties. In section 3, we investigate the algorithm's asymptotic behavior for extreme values of the probability p . In section 4, we present results for special cases involving round-robin tournaments. We then examine recent historical outcomes from real NCAA Division I-A seasons in section 5. In section 6, we discuss properties of the graphs defined by the games played in a given year according to real NCAA Division I-A schedules, paying special attention to hierarchical structure and the interplay between that structure and random-walker rankings. We conclude in section 7 by discussing some possible generalizations of this ranking algorithm.

2. RANKING WITH RANDOM WALKERS. For each team i we denote the number of games it played by n_i , its wins by w_i , and its losses by l_i . A tie, which was possible prior to the current NCAA overtime format, is treated as half a win and half a loss, so $n_i = w_i + l_i$ always holds. The number of random walkers declaring their preference for team i is denoted v_i , and the condition that the total number of voters remain constant is given by $\sum_i v_i = Q$.

If team i beats team j , then the average rate at which a walker voting for team j changes its allegiance to team i is proportional to p , and the rate at which a walker already voting for team i switches to team j is proportional to $1 - p$. For simplicity, we ignore the dates of games, selecting each of the n_i games played by team i with equal probability. To avoid rewarding teams for playing more games, the rate at which a given voter considers a given game is taken to be independent of n_i . Under this selection of rates, we find it more natural to express the independent random-walker dynamics using ordinary differential equations (ODEs) instead of Markov chains, though our entire discussion can certainly be recast in terms of Markov chains, in which case the approach has some similarities with the PageRank citation ranking [3] underlying the Google search engine (see [13]). Formulating the present problem in terms of ODEs has the added advantage of avoiding complications due to cycles of different lengths (such cycles could alternatively be removed through explicit time-averaging).

The expected rate of change of the number of votes cast for each team in this random walk is quantified by a homogeneous system of linear differential equations,

$$\mathbf{v}' = \mathbf{D}\mathbf{v}, \tag{1}$$

where \mathbf{v} is the T -element vector of the number v_i of votes cast for each of the T teams, and the elements of the square matrix \mathbf{D} are

$$\begin{aligned} D_{ii} &= -pl_i - (1 - p)w_i, \\ D_{ij} &= \frac{1}{2}N_{ij} + \frac{(2p - 1)}{2}A_{ij} \quad (i \neq j), \end{aligned} \tag{2}$$

in which N_{ij} is the number of games played between teams i and j and A_{ij} is the number of times team i beats team j minus the number of times i loses to j . That is, if N_{ij} belongs to $\{0, 1\}$, then

$$A_{ij} = \begin{cases} +1 & \text{if team } i \text{ beat team } j, \\ -1 & \text{if team } i \text{ lost to team } j, \\ 0 & \text{if team } i \text{ tied or did not play team } j. \end{cases} \tag{3}$$

When two teams play each other multiple times, we obtain A_{ij} as summed over those games. Because $1/2 < p < 1$, the off-diagonal elements D_{ij} are nonnegative and vanish if and only if $N_{ij} = 0$.

Ideally, one would consider the giant connected component in the college football schedule network, including Division I-A as a subgraph, but it was easier to analyze the data (obtained from [9] and [23]) when the information was selectively restricted to the graph of Division I-A teams. Because many Division I-A teams play some non-I-A opponents, we represent all of these connected non-I-A teams collectively as a single node. These teams usually do not fare well against Division I-A competition, so this new “team” achieves a low ranking and does not significantly affect the random walker populations, except to penalize the Division I-A teams they defeat and to maintain the constraint that the total number of votes Q remain constant (i.e., voters do not leave the graph).

Equilibrium. The matrix \mathbf{D} encompasses all the connections and win-loss outcomes between teams. The steady-state equilibrium of (1,2) satisfies

$$\mathbf{D}\bar{\mathbf{v}} = \mathbf{0} \tag{4}$$

and gives the expected populations $\bar{\mathbf{v}}$ of the random walkers voting for each team. This information can then be used directly to rank the teams. Despite the simplistic behavior of an individual random walker, the behavior of an aggregate of voters (or equivalently, because of the independence assumption, the long-time average of a single voter) appears to yield reasonably robust orderings of the top teams. Unsurprisingly, the number of votes cast for a given team varies substantially for different values of p ; nevertheless, the relative ranking of the top few teams can remain similar across a wide range of p , as we discuss for recent historical examples in section 5.

The equilibrium point $\bar{\mathbf{v}}$ lies in the null-space of \mathbf{D} ; that is, it is an eigenvector associated with a zero eigenvalue. We stress that this equilibrium does not require a no-net-flow detailed balance along each edge; rather, we only require zero net flow out of each node. For instance, a schedule of three teams (i , j , and k) in which each plays only two games such that i beats j , j beats k , and k beats i leads to a cyclic flow of votes around the triangle with a statistical equilibrium that arises when each team receives an equal number of votes.

An important property of these random walkers is that the matrix \mathbf{D} yields a single attracting equilibrium $\bar{\mathbf{v}}$ for a given p in $[1/2, 1)$, provided the underlying graph representing games played between teams consists of a single connected component. This can be proved by recasting (1)–(4) as an eigenvalue problem and applying the Perron-Frobenius theorem, as described by [11], provided the graph consists of a single connected component and $p < 1$. In the absence of these conditions, the Perron-Frobenius theorem cannot be applied because the resulting matrices are no longer irreducible. Alternatively, given the random-walker interpretation built into the rate matrices we define, one can easily demonstrate that the expected populations achieve a unique attracting state:

1. The column sums of \mathbf{D} vanish because the sum of the populations remains constant: $0 = Q' = \sum_i v'_i = \sum_i \sum_j D_{ij} v_j = \sum_j (\sum_i D_{ij}) v_j$ for all \mathbf{v} , requiring that the inner sum vanishes (i.e., the dynamics confine v_j to a hyperplane of codimension 1).
2. The off-diagonal elements of \mathbf{D} are nonnegative and—once the graph consists of a single connected component—it can be shown that all off-diagonal elements of the d th power of the short-time approximate mapping matrix $(\mathbf{I} + t\mathbf{D})^d$ are positive for sufficiently small nonzero t , where \mathbf{I} is the identity and d is the diameter of the graph. Because of this property, any vertices with $v_j = 0$ have growing populations. In other words, given nonnegative v_j with positive total

population Q , all average flows along the $v_j = 0$ faces enter the hyperquadrant in which $v_j > 0$ for all j .

3. Finally, because (1) is a linear, constant coefficient system, it can be shown that the only possibility consistent with the foregoing observations is that the null-space of \mathbf{D} is one-dimensional (there is a single eigendirection associated with eigenvalue zero), and that there is a unique attracting sink $\bar{\mathbf{v}}$ in the constant-population hyperplane at the point of its transverse intersection with the null eigenvector.

This argument breaks down if either the graph is not connected or $p = 1$, because subgraphs with zero walker population can remain so in such situations.

Statistics. Any initial voter distribution eventually randomizes completely, so the steady-state distribution of the number of votes \bar{v}_i cast for the i th team is binomial (for Q trials) with probability \bar{v}_i/Q , mean \bar{v}_i , and variance $\bar{v}_i(1 - \bar{v}_i/Q)$. The joint probability density function of two vertices is not perfectly independent, as the sum over all vertices equals the number of random walkers Q . However, it is still obtained from a binomial distribution of Q random trials across the vertices. (The two of interest have probabilities $r_i = \bar{v}_i/Q$ and $r_j = \bar{v}_j/Q$.) We can exploit this fact to measure the confidence in the relative ranking of two teams in terms of the minimum number of voters Q_{\min} required to ensure that the expected difference between the number of votes cast for each team is larger than the standard deviation of that difference:

$$Q_{\min} = \frac{r_i + r_j - (r_i - r_j)^2}{(r_i - r_j)^2} = \frac{r_i + r_j}{(r_i - r_j)^2} - 1. \quad (5)$$

Because the statistical properties of the random walkers follow directly from the linear algebra problem (1)–(4), there is no need to simulate independent random walkers to obtain rankings. This simplicity disappears if interactions between random walkers are included, as considered briefly in section 7.

3. ASYMPTOTICS AT LARGE AND SMALL p . For a given probability p the expected populations depend in a complex manner on the details of game schedules and outcomes. In an attempt to clarify the effects of selecting a given p , it is instructive to investigate analytically the limiting behaviors near $p = 1/2$ and $p = 1$. We demonstrate, in particular, that the main contributions near $p = 1/2$ include a measurement of schedule strength, whereas behavior near $p = 1$ is dominated by undefeated teams and by subgraphs of teams that go undefeated against teams outside the subgraph.

On any given Saturday. Consider $p = 1/2 + \varepsilon$, where $\varepsilon \ll 1$. The rate matrix (2) becomes

$$D_{ij} = \frac{1}{2}\Delta_{ij} + \varepsilon\tilde{D}_{ij},$$

where Δ is the graph Laplacian: $\Delta_{ij} = 1$ ($i \neq j$) if nodes i and j are connected (the two teams played each other) and $\Delta_{ii} = -n_i$. By (2), $\tilde{\mathbf{D}}$ has the same elements as \mathbf{A} off the diagonal and the values $w_i - l_i$ on the diagonal. A power series of the equilibrium probabilities, $\bar{v}_j = \bar{v}_j^{(0)} + \varepsilon\bar{v}_j^{(1)} + \varepsilon^2\bar{v}_j^{(2)} + \dots$, then satisfies

$$0 = \frac{1}{2}\Delta\bar{\mathbf{v}}^{(0)} + \sum_{k=1}^{\infty} \varepsilon^k \left[\frac{1}{2}\Delta\bar{\mathbf{v}}^{(k)} + \tilde{\mathbf{D}}\bar{\mathbf{v}}^{(k-1)} \right], \quad (6)$$

subject to the normalization condition $\sum_j \bar{v}_j^{(k)} = Q\delta_{k0}$ for Q voters ($\delta_{k0} = 1$ when $k = 0$, otherwise $\delta_{k0} = 0$).

The $O(\varepsilon^0)$ contribution requires $\bar{v}_j^{(0)} = Q/T$ for each j , distributing the Q votes equally across the T nodes of the graph. With $\tilde{D}_{ij}\bar{v}_j^{(0)} = 2(w_i - l_i)Q/T$, the $O(\varepsilon^1)$ condition becomes

$$\sum_j \Delta_{ij}\bar{v}_j^{(1)} = -\frac{4Q}{T}(w_i - l_i). \tag{7}$$

That is, the first correction $\bar{v}_j^{(1)}$ at p near $1/2$ is a potential that satisfies a discrete Poisson equation (subject to the constraint $\sum_j \bar{v}_j^{(1)} = 0$) with charges proportional to the win-loss record of each team. It thus incorporates the record of the j th team and is also heavily influenced by the records of the nearest neighbors and other close teams in the graph. In other words, the first correction is strongly influenced by a “strength of schedule” notion. Furthermore, it is only with the second-order term $\bar{v}_j^{(2)}$ that information pertaining to specific games won or lost by a given team begins to be incorporated, as $\bar{v}_j^{(1)}$ includes only net records in (7).

Winner takes all. The asymptotic behavior for $p = 1 - \varepsilon$ ($\varepsilon \ll 1$) is more complicated because the limiting state depends on the number of undefeated teams and other schedule details. The single-equilibrium argument of section 2 breaks down at $p = 1$ because off-diagonal elements of $(\mathbf{I} + t\mathbf{D})^d$ are not necessarily positive. There can then be multiple equilibrium states, but only one of these states is achieved in the limit as $p \rightarrow 1$.

The simplest situation to consider asymptotically occurs when a single undefeated team garners all random walker votes for $p = 1 - \varepsilon$ as $\varepsilon \rightarrow 0$. This condition requires both that there be only a single undefeated and untied team and that there be no subgraphs of other teams in the network that collectively win all of their games against teams outside that subgraph. The transition rates are then written $D_{ij} = D_{ij}^{(0)} - \varepsilon\tilde{D}_{ij}$, and we again expand

$$\bar{v}_j = \bar{v}_j^{(0)} + \varepsilon\bar{v}_j^{(1)} + \varepsilon^2\bar{v}_j^{(2)} + \dots$$

Here, $\mathbf{D}^{(0)}$ agrees with $(\mathbf{N} + \mathbf{A})/2$ off the diagonal but has the negation of the number of losses by the corresponding teams on the diagonal (recall that a tie counts as half a win and half a loss), and $\tilde{\mathbf{D}}$ remains as defined earlier in the perturbation around $p = 1/2$. The limiting state $\bar{v}_j^{(0)} = Q\delta_{ju}$ casts all Q votes for the single undefeated team (“ u ”). Calculation of the first-order correction then requires solution of $\mathbf{D}^{(0)}\bar{\mathbf{v}}^{(1)} = \mathbf{b}$, where $b_j = Q\tilde{D}_{ju}$, which offers neither simplification nor intuition beyond the original rate equations (1)–(4).

4. ROUND-ROBIN EXAMPLES. The asymptotic analyses of the previous section were necessarily limited by the generality of possible schedule topologies. As a means of developing further intuition, we consider the special cases of round-robin tournaments in which every team plays every other team exactly once.

On any given Saturday (revisited). Returning to the case $p = 1/2 + \varepsilon$, consider a round-robin tournament of T teams, each of which plays exactly $T - 1$ games, one against each of the available opponents. Then the graph Laplacian is the matrix with

1s off the diagonal and $-(T - 1)$ for each diagonal entry. Subject to the constraint $\sum_j \bar{v}_j^{(k)} = 0$ ($k > 0$), we immediately obtain $\sum_j \Delta_{ij} \bar{v}_j^{(k)} = -T \bar{v}_i^{(k)}$, so (6) yields

$$\bar{v}_i^{(k+1)} = \frac{2}{T} \tilde{D} \bar{v}_i^{(k)}.$$

The zero-sum constraint is maintained because the column sums of \tilde{D} are identically zero by definition. This simple iterative relation for $\bar{v}_i^{(k+1)}$ can then be summed when $\epsilon < 1/2$ (i.e., $p < 1$) to arrive at

$$\bar{v} = \left[I - \frac{2\epsilon}{T} \tilde{D} \right]^{-1} \bar{v}^{(0)}.$$

We make special note of the first-order correction. In section 3, we saw that strength of schedule and the direct win-loss record both appear at $O(\epsilon)$. Hence, one expects the win-loss record of an individual team to determine its $O(\epsilon)$ contribution fully in the round-robin case, where everyone playing everyone else removes schedule inequities. Indeed, equation (7) gives

$$\bar{v}_i^{(1)} = \frac{4Q}{T^2} (w_i - l_i) \tag{8}$$

when applied to round-robin tournaments. Stated differently, the asymptotic rankings near $p = 1/2$ in a round-robin tournament are linear, \bar{v}_i , and the slopes are set by the win-loss records.

Perfectly ordered teams. Because the asymptotic expansion for $p = 1 - \epsilon$ is complicated by the difficult determination of the base state ($\epsilon = 0$), we consider this expansion only for the round-robin case of T “perfectly ordered” teams, which we define as the special case where team i beats team j whenever $i < j$. In this situation, the $\mathbf{D}^{(0)}$ matrix of section 3 is upper triangular, with 1s above the diagonal and $D_{ii} = -l_i = -(i - 1)$. Because there are no cycles here, it is clear that the single undefeated team garners all votes in the limit as $\epsilon \rightarrow 0$, so $\bar{v}_i^{(0)} = Q \delta_{i1}$. We can then show that

$$\bar{v}_i^{(1)} = \begin{cases} -(T - 1) & \text{if } i = 1, \\ T/[l_i(l_i + 1)] & \text{if } i > 1. \end{cases}$$

Mixed ordering. Finally, it is worth asking whether round-robin tournaments can give any indication about useful values of the bias parameter p . Specifically, it is reasonable to expect that teams in a round-robin schedule should be ranked in a manner consistent with their win-loss records, as their schedules contain no inequities. A 6-5 team in a 12-team round robin should presumably be ranked higher than a 5-6 team, even if only marginally so. As we already saw from (8), the $O(\epsilon)$ term in an expansion with $p = 1/2 + \epsilon$ for a round-robin competition does indeed agree with the rank ordering given by win-loss records.

Do the terms that are higher order in ϵ continue to respect the win-loss ordering in a round-robin setting? Equivalently, what happens for values of p further from $1/2$? One might reasonably ask whether this win-loss ordering is generically preserved for all p in the range $1/2 < p < 1$ (it is not). It is then natural to ask whether the win-loss ordering is always preserved up to “crossing” values bounded away from $1/2$. That

is, for a given round-robin outcome, we define p_c to be the minimum p ($\geq 1/2$) such that the random-walker ordering crosses from consistent to inconsistent with win-loss records. We then ask whether p_c is bounded from below.

However, it seems clear from examples of specific outcomes that there is no lower bound for p_c except for $p = 1/2$ (where, by definition, all teams are ranked equally). We obtain p_c arbitrarily close to $1/2$ through a simple modification to the perfectly-ordered tournament. Starting from a win-loss matrix of T teams where team i beats j if $i < j$, we modify only the games played by the team with the best losing record. To be precise, for even T we change only games played by team $k = (T/2) + 1$, with $(T/2) - 1$ wins and $T/2$ losses. We now swap the win-loss outcome of every game played by team k except for the game between k and $k - 1$, which we maintain as a win for team $k - 1$. These outcome switches modify the win-loss record of every team except for teams k and $k - 1$; in particular, the latter still has a better record than the former. Nevertheless, we observe numerically that $(p_c - 1/2) \sim T^{-1}$ for these explicitly-constructed mixed-ordered round-robin events, with team k ranked above team $k - 1$ above p_c .

The realization that there is no lower bound for p_c away from $1/2$ indicates an obvious limitation to this simply-constructed ranking system. Specifically, because the random walkers inherently represent first-place votes, rank-ordered crossings involving teams ranked $\#T/2$ and $\#(T/2) + 1$ are not very surprising. The number of votes cast for each team in the statistical equilibrium is of course important, in that the few votes cast for the lowest-ranked teams by design impact the number of votes cast for each team they play, ensuring that strength of schedule is inherently incorporated. However, the emphasis on highly-ranked teams means that a team can improve its ranking by beating a highly-ranked team more than it might be penalized for losing to a lower-ranked team. These round-robin examples then clearly call into question the accuracy of the precise rankings of those middle teams and thus lead to questions about the scheme as a whole. A system based only on first-place votes should presumably be strongest in its ranking of the top teams, though we have no mathematical proof that these walkers do so in any “optimal” sense. This motivates us to consider how the random-walker rankings fare in comparison with the historical record.

5. RECENT HISTORY. The utility of a ranking algorithm lies in its performance in the face of real data. Accordingly, we investigated college football rankings for each season from 1970 to 2005, restricting our discussion here to 2001 and 2002, as these seasons represent recent extreme situations in attempting to pick the top two teams (see, for example, [1]). The 2003, 2004, and 2005 seasons are discussed on our web page [16], where rankings for future seasons will also be maintained.

The only certainty in the 2001 pre-bowl rankings was that Miami belonged in the National Championship Game, because it was the only undefeated team in Division I-A. Indeed, both polls and all eight algorithms used by the BCS that year picked Miami #1 going into the bowl games. That season’s controversy concerned Nebraska’s selection as the #2 BCS team, narrowly surpassing BCS #3 Colorado despite Colorado’s late-season rout of Nebraska. The fact that BCS #4 Oregon had been ranked #2 in both polls was also mentioned on occasion. After the bowl games, in which Miami defeated Nebraska and Oregon defeated Colorado, it was Oregon’s absence from the championship game that became the centerpiece of national controversy. The random walkers select Oregon #2 for $p > .5$ up to $p \approx .62$, above which Nebraska takes #2 in a narrow range up to $p \approx .68$. Above that value, the random walkers defy conventional wisdom by selecting BCS #6 Tennessee as #2. In fact, they choose Tennessee as #2 over the widest range of probabilities (see Figure 1a). This ranking is explained

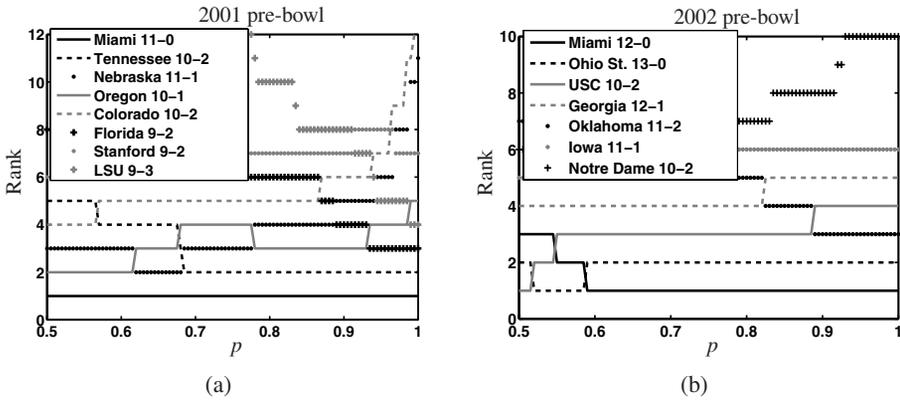


Figure 1. Pre-bowl rank orderings of teams by the expected populations of random walkers at different values of the probability p of voting for the winner of a given game for (a) 2001 and (b) 2002.

in part by the fact that the simplest random-walking voter algorithm presented here does not distinguish games based on the date played. Tennessee had been the most likely team to be picked to face Miami until they lost the Southeastern Conference (SEC) championship game on the final day before the BCS selections. Even with the loss (because the date of that loss does not affect things here), the random walkers congregate near Tennessee, in part because the SEC as a whole is highly ranked that season. Indeed, in the limit as $p \rightarrow 1$, Florida is ranked #3 and LSU is ranked #4, with Oregon falling to #5 and both Nebraska and Colorado falling completely out of the top ten. This SEC near-dominance is generated by a number of nearly-undefeated sub-graphs: Tennessee (10-2) lost to Georgia and lost to LSU the second time they played (in the SEC championship), Florida (9-2) lost to Auburn and Tennessee, and LSU (9-3) lost to Mississippi, Florida, and to Tennessee in their first meeting. Not counting games against each other, this trio of closely-linked teams had a collective 24-3 record prior to the bowl games, with all three losses against SEC conference opponents, two of whom were played multiple times by this group (Florida beat Georgia and LSU beat Auburn). Those three losses came against teams who also had all but one of their losses in the SEC (Auburn lost to Syracuse). Florida falls to #8 at smaller values of p (closer to $1/2$), and LSU is not even in the top ten for p below $\approx .77$. Nevertheless, they continue to help Tennessee’s ranking.

In contrast, the BCS system worked virtually without controversy in selecting teams for the National Championship Game at the end of the 2002 season, as there were precisely two undefeated teams, both from major conferences. Both polls picked Miami and Ohio State as the top two teams, in agreement with six of the seven ranking algorithms used that year. The only nonconformist was the *New York Times* ranking system, which picked Miami and USC as the top two teams—the latter presumably in part due to its difficult schedule. For $p \approx 1/2$, the random walkers also rank USC in the top two based on the strength of its schedule (see Figure 1b), but they agree across most values of p that the top two teams are Miami and Ohio State.

One can explore the differences between the 2001 and 2002 pre-bowl results further by exploiting the statistical properties of expected vote totals to express a measure of confidence in the resulting rankings. The Q_{\min} required to distinguish successfully between the top rank-ordered pairs of teams, defined by (5) in section 2, is plotted for the 2001 and 2002 pre-bowl rankings in Figure 2. In particular, we note that the relative numbers of voters required to distinguish #1 from #2 in 2001 and #2 from #3 in

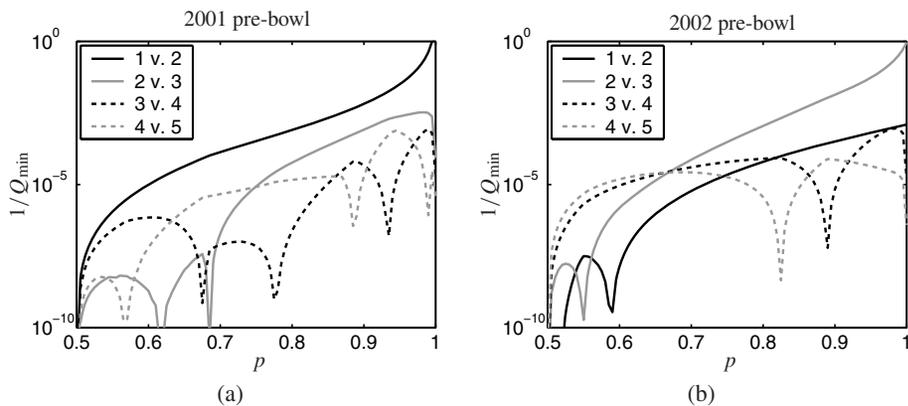


Figure 2. Degree of confidence in the ordering of pairs of teams in the (a) 2001 and (b) 2002 pre-bowl rankings, as quantified by $1/Q_{\min}$, where Q_{\min} denotes the minimum number of independent random walkers necessary to ensure that the standard deviation of the difference between the expected populations of two teams is smaller than the expected difference (see equation (5)).

2002 are significantly smaller (indicating a higher degree of confidence in the chosen ordering) than, in particular, the distinctions between #2 and #3 in 2001 or #1 and #2 in 2002. One should, of course, be careful in applying this measure of confidence too broadly, because the percentage of total votes that remain available to distinguish #4 from #5 will in general be smaller than those available to distinguish #1 from #2. Accordingly, direct comparisons of the same rank distinction across different years are more reasonable. For example, observe the typically lower degree of confidence in distinguishing #3 from #4 and #4 from #5 in 2001 (when Nebraska, Colorado, Oregon, and Tennessee were all trying to lay claim to the #2 spot) compared with the situation in 2002.

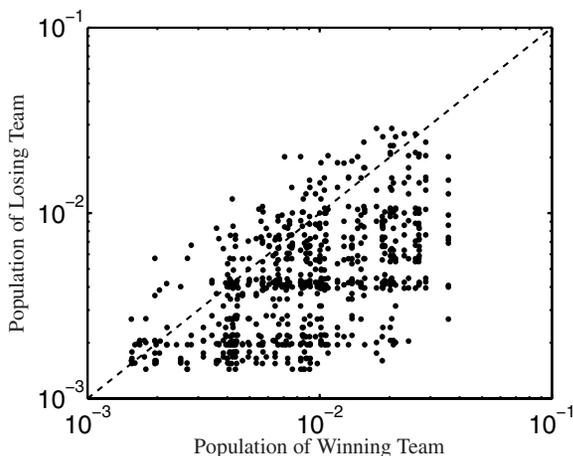


Figure 3. Winning and losing teams plotted according to the 2001 pre-bowl rankings of each team at $p = 0.8$, given by the expected fraction of random walkers populating (“voting for”) each team.

After seeing these results, we should discuss at least briefly which values of p might yield good rankings. Perhaps neither the dominance of strength of schedule near $p = 1/2$ (as illustrated, for example, by USC in 2001) nor the emphasis on undefeated

seasons near $p = 1$ (e.g., BYU in 1984) are appropriate. Rather, we might naively argue that a balanced value of p is preferred.

Alternatively, we could consider various objectives for optimizing p . For instance, Figure 3 shows the organization of the win-loss outcome of every game in the 2001 pre-bowl schedule according to the random walker populations determined with $p = 0.8$. The votes are not (of course) strictly ordered according to the winner and loser of each individual game, but the winners have more votes on average. Instances where a higher-ranked team has lost to a lower-ranked team are frequently referred to as “ranking violations” and can be used to construct one measure of the quality of different ranking systems (see the comparisons page maintained by Massey [15]). Additionally, the goal of minimizing the number of such violations and determining rank orderings from the multitude of such nonunique minimizations can itself be used to define ranking algorithms [5], [18]. An obvious optimization procedure here is to select p to minimize the number of ranking violations. While we observe that this optimal p varies from year to year, it frequently takes a value near the center of the allowed interval. Other measures of the quality of the ranking may be naturally inspired by Figure 3; for example, we might minimize the violations in another norm, such as one giving their distance from nonviolation. Another approach based on logistic regression of a generalized version of the present ranking system has been implemented by Kvam and Sokol [12] for college basketball, where the best p transition probabilities include information about point spread and home-court advantage. Finally, we might wonder whether some optimization would connect this class of “direct methods” [11] to the more statistically-sophisticated maximum likelihood methods originally used for paired comparisons in the pioneering works of Zermelo [24] or Bradley and Terry [2]. Rather than continuing these lines of inquiry here, we instead focus our remaining attention on trying to understand the connections between our biased random walkers and the properties of the underlying networks.

6. NETWORK STRUCTURE. The voting automatons randomly walk on a graph consisting of the Division I-A football teams (vertices) connected by the games played between the teams (edges). We note that this is not the only ranking system motivated by direct interest in the underlying network; indeed, while the random walkers here provide rankings through their dynamics on the network, Park and Newman [19] have developed a ranking system determined completely by the directed graph defined by wins. Because the random walkers propagate in a strongly heterogeneous network topology, it is important to try to understand how that topology affects the walkers’ behavior and the resulting rankings.

Each NCAA Division I-A football season consists of 650–750 games between about 115 teams (119 in 2005). In every season since 1990, this graph becomes a single connected component by the third or fourth week of the season (without counting faux connections via the single “non-I-A” node that we include for simplicity). The relative quickness in achieving a single connected component (after only about two hundred games) results in part because schools typically play many of their nonconference games at the beginning of a season. The degree of each vertex—that is, the number of games played by each team—varies in a narrow range. Each vertex has between ten and thirteen edges prior to the bowl games and between ten and fourteen connections after the bowl games. The diameter of the graph, determined by counting the number of edges along the longest geodesic path, is 4 in every post-bowl graph since 1970. We also considered the local clustering coefficient C_i for the i th team in the network (see [21], [17]), given by

$$C_i = \frac{\text{number of triangles connected to vertex } i}{\text{number of triples centered on vertex } i}. \quad (9)$$

Unsurprisingly, clustering coefficients provide one means of identifying the strong heterogeneity of the network. Each conference typically has a different average local clustering coefficient, which also varies from the coefficients computed for independent teams such as Notre Dame and Navy.

Several other network properties can also be calculated (including average path lengths and various notions of centrality and connectedness; see, for example, [17]), but such computations do not necessarily help explain the random-walker statistics. An important exception is the graph's "community structure" [8], which indicates the hierarchies present in the network and is useful for understanding the nature of the conference scheduling and the resulting effect on the random-walker statistics. We computed community structure using the notion of "edge betweenness," defined as the number of geodesics that traverse each edge, using the algorithm given by [8]. Briefly, the edge with the highest betweenness is removed from the graph, and the betweenness is recalculated for this modified graph to determine the next edge to remove; the process is then repeated until no edges remain. The removal of some of these edges breaks a connected component of the graph into two parts, grouping the network into a hierarchy of communities as the algorithm is iterated. Girvan and Newman [8] demonstrated that their algorithm closely reproduced the predefined conference structure of the 2000 football schedule, and we found similar results for other years.

Using the 2001 season as an example, Figure 4 portrays the college football community structure. The conferences and their subdivisions are reasonably reconstructed based on their relative strengths of community, and the tree ("dendrogram") in the figure indicates the relative closeness of different conferences and of the independent teams. Note, for example, the close connections between Notre Dame, Navy, and the Big East (from Virginia Tech counterclockwise to Miami (Florida)).

This community structure is intimately linked to the dynamics of the random-walking voters, as the specific pairings of interconference games and the outcomes of those games strongly influence the flow of voters into and out of the given conferences and more general structures such as the divisions inside large conferences and larger hierarchical groups of conferences. The 2001 pre-bowl community structure in Figure 4 is gray-scaled according to the average number of voters per team at each level of the hierarchy (for $p = 0.7$). Such a plot indicates the relatively high vote counts given to the SEC, Pacific-10 (Pac-10), and Big 12; it also shows the significantly smaller average vote counts for Big East teams, despite Miami's first-place standing.

We further quantify the importance of the relationships between conferences by directly measuring the effect of reversing the outcomes of individual games. Keeping the games in the order in which their respective edges were removed in developing the community structure, we measure the difference between the original voter populations and the new populations calculated with the win-loss outcome of that single game reversed. The dominant effect of such reversals is to change the rankings of the two teams involved in that game, so we calculate the change to the global distribution of votes with the quantity $\sum_{i \neq j,k} |\bar{v}_i|^2$, where the edge removed corresponds to a game between teams j and k . Plotting this quantity (see Figure 5) versus the order of the edge removed reveals a sharp transition in average magnitude between the first approximately two hundred edges and those that follow. This corresponds roughly to the number of edges removed in the community structure determination at which the hierarchy breaks up into the different conferences; these first roughly two hundred

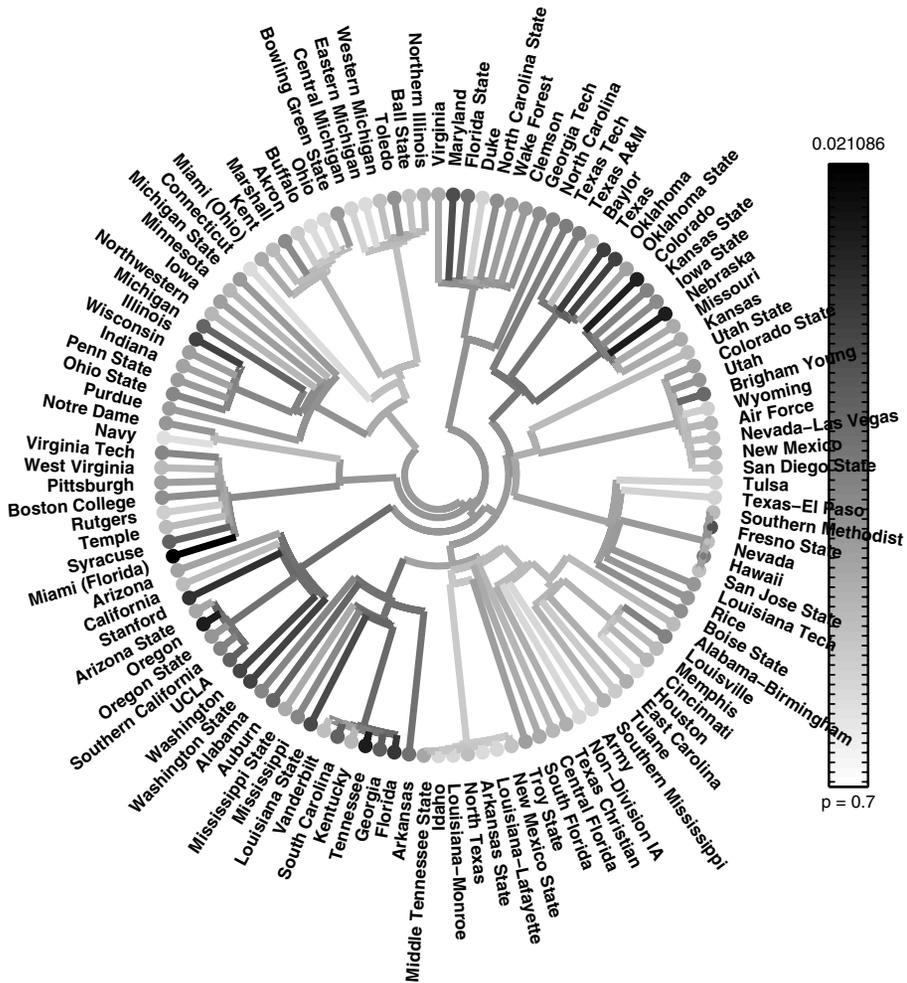


Figure 4. Graphical depiction of the community structure of the 2001 pre-bowl network, with gray-scale coding of the average votes per team for each community at $p = 0.7$.

edges removed are predominantly interconference games, whereas those that follow are intraconference games.

7. DISCUSSION. We have developed a simply-defined ranking algorithm in which random walkers adjust their “votes” for the best team on the network of teams connected by their head-to-head games, with a single explicit parameter describing the preference towards selecting the winner of a given game. We investigated the asymptotic behavior of this algorithm in the two extremes of the probability parameter, paying special attention to round-robin tournaments, and explored the results of the 2001 and 2002 NCAA Division I-A college football seasons in detail. More recent seasons are discussed on our website [16]. Finally, we have connected the rankings to the underlying network of games played by Division I-A teams, quantitatively demonstrating the importance of interconference game outcomes and the relation to the community structure of the graph.

Of course, many generalizations of the random-walker ranking algorithm described here are possible, ranging from trivial redefinitions of the rate matrix \mathbf{D} to fundamental

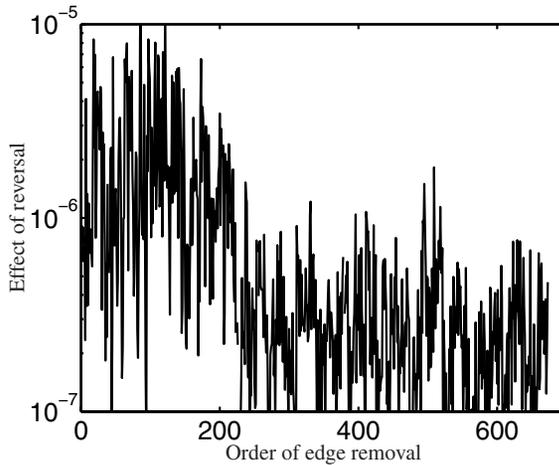


Figure 5. The effect of reversing the outcome of a single game played between teams j and k , quantified by $\sum_{i \neq j,k} |\bar{v}_i|^2$ (for $p = 0.7$) and plotted versus the order of that game according to edge removal in the community structure determination.

changes in the mathematical tools required to investigate the random-walking voters. The simplest generalizations are those that modify the rate matrix \mathbf{D} without changing the independence of the random walkers themselves. For instance, one can readily incorporate margin of victory, home-field advantage, and game date into the definition of \mathbf{D} by replacing the constant probability p of voting for the winner with a function that includes these components (see, for example, [12]). The resulting transition rates of walking each direction on a single edge are still defined by the outcome of the game represented by that edge, and the associated linear algebra problem determines the probability distribution of each state. It would be natural to make the probability of going towards the winner along a given edge higher for a larger margin of victory or for a game won on the road. However, incorporating any such qualitative assertions into quantitative variations in the transition rates requires adding more parameters to the ranking algorithm and determining reasonable values of those parameters, in stark contrast to the minimalist philosophy espoused here.

Alternatively, each random walker can be assigned two votes instead of one. This change is particularly sensible if the point is to select the two teams to play head-to-head in the National Championship Game. We considered such rankings generated from random walkers, each of which holds two equal votes (as opposed to a #1 vote and a separate #2 vote), using the same probability parameter p , subject to the additional constraint that a given voter must cast the votes for two different teams. This two-vote constrained random walk is most easily understood in terms of independent random walks on the (significantly larger!) network in which each vertex represents a possible pair of votes and the edges between vertices include games played between teams representing one of the two votes, with the other vote held fixed. This again immediately reduces to a linear algebra problem for the expected percentage of votes garnered by each team, although it has much higher rank: $T(T - 1)/2$ for T teams. Clearly, further increases in the number of votes given to each random walker would quickly make the state space so large that solving the exact linear algebra problem would no longer be computationally feasible.

As examples, we considered this two-vote generalization for pre-bowl rankings for both 2001 and 2002. Our results were unremarkably similar to our single-vote rank-

ings. In particular, in comparison with the single-vote 2001 case, Miami can (of course) obtain only half the votes in the limit as $p \rightarrow 1$ because of the constraint that each walker casts the two votes for two different teams, leaving fifty percent of the votes available to select a #2 team. That fifty percent becomes widely divided among the available candidates, with Tennessee and Oregon getting the largest shares at roughly five percent each. Meanwhile, this major change in the expected populations causes only relatively small changes in the rank orderings, except at extreme values of p , where Tennessee and the rest of the SEC do not fare quite as well here near $p = 1$ as they do in the single-vote scheme (though Tennessee still maintains the #2 spot at most values of p). At $p = 0.75$, the single-vote and two-vote systems agree on the same top sixty teams in the 2001 pre-bowl rankings, save for swaps in the orderings of #19-20 and #48-49; at $p = 0.9$, the top twenty-five are identical; at $p = 0.95$, however, there are switches in the orderings of #3-4, #5-6, and #9-10 (SEC teams Florida, LSU, and Georgia all do better in the single-vote algorithm), while the rest of the top twenty-five remains identical. Not unexpectedly, the 2002 two-vote rankings are very similar to the single-vote values, with Miami and Ohio State splitting the votes in the limit as $p \rightarrow 1$. Even at $p = 0.95$, the top eighteen teams are identical except for a reversal in the ordering of #6-7.

One can also consider generalizations that destroy the independence of individual random walkers. For example, voter decisions could be influenced by the number of other walkers voting for each team in a head-to-head game. Whether they are inclined to follow the crowd or to try to be nonconformist, such dependence between the random walkers makes the calculation of their aggregate behavior nonlinear and removes most of our knowledge about the probability distributions of votes per team. Another interesting generalization would be to weigh more strongly the effects of upsets by increasing the flow of votes towards a lower-ranked team that beats a team with more votes. Of course, this flow increase might reverse the ordering of the two teams, thereby removing the upset character and reducing the flow towards the winning team of that game, so there may not even be a statistically-steady ordering of the two teams. A similar complication occurs if one breaks the independence of the walkers by adding a bonus for beating a team ranked in (for example) the top ten that reduces the probability of voting for the loser. This reduced flow towards the losing team could then knock them out of the top ten, thereby causing the bonus to disappear, and allowing the team to rise back into the top ten, and so on. Obviously, the study of any of these interacting random walkers is significantly more difficult than the independent walkers considered in this article.

As a last consideration, we return to our discussion in section 4 of crossing probabilities p_c for round-robin competition and the observation that p_c can be very close to $1/2$ when a team with a worse record won its games against quality opponents, such as the specific mixed ordering we considered. The random walkers then reward a team more for its high-quality wins than they penalize it for its low-quality losses. This issue can be easily corrected by introducing a new ranking according to the difference of expected vote populations obtained with parameter p (“first-place votes” rewarding high-quality wins) and those obtained with $1 - p$ (“last-place votes” penalizing low-quality losses). For the specific mixed ordering considered in section 4 this “first-last” generalization gives $p_c \gtrsim .77$ for large T , while Monte Carlo searches preliminarily suggest that p_c may indeed be bounded away from $1/2$ for these first-last random walker rankings for round-robin tournaments. While this improvement is mathematically more satisfying than the situation for the original “first-only” rankings, the first-only and first-last rankings nevertheless generally agree on the top teams for real football seasons. For instance, in the recently-concluded 2005 season these two

pre-bowl rankings at $p = 0.75$ agree on the ordering of the top twelve teams except for a #10-11 swap, with the revised (“first-last”) system giving a slightly smaller number of ranking violations than the first-only system (complete rankings are available from [16]).

After eight seasons, the Bowl Championship Series remains as controversial as ever. Even when the system yields an uncontroversial National Championship Game because two teams clearly separate themselves from the field (as in 2002 and 2005), the BCS is still unable to escape controversy. The treatment of the so-called mid-major (or “non-BCS”) conferences remains an important issue (see, for example, [4]), leading to a December 2005 Congressional hearing in a House Energy and Commerce subcommittee [10]. We remain committed to the proposition that the use of algorithmic rankings for determining the college football postseason will only become widely accepted when those rankings have been reasonably explained to the public. In that context, the random walker rankings (and their first-last generalization) provide reasonable ways to rank teams algorithmically with methods that can be easily explained and broadly understood.

ACKNOWLEDGMENTS. We are grateful to both Kenneth Massey and Mark Newman for several discussions over the course of this project, to Michael Abraham for developing some of the codes used in our analysis, and to the anonymous referees for their helpful criticisms. This work was supported in part by an NSF VIGRE grant (DMS-0135290) to the Georgia Institute of Technology, where this work began.

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