A comparison of preseason collegiate football polls
with corresponding end-of-the-year rankings
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or each poll, the order of its top 25 (and 5, 10, 15 and 20) teams compared to the order of those same teams in the final poll. The highest percentile of any poll for any year. This poll had an inversio number of 43 (out of 300 max), and a percentile of 999999839
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Out-of-order rankings and inversion numbers
The number of "out-of-order rankings" is the sum of the total number of other ranks each rank is out of order with. For example, in the right most column below,
the 5 incorrectly comes before the $4,3,2$ and 1 , the 4 , the 4 incorrectly comes before the 3,2 and 1 , and so on, for $4+3+2+1=10$ total out-of-order rankings. It turns out that this is always simply the inversion number of the permutation. The inversion number of a permutation is the minimal number of interchanges of consecutive elements necessary to rearrange them in their natural order. The
inversion number of a particular permutation is unique, although the steps that inversion number of a particular permutation is unique, although the steps tha take you from that permutation to the natural ordering are not unique . [2] At right are progressively more
out-of-order permutations and out-ot-order permutations ar
their inversion numbers for permutations of the numbers 1 to 5 . In ordering teams, a lower inversion is better, as it means the predicted order is closer to the actual outcome

## Computing probability distributions:

There are $n!$ permutations of $n$ items (in this case, teams to order). The maximum inversion number for a permutation of $n$ items (teams)
is $n(n-1) / 2$. The minimal inversion number, of course, is 0 . For example, is $n(n-1) / 2$. The minimal inversion number, of course, is 0 . For example,
a permutation of 5 items has a maximum inversion number of 10 , as seen in the right most column of the table above. A permutation with this maxima
inversion number would correspond to a list of teams whose predicted order was exactly opposite of the actual order. This happened three times in our study. In these cases, the preseason poll gave
the worst possible prediction for the final outcome: the teams were in the exact opposite order. the worst possible prediction for the final outcome: the teams were in the exact opposite order. For each permutation of size $n$, an explicit formula for computing the number of occurrences $I_{n}(k)$ of
each inversion number $k, k=1$ to $n(n-1) / 2$, is at right. [3] each inversion number $k, k=1$ to $n(n-1) / 2$, is at right. [3]
We use this to compute the probability (relative frequency) distribution for $n=5,10,15,20$ and 25 , the corresponding cumulative probability distributions, and the corresponding percentiles for what
fraction of the $n!$ permutations each inversion number (i.e. the preseason poll it corresponds to) each inversion number is better than. A percentile of 0 corresponds to the maximal inversion number, and means the preseason ordering was better than none of the $n!$ possible orderings of the teams. This happened for the two preseason polls mentioned above, A percentile near 100\% means the preseason prediction was better than nearly all of the other possible team orderings.


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## Summary

We looked at how well preseason polls predict the relative end-of-the-year rankings in NCAA football. That is, rather than
address the issue of predicting the actual top 25 teams and their order, we looked at how each poll's preseason top 25 (and top $5,10,15$, and 20) teams ended the season ranked relative to each other.
We measured how well the ordering of a poll's teams predicts the final poll simply by looking at how many pairwise comparisons of teams are out of order (the more out of order, the worse the poll's prediction). It turns out this measure is simply the inversion umber of that poll relative to the final poll. Thus we simply found the inversion number for each poll's ordering of teams relative rankings for each year. We considered polls compiled at [1] for which we had data from all six years of 2001-2006.


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For each poll, compare its own top 5, 10, 15, 20 and 25 For each poll, compare its ordering of the top 5 and the op 10 teams present in all computer polls.
(sports writers) and號 o its own final poll.

Further questions to consider
 For each ranked team, how does variance amongst the various polls correlate with the agreement
between the average rank for that team and its final poll position? For each preseason poll, how does the average or cummulative error/difference between that poll an
the average of all polls correlate with how accurately that poll predicts the final poll? What weighting (e.g. by finding least squares solutions) of the polls best predicts the final pol What weighting (e.g. by finding least squares solutions) of the polls best predicts the final poll?
How much does when each preseason poll is released in the summer affect that poll's reliability?

## References

[1] College Football Preseason Magazines, compiled at http://preseason.stassen.com. ${ }^{[22]}$ T. Muir, A Treatise on the Theory of Determinants, New York: Dover, 1960 . [3] D. E. Knuth, The Art of Computer Programming, Addison-Wesley, Reading, MA, vol. 3, p. 15.


[^0]:    Observations and conclusions:

    In general, the polls do a good job (better than we expected) at predicting the final outcomes of relative rankings of teams. Most polls were above the $90^{\text {th }}$ percentile in most cases. Accurately ordering just a few teams proved more difficult than ordering several teams. This is clearly seen in the percentile plots for each year, as well as the Mean and Standard deviation plots:
    percentiles increase and standard deviations decrease as the number of teams $n$ being ordered increases. This increase in percentiles as the number of teams $n$ being ranked increases is explain percentiles increase and standard deviations decrease as the number of teams $n$ being ordered increases. This increase in percentiles as the number of teams $n$ being ranked increases is explained by
    the plots of Probability distribution, Cumulative probability distribution, and Percentiles: for increasing $n$, an increasing proportion of inversion numbers is concentrated in the center. In short, while it was a bit difficult to accurately predict the relative rankings of just a few teams, it is even more difficult to not do well in ordering a large number of teams. One extreme example of this is the 2004 Stree and The polls with the best results are those with larger and more diverse group of voters. In particular, the USA Today and AP polls generally seemed to perform better than any of the others. Moreover,
    while they did well relative to final computer rankings, they did even better when comparing their preseason polls with their own final polls. This suggests one (or both) of two things: where a team ends up ranked in a poll is to some degree dependent on where it started in that poll; or whatever bias those who vote in a particular poll have in their preseason voting is still evident in their final voting. Overall Athlon, Phil Steele, and Game Plan seemed to be the worst performers, as seen in both the mean and standard deviation over 2001-2006, as well as most of the individual years. Two polls (ATS Cons. and Sporting News) who were at or below the $50^{\prime \prime}$ percentile in ranking their own top 5 over all of 2001 - 2006; a purely random ordering of their top 5 would have been better. Some years don't go at all as predicted. As seen in both the Mean over all polls and the Standard deviation over all polls, as well as the individual years, 2002,2005 and 2006 were especially hard to
    predict. In particular, many of the 2006 preseason polls for top 5 and top 10 were below the 50 th percentile. On the other hand, 2004 went quite as predicted, as seen in the various plots.

