## 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 take you from that permutation to the natural ordering are not unique. [2]

At right are progressively more out-of-order permutations and 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.

Inversion number										
0	1	2	3	4	5	6	7	8	9	10
1	1	1	3	3	3	3	3	3	5	5
2	3	3	1	4	4	4	4	5	3	4
3	2	4	4	1	1	5	5	4	4	3
4	4	2	2	2	5	1	2	2	2	2
5	5	5	5	5	2	2	1	1	1	1

## 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, 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 maximal inversion number would correspond to a list of teams whose predicted order was exactly opposite



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 increases 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 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 Street and Smith's preseason top 25 (see far upper right), which has a seemingly unexceptional inversion number of 43 (maximum possible 300), with a remarkable corresponding percentile of 99.9999839.

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. 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<sup>th</sup> 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, 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<sup>th</sup> percentile. On the other hand, 2004 went quite as predicted, as seen in the various plots.

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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* number of that poll relative to the final poll. Thus we simply found the inversion number for each poll's ordering of teams relative to the final end-of-the-season rankings, for which we simply used the average of the computer polls used in computing the BCS rankings for each year. We considered polls compiled at [1] for which we had data from all six years of 2001 – 2006.





# **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<sup>th</sup> percentile in most cases.

# A comparison of preseason collegiate football polls with corresponding end-of-the-year rankings

[1] College Football Preseason Magazines, compiled at http://preseason.stassen.com. [2] 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.

For each poll, the order of its top 25 (and 5, 10, 15 and 20) teams is compared to the order of those same teams in the final poll. The results below, for Street and Smith's 2004 preseason poll, had the highest percentile of any poll for any year. This poll had an inversion number of 43 (out of 300 max), and a percentile of 99.99999839.

	S & S preseason		Fii	nal computer		
ginal order	1	USC	1	USC	1	
	2	Georgia	2	Oklahoma	3	
	3	Oklahoma	3	Georgia	2	
	4	LSU	4	LSU	4	
	5	Florida State	5	5 Iowa		
	6	Texas	6	Texas	6	
	7	Miami	7	Miami	7	
	8	Michigan	8	Michigan	8	
	9	Florida	9	Florida State	5	
	10	Tennessee	11	Ohio State	12	lei
	11	Iowa	12	Utah	21	orc
	12	Ohio State	13.5	Tennessee	10	
	13	Auburn	13.5	Auburn	13	te
	14	Virginia	15	California	17	nι
riç	15	West Virginia	16	Florida	9	L
0	16	Clemson	17	Maryland	18	Ре
	17	California	18	Purdue	22	
	18	Maryland	21	Clemson	16	
	19	Missouri	25	Virginia	14	
	20	Wisconsin	26	Wisconsin	20	
	21	Utah	29	Minnesota	24	
	22	Purdue	31	West Virginia	15	
	23	Memphis	38	Missouri	19	
	24	Minnesota	40	Memphis	23	
	25	Toledo	42	Toledo	25	

			Actual		Relative to max		
	n	max	90	99	90	99	
	5	10	1	0	0.100	0.000	
	10	45	14	8	0.311	0.178	
	15	105	38	28	0.362	0.267	
	20	190	74	59	0.389	0.311	
0.5*max max	25	300	121	100	0.403	0.333	

## Further questions to consider

We had planned to do most of these (we had actually started on some of them!) as part of this project, but ran out of time. 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 and 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 poll? How much does when each preseason poll is released in the summer affect that poll's reliability?

### References