

Distribution of grades from aerobatic judges, goodness of fit to normal

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Abstract

The sport of competition aerobatics is flown by pilots and graded by judges observing from the ground. Aerobatic competitions at the world level are scored using a statistical scoring system that treats judge grades as if they are normally distributed. This paper reports goodness of fit to normal for judge grades from a large number of aerobatic contests.

1 Aerobatic Competition

Aerobatics, as practiced by the World Air Sports Federation (FAI) Aerobatics Commission (CIVA) and by the International Aerobatic Club (IAC), is a judged sport. The pilot competitors perform in front of judges, who give grades to the pilots. In this way, it is similar to figure skating, gymnastics, and diving.

CIVA flies a handful of European and World contests each year. Results are posted online [2] in human readable format. The largest contests are the World Aerobatic Championship [5] and the World Advanced Aerobatic Championship, which attract about sixty pilots, mostly from Europe and the United States.

The airplanes flown at the world level cost as much as \$400,000 U.S. dollars. The pilots as individuals and as part of national teams invest years of training and practice whose value equals or exceeds that of the airplane. The total investment brought by pilots and national teams to the CIVA world contests can be estimated at about forty million U.S. dollars.

The IAC flies about forty regional contests and one

national contest per year in the United States. Results from IAC contests are posted online [4] in human and machine readable formats.

In aerobatics, pilots fly figures made up of a basic flight path overlaid with rolls, in which the airplane moves about its fuselage while its center continues on the flight path.

A “flight program” consists of each of the competing pilots flying a sequence of figures in front of the judges. The sequences of figures are predetermined for the flight program by any one of several methods. Judges receive the sequences that each pilot will fly in order to evaluate the sequence actually flown against the sequence committed to fly by the pilot.

1.1 Grading

The judges give each figure a grade from zero to ten in half point increments. They start from a perfect score of ten, and systematically deduct for flaws in the direction of the flight path, radius of loops, and degrees of roll. Thus, a flight program produces a three-dimensional matrix of grades consisting of Pilot X Judge X Figure. Each pilot receives one grade from each judge for each figure.

To complicate the grading slightly, a zero grade can take multiple forms. One form is that incremental flaws resulted in deductions that summed to ten or more. This is known as a “soft zero”. A second form is that the figure flown did not match the figure that was supposed to be flown. It might have been missing a roll element or not have been flown along the prescribed flight path. This is known as a “hard zero”. CIVA uses a form known as a “presentation

zero” that a judge may use to indicate suspicion of a hard zero. A “conference zero” indicates that the judge changed their grade to a hard zero in review following the performance of the pilot.

A judge may also give a grade of “average”. A grade of average indicates that the judge was either distracted or unsure of the figure that was prescribed to be flown and therefore unable to evaluate the figure performed against the figure prescribed. It is preferred that the judge give an average under these conditions, rather than make-up a grade. The effect of averages is a reduction in the number of judges evaluating the figure.

1.2 Scoring

CIVA contests use a statistical system of converting judge grades to scores documented in the FAI sporting code as FPS [3]. The system normalizes judge grades using their mean and standard deviation, then determines upper and lower bounds based upon the mean and standard deviation of the grades from all of the judges. It then replaces individual judge grades exceeding these bounds with fitted (mean, normalized) grade values before computing a final score for each pilot.

The FPS makes the normalization and outlying grade computations using grades from figure groups, which usually consist of grades for one figure flown by all of the pilots in one flight program, and with all of the grades from one flight program.

This paper examines whether the distribution of individual judge grades from aerobatic contests fit the normal distribution as used by the CIVA FPS.

2 Measurements

We apply a number of standard measures of goodness of fit. The measures used are Chi-Square, Anderson-Darling, Shapiro-Wilk, Lilifords, and Cramer-von Mises.

The data is rounded. A judge does not have a continuous range between zero and ten, but must round to the nearest half grade. This means that it must either be treated as discrete, using buckets as with

Chi-Square, or given random perturbations in order to make them continuous.

2.1 Clustering for Chi-Square

In order to apply the Chi-Square metric, we need to cluster grades which were given by the judge less than six times together with neighboring grades.

Example

The optimal method for doing this is the one that has least impact on the mean and variance of the data. The method described by Greenacre [6] and implemented by the greenclust [9] R package provides one; however, it reorders the clusters. We need to join only adjacent clusters, to maintain the order.

Another paper [7] from ten authors at NASA Ames and San Jose State University maintains order of partitions, but does not enable the constraint of minimum partition size. This and other algorithms for k-shape ordered partitioning require a cumulative function that measures the quality of each partition. Here, we find that the mean and variance do not always decrease or increase when joining two clusters.

The constraints at play here are:

1. A minimum number of six grades in any cluster
2. Only adjacent clusters may be combined
3. Combine the least number
4. Have the weighted mean and variance close to the original

Where n is the number of grade values in the range of grades, we explore the 2^{n-1} combinations of joins using the heuristic of choosing to first try joining clusters with the smallest number of grades, and a bound of minimum count of joins. The partition is complete when no cluster contains less than six grades. If two solutions have the same number of joins, we select the one with minimum of $(\mu' - \mu) + (\sigma' - \sigma)$, in which $\mu' - \mu$ is the difference in the weighted mean, and $\sigma' - \sigma$ is the difference in the weighted variance.

We report the mean, variance, and p value goodness of fit for both the clustered normal model and the normal model generated by FPS.

In order to reduce the number of combinations to explore, we apply a pre-processing step that combines strings of zero sized clusters into one together with the lower numbered cluster neighboring the string. Strings of zero sized clusters appear frequently in the data. This pre-processing step avoids having the algorithm try all combinations of zero sized clusters.

2.2 Number of grades

The grade clusters must satisfy two constraints in order to get a goodness of fit metric from the Chi-Square method.

First, there need to be at least six clusters. The number of degrees of freedom for the Chi-Square metric is then, at minimum six minus one, minus two for the two estimated values— mean and standard deviation. This means that, with six clusters we have three degrees of freedom. Three degrees of freedom is the minimum we believe will give a meaningful goodness of fit test.

Second, there need to be at least six instances within each cluster. This is the stricter criterion that leads to reduction in number of clusters.

Needing at minimum six clusters with six grades, in a uniform distribution we would need thirty-six grades. The distributions are not uniform, so we nearly double that number. We combine figure grades following the FPS ordering of figures in order to produce a minimum of sixty grades per group.

Finally, we produce a measure with all of the grades from a judge for a flight.

2.3 Shapiro-Wilk

The Shapiro-Wilk test for goodness of fit requires that all of the values are unique. In order to use the Shapiro-Wilk test, we cannot use the grades without perturbing them in order to make them unique. In one view, the grades given by the judges are severely rounded to increments of 0.5 from a continuum of performances by the pilots.

Two methods to perturb the grades are

- add values selected from a random uniform distribution between -2.5 and 2.5.

- add values selected from a random normal distribution.

Applying a uniform distribution is the Smirnov transformation described in [8]. The method uniformly and reliably perturbs the data within the range and has the advantage of prior use in practice. A disadvantage is that the mean of the perturbed values can end-up anywhere between -2.5 and 2.5 added to the actual grade.

Using the random normal distribution ensures that the mean of the perturbed values will remain close to the actual grade value. The disadvantage is that we must choose a standard deviation for the random normal distribution. The standard deviation must be such that the resulting perturbations are extremely rarely, with very low probability, outside of the range -2.5 to 2.5. A second, potential disadvantage is that this is a variation of the Smirnov transformation that, so far as we know, we are inventing for this study

We chose to use for standard deviation a value that approximates the distribution of Bates [1]. The Bates distribution has the advantage of being distributed along a fixed interval around a mean, with decreasing probability for values further from the mean. A mean of zero and variance of $1/12n * 5$, where n is the number of instances of the grade, when used with the normal distribution, approximates the distribution of Bates between -2.5 and 2.5.

We perturbed the grades using random values chosen from a normal distribution with mean equal to zero and standard deviation equal to $\sqrt{5/12n}$. Choosing a standard deviation dependent on the number of instances of the grade causes the perturbations to remain closer to zero when there are more instances of a grade and within the -2.5 to 2.5 range. We report the p-value for the Shapiro-Wilk normality test after perturbing the grades.

3 Judge grade distributions for all figures

We now look at distributions of all of the grades given by a judge for a given flight— all pilots and all figures.

| Known | Unknown | Unknown II | Flight 1 |
|-------|---------|------------|----------|
| 1488 | 1160 | 27 | 19 |

Table 1: Distribution of flight formatsn for all-figures measurements

We look only at flights for which there were more than five pilots and more than eleven grades given.

We also look only at flights in which all of the pilots flew the same figures. To do so, we select for the flight format, taking only Known, Unknown, second unknown, second and third known flights. The distribution of flight formats is as in Table 1:

In all, we look at 2,511 powered flights and 183 glider flights. The flights breakdown by category is as in table 2.

Pilot count is the number of pilots who participated in a flight. Grade count is the number of pilots times the number of figures, equals the number of grades given by a judge for all of the figures and pilots in a flight. Their distributions in this data set are as in Table 3.

The correlations between the four measures are strong, with the exception of Lilifords to Shapiro-Wilk. Find their values in Table 4.

Table 5 shows summary results from the various goodness of fit tests. The numbers for measures found to be valid and invalid cover all of the results. The other two columns contain counts of p-value results from valid measures greater than and less than or equal to the traditional cutoff of 0.05.

The null hypothesis for these tests is that the distributions fit a normal distribution. Using the traditional cutoff, the Chi-Squared test finds no support for fit to normal in roughly half of the cases. The other tests almost never find support for fit to normal.

We can go deeper by looking at the distributions of p-values and then looking at some specific examples within the various quantiles.

Table 6 shows the spread of p-values from the various tests. The numbers are from only those tests reported as valid. The minimum values from the data are always zero, and so omitted from the table.

Note that except for Chi-Squared, the mean value

is greater than the third quantile value, demonstrating that more than three-quarters of the values fall below the mean.

We can look at plots of the distributions to find more insights about the fits. One power study [10] finds that the Anderson-Darling test is among three most powerful. It has high correspondence with the other tests. In the following, we show two plots side-by-side for representative p-values from the Anderson-Darling measure. The left plot is a histogram of the judge grades with derived normal curve superimposed. The right plot is a standard Q-Q plot using the derived normal curve.

At the smallest p-value seen in Figure 1 we find a skew toward higher grades. The judge graded a majority of 9.0 with a mean grade of 8.5. The scarce 4.0 will always be seen as an outlier with respect to the normal curve. The upper tail of the normal curve exceeds the highest grade.

At the first quantile upper limit seen in Figure 2 we also find a skew toward the higher grades, but also a longer tail to the lower grades. The upper tail of the normal curve exceeds the highest grade.

At the second quantile upper limit seen in Figure 3 we have a bimodal distribution in which the judge gives a large number of 7.0 and 9.0 with fewer grades given with values 7.5, 8.0, 8.5 and then a lesser number given with values 5.0, 6.0, 6.5, 9.5, and 10.0. That the upper tail of the normal curve exceeds the highest grade is beginning to look like a pattern.

At the third quantile upper limit seen in Figure 4 the picture has improved somewhat. There are a few too many grades with value 6.0 and 8.0, too few with grades 7.5 and 10.0. To fit the curve, the judge should have given a dash of grades with value 10.5, which is not a valid grade.

At the maximum value seen in Figure 5 we have a judge who spreads their grades out more than in the other examples. The spread does show a strong, though excessive peak at the mean grade of 7.0. There are a few too many grades with value 4.0, 5.0, 8.0, and 9.5. There are too few with values 5.5, 7.5, and 8.5. This judge almost manages to get the entire normal curve within the range of grades; however, the upper tail still exceeds the maximum grade of 10.0.

| | | | | |
|---------|-----------|--------------|----------|-----------|
| primary | sportsman | intermediate | advanced | unlimited |
| 177 | 1160 | 854 | 444 | 59 |

Table 2: Distribution of categories for all-figures measurements

| | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|-------------|------|---------|--------|-------|---------|------|
| Pilot Count | 6 | 7 | 8 | 9.277 | 11 | 26 |
| Grade Count | 35 | 65 | 81 | 94.55 | 110 | 359 |

Table 3: Distribution of pilot and grade counts for all-figures measurements

| | sw | lf | ad | cvm |
|-----|-------|-------|-------|-------|
| sw | 1.000 | 0.432 | 0.792 | 0.616 |
| lf | 0.432 | 1.000 | 0.709 | 0.814 |
| ad | 0.793 | 0.709 | 1.000 | 0.937 |
| cvm | 0.616 | 0.814 | 0.937 | 1.000 |

Table 4: Correlation of all-figures measurements

| | Invalid | Valid | > 0.05 | <= 0.05 |
|-------------|---------|-------|--------|---------|
| chiSq.t.p | 1149 | 1545 | 934 | 611 |
| chiSq.d.p | 1149 | 1545 | 821 | 724 |
| sw.p.value | 0 | 2694 | 106 | 2588 |
| lf.p.value | 0 | 2694 | 36 | 2658 |
| ad.p.value | 0 | 2694 | 32 | 2662 |
| cvm.p.value | 0 | 2694 | 47 | 2647 |

Table 5: All figure GOF measure p-value summary

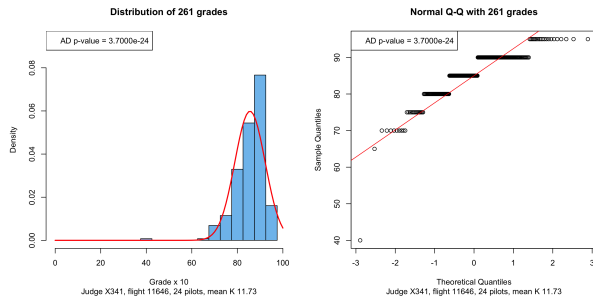


Figure 1: All figures example at minimum Anderson-Darling p-value

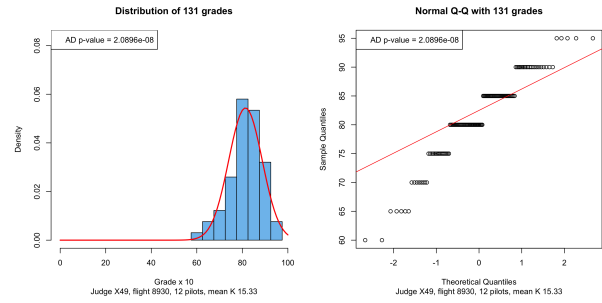


Figure 2: All figures example at first quantile Anderson-Darling p-value

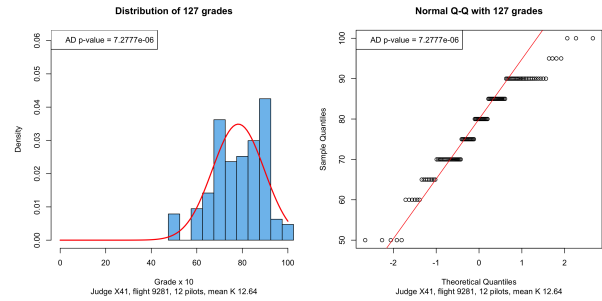


Figure 3: All figures example at second quantile Anderson-Darling p-value

| | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|-------------|-----------|-----------|-----------|-----------|-----------|
| chiSq.t.p | 0.006 | 0.126 | 0.272 | 0.491 | 0.999 |
| chiSq.d.p | 0.002 | 0.067 | 0.216 | 0.358 | 0.993 |
| sw.p.value | 0.012e-04 | 0.896e-04 | 0.785e-02 | 0.209e-02 | 0.452 |
| lf.p.value | 0.0 | 9.200e-07 | 2.462e-03 | 1.121e-04 | 2.208e-01 |
| ad.p.value | 2.000e-08 | 7.280e-06 | 2.612e-03 | 3.129e-04 | 1.912e-01 |
| cvm.p.value | 4.400e-07 | 2.942e-05 | 3.327e-03 | 5.980e-04 | 2.781e-01 |

Table 6: All figure GOF measure p-value distributions

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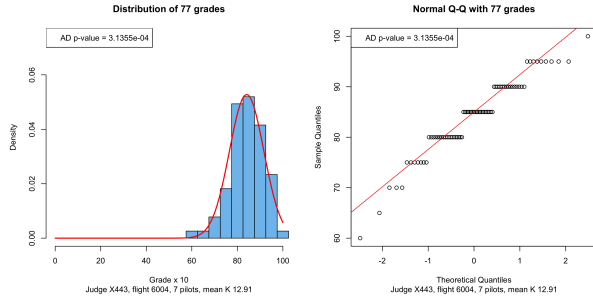


Figure 4: All figures example at third quantile Anderson-Darling p-value

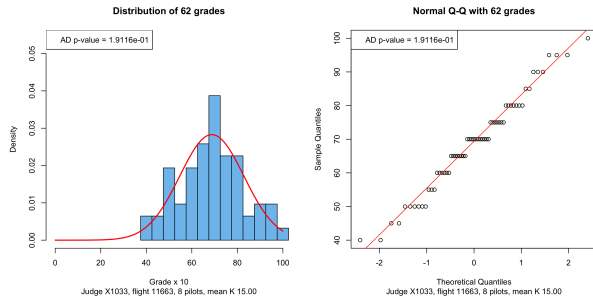


Figure 5: All figures example at maximum Anderson-Darling p-value

- [10] Janet Chaseling Michael Steel and Cameron Hurst. Comparing the simulated power of discrete goodness-of-fit tests for small sample sizes. In *ASIMMOD*, pages 210–216, 2007.