



Nonparametric Goodness-of-Fit Tests for Discrete Null Distributions

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Abstract

A general theory for extending nonparametric goodness-of-fit tests to discrete null distributions has existed for several decades. Despite this, modern statistical software have generally failed to provide this methodology to users. The packages **ks.test** and **cvm.test** serve to fill this need in the R language for the two most popular nonparametric tests. The structure of these two packages are explained and examples to their specific usage are presented. Particular attention is given to the various numerical issues that arise in their implementation.

*** try to clean up, avoid package function issue, make it a general contribution if possible.

Keywords: Cramer von Mises, goodness-of-fit tests, Kolmogorov-Smirnov, R.

1. Introduction

Example code:

```
> 1 + 1
```

```
[1] 2
```

Given a particular null distribution, goodness-of-fit tests are used in order to test whether it is likely that the data were generated via the null distribution.

While almost any hypothesis test can be viewed as a variant on a goodness-of-fit test, the term is typically applied to those tests which are nonparametric in nature. That is, they do not conduct the hypothesis testing through the explicit calculation of the parameters generating the data. Instead, they generally attempt to calculate differences between the empirical distribution of the observed data and the overall distribution of the null model. In many

cases these tests are preferential since they tend to have an increased power for interesting deviations from the null model, in exchange for failing to detect less interesting deviations due to factors such as measurement error. By far the most popular of these nonparametric tests are due to Kolmogorov and Smirnov, followed closely by several variants on an estimation procedure proposed by Cramer von Mises.

While the original aim of nonparametric goodness of fit tests was meant for continuous null distributions, discrete versions have existed since the early 1970s. Unfortunately, current statistical software has largely failed to incorporate them. This has left the end-user to either use only parametric tests, such as Pearson’s Chi-Squared test, or to incorrectly apply the functions meant for continuous distributions. As shown in section 5, the latter can be particularly dangerous in the small sample setting. The packages **ks.test** and **cvm.test** serve to fill this void for users operating in the R environment.

** Ditto on wordsmithing the contribution (package function, etc...).

2. Kolmogorov-Smirnov Test

2.1. Overview

Of all the methods for nonparametric goodness-of-fit tests, by far the most popular is the method devised by Kolmogorov and Smirnov. It is the only such test built into the base of R. The idea behind it is fairly simple. Given the cumulative distribution function $F_0(x)$ of the continuous null distribution, and the empirical distribution function $F_{data}(x)$ of the observed data, one constructs the statistic:

$$D = \sup_x |F_0(x) - F_{data}(x)| \quad (1)$$

The distribution of D under the null model does not depend on which null distribution is being used, making this a computationally attractive method. For a standard treatment of the test and its performance relative to other algorithms see [Slakter \(1965\)](#). Two common alternatives of the above test statistic exist. The absolute value is discarded and the rest is either left alone (the ‘greater’ testing alternative) or the supremum is replaced with a negative infimum (the ‘lesser’ hypothesis alternative). These can be helpful depending on the nature of the alternative hypotheses for which the test is desired to be powerful towards.

The extension of this result to non-continuous null distributions does not have such a clean solution. The formula of the test statistic D remains unchanged, however the distribution of the testing statistic is much more difficult. Unlike in the continuous case, it ultimately depends on which null model was chosen; this makes it impossible to simply read p-values directly off of a fixed table. It was known since at least the 1950’s that using the tables for continuous distributions resulted in conservative p-values; it was not until [Conover \(1972\)](#) that a method for computing exact p-values in this case was developed.

2.2. Implementation

The implementation of the discrete Kolmogorov-Smirnov function consists of two parts. First the particular test statistic needs to be calculated, and then the p-value for that particular statistic must be computed.

often not the case. Consider two non-decreasing functions f and g , where the function f is a step function with jumps on the set $\{x_1, \dots, x_N\}$ and g is continuous. If we want to determine the supreme of the difference between these two functions notice that:

$$\sup_x |f(x) - g(x)| = \max_i \left(|g(x_i) - f(x_i)|, \lim_{x \rightarrow x_i} |g(x) - f(x_{i-1})| \right) \quad (2)$$

$$= \max_i (|g(x_i) - f(x_i)|, |g(x_i) - f(x_{i-1})|) \quad (3)$$

Computing the maximum over these $2N$ values (with f equal to $F_{data}(x)$ and g equal to $F_0(x)$ as defined above) is clearly the most efficient way to compute the Kolmogorov-Smirnov test statistic when given a continuous null distribution. When the function g is not continuous, notice that this formula no longer works since in general we cannot replace the limit of g with its value at x_i . If it is known that g is also a step function, we could replace the formula for some small ϵ by:

$$\sup_x |f(x) - g(x)| = \max_i (|g(x_i) - f(x_i)|, |g(x_i - \epsilon) - f(x_{i-1})|) \quad (4)$$

Where the discontinuities in g are at least a distance ϵ apart.

3. Cramer von Mises Tests

3.1. Overview

While the Kolmogorov-Smirnov test is the most well known of the non-parametric goodness of fit tests, there is another family of tests which has been shown to be more powerful to a large class of alternatives distributions. The original was developed jointly by Harald Cramer and Richard von Mises ([Cramer 1928](#); [von Mises 1928](#)), and further adapted by [Anderson and Darling \(1952\)](#), and [Watson \(1961\)](#). The test statistics are, respectively, given as:

$$\begin{aligned} W^2 &= n \cdot \int_{-\infty}^{\infty} [F_{data}(x) - F_0(x)]^2 dF_0(x) \\ A^2 &= n \cdot \int_{-\infty}^{\infty} [F_0(x) - F_0(x)^2]^{-1} [F_{data}(x) - F_0(x)]^2 dF_0(x) \\ U^2 &= n \cdot \int_{-\infty}^{\infty} [F_{data}(x) - F_0(x) - W^2]^2 dF_0(x) \end{aligned}$$

Where F is either the cumulative distribution of the null model or the empirical cumulative distribution of the observed data. As in the Kolmogorov-Smirnov test statistic, these all have distribution free null distributions in the continuous case.

It has been shown that these tests can be more powerful than Kolmogorov-Smirnov tests to certain deviations. As they all involve integration over the whole range of data, rather than one supremum, it is not surprising that they are generally best when the true alternative distribution deviates a little over the whole range of data rather than deviating a lot over a small range. For a complete analysis of the relative powers of these tests see [Stephens \(1974\)](#).

Generalizations of the Cramer-von Mises tests were developed in [V Choulakian \(1994\)](#). Much like for the Kolmogorov-Smirnov test, the theoretical form of the test statistics are unchanged; although the discreteness allows for a slightly simpler representation. The null distribution of the test statistics are again distribution dependent, unlike the continuous version. The methods do not suggest finite sample results, but rather show that the asymptotic null distribution is equal to a weighted sum of independent chi-squared variables (the weights depending on the particular distribution). This asymptotic distribution is what we implement here; the original papers shows that this approximation

3.2. Implementation

Calculation of the three test statistics is done by straightforward matrix algebra as given in [V Choulakian \(1994\)](#). Determining the form of the asymptotic null distribution is also easy using the built-in eigenvalue decomposition functions. The only difficulty in the process involves actually calculating the percentiles for these weighted chi-squares.

The method used for calculating the distribution of a weighted sum of independent chi-squared variables is given in [Imhof \(1961\)](#). A general method for computing any quadratic form of normals is presented, which is easily adapted for our case since each chi-squared variable has only one degree of freedom. The exact formula given for the distribution function of Q , the weighted sum of chi squares, is:

$$\mathbb{P}\{Q \geq x\} = \frac{1}{2} + \frac{1}{\pi} \int_0^\infty \frac{\sin \theta(u, x)}{u \rho(u)} du$$

For continuous functions $\theta(\cdot, x)$ and $\rho(\cdot)$ which depend on the actual weights used.

There is no analytic solution to the integral, but integration can be carried out using numerical techniques. This seems fine in most situations, but numerical issues do become a problem in the regime of large test statistics x . The function $\theta(\cdot, x)$ is linear in x , and thus as the test statistic grows the corresponding period of the integrand decreases. As the function acquires too many inflection points, the approximation becomes unstable. This is further magnified by this occurring when p -values should be very small; thus tiny fluctuations which would be undetectable elsewhere are quite prominent. Figure ? shows the non-monotonicity of the function as the test statistic grows.

There is fortunately a simple conservative approximation which can get around this numerical problem. Given the following inequality:

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^p \lambda_i \chi_1^2 \geq x\right) &\leq \mathbb{P}\left(\lambda_{max} \sum_{i=1}^p \chi_1^2 \geq x\right) \\ &= \mathbb{P}\left(\chi_p^2 \geq \frac{x}{p \lambda_{max}}\right) \end{aligned}$$

We see that the values for the weighted sum can be bounded by a simple transformation and a chi-squared distribution of a higher degree of freedom.

4. Kolmogorov-Smirnov and Cramer von Mises in R

For the user, the function `cvm.test` was designed to work in exactly the same manner as `ks.test` in R. This alleviates the need to learn a new set of input and output instructions

and hopefully will increase the usage of these tests. As there is no default functionality in R for continuous Cramer-von Mises, subsequent versions of the package should also originally implement the continuous case even though this is not what we concentrate on here.

5. Examples

6. Discussion

Go into more detail about reasons for using these versus chi-squared type tests. (*)

Issues revolving around incorrect usage of default `ks.test()` in R because of continuity error (i.e. `ks.test(1:2, ecdf(1:2))`)

Further discuss numerical issues; `ks -> n` over 30 has problems, `CvM -> integrate` function can sometimes refuse to run because of failure to calculate integral.

Benefits and drawbacks of using simulation to gather p-values. (*)

Possibly go into a brief discussion of classes and class inheritance in R. The use of ‘`htest`’ in our functions; benefits and issues with using it. Particularly troublesome in `ks.test` where we have a range of p-values.

Two-sample cases; no theory for discrete distributions. Why? Distribution dependence messes things up. Discuss this for sure. (*)

For further generalizations of tests see [de Wet and Venter \(1994\)](#)

7. Examples

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