

Performances of Shannon's Entropy Statistic in Assessment of Distribution of Data

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Abstract. Statistical analysis starts with the assessment of the distribution of experimental data. Different statistics are used to test the null hypothesis (H_0) stated as *Data follow a certain/specified distribution*. In this paper, a new test based on Shannon's entropy (called Shannon's entropy statistic, H_1) is introduced as goodness-of-fit test. The performance of the Shannon's entropy statistic was tested on simulated and/or experimental data with uniform and respectively four continuous distributions (as *error function, generalized extreme value, lognormal, and normal*). The experimental data used in the assessment were properties or activities of active chemical compounds. Five known goodness-of-fit tests namely Anderson-Darling, Kolmogorov-Smirnov, Cramér-von Mises, Kuiper V, and Watson U^2 were used to accompany and assess the performances of H_1 .

Keywords: Shannon's entropy; statistic; continuous distribution; tests of goodness-of-fit.

1. Introduction

Different statistical tests are used to assess the agreement between theoretical probability models and measured data as an early step in the statistical analysis of experimental data. Kolmogorov-Smirnov (KS) [1,2], Anderson-Darling (AD) [3,4], Pearson's Chi-square (CS) [5, 6], Cramér-von-Mises (CM) [7, 8], Shapiro-Wilk (SW) [9], Jarque-Bera (JB) [10-12], D'Agostino-Pearson [13], Lilliefors [14], or Shapiro-Francia (SF) [15] are just several tests that are classically implemented in commercial or non-commercial statistical software. Kolmogorov-Smirnov test is an order statistic that applied only on continuous distributions and is known to be less sensitive at the tails of the distribution [16]. Cramér-von-Mises [7,8] and AD [3,4] are refinements of the KS test that gives more weight to the tails [17], both tests being known as empirical distribution function (EDF) tests [18]. The critical values of AD test depend of the distribution that is tested. Pearson's Chi-square is an alternative to the K-S and A-D tests and its application is valid only if the values in each bin exceed five [18].

A small group of known theoretical probability distributions is usually used to describe or to approximate measured data, and the normal distribution is the most extensively used [19]. A parametric test is applied whenever data follow the normal distribution; otherwise a non-parametric test

fit better to analyze the experimental data [20-22]. The normal distribution was by far the most studied. Monte Carlo experiments conducted on different sample sizes showed that SW test is the most powerful while opposite KS test is less powerful in the assessment of normal distribution [23]. Tui proved that Anderson-Darling assures validity and inference based on t-statistic compared with JB, SF, D'Agostino & Pearson, and AD & Lilliefors [24]. Islam applied stringency concept using the LR-tests to rank the normality tests and concluded that the best normality test is Anderson-Darling [25]. Mbah and Paothong used the expected p-value approach to characterize the normality test and showed that SF test is the best statistic in detecting deviation from normality when compared with KS, AD, CM, Lilliefors, SW, CS, JB, and D'Agostino [26]. The scientific community shows attention not just to the assessment of the existing tests but also to development and validation of new tests. New approaches are reported to test certain distributions of measured/observed data, such as mean and quantile statistics based on the posterior predictive distribution [27], quantile-mean covariance [28], empirical distribution function [29], maximum entropy [30], Kullback-Leibler measure [31], sums of squares in decomposition of the Shapiro-Wilk-type statistic [32], Euclidean distance between sample

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elements for assessment of multivariate normality [33], or entropy estimators [34].

2. Materials and methods

Shannon's Entropy Statistic

The use of entropy as a test statistic is not a novel approach. Vasicek introduced in 1976 using entropy (the entropy of a normal distribution exceeds the values of any other distributions) a new goodness-of-fit test for normal distribution [35]. In the same year, Prescott tested the sensitivity of the normality test introduced by Vasicek and showed that the new test is less sensitive to the outliers [36]. The test introduced by Vasicek was also used to test other distributions (exponential, Gamma, uniform, Beta(2,1), and Cauchy) and obtained the highest power as compared with KS, CM, Kuiper, Watson U^2 , AD, and SW tests for *exponential* (85%) and for *uniform* distribution (44%) while the smallest power was obtained for *Cauchy* distribution [36]. Different approaches were applied to estimate entropy and based on the new introduced estimators (e.g. modified Vasicek's estimator [37,38], Noughabi's entropy estimator [39]) new goodness-of-fit tests were developed and performances in testing the normal [40-42], lognormal [43], uniform [44-46], exponential [47], beta [47,48], Poisson [49], Weibull [43], Gamma [43], Pareto [50,51], Student and exponential distribution [52] were studied.

A statistic provides the correct conclusion in regards of null hypothesis (H_0) whenever data did not contain any outlier or extreme value [53]. A simple question arise: *It is possible to construct a statistic able to provide the closest to the true answer in regards of testing the H_0 ?* A solution could be found by adapting the method proposed by Fisher [54] and discussed in the context of combining probability from multiple statistics [55]. An overall result based on several statistics is the best solution since most of the distributions has more than one degree of freedom. The degrees of freedom did not decrease by combining tests and could be considered independent since different tests implement different methods. In this regards, more than one statistics may fully cover the variation induced by the associated degrees of freedom.

Goodness-of-fit test based on entropy already showed to be less sensitive to the presence of extreme values or outliers [36] so combining its results with other goodness-of-fit tests could provide a good overall solution. Shannon's entropy generally refers to disorders or uncertainties [56] and here is introduced as statistic (H1) for evaluation of the distribution of experimental data. Its formula is given by Eq (1):

$$H1 = -\sum_{i=0}^{n-1} f_i \cdot \ln(f_i) + (1 - f_i) \cdot \ln(1 - f_i) \quad (1)$$

where $H1$ is Shannon's entropy statistic, n is the sample size, i iterates (in ascending order) the observations in the sample, f_i is the cumulative distribution function (CDF) associated with the observation (sorted in ascending order).

Shannon entropy was defined as a statistic for measurement of the distance between theoretical and observed distribution in a similar manner as other statistics (see Eq (2)-Eq (6)).

Several specific features made the Shannon's statistic enough different by all other investigated statistics. Shannon's statistic is calculated without sorting the CDF (cumulative distribution function) values, as other statistics need. Thus, Shannon's statistic is a 'clutter' statistics in the perfect agreement with the basic concept of entropy as a measure of disorder. The Shannon's approach additively cumulates the entropy of each CDF value from the binary division that is constructed in the probability space of $[0, 1]$.

The algorithm presented in Figure 1 was applied for H1 statistic.

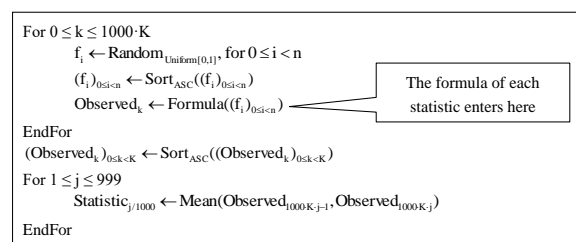


Figure 1. The steps applied to build the probability association map for the H1 statistic. The K was set to a large numeric value, e.g. 10,000 as presented below, k iterates the domain defined by 0 and K , and j iterates the control points of probability thresholds $p_j = j/1,000$, e.g. 0.001, 0.002, ..., 0.999.

The algorithm presented in Figure 1 worked with a fixed value of the sample size (n) but can also be used by successive iterations for the value of n starting with $n = 2$. The large K value and eventually repeated resampling are used for increasing the resolution of the statistic's values. For the same purpose, for a value $0 \leq x \leq 1$ the random is conducted in two steps, first for mantissa $((10,000 + \text{Random}(90,000))/100,000)$, and second for exponent (repeat $k := \text{Random}(10)$; if $(k=0)$ then $p[i] := p[i]/10$; until $(k > 0)$). Furthermore, Mersenne Twister method [57] was involved to simulate randomness. The inverse of the statistic probability function from the above-provided algorithm was used to find the answer for H_0 by H1 statistic.

Evaluation Methodology

Comparison Statistics

Five goodness-of-fit tests were also applied for each investigated null hypothesis:

- Anderson-Darling statistic (AD) [3,4]:

$$AD = -n - \frac{1}{n} \sum_{i=0}^{n-1} (2 \cdot i + 1) \cdot \ln(f_i \cdot (1 - f_{n-1-i})) \quad (2)$$

- Kolmogorov-Smirnov statistic (KS) [1,2]:

$$KS = \sqrt{n} \cdot \max_{0 \leq i \leq n-1} \left(f_i - \frac{i}{n}, \frac{i+1}{n} - f_i \right) \quad (3)$$

- Cramér-von Mises statistic (CM) [7,8]:

$$CM = \frac{1}{12 \cdot n} + \sum_{i=0}^{n-1} \left(\frac{2i+1}{2 \cdot n} - f_i \right)^2 \quad (4)$$

- Kuiper V statistic (KV) [58]:

$$KV = \sqrt{n} \cdot \left(\max_{0 \leq i \leq n-1} \left(f_i - \frac{i}{n} \right) + \max_{0 \leq i \leq n-1} \left(\frac{i+1}{n} - f_i \right) \right) \quad (5)$$

- Watson U² statistic (WU) [59]:

$$WU = \frac{1}{12 \cdot n} + \sum_{i=0}^{n-1} \left(\frac{2i+1}{2 \cdot n} - f_i \right)^2 + n \left(\frac{1}{2} - \frac{1}{n} \sum_{i=0}^{n-1} f_i \right)^2 \quad (6)$$

where *AD* is the statistic of the Anderson-Darling test, *KS* is the statistic of the Kolmogorov-Smirnov test, *CM* is the statistic of the Cramér-von Mises test, *KV* is the statistic of the Kuiper V test, *WU* is the statistic of the Watson U² test, *n* is the sample size, *i* iterates (in ascending order) the observations in the

sample, *f_i* is the cumulative distribution function (CDF) associated with the observation (sorted in ascending order).

Simulated Datasets

A simple random technique was used to generate forty-five samples of data following uniform distribution with volumes equal with 15, 20, 30, 40, and 50. Note that even this method is standardized operates with the same string of probabilities, case which is not seen when experimental data are investigated. These simulated datasets were used to characterize the new statistic (H1) as compared with statistics from Eq (2)-Eq (6).

Experimental Datasets

Measured/observed properties/activities on a series of chemical compounds with sample size from 13 to 1714 were used to assessment the Shannon's statistic. The main characteristics of the datasets included in the evaluation are provided in Table 1.

Four statistic one-tailed null hypotheses (H₀) were evaluated on experimental data:

1. H₀: The experimental data follow the *error* distribution
2. H₀: The experimental data follow the *generalized extreme value* distribution
3. H₀: The experimental data follow the *lognormal* distribution
4. H₀: The experimental data follow the *normal* distribution

Table 1. Characteristics of datasets used in the assessment (n=sample size).

Set	Compounds	Property/Activity	n	Ref
01	phenols	antioxidant activity	42	[60,61]
02	drug-like compounds	blood-brain barrier permeability	129	[62]
03	estrogen receptors binders	binding activity	144	[63]
04	pure chemicals	heat of combustion	1714	[64]
05	different active compounds	carcinogenicity (LD50)	39	[65]
06	nitrocompounds	carcinogenic potency	55	[66]
07	substituted anilines and phenols	toxicity to <i>V. fischeri</i>	57	[67]
08		toxicity to <i>P. subcapitata</i>	58	[67]
09	phenols	toxicity to <i>Tetrahymena pyriformis</i>	250	[68]
10	deacetylase LpxC-2-aryloxazolines, aroylserines, and 2-arylthiazolines	inhibitors on <i>Pseudomonas aeruginosa</i>	51	[69]
11	LpxC inhibitors	inhibitory activity on gram-negative	41	[70]
12	drug-like compounds	aqueous solubility	166	[71]
13	sulfonamide	inhibition activity on carbonic anhydrase I	40	[72]
14		inhibition activity on carbonic anhydrase II	40	[72]
15		inhibition activity on carbonic anhydrase IV	40	[72]
16	sulfonamides	pKa	29	[73]
17	aromatic sulfonamides	inhibition activity on carbonic anhydrase II	43	[74]
18	sulfonamides	inhibition activity on carbonic anhydrase II	47	[75]
19	aromatic/heterocyclic sulfonamides	inhibition activity on carbonic anhydrase	38	[76-78]
20	paclitaxel	antimitotic activity - B16 melanoma	18	[79]
21		antimitotic activity - MCF-7	17	[79]
22		antimitotic activity - MCF-7-ADR	16	[79]
23	taxoids	resistance index to MCF-7 cell lines	63	[80]

Set	Compounds	Property/Activity	n	Ref
24	taxoids	cell growth inhibitory activity	35	[81]
25	c-Src inhibitors	anticancer activity	80	[82]
26	different compounds	boiling points	196	[83]
27		heats of vaporization	19	[83]
28	carboquinone derivative	minimum effective dose	37	[84]
29	cyclic peroxy ketals	half maximal inhibitory concentration	18	[85]
30	organic pollutants	oxidative degradation	33	[86]
31		degradation	33	[87]
32	(benzo)triazoles	fish toxicity	97	[88]
33	thiophene and imidazopyridine derivatives	inhibition activity of the Polo-Like Kinase 1	136	[89]
34	substituted phenylaminoethanones	average antibacterial activity	17	[90]
35		average antifungal activity	17	[90]
36		average antimicrobial activity	17	[90]
37	acetylcholinesterase inhibitors	inhibition activity	110	[91]
38	antimony(III) complexes	glutathione reductase inhibitor	14	[92]
39	polychlorinated diphenyl ethers	298 K supercooled liquid vapor pressures	107	[93]
40		aqueous solubility	107	[93]
41	hexahydroquinoline derivatives	calcium channel antagonist activity	13	[94]
42	volatile organic compounds	draize eye score	126	[95,96]
43	polychlorinated biphenyls	relative retention times	209	[97]
44	drug-like compounds	blood-brain barrier permeability	122	[62]
45	protein kinase inhibitors	inhibitory activity	77	[98]
46	curcumin analogs	IL6 inhibition activity	23	[99]
47		TNF inhibition activity	23	[99]
48	4-aminoquinoline analogues	antiplasmodial activity against chloroquine-susceptible <i>Plasmodium falciparum</i>	68	[100]
49		antiplasmodial activity chloroquine-resistant <i>Plasmodium falciparum</i>	68	[100]
50	nitrofuranyls	antitubercular agents	110	[101]

B16 melanoma = a murine tumor cell line; MCF-7 = a breast cancer cell line;
IL6 = Interleukin 6; TNF = Tumor necrosis factor

Evaluation Approach

The approach presented in Figure 2 was used to assess the proposed Shannon's entropy statistic. The values of CDF (cumulative distribution function)

were calculated with EasyFit program (MathWave Technologies) for both simulated and experimental/observed datasets and each investigated distribution.

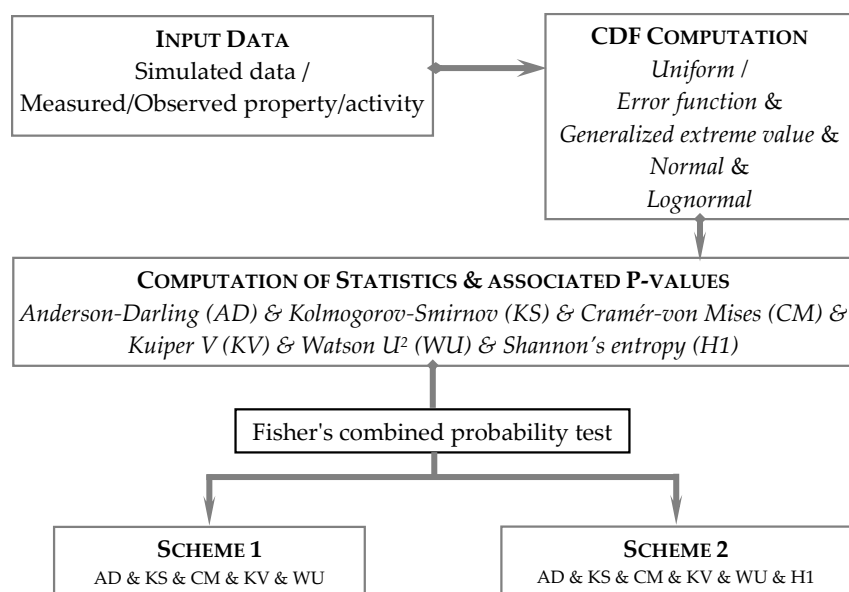


Figure 2. Flowchart illustrating the steps involved in assessment of Shannon's statistic.

The computation of investigated statistics and of the associated p-values was done for each distribution and each dataset using the algorithm of the statistic-probability association map (Figure 1) and several *.php programs:

- Anderson-Darling (AD): <http://l.academicdirect.org/Statistics/tests/AD/>
- Kolmogorov-Smirnov (KS): <http://l.academicdirect.org/Statistics/tests/KS/>
- Cramér-von Mises (CM): <http://l.academicdirect.org/Statistics/tests/CM/>
- Kuiper V (KV): <http://l.academicdirect.org/Statistics/tests/KV/>
- Watson U² (WU): <http://l.academicdirect.org/Statistics/tests/WU/>
- Shannon's entropy (H1): <http://l.academicdirect.org/Statistics/tests/H1/>

The Fisher's combined probability test [54] was used to control the error rates using an adjusted significance level to diminish the possible influence

of the positively correlated tests. All possible pairs of comparison adjust the significance level as $\alpha^* = \alpha/[q \cdot (q-1)/2]$, where q = the number of the tests. Two different schemes were used to test the contribution of H1 to the overall conclusion relating H₀. The first one (scheme 1) includes all statistics excepting the H1 ($\alpha_1^* = 0.0050$, and the second one (scheme 2) includes all investigated statistics, inclusive H1 ($\alpha_2^* = 0.0033$). Despite the fact that the input data are the same, each statistic (Eq(1)-Eq(6)) had its proper formula, formulas that are independent from each other as proved by Dijkstra [102].

3. Results and discussions

Results on Simulated Data

The uniform distribution was rejected at least one out of 45 runs by all investigated statistics for $n = 15, 20, 30, 40,$ and 50 (Table 2).

Table 2. Results on simulated data: number of individual rejections and the combined tests rejections.

<i>n</i>	H₀: Data follow uniform distribution. H₀ rejection ($\alpha = 5\%$)						Scheme 1	Scheme 2
	AD, n (%)	KS, n (%)	CM, n (%)	KV, n (%)	WU, n (%)	H1, n (%)	($\alpha^* = 0.50\%$)	($\alpha^* = 0.33\%$)
15	2 (4.44)	3 (6.67)	2 (4.44)	1 (2.22)	1 (2.22)	4 (8.89)	5 (11.11)	8 (17.78)
20	1 (2.22)	2 (4.44)	0 (0.00)	3 (6.67)	4 (8.89)	2 (4.44)	8 (17.78)	7 (15.56)
30	3 (6.67)	4 (8.89)	3 (6.67)	3 (6.67)	2 (4.44)	3 (6.67)	2 (4.44)	2 (4.44)
40	4 (8.89)	3 (6.67)	2 (4.44)	1 (2.22)	2 (4.44)	1 (2.22)	1 (2.22)	1 (2.22)
50	3 (6.67)	2 (4.44)	1 (2.22)	4 (8.89)	4 (8.89)	2 (4.44)	2 (4.44)	2 (4.44)

AD=Anderson-Darling, KS=Kolmogorov-Smirnov, CM=Cramér-von Mises, KV=Kuiper V, WU=Watson U², H1=Shannon

Overall, the rejection of H₀ by the combined test of significance is observed when three or more test individually rejected the H₀ and this behavior is the same with or without the inclusion of H1 statistic. In some cases, certain goodness-of-fit test (such as KS for $n=15, 20$, WU for $n=20$, H1 for $n=15$) test transmit its individual significance to the combined test.

Results on Experimental Data

Different behavior of H1 statistic is observed when the assessment is conducted on experimental data. The number of H₀ rejections by each individual test varied from 0 (H1) to 21 (KV) and proved smallest when Shannon's entropy was used as statistics (Table 3). On average, the highest percentage of rejections was given by Kuiper V

statistic and was closely followed by Watson U² statistic.

The results presented in Table 3 shows that the trend of H1 statistic is not to reject the null hypothesis and this behavior can be explained by its formula (see Eq(1)), leading to a test more tolerant to extreme values or outliers. This behavior could be either a disadvantage (the hypothesis of association is not rejected even if it is false) or an advantage (the presence of outliers, which in most of the cases are data collection accidents, make other statistics to reject the null hypothesis much easiest even if this hypothesis is true). Therefore, the proposed H1 statistic is more tolerant to such errors.

Table 3. Reject H₀? Number of rejections and associated percentage by statistics (at a significance level of 5%).

Distribution	AD, n (%)	KS, n (%)	CM, n (%)	KV, n (%)	WU, n (%)	H1, n (%)
<i>error</i>	9 (18.75)	12 (24.00)	11 (22.00)	19 (38.00)	17 (34.00)	0 (0.00)
<i>generalized extreme value</i>	6 (13.33)	5 (10.00)	4 (8.00)	13 (26.00)	11 (22.00)	3 (6.67)
<i>lognormal</i>	4 (8.00)	7 (14.00)	4 (8.00)	18 (36.00)	16 (32.00)	3 (6.00)
<i>normal</i>	8 (16.67)	14 (28.00)	10 (20.00)	21 (42.00)	20 (40.00)	0 (0.00)

AD=Anderson-Darling, KS=Kolmogorov-Smirnov, CM=Cramér-von Mises, KV=Kuiper V, WU=Watson U², H1=Shannon

Without any exception, the median of number of failure to reject the H_0 (p -value > 0.05 for each individual test) was equal with the number of investigated tests (5 for scheme 1, and 6 for scheme 2, see Table 4). The variation of quartiles was more monotone when H1 was included in the combined test

while the most heterogeneous behavior was seen when the *normal* distribution was investigated (Table 4). The inclusion of H1 statistic in assessment of distribution smoothest the characteristics of summary statistics for *error*, *generalized extreme value*, and *lognormal distributions* (see Table 4).

Table 4. Failed to reject H_0 : median, inter-quartile ranges (1st quartile–3rd quartile), and perfect concordance between investigated scheme.

Distribution	Scheme 1 median (Q1–Q3)	Scheme 2 median (Q1–Q3)	Perfect concordance* between schemes, no. (% [95%CI])
<i>error</i>	5 (3–5)	6 (4–6)	30 (60 [46–74])
<i>generalized extreme value</i>	5 (4–5)	6 (4–6)	32 (64 [50–78])
<i>lognormal</i>	5 (3–5)	6 (4–6)	31 (62 [48–76])
<i>normal</i>	5 (2–5)	6 (3–6)	29 (58 [44–72])

* perfect concordance was defined as an agreement on H_0 obtained between all tests in both scheme (5 tests in Scheme 1 and 6 tests in Scheme 2); 95%CI = 95% confidence interval

To identify the behavior of proposed H1 statistic, the absolute difference between p -value of this statistic and respectively p -value of each other investigated statistic were counted. The p -values of the H1 proved closest to Anderson-Darling p -value

for *error* and *normal* distributions (Figure 3). In the assessment of *generalized extreme value* distribution, the p -values of the H1 proved closest to Kuiper V statistic (Figure 3).

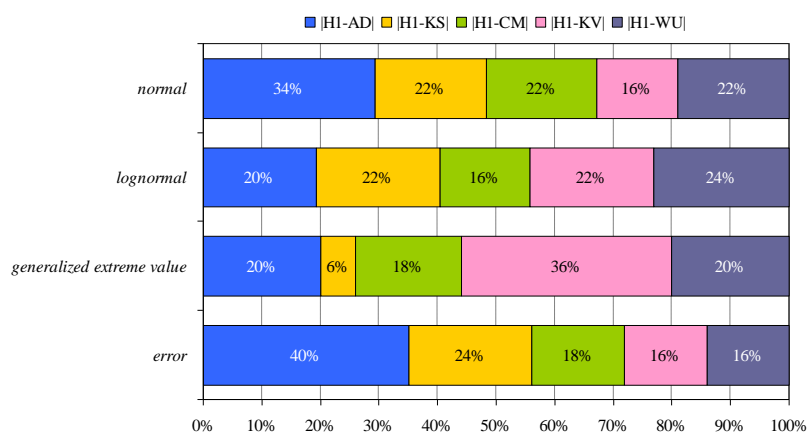


Figure 3. Minimum absolute difference between Shannon's (H1) p -value and p -values of other investigated statistics (AD=Anderson-Darling, KS=Kolmogorov-Smirnov, CM=Cramér-von Mises, KV=Kuiper V, and WU=Watson U^2).

With the exception of *generalized extreme value* distribution, for several datasets opposite conclusions regarding H_0 was drawn by H1 statistic compared to all other investigated statistics (see Figure 4):

- *Error* distribution: set04, set26, and set34.
- *Lognormal* distribution: set04.
- *Normal* distribution: set04, set13, set14, set15, set26, and set34.

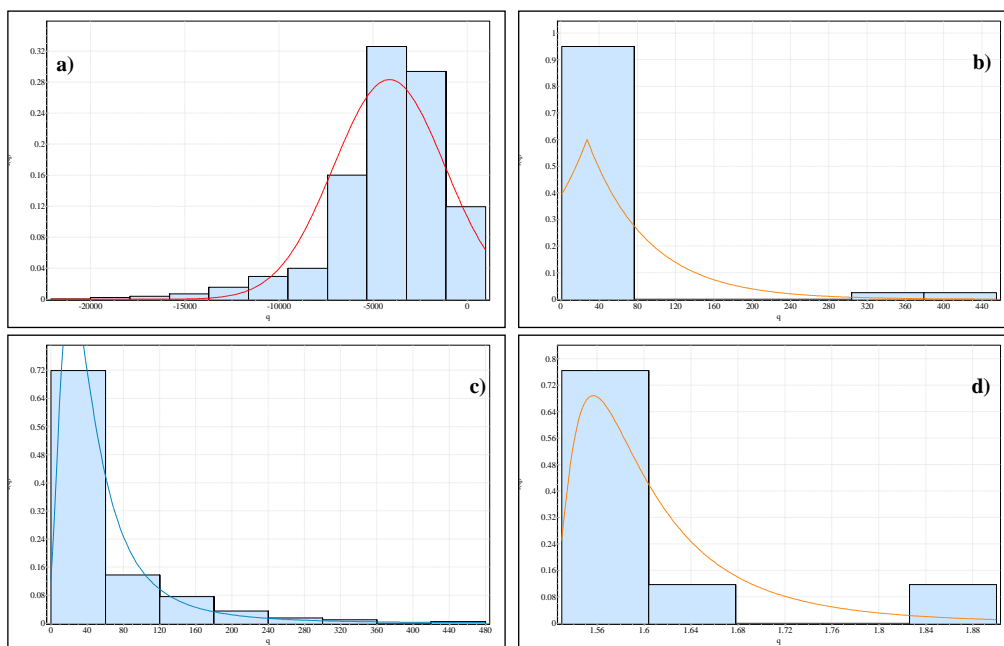


Figure 4. Shannon's opposite conclusion by example: a) set04 (H_0 rejected by AD=Anderson-Darling, KS=Kolmogorov-Smirnov, CM=Cramér-von Mises, KV Kuiper V, and WU=Watson U^2 with $p < 0.0001$ while Shannon's statistic failed to reject H_0 with $p = 0.4124$ for *error* distribution, $p = 0.9999$ for *lognormal* distribution, and $p = 0.9996$ for *normal* distribution); b) set13 (H_0 rejected by AD, KS, CM, KV, and WU with $p < 0.0001$ while Shannon's statistic failed to reject H_0 with $p = 0.9999$ for both *error* and *normal* distribution); c) set26 (H_0 rejected by AD, KS, CM, KV, and WU with $p < 0.0001$ while Shannon's statistic failed to reject H_0 with $p = 0.8266$ for *error* distribution, $p = 0.9999$ for *normal* distribution); d) set34 (H_0 rejected by AD, KS, CM, KV, and WU with $p < 0.04$ while Shannon's statistic failed to reject H_0 with $p = 0.7878$ for *error* distribution, $p = 0.9423$ for *normal* distribution).

The overall combine test showed different results in the assessment of investigated distributions in both

investigated scheme when the analysis was conducted at adjusted significance levels (Table 5).

Table 5. Reject H_0 ? Results of overall combine test of significance.

Distribution	Scheme 1		Scheme 2	
	no.	% [95%CI]	no.	% [95%CI]
<i>error</i>	14	28 [16–42]	11	22 [30–58]
<i>generalized extreme value</i>	7	14 [6–26]	5	10 [4–22]
<i>lognormal</i>	10	20 [10–34]	8	16 [6–30]
<i>normal</i>	16	32 [20–46]	15	30 [18–44]

The inclusion of Shannon's statistic in the overall combine test has the smallest effect on the *normal* distribution, decreasing the rejection of H_0 by 2%, closely followed by *generalized extreme value* and *lognormal* distribution, decreasing the rejection of H_0 by 4%. The largest effect on the overall combined test induced by the H1 statistic was observed on *error* distribution, for which the decreasing the rejection of H_0 by 6%.

The concordance analysis (identical conclusion in both scenarios) shows the highest value for *generalized extreme value* distribution and the lowest value for *normal* distribution (Table 4). The value of probability associated with the rejection of the tested hypotheses systematically becomes larger in the scheme that includes the Shannon's entropy. The

analysis of the Shannon's p-value relative to each other investigated statistics showed that these values are closest to Kuiper V for *normal* distribution, to *Cramér-von Mises* for *lognormal* distribution, to Kolmogorov-Smirnov for *generalized extreme values* distribution, and respectively to Kuiper V and Watson U^2 for *error* distribution (see Figure 3).

In our analysis, we investigated how the combined test aggregate the information from different tests on the same H_0 . The main shortcoming of this approach is given by its asymmetrical sensitivity to small p-values leading to the increase of type I error (incorrect rejection of H_0) [103]. To diminish this shortcoming, an adjustment of the significance level was used, which could be seen as too conservative approach. However, this adjustment protects against the danger

of overclaiming the significant results but with the cost of the possibly underclaiming. The problem of combining test of significance have been debated in the scientific literature mainly in regards of testing means [104-106]. Several methods have been introduced, the main known being the Stouffer's method (applied to one-tailed tests, also known as Z-transform test when the p-values are converted as normal standard derivatives [107]), and its derivate as weighted Z-method [108,109] mainly used in meta-analysis. Several different approaches have been published but no consensus exists in the scientific literature in regards of performances of these tests. Some authors sustain that the Fisher and/or its derivate [110] is the best while other authors sustained that other tests are best performing combined tests of significances [111,112]. However, our team works in this moment to identify as many as possible of such approach, to test them and to apply them to investigate the performances of H1 statistics. Furthermore, the new introduce H1 statistic need to be compared with other similar approaches that use

entropy as estimator in testing the distribution of data.

4. Conclusions

The contribution of the proposed H1 statistic to the final decision in assessment of the probability distributions has been investigated and a general tendency of the H1 to counterbalances the tendency of rejection the null hypothesis by the combined test of significance is observed on experimental data. The effect, however, could be insignificant since the practical outcome in the number of rejections is amended downwards in only 3 out of 50 cases. Furthermore, this effect of the H1 statistic must be assessed on different constrains and conditions.

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Conflicts of Interest: The authors declare no conflict of interest.

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