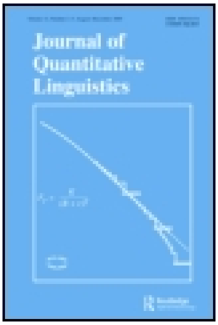

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A Statistical Study of Failures in Solving Crossword Puzzles*

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ABSTRACT

Crossword puzzles are the most popular form of linguistic puzzles; for the solver they are intellectually challenging and entertaining as well. An interesting exercise for this author, a keen solver of the British-style 'cryptic' crossword puzzles, has been the statistical distribution of the number of unsolved clues (x) in a puzzle. Data are cumulated over a decade (total number of puzzles 3404). The large sample size makes it possible to examine the tail of the distribution at large x, up to 12. It is found that the Poisson distribution with one free parameter (λ) is inadequate, but the negative binomial distribution (NBD) with two free parameters (p, k) fits the distribution well as vouched by a χ^2-test. The NBD can be interpreted as a "mixture" of Poisson and Gamma distributions. It is suggested that this is an appropriate model for the distribution of x.

Surprisingly, a 3-parameter lognormal distribution (LND2) also fits the observed distribution of x equally well. The popular model for LND – theory of proportional effect – does have some relevance for the crossword puzzle solving. It appears that the dichotomy (NBD and LND2) exists only for a limited range of (p, k) of the NBD. Both the NBD and LND2 have wide application in many branches of science. It is conjectured that NBD may apply to all crossword puzzles and all solvers. The present work has relevance to linguistics, especially the co-existence of random and orderly features as reflected in the many statistical regularities of language texts.

1. INTRODUCTION

Crossword puzzles are the most popular word puzzles and are daily features in almost all the widely-read newspapers and magazines in the world. Typically a puzzle consists of a square grid (say 15 × 15) with words, "across" and "down" (crosswords) delineated by a

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symmetrically-placed set of black squares. The number of words is about 30 (28 to 34 in most 15×15 grids) roughly shared equally by ‘‘across’’ and ‘‘down’’ and each crossword is the solution of a ‘‘clue’’ accompanying the grid. Occasionally a clue can include more than one crossword. The placement of the black squares is subject to the condition that the grid pattern remains the same when rotated by 180°. To begin with, the grid is blank and the solver has to fill in the words with the help of the clues.

Crossword puzzles can be broadly classified into two types: (1) the American style and (2) the British style (cryptic). There is considerable difference between the two in the grid structure, types of words and the style of the clues. In Britain, Europe and India the cryptic puzzles are very popular. The puzzle described in the previous paragraph is an example of a cryptic puzzle.

In this study we consider only the cryptic crossword puzzles. An interesting statistic worthy of investigation by a solver is the probability distribution of the number of unsolved clues in the grid or the number of incomplete words (‘‘failures’’). The distribution clearly depends on many factors including the skills of the composer and the solver and the clueing style. But these are not generally relevant for the purely statistical study. We will discuss this aspect later.

2. CROSSWORD PUZZLES: DATA ON FAILURES IN SOLUTION

I have been an enthusiastic solver of crossword puzzles for over 40 years. In my active professional life in Mumbai, the puzzles were from the daily *Times of India* and later after my retirement in Chennai, from the daily *The Hindu*. When the idea of a statistical study of failures arose about 25 years ago, I started to standardize my style and strategy of solving and recorded the number of unsolved clues (failures). The results are data accumulated over five years (1987–1991) for *Times of India* (TOI) puzzles and over five years (2004–2008) for *The Hindu* (TH). They are presented in Table 1.

Weekday and Sunday crossword puzzles are analysed separately because they are clearly of different types: while the weekday puzzles are ‘‘Indian’’ with local flavour, the Sunday puzzles are of British origin with allusion to British life and locales and are distinctive in their clueing pattern. This is true both for TOI and TH Sunday puzzles. N(OBS) are the number of puzzles with the number of failures (x) equal to 0, 1, 2, ...

Table 1. Crossword puzzles: failure analysis data.

	HW	HS	TW	TS	ALLCW
x	N(OBS)	N(OBS)	N(OBS)	N(OBS)	N(OBS)
0	598	70	933	124	1725
1	340	52	340	49	781
2	241	54	119	29	443
3	134	24	48	13	219
4	65	13	16	9	103
5	48	11	10	3	72
6	17	4	1	3	25
7	9	1	1	3	14
8	8	1			9
9	4	2			6
10	1	3			4
11					
12	1				1
13	2				2
Total	1468	235	1468	233	3404

HW: *The Hindu* weekdays, HS: *The Hindu* Sundays, TS: *Times of India* Sundays, TW: *Times of India* weekdays, ALLCW: Sum of all preceding four.

Values of x are in column 1 and N(OBS) in columns 2 to 6. The last column is for the totality of puzzles (sum of columns 2 to 5). We note at a first glance: (1) the number of failures can be as high as 10 – the distribution in x has long tails. For example for ALLCW, out of a total of 3404 puzzles only 1725 (about 50 %) account for no failures ($x = 0$) and about 1% account for $x \geq 7$. (2) There is considerable variation in the distribution of x in the four categories HW, HS, TW and TS.

3. NEGATIVE BINOMIAL DISTRIBUTION FOR THE PROBABILITY OF FAILURES

We can consider the observations as an example of random count data of integer values ($x = 0, 1, 2, \ldots$). The first choice to fit such a distribution is usually the Poisson distribution (PD), which depends only on one parameter λ.

$$\text{PD: Prob}(x) = e^{-\lambda}\lambda^{x}/x! \ (\lambda > 0, x = 0, 1, 2, \ldots). \tag{1}$$

(Verify that the sum of Prob(x) over all possible integer values of x is 1.) Given a numerical value for λ the PD can be obtained for all x. The two most fundamental measures of any frequency distribution are the mean ($m = \langle x \rangle$) the weighted average of x and the standard deviation s ($= \surd(\langle x^2 \rangle - \langle x \rangle^2)$). For PD it is easily seen that $m = s^2$ and further both equal λ. So the Poisson parameter λ is actually the mean m of the distribution (see, for example, Feller, 1972).

When variance s^2 exceeds m the data is "over-dispersed" with a long tail and an additional parameter, besides λ, is required to characterize the distribution. The negative binomial distribution (NBD) is often invoked for such data (Feller, 1972). The probability distribution or the density function is given by

$$\text{NBD: } P(x) = \text{Prob}(x) = \{\Gamma(k+x)/[\Gamma(k)x!]\}p^k q^x \quad (k > 0, x = 0, 1, 2, \ldots). \tag{2}$$

where p and k are the two parameters and $q = 1 - p$. Here $\Gamma(k)$ is the Gamma function defined by $\Gamma(k) = (k-1)\,\Gamma(k-1)$ for $k > 1$. When k is an integer $\Gamma(k) = k(k-1)(k-2)\ldots 1 = k!$. $\Gamma(1) = 1$.

In Table 2, the mean m and the standard deviation s are given for HW, TW, HS and TS (e.g. for HW $m = 1.3876$, $s = 1.7302$). Clearly variance s^2 exceeds m in all cases and it is worth trying a fit to NBD. The parameters p and k of NBD can be derived from the data (m and s): $p = m/s^2$ and $k = m\,p\,(1-p)$. Knowing p and k, Prob(x) can be easily calculated with the recurrence relations (implied by Equation (2)):

$$P(0) = p^k \qquad (x = 0) \tag{3a}$$

$$P(x+1) = P(x)[q(k+x)/(1+x)] \qquad (x = 1, 2, \ldots, n-1). \tag{3b}$$

These probabilities are multiplied by N_T (total number of puzzles in the category given in the last row of Table 1) and given in Table 2 as N(EXP) (columns 3, 5, 7, 9, 11). It is a pure coincidence that N_T is the same for HW and TW (1468).

Even a casual comparison of N(OBS) (repeated from Table 1) and N(EXP) suggests very good agreement between the two since in most cases the absolute difference $|\,N(\text{EXP}) - N(\text{OBS})\,| < \surd N(\text{EXP})$, the sampling error. However, a more objective test for 'goodness of fit of a hypothesis' – in this case the NBD – to observed data is the "χ^2-test"

Table 2. Negative binomial fits to failure data.

	HW		TW		HS		TS		ALLCW	
x	N(OBS)	N(EXP)	N(OBS)	N(EXP)	N(OBS)	N(EXP)	N(OBS)	N(EXP)	N(OBS)	N(EXP)
0	598	584	933	932	70	70	124	121	1725	1716.00
1	340	375	340	339	52	59	49	55	781	813.00
2	241	222	119	125	54	41	29	28	443	414.00
3	134	127	48	46	24	26	13	14	219	216.00
4	65	71	16	17	13	16	9	8	103	114.00
5	48	40	10	6	11	10	3	4	72	60.54
6	17	22	1	2	4	6	3	2	25	32.30
7	9	12	1	1	1	3	3	1	14	17.28
8	8	7			1	2			9	9.27
9	4	4			2	1			6	4.98
10	1	2			3	1			4	2.68
11	0	1							0	1.45
12	1	1							1	0.78
13	2	0							2	0.42
Total	1468	1468	1468	1468	235	235	233	233	3404	3404.00
m	1.388		0.578		1.813		1.013		1.042	
s	1.730		0.958		1.972		1.490		1.514	
ndf	7		3		4		3		8	
χ^2	9.75		3.10		6.44		1.21		9.70	

(chi squared test). The χ^2 is given in a quasi-symbolic form as $(\text{O-E})^2/\text{E}$ summed over all the observed (O) and expected (E) values of N for $x = 0$, 1, 2, ... n. The χ^2 values and the number of degrees of freedom n_{df} are given in Table 2. Here $n_{df} = n - 1 - l$ where n is the number of pairs (O, E) and l is the number of parameters derived from the data (Cramer 1955). Here $l = 2$ and $n_{df} = n - 3$. For example for HW, $\chi^2 = 9.75$ and $n_{df} = 7$. From the χ^2 tables (Cramer, 1955) one finds that for $n_{df} = 7$, χ^2 will exceed 12.00 with a probability 0.1 (a value generally adopted for testing goodness of fit). Similarly for $n_{df} = 8, 4, 3$, χ^2 will exceed 13.4, 7.8 and 6.25 respectively with probability 0.1. Therefore the observed χ^2 values (9.75, 3.10, 6.44, 1.21 and 9.70) in Table 2 are all acceptable. In other words the hypothesis of NBD cannot be rejected. In Figure 1 are given the N(OBS) and N(EXP) vs. x for all the five sets of data.

4. WHY IS THE NBD A CLOSE FIT TO CROSSWORD PUZZLE FAILURE DATA?

To understand the effectiveness of NBD for the distribution of the number of failures in crossword puzzles, we have to first understand the genesis of the Poisson distribution based on the concept of Bernoulli trials. Consider repeated independent trials (or experiments) with only two possible outcomes: failure with probability u and success with probability v $(= 1 - u)$. Such trials are called Bernoulli trials. In a string of n trials the probability of x failures and $n - x$ successes is given by the binomial distribution (BD):

$$\text{BD: Prob}(x, n) = \tbinom{n}{x} u^x v^{n-x} \qquad (x = 0, 1, 2, \ldots, n). \tag{4}$$

Here $\binom{n}{x}$ stands for $n(n-1)\ (n-2)\ \ldots\ (n-x+1)/x!$. The name binomial distribution (BD) arises from the fact that the above is the xth term in the binomial expansion $(u + v)^n$. We note incidentally that when summed over all x we get $(u + v)^n = 1$, since $v = 1 - u$.

When the number of trials n is large and u is low so that $nu = \lambda$ is a small number, then the BD becomes the PD (Cramer, 1955) like in Equation (1):

$$\text{PD: Prob}(x) = e^{-\lambda}\lambda^x/x! \qquad (\lambda > 0, x = 0, 1, 2, \ldots, n).$$

It is a remarkable fact that PD has universal application: e.g. radioactive disintegration, bomb hits of London during the war, wrong connections

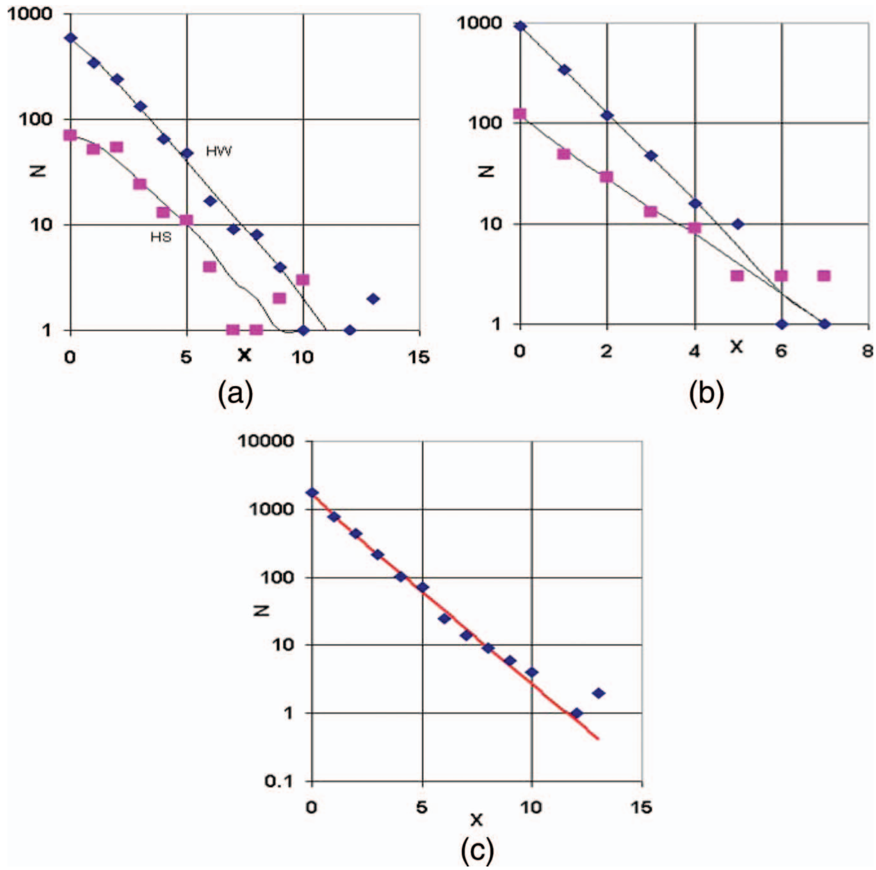

Fig. 1. Plots of N(OBS) and N(EXP) vs. x (NBD). N(OBS) are the observed values and N(EXP) the corresponding values expected for the negative binomial distribution (NBD). x is the number of failures (a) *The Hindu* (HW, HS), (b) the *Times of India* (TW, TS), (c) *The Hindu* and the *Times of India* (ALLCW). The markers are for the observed data and the lines are the best-fit NBD to data.

in telephone exchange, bacteria cluster counts in blood samples, etc. (Feller, 1972). Note that PD is a discrete distribution, only for integral values of x. The key requirements for PD are low constant probability of failure (u), large sample size (n) and the independent nature of the trials.

It is clear that PD is inadequate for our data (Section 3, paragraph 3) because the number of crosswords in a puzzle is small and more importantly the probability of failure u is not the same for all puzzles because of their in-built diversity, e.g. different composers, styles of cluing, deliberate introduction of variation in the complexity of a puzzle. Such variability is reflected in the real world of crossword puzzles and the observed data will include a mixture of numerous PD's with different characteristic parameters (say $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots$). One can model this fact by postulating that λ is distributed with a probability density function $g(\lambda)$ with $\lambda > 0$. Note λ is a real number, not just an integer. Then the probability of failures for a given x will be the sum of probabilities contributed by PD's with different λ's weighted by their density $g(\lambda)$. So we have Prob(x), which is a "mixture distribution" (MD):

$$\text{MD: Prob}(x) = \int_o^\infty \text{Poisson } (x|\lambda)\ g(\lambda)\ d\lambda \tag{5}$$

If $g(\lambda)$ is a gamma distribution $\Gamma(\lambda)$, then it can be shown that the "mixture distribution" is NBD (Feller 1972)!

$$\text{Gamma distribution: Prob}(\lambda) = \lambda^{(\alpha-1)}e^{-\lambda/\beta}/[\Gamma(\alpha)\beta^{\alpha}] \qquad \alpha > 0,\ \beta > 0. \tag{6}$$

It has two parameters: α the shape parameter and β the scale parameter. The choice of a Γ-distribution for $g(\lambda)$ is very appropriate because it is very similar to the PD; in fact one may regard the Γ-distribution as – in some sense – a generalization of PD for a continuous variable (λ). Compare Equations (1) and (6); by setting $\beta = 1$ and noting that Γ-function is the factorial function. Equation (5) becomes

$$\text{MD: Prob}(x) = \{\Gamma(\alpha + x)/[\Gamma(\alpha)x!]\}(1+\beta)^{-\alpha}\{1 - (1/(\beta + 1)\}^{x}. \tag{7}$$

By averaging over λ, λ drops out of Equation (7) and the NBD depends only on α, β of the Γ-distribution.

Comparing Equations (7) and (2) we note that α, β are related to p, k as follows: $\alpha = k$ and $\beta = (1-p)/p$.

Values of α, β, p, k for all the five sets of crosswords failure data (HW, TW, HS, TS, ALLCW) are given in Table 3. The corresponding Γ-distributions (Equation 6) are plotted in Figures 2(a), (b), (c). We note the following: in all the five sets p values are almost the same (≈ 0.46) for all except TW (0.63). Similarly β values are close to 1.20 in all except for

Table 3. Negative binomial distribution parameters.

Parameter	HW	TW	HS	TS	ALLCW
p	0.464	0.629	0.466	0.455	0.455
k	1.199	0.983	1.583	0.844	0.869
alpha	1.199	0.983	1.583	0.844	0.869
beta	1.157	0.589	1.145	1.200	1.172

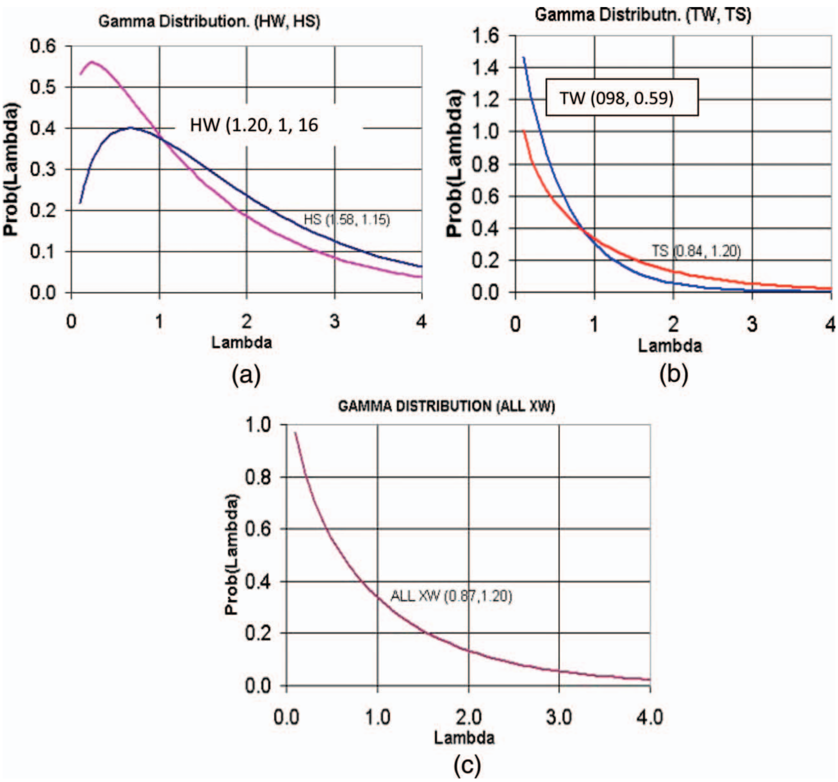

Fig. 2. Plots of gamma distribution function, one of the components of the mixture distribution in the NBD. (a) *The Hindu* (HS, HW), (b) the *Times of India* (TS, TW), (c) *The Hindu* and the *Times of India* (ALLCW). The numbers in parentheses are alpha and beta of the Gamma distribution. See text for details.

TW (0.589). α ($=k$) values range from 0.84 to 1.6. ALLCW and TS have nearly identical parameters and so have the same $p(x)$ for $x=0$, 1, 2, … , n.

We can therefore answer the question posed at the beginning of the section. While the basic statistical description of $p(x)$ is Poissonian in character, because of variation in its characteristic parameter λ across the diverse puzzles that constitute the total sample ($N_T = 3404$) a generalization of PD invoking a distribution in λ (Γ-distribution) is natural. This leads to a mixture distribution, which is the NBD. Whereas PD depends only on one parameter (λ), NBD depends on two (p, k). The additional parameter essentially helps in obtaining the needed over-dispersion (variance > mean), already mentioned (Section 3) whereas in PD, variance = mean. When interpreted as a "mixture distribution" the NBD is equivalently characterized by α, β (instead of p, k), which determine the Γ-distribution.

Now we ask: "Is it reasonable to expect NBD to apply for every solver?" According to the model described, the complexity of crossword puzzles and their variability will depend both on the solver and the composer(s). There is no reason to suppose the NBD will not apply universally to all crossword puzzles and solvers. So, for each solver of crossword puzzles, one can expect NBD to apply, each with a characteristic pair of parameters (p, k) that quantifies the gap between the skills of the composer and solver. For the author (p, k) = (0.455, 0.869) (Table 3 ALLCW).

Some readers will be curious about the term "negative" in NBD. It turns out that Equation 2 (NBD) can be rewritten as p^k times $\binom{-k}{x}(-q)^{-k}$. The latter part is the xth term in the binomial expansion of $(1 - q)^{-k}$, which has a negative power index.

5. NBD MODELS IN SCIENCE

NBD has diverse applications in behavioural science, e.g. in insurance industry and marketing of branded products. Car accidents are modelled by NBD, which is used in determining the insurance premium rates known as "tarification" in insurance industry (Dionne & Vanasse, 1988). In general the number of accidents – low-probability events – among a group of people is not a PD but an NBD (Greenwood & Yule, 1920). In marketing, in a given period the purchase of a branded product by a random group of consumers follows NBD, which is used to predict purchase patterns (Ehrenberg, 1990). For a comprehensive treatment of NBD and its applications see the recent *Book of Negative Binomial*

Regression by Joseph M. Hilbe (2007). For a lucid exposition of NBD modelling see Johnson and Vieux (2006). As an example from physical sciences: in high-energy particle physics when two energetic elementary particles (like protons from an accelerator) collide, the multiplicity distribution of the newly-produced secondary particles in the collision conforms to NBD (Giovannini & Van Hove, 1986).

There are numerous ways of modelling statistical data or even a particular distribution like NBD. It is claimed "there are at least a dozen distinct probabilistic processes that give rise to NBD" (Boswell & Patil, 1970). The "mixture distribution" (Poisson-cum-Gamma distribution) model is only one of them.

As a likely alternative probabilistic model for NBD we mention the following without going into details. NBD is an approximation to the Polya distribution based on the "urn model" (Feller, 1972). The urn has black (b) and red (r) balls. A ball is drawn at random, its colour noted and replaced in the urn. Then some more balls (c) of the *same* colour are added. Now the procedure is repeated (drawing a ball at random). The Polya distribution $p(n_1, n)$ is the probability that in a total of n drawings, n_1 are black (in any order). In this scheme, drawing of either color increases the probability of the same colour at the next drawing (a "contagious" effect). Under certain approximations the Polya distribution becomes NBD.

It is also possible some probability distribution, other than NBD can fit the failure data in crossword puzzles. Note the cautious claim made in Section 3 that the "hypothesis of NBD cannot be rejected" implying that there may exist other hypotheses which meet the test criteria.

In the next section we pursue this idea further. It is to be emphasized that large sample sizes help in reducing uncertainties in modelling statistical data. The present sample size (3404) is modest, but it is 10 years worth of patient work in documenting the failure data in crossword puzzles. I believe this data is perhaps unique in puzzle solving behaviour although it pertains to an individual (in this case the author).

In early stages of my investigation (about 20 years ago) of crossword puzzle failure data in a year (small sample size of about 300) it appeared that a lognormal distribution would fit the data (Aitchison & Brown, 1957). As the sample size increased over the years, it was clear that a simple lognormal distribution (2-parameter) is not a good fit to the observations. Then it was discovered that NBD would work! However, I never gave up trying lognormal type of distributions since they have some attractive features in modelling. Actually it turns out that a 3-parameter lognormal distribution will satisfy the observed data with χ^2 values comparable to those obtained with NBD.

6. THE LOGNORMAL DISTRIBUTION

The normal density function (ND) is given by

$$\text{ND: Prob}(x) = (1/\sigma\sqrt{2\pi})\exp\left[-(x-m)^2/2\sigma^2\right] \quad -\infty < x < \infty \tag{8}$$

where m is the mean and σ is the standard deviation. The function is symmetric about $x = m$ and is "bell-shaped". An important variant of the ND is the lognormal distribution (LND); in LND, In x is normally distributed:

$$\text{LND1: Prob}(x) = (1/\sigma\sqrt{2\pi})(1/x)\exp\left[-(\ln\ x-m)^2/2\sigma^2\right] \quad x > 0. \tag{9}$$

Here ln x is the natural logarithm of x. Unlike ND, LND is skewed with a long tail – just like the NBD – with two parameters (m, σ). Yet another version of LND is the 3-parameter function in which ln $(x + X_0)$ is normally distributed.

$$\begin{aligned} \text{LND2: Prob}(x) = {} & (1/\sigma\sqrt{2\pi})[1/(x+X_0)] \\ & \exp\left\{-[\ln(x+X_0)-m]^2/2\sigma^2\right\} \quad x > X_0 \end{aligned} \tag{10}$$

X_0 can be positive or negative (Cramer, 1955). When $X_0 = 0$, LND2 reduces to LND1.

To fit ND to an observed probability distribution $p(x)$ we proceed as follows. Rewriting Equation (8).

$$\begin{aligned} \text{ND: Prob}(x) &= (1/\sigma\sqrt{2\pi})\exp(-z^2/2) \\ \text{where } z &= (x-m)/\sigma \qquad -\infty < z < \infty. \end{aligned} \tag{11}$$

Here z is the standardized normal variable. The cumulative probability p $(x \leq X)$ is

$$G(X) = (1/\sigma\sqrt{2\pi})\int_{-\infty}^{X} \exp(-z^2/2)dz. \tag{11a}$$

For a given $G(X)$ there is a corresponding unique value $Z(X)$ which can be obtained from standard tables of ND (Cramer, 1955). From the observed probability distribution $p(x)$ we obtain the cumulative probability $p(x \leq X) = p(0) + p(1) + p(2) + \ldots\ p(X)$.

By setting the above equal to $G(X)$ in Equation (11a) we obtain the corresponding $Z(X)$. From Equation (11)

$$Z = (X - m)/\sigma \text{ or } X = \sigma Z + m. \tag{12}$$

A plot of X vs. Z is linear with the intercept on X-axis equal to m and slope σ. Observationally a number of pairs (Z, X) can be plotted and the constants m, σ obtained by linear regression analysis. For LND1 Equation (12) becomes

$$\ln\ X = \sigma Z + m \tag{12a}$$

and for LND2

$$\ln\ (X + X_0) = \sigma Z + m. \tag{12b}$$

I tried to fit the observed probability of failures $p(x)$ (Table 1) to LND1 (Equation (12a)) and found that ln x vs. Z is not linear; the curve is convex instead of a straight line. Instead, LND2 with an additional parameter X_0 provides a very good linear fit of ln $(X + X_0)$ vs. Z. First, X_0 has to be obtained from the data before using linear regression of Equation (12b). For this, three points (X_1, Z_1) (X_2, Z_2) (X_3, Z_3) were chosen for Equation (12b) (Cramer, 1955); $X_1 = 0$, $X_2 = 3$, $X_3 = 8$ and the corresponding Z_1, Z_2, Z_3 respectively. Then one can solve for unknowns X_0, m, σ. But here the three points were used only to fix X_0 and using this known X_0 linear regression can be used with about 10 points to determine σ and m. This was done only for two sets of data HW and ALLCW for which significant tails of the distribution of failures were available.

In Figure 3 (a), (b) the plots of Equation (12b) are shown for HW and ALLCW. In Figure 4 (a), (b) the observed $p(x)$ and the corresponding lognormal values are compared. As for the χ^2 values, the n_{df} is 7 $(= 11 - 4)$ and χ^2 values > 12.0 are expected with probability 0.1. The observed values are 6.1 for HW and 9.3 for ALLCW. Again, we conclude that the fits of LND2 (3-parameter) are acceptable. In Table 4 are given the parameters of LND2 (X_0, m, σ) and also the parameters of NBD (p, k) for comparison.

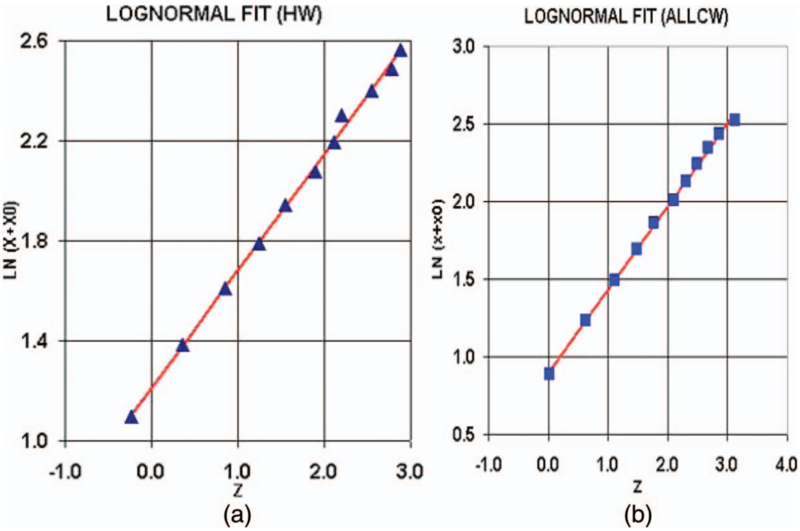

Fig. 3. Plot of ln $(X + X\text{o})$ vs. Z. (a) HW, (b) ALLCW. The straight line is the best fit to data (linear regression).

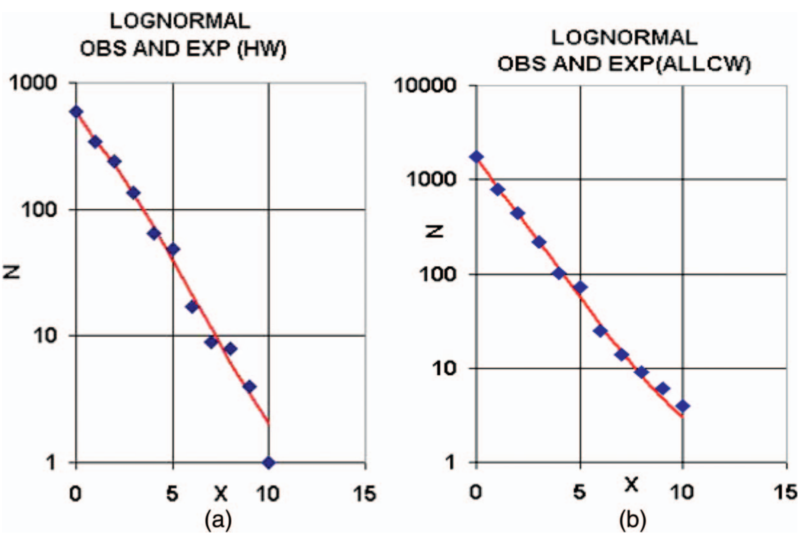

Fig. 4. Plots of N(OBS) and N(EXP) vs. x. (Lognormal). N(OBS) are the observed values and N(EXP) the corresponding values expected for the lognormal distribution LND2. x is the number of failures (a) *The Hindu* (HW), (b) *The Hindu* and the *Times of India* (ALLCW). The markers are for observed data and the lines are the best fit to LND2 data.

Table 4. Comparison of NBD and LND2 parameters.

	NBD		LND2		
	p	k	X_0	m	sigma
HW	0.464	1.199	3.000	1.214	0.467
ALLCW	0.455	0.869	2.432	0.895	0.536

7. A MODEL FOR LOGNORMAL DISTRIBUTION

Lognormal distribution appears frequently in natural and behavioral sciences: e.g. in biology, the sizes of organs and in economics, values of income (Aitchison & Brown, 1957; Crow, 1988; Cramer, 1955). In statistical linguistics, texts are structured in different hierarchical levels: letters of the alphabet, syllables, words, phrases, sentences, paragraphs, etc. At all levels the lognormal distribution is pervasive (Dolby, 1971): e.g. word-length (the number of letters in a word) and sentence-length (the number of words in a sentence) conform to a lognormal distribution (LND1) (Naranan & Balasubrahmanyan, 1992b, 2005b). For other interesting applications of LND see Naranan (1992). A popular model for such statistics is the "theory of proportional effect". Briefly the theory is the following. For example, suppose the size of an organ (x) is a cumulative sum of many (n) independent small incremental steps. Further let the *fractional* increase dx/x at each step be a random number ε so that

$$dx_i/x_i = \varepsilon_i \ (i = 1, 2, 3, \ldots, n). \tag{13}$$

This is characteristic of exponential growth. Summing over all steps

$$\int_{x1}^{xn} dx_i/x_i = \varepsilon_1 + \varepsilon_2 + \varepsilon_3, \ldots, \varepsilon_n \text{ or } \ln\ x_n = \ln\ x_1 + \varepsilon_1 + \varepsilon_2 + \varepsilon_3, \ldots, \varepsilon_n.$$

If x_1 is also a random variable, then ln x_n is a sum of independent random variables. It follows from the central limit theorem that ln x_n is normally distributed or x_n is lognormally distributed (Cramer, 1955). Such a growth is called a random or stochastic *multiplicative* process. Note the key ingredient in the model is the "current value" is dependent on all the "past values", or the previous history of the growth process. In contrast a random *additive* process (i.e. $dx_i = \varepsilon_i$ instead of $dx_i/x_i = \varepsilon_i$ from Equation (13) leads to the normal distribution for x_n.

The above model can be suitably modified for the 3-parameter LND2 (Equation (10)) by postulating

$$dx_i/(x_i + X_0) = \varepsilon_i \ (i = 1, 2, 3, \ldots, n) \tag{13a}$$

to replace Equation (13), leading to a lognormal distribution for $(x_i + X_0)$, where X_0 is a constant. This implies dx_i is proportional to $(x_i + X_0)$ and not x_i; in other words, both additive and proportionate effects are in operation.

Does the theory of proportionate effect have any relevance for the distribution of the number of failures in crosswords, $p(x)$? There is a feature in the accumulation of "failures" in a puzzle, which has some resemblance to the proportional effect. The first failure occurs at random in the grid ($x = 1$). But when $x = 2$, the second failure is more likely to occur in a crossword that intersects the first failure, because it gets no help from the first failure (which is an unknown word). Similarly when $x = 3$ the third failure is more likely to be one of the words intersecting either or both the first and second failures. It is clear that there is a semblance of proportional effect here although it is difficult to quantify. The proportional effect is only partial since a new failure can also occur in a random crossword on the grid. This additive effect may also contribute to the "evolution" of the number of failures. Observationally too, I have noticed that failures have a tendency to occur in one or more clusters in the grid. The LND2 with an extra parameter X_0 may be a good way to model this fact. Admittedly the model is semi-quantitative at best. It is worth citing here an analysis of the popular board game "Snakes and Ladders". It is claimed that the number of moves to reach the end of the game – after ascending the ladders and descending the snakes – follows a lognormal distribution. In this game, it is obvious that the "current position" of a player on the board depends on all the previous moves, although each move is decided randomly by throwing a dice.

8. COMPARISON OF NEGATIVE BINOMIAL AND LOGNORMAL DISTRIBUTION MODELS

It is not often that we find observations that are equally well described by two different well-known and popular statistical distributions. Here we have the distribution $p(x)$ of x the number of unsolved clues in a crossword puzzle, satisfying the "goodness of fit of hypothesis" test – the χ^2 test – of two different hypothetical statistical distributions equally well. They are the 2-parameter NBD and the 3-parameter LND2. Can we choose one as better than the other? Obviously, the 2-parameter NBD has one free parameter less than the 3-parameter LND2 for adjusting the data to theory, and is the preferred one. It is possible that an increase in sample size N_T will help resolve the dichotomy. (I have already mentioned that small samples of data seem to fit a 2-parameter LND1). But this requires more data from more solvers.

It appears that LND2 may mimic NBD in a narrow range of values of the parameters p and k characterizing the NBD. Here we have $p \approx 0.46$ and $k = 0.9 - 1.2$ (Table 4) characteristic of the solver (author). For other values of (p, k) – other solvers and/or puzzles – the correspondence of NBD and LND2 may not hold. In other words, NBD may be the only one that is relevant for all puzzles and solvers.

Viewing the same set of observations from two different angles will add to our understanding of the underlying mechanisms governing them. Both NBD and LND have wide ranging applications and are well supported by robust theory. Robustness is also evident in the data since the totality of data (ALLCW) as well as its 4 constituents (HW, HS, TW, TS) all conform to NBD (Tables 2, 3). Similarly ALLCW and its constituent HW both conform to LND2 (Table 4). This suggests that superposition of multiple sets of data still conforms to the same distribution (NBD and LND2) that applies to the individual sets.

As regards the modelling of data: NBD offers a straightforward and plausible interpretation as a mixture of Poisson and Gamma distributions. For LND2 there is some indication of the applicability of the theory of proportional effect. In summary the NBD has a clear advantage over the LND2.

For a comprehensive compendium of Poisson, negative binomial, Polya, lognormal distributions, their variants and the interrelationship among some of them, see Wimmer and Altmann (1999).

9. CONCLUSIONS AND SUMMARY

I believe the observation on the distribution of the number of unsolved clues in cryptic crossword puzzles presented here is perhaps unique in behavioural science, e.g. the puzzle-solving behaviour of linguistic puzzles. The sample size of total data (3404) – gathered over a decade by the author – is substantial enough to examine the details of the distribution. Considering that crossword puzzle solving is a major recreational and intellectual activity in the masses, the study is likely to be important for understanding the nature of puzzle solving. It is pertinent to note that crossword puzzle solving is a recommended pursuit for helping ward off dementia in old age. The investigation is also of linguistic significance since the clues reflect creative and innovative aspects of word usage in syntactic and semantic sense. For a novice, the cryptic crossword clues make little sense and even appear "insane" and "crazy". The composer revels in various tricks of word-play: anagrams, puns, reversals, words nested in words etc. (see, for example, Balfour, 2008). In this the British cryptic puzzles differ from their American counterparts. The grids are dense in the American puzzles and skeletal in the cryptic. There are 70 to 80 crosswords in a 15 × 15 American puzzle compared with 28 to 34 in cryptic puzzles. The denser packing of words in the American version is made possible by resorting to words (as solutions) that are very rare and unfamiliar – most of them not in dictionaries – acronyms, etc. But to compensate for the challenge, the clueing is straightforward unlike the convoluted and sometimes "Rube-Goldberg" style of clueing in cryptic puzzles (Gaffney, 2006).

Language as a tool for communication – its most compelling rationale – is simple, direct and lucid in normal usage; as a puzzle it is meant to intrigue and entertain. For the solver it is not only an intellectual challenge, but also enjoyable. At the other extreme is secret coded communication or cryptography. Singh (2000) alludes to a connection between skills in crossword puzzle solving and code-breaking (cryptanalysis). In 1942, during World War II, the British government recruited staff for the project to crack the German secret code, Enigma. One of the main criteria for eligibility was the ability to completely solve a crossword puzzle in 12 minutes or less. The British crossword puzzles perhaps derive their popular label "cryptic" from cryptography.

Just as in linguistics there are surprising regularities such as Zipf's Law of word frequencies (Zipf, 1949; Baayen, 2001), in the solving of crossword puzzles too there are statistical regularities as demonstrated in this article. Both linguistic discourses and the sets of clues in crossword puzzles are free creations of the mind, yet they exhibit some regular and universal statistical behaviour. Randomness plays an important role in puzzle solving as exemplified in the NBD model, which is an extension of the Poisson distribution characteristic of random counting. This is interesting because the puzzles themselves are purely games of skill and not chance and the word solutions to clues are unique.

Many complex systems, well-organized hierarchical structures like a language text or a DNA sequence for example, exhibit co-existing order and randomness. For a detailed discussion see Balasubrahmanyan and Naranan (1996, 2005a).

What are the desirable future investigations in crossword puzzle solving? A large sample size (N_T) is crucial for statistical analysis of data with long tails. This can be achieved in three ways: (A) many crossword puzzles and one solver, (B) one crossword puzzle and many solvers and (C) many puzzles and many solvers. The present attempt is an example of (A). To achieve (B), the following is suggested. A composer of a published puzzle can add a footnote requesting each solver, who tried to complete the puzzle, to send his number of unsolved clues by SMS to him. The composer can then make the data collected available to anyone interested in analysing it. Repetition of (A) and or (B) will make up category (C). There is a case for an organized group of solvers undertaking the exercise. With many crossword puzzle aficionados in long-standing pursuit of the hobby there is great potential for immense volume of statistical data. It will be interesting to see if the American-type puzzles too show similar statistical properties.

In summary, solutions to cryptic crossword puzzles accumulated over a decade by the author (total sample 3404) yield a probability distribution $p(x)$ of the number of failures. First the total sample is divided into four groups and each analysed separately for fit to a statistical distribution. The Poisson distribution with a single parameter (λ) is a poor fit to $p(x)$. The negative binomial distribution (NBD), a generalization of the Poisson distribution with two parameters (p, k) fits very well all the sets of data separately and in totality (Table 2, 3; Figures 1, 2). The pair (p, k) is characteristic of the solver; in this case the author has $(p, k) = (0.455, 0.869)$. When a group of puzzles of varying complexity is involved their combined effect on $p(x)$ can be regarded as yielding a mixture distribution of x, in which a fixed λ is replaced by a varying λ distributed according to the Gamma distribution.

The $p(x)$ is also equally well fit by a 3-parameter lognormal distribution. For total data (ALLCW) the three parameters (X_0, m, σ) are (2.42, 0.895, 0.536). It is suggested that the dichotomy – two different statistical distributions fitting the same data – may be true only for a narrow range of (p, k) values. For another solver with different (p, k) only the NBD may be a valid choice. Further, NBD is the preferred distribution because it has only two free parameters instead of three. The mixture distribution model of NBD is a plausible one reflecting reality, whereas the model for LND based on the theory of proportional effect is somewhat qualitative.

This investigation is new in behavioural science (linguistics, word puzzle solving) and warrants more data gathering from a group of puzzle solvers. I conclude with a conjecture that is prompted by the model proposed for the observations (Section 3). Negative Binomial Distribution will prove to be appropriate for all crossword puzzles and all solvers and therefore universal.

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