Neutrosophic Regression and Possible Nonlinearity of Hubble Law: Some Preliminary Remarks

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ABSTRACT

It is known to experts, that in the nonlinear regression analysis, because numerous curve fitting methods exist, which allow the statistician to cook up the data according to what he/she wants to see. Such a deep problem in nonlinear regression methods will be discussed in particular in the context of analyzing Hubble diagram from various existing data. It is our aim to distinguish the raw data and foregone conclusions, in order to arrive at a model-independent conclusion. As a preliminary remark, we deem that it remains possible that the Hubble law exhibits nonlinearity, just like proposed by Segal & Nicoll long time ago. More researches are needed to verify our proposition.

1. Introduction: finding the best way for nonlinear regression

Modern measurement techniques allow researchers to gather ever more data in less time. In many cases, however, the primary or raw data have to be further analyzed, be it for the verification of a quantitative model (theory or hypothesis) thought to describe experimental data, quantitative comparison with other data, better visualization or simply data reduction. To this end, a wealth of information collected during a measurement or a series of measurements has to be reduced to a few characteristic parameters. This can be done by regression analysis, a statistical tool to find the set of parameter values that best describes the experimental data by assuming a certain relationship between two or more variables.[3]

But we should always remember the saying of Mark Twain in Chapters from My Autobiography, published in the North American Review in 1906. "Figures often beguile me," he wrote, "particularly when I have the arranging of them myself; in which case the remark attributed to Disraeli would often apply with justice and force: *'There are three kinds of lies: lies, damned lies, and statistics.'*"[1]

The above saying seems to be quite relevant in the nonlinear regression analysis, because numerous curve fitting methods exist, which allow the statistician to cook up the data according to what he/she wants to see.

Two of the sources of such a problem especially in nonlinear curve fitting, are namely: Gauss-Newton method and also model indeterminacy. Yes, there are new methods such as Levenberg-Marquardt algorithm for nonlinear regression, but it seems such an algorithm will not be free from problems arising from model indeterminacy.

Such a deep problem in nonlinear regression methods will be discussed in particular in the context of analyzing Hubble diagram from various existing data. It is our aim to distinguish the raw data and foregone conclusions, in order to arrive at a model-independent conclusion. As a preliminary remark, we deem that it remains possible that the Hubble law exhibits nonlinearity, just like proposed by Segal & Nichols long time ago.

Nonetheless, this is only an early investigation. More researches and observations are recommended to verify our propositions.

2. Neutrosophic regression and fundamentals of regression analysis

Quantitative experiments aim at characterizing a relationship between an independent variable (x), which is varied throughout a measurement, and a dependent variable (yobs), which is observed/measured as a function of the former. The fitting method presented in this protocol requires that the independent variable can be measured with much greater precision than the dependent variable1. In other words, experimental errors (uncertainties) in the independent variable are small compared with errors in the dependent variable (see below). This is usually the case with experiments in which the value of the independent variable follows a predetermined trajectory and the experimental readout reports on the value of the dependent variable. The primary output of a measurement is a set of conjugated independent and dependent variables, which is called data or dataset. In addition to an experimental dataset, regression analysis requires a regression equation (also termed fitting function). This is a mathematical relationship describing the dependence of the dependent variable on the independent variable using one or more parameters. These parameters (also called adjustable parameters, fitting parameters or coefficients) are the same for every data point, i (i.e., every combination of xi and yi). In the simplest example of a proportionality (y = a × x), the only parameter, a, is the slope of a straight line through zero.[3]

According to FS [2], the Neutrosophic Least-Squares Lines that approximates the neutrosophic bivariate data $(x1,y1),(x2,y2),\ldots,(xn,yn)$ has the same formula as in classical statistics

$$\hat{y}=a+bx \tag{1}$$

where the slope

$$b=\Sigma xy-[(\Sigma x)(\Sigma y)/n]\Sigma x2-[(\Sigma x)2/n] \tag{2}$$

and the y – intercept

$$a=\bar{y}-b\bar{x} \tag{3}$$

with $\bar{x}$ the neutrosophic average of x, and $\bar{y}$ the neutrosophic average of y.[2]

While Smarandache meant his approach can be used for analyzing neutrosophic sets, in this paper we consider it is possible to use this approach of neutrosophic regression for analyzing astronomical data, such as Hubble data.

To include error and indeterminacy in our linear regression model we can rewrite equation (1) as follows:

$$\hat{y}=a+(b+\varepsilon+i)x \tag{4}$$

Where ε and i represent error and indeterminacy in the data.

Of course, this simple linear regression will be more complicated when we start to analyze nonlinear data. The problems is seemingly more acute if we want to determine purely from data, when they start to become nonlinear.

We should keep in mind that for nonlinear data, there are a number of methods we can use:

Optimization algorithms of current application (for the search of minima):

– steepest descent

– inverse Hessian (Newton-Raphson) method

– Levenberg-Marquardt method

– conjugated gradient method

– relaxation method (Barbasin-Krasovskii)

– Monte-Carlo methods

Many software exist for least square fitting of both linear and nonlinear data, including NLREG and also Solver function in MS Excel. Besides, there are other ways such as Python and also Mathematica. Nonlinear pattern recognition may also be done by employing more modern approaches such as neural network technique.[7] Now we will discuss how such a nonlinear least square may be useful in analyzing astronomical data, such as Hubble diagram.

3. Possible nonlinearity of Hubble law

Although traditionally the so-called Hubble law is assumed to be linear, there are some grounds to let go that assumption. For instance, Segal and Nicoll have argued in favor of nonlinearity of Hubble law.[10]

Here we include the abstract section of Segal and Nicoll's paper:

Contributed by I. E. Segal, August 24, 1992

ABSTRACT The Hubble (linear) redshift–distance law predicts values for directly observed quantities that are quite deviant from their actual values in infrared astronomical satellite (IRAS) galaxy samples. These samples are objectively defined, have modern measurements, are presently the largest such samples to which the Hubble law is theoretically applicable, and are otherwise generally considered to be statistically appropriate. The Hubble law predicts in particular that the dispersion in log flux will be much greater than it is observed to be. This type of deviation is fundamentally incapable of explanation via the assumption of any physically known type of perturbation. The Lundmark (quadratic) redshift–distance law predicts values for these directly observed quantities that are consistent with, and in fact quite close to, their actual values in the same samples. The predictions of a cubic law are typically deviant from observation but somewhat less so than those of the Hubble law. The Lundmark law accurately predicts the deviations from observation of statistical estimates predicated on either the Hubble or the cubic law. Parallel predictions for the latter laws for the results of statistical estimation predicated on the alternative laws are typically quite inaccurate. The Hubble and Lundmark laws are predicted at the low redshifts of the IRAS galaxy samples by generic big bang cosmology (BBC) and chronometric cosmology (CC), respectively. The present results confirm earlier studies of a variety of objectively defined samples of discrete sources in other wave bands that were contraindicative of BBC and indicative of CC.

The Hubble law (1) is the origin of big bang cosmology (BBC) and by far its most important falsifiable prediction. It is very important that it be tested rigorously by modern statistical methods and accurate measurements on objectively defined samples.

We do not want to enter into arguments or interpretations whether Hubble law represents cosmological redshift or not, but we wish to extract the conclusion in a model-independent way. (There is rigorous algorithm aiming at such tests, called PEST: model independent parameter estimation.[11])

More careful data analysis seems to point to possible nonlinearity in Hubble datasets, although more observations are necessary, both at low redshift data and also for high redshift data. See some figures below and also Appendix I.

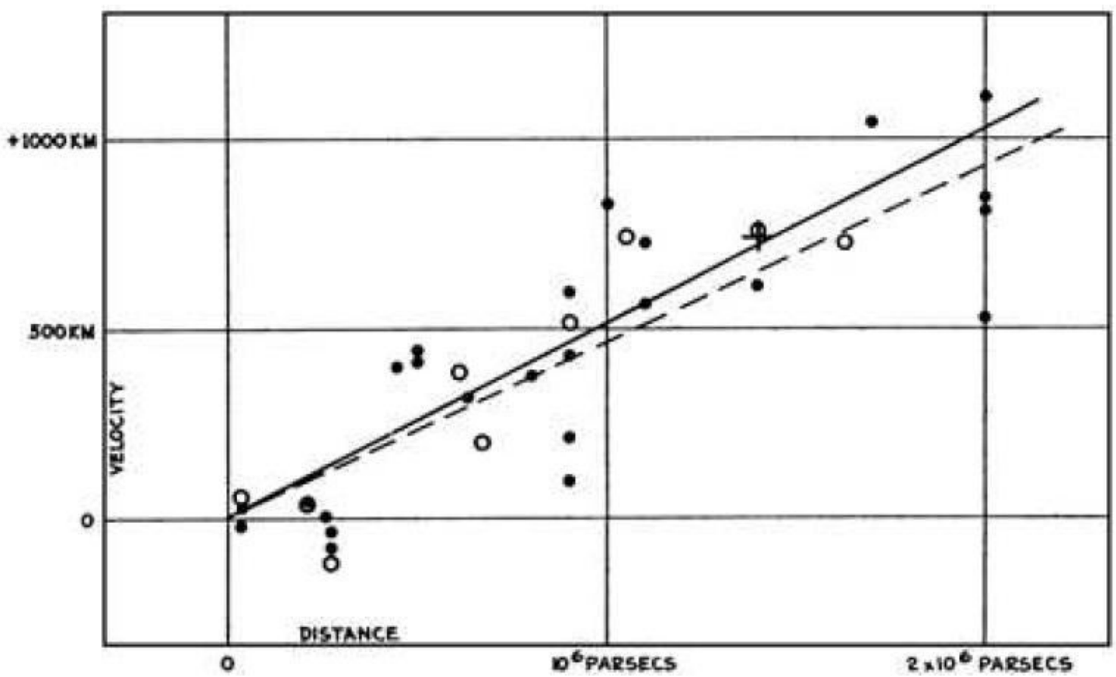

Figure 1. Hubble's original 1929 plot [23]. Note the rather large scatter in the data.

From Cattoen & Visser [13].

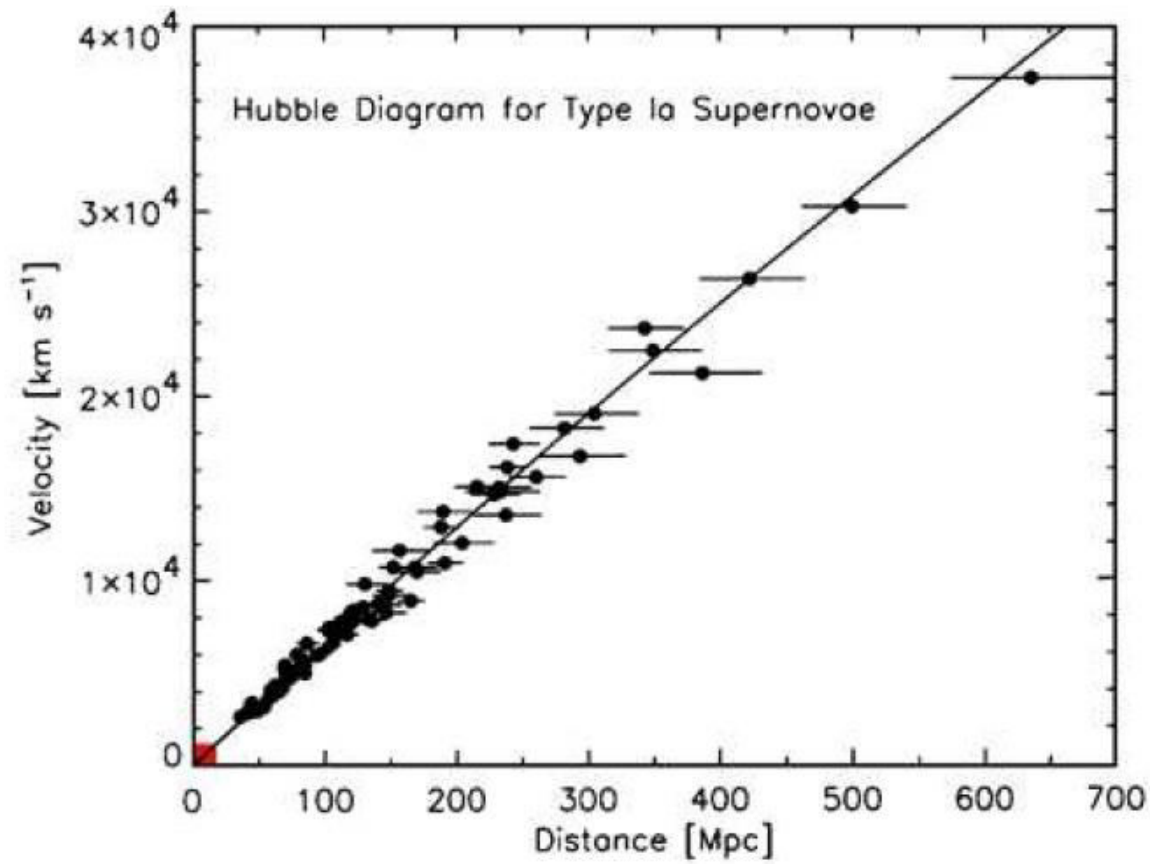

Figure 2. Modern 2004 version of the Hubble plot. From Kirshner [24]. The original 1929 Hubble plot is confined to the small red rectangle at the bottom left.

From Cattoen & Visser [13].

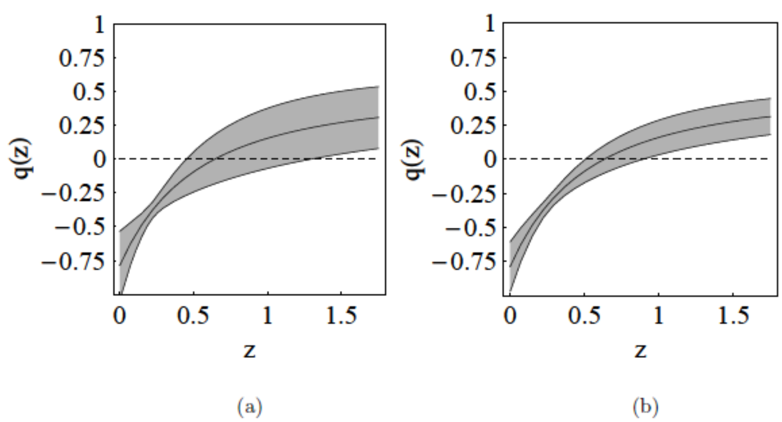

FIG. 1: The best fits of $q(z)$ with respect to redshift z constrained from the 192 ESSENCE SNe Ia data (a) and its combination with the 9 observational $H(z)$ data (b).

Figure 3. from Jianbo Lu [12]

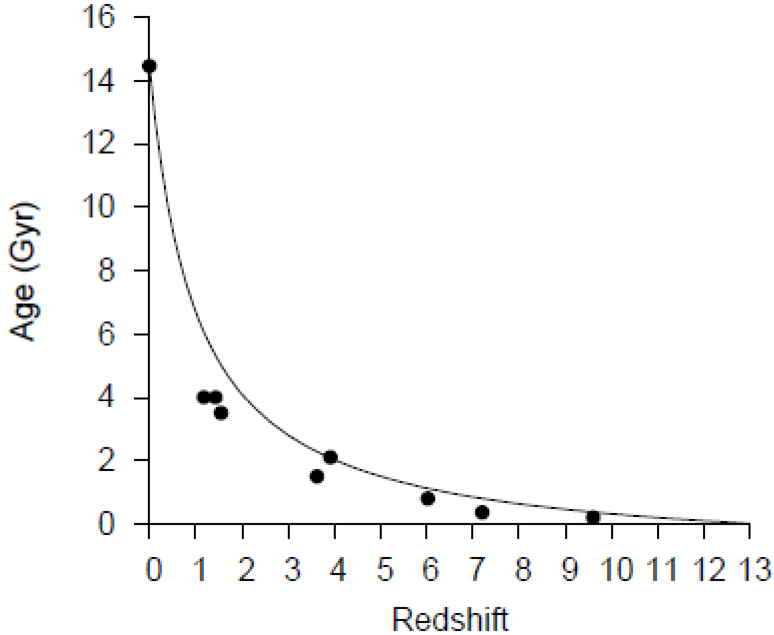

Figure 1: Age-redshift (z_λ) relationship. Filled circles: ages of nine early-type stars, galaxies and quasars (see text). Plain line: upper bound ex-

Figure 4: from Sanejouand [14]

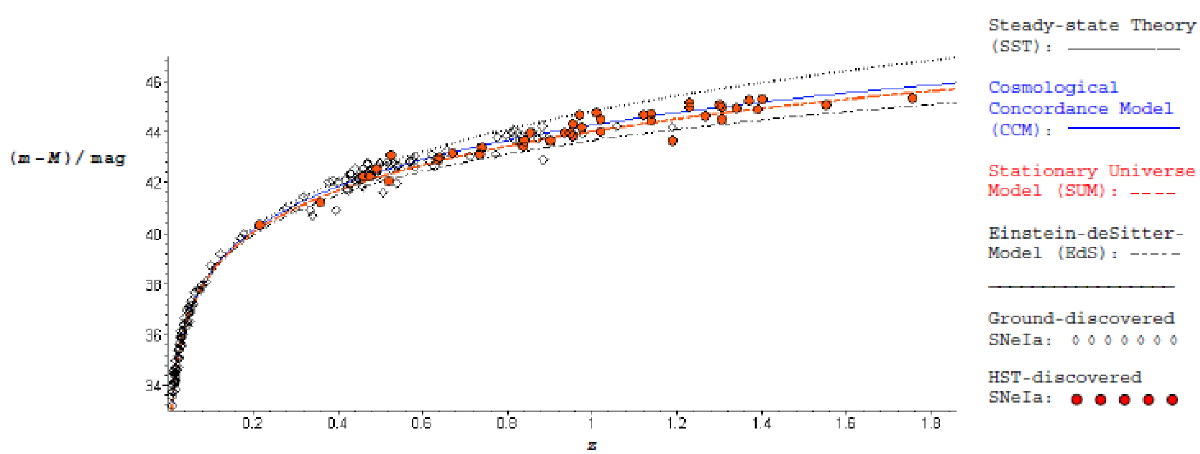

Fig. 5

Inserting the red line of the SUM-prediction shows:
Evidently the SUM does fit the data much better than EdS or SST.
However ...

Figure 5. Ostermann argues in favor of Steady State Universe [16]

While the above data analysis of Hubble law vary depending on different authors' preferences, apparently we can agree with Segal & Nicoll that Chronometric cosmology (CC) or Steady-State Universe cannot be ruled out. Does it mean that we should reconsider quasi-steady state models of Hoyle-Narlikar and perhaps also Conrad Ranzan's Dynamic Steady State (DSSU)?

4. Concluding Remarks

Although traditionally the so-called Hubble law is assumed to be linear, there are some grounds to let go that assumption. For instance, Segal and Nicoll have argued in favor of nonlinearity of Hubble law. More robust methods are advised to analyze astronomical data in a model-independent way, including the so-called Excel Solver and also Neural Networks method (Wolfram Mathematica).

Moreover, Neutrosophic Regression may offer a new perspective in developing nonlinear least square methods by including model error and indeterminacy. We reserve this for future work.

Nonetheless, this is only an early investigation. More researches and observations are recommended to verify our propositions.

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Appendix I:

182 Gold SNe Ia data

No.	z	mu
1	0.478	42.48
2	0.425	41.69
3	0.62	43.11
4	0.57	42.8
5	0.3	41.01
6	0.38	42.02
7	0.43	42.33
8	0.508	42.19
9	0.518	42.83
10	0.334	40.92
11	0.44	42.07
12	0.5	42.73
13	0.46	41.81
14	0.63	43.26
15	0.828	43.59
16	0.459	42.67
17	0.511	42.83
18	0.474	42.81
19	0.537	42.85
20	0.477	42.38
21	0.455	42.29
22	0.815	43.75
23	0.949	44
24	1.056	44.35
25	0.278	41.01
26	1.199	44.19
27	0.47	42.76
28	0.5	42.74
29	0.54	41.96
30	0.47	42.73
31	0.49	42.4
32	0.884	44.22
33	0.882	43.89
34	0.57	42.87
35	0.528	42.76
36	0.771	43.12

37	0.832	43.55
38	0.798	43.88
39	0.811	43.97
40	0.815	44.09
41	0.977	43.91
42	0.4	42.04
43	0.615	42.85
44	0.48	42.37
45	0.45	42.13
46	0.388	42.07
47	0.495	42.25
48	0.828	43.96
49	0.538	42.66
50	0.86	44.03
51	0.778	43.81
52	0.58	43.04
53	0.526	42.56
54	0.172	39.79
55	0.18	39.98
56	0.472	42.46
57	0.43	41.99
58	0.657	43.27
59	0.32	41.45
60	0.579	42.86
61	0.45	42.1
62	0.581	42.63
63	0.416	42.1
64	0.83	43.85
65	0.43	42.36
66	0.74	43.35
67	0.543	42.67
68	0.04	36.38
69	0.033	35.53
70	0.056	37.31
71	0.036	36.17
72	0.058	37.13
73	0.046	36.35
74	0.061	37.31
75	0.028	35.53
76	0.029	35.7
77	0.032	36.08
78	0.038	36.67
79	0.025	35.4

80	0.026	35.35
81	0.03	35.9
82	0.05	36.84
83	0.026	35.63
84	0.075	37.77
85	0.101	38.7
86	0.045	36.99
87	0.043	36.52
88	0.079	37.94
89	0.088	38.07
90	0.063	37.67
91	0.071	37.78
92	0.025	35.09
93	0.052	37.16
94	0.05	37.07
95	0.024	35.09
96	0.036	36.01
97	0.049	36.55
98	0.027	35.9
99	0.124	39.19
100	0.034	36.19
101	0.029	36.13
102	0.053	36.95
103	0.031	35.84
104	0.026	35.57
105	0.036	36.39
106	1.755	45.35
107	0.475	42.24
108	0.95	43.98
109	0.84	43.67
110	0.954	44.3
111	0.9	43.64
112	0.935	43.97
113	0.67	43.19
114	0.735	43.14
115	0.64	43.01
116	1.34	44.92
117	1.14	44.71
118	1.305	44.51
119	1.3	45.06
120	0.97	44.67
121	1.37	45.23
122	1.02	43.99

123	1.23	45.17
124	1.14	44.44
125	0.975	44.21
126	1.23	44.97
127	0.954	43.85
128	0.74	43.38
129	0.46	42.23
130	0.854	43.96
131	0.839	43.45
132	1.02	44.52
133	1.12	44.67
134	1.01	44.77
135	1.39	44.9
136	0.504	42.61
137	0.582	43.07
138	0.496	42.36
139	0.679	43.58
140	0.331	41.13
141	0.688	43.23
142	0.8	43.67
143	0.532	42.78
144	0.449	42.05
145	0.371	41.67
146	0.463	42.27
147	0.461	42.22
148	0.285	40.92
149	0.633	43.32
150	0.949	43.69
151	0.695	43.21
152	0.627	42.93
153	0.905	43.89
154	0.604	42.7
155	0.791	43.54
156	0.592	42.75
157	0.415	41.96
158	0.357	41.63
159	0.43	41.96
160	0.62	43.21
161	0.643	43.21
162	0.47	42.45
163	0.61	42.98
164	0.263	40.87
165	0.358	41.66

166	0.73	43.47
167	0.552	42.65
168	0.337	41.44
169	0.822	43.73
170	0.95	44.14
171	0.34	41.51
172	0.613	43.15
173	0.55	42.67
174	0.87	44.28
175	0.249	40.76
176	0.571	42.65
177	0.557	42.7
178	0.369	41.67
179	0.707	43.42
180	0.756	43.64
181	0.811	44.13
182	0.961	44.18