

N B Interpolation Technique for Improved Arbitrarily missing values in Data Mining

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ABSTRACT

Article Info Volume 9, Issue 2 Page Number : 79-85 Publication Issue : March-April-2022 Article History Accepted : 01 April 2022 Published: 05 April 2022 In data mining in order to reduce the numerical computations associated to the repeated application of the existing interpolation formula in computing a large number of interpolated values, a formula has been derived from Newton's backward interpolation formula for representing the numerical data on a arbitrarily missing vales in database. A suit approach of the formula to numerical data has been shown in the case of representing the data on the dataset global carbon dioxide emissions from fossil fuel burning by Fuel Type corresponding as a method of time. The formula is suitable in the situation where the values of the argument are at equal interval.

Keywords : Data Mining, Interpolation, Newton's Backward Interpolation Formula, Numerical Data.

I. INTRODUCTION

In the extraction of data, in the case of the interpolation by the existing formulas, and the value of the corresponding variable dependent on each value of the independent variable must be calculated again from the formula used putting in the value of the independent variable. It is true, interpolate the values of the corresponding variable dependent on an undetermined value of the independent variable by means of an existing interpolation form, if necessary to apply the formula for each separate value for, and, for the time being, the numerical value of the variable of

the dependent variable from personal data such as should be done in one of the casinos. To get rid of these repeated numerical calculations a part of the given data, if you can think of an approach that in the representation of the numerical data given for the salvation of lost values.

II. A Suit Approach of Newton Backward Interpolation method

The proposed method is based on replacing missing attribute values by the artificially generated values. The proposed method is based on replacing missing

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attribute values by the artificially generated values. This method is very much useful for numerical attributes. In general, this method is search of closest fit value which is very close to the true mean of the attribute and closest to the value of just preceding and succeeding value of the missing values. In the process of generation of closest fit values for missing value place, therefore, here it is possible to randomly take values as a table value for the direct interpolation table. Now searches for cases lost in the attribute begin. The first case of missing value is indicated by the subscript X [I], the search for the corresponding missing value of Y [I] is given.

First the searches of missing case in the attribute get start. The first missing value case is pointed by the subscript of the attribute and denoted by the variable, *Pred* is denoted from X[I]-1. Now take X0,X1,X2,X3,X4,X5 and their corresponding Y0 ,Y1, Y2,Y3,Y4,Y5 values from the database. here X5 value is given but Y5 is missing value. When search or scan pointer point out the empty subscript of the attribute, which is actually the missing values case in the attribute. The missing value case is pointed by the subscript of the attribute and is denoted by the variable. In this situation, the first subscript is given. We have to find empty or NULL values for Y corresponding to X. Now we have to point out on value which is corresponding value of Y in attribute X. Now, If (X [I] = NULL) then *we* have to record the Preceding value as

Pred = X[I]-1(2.1)
Here H is called the interval of difference , $H = X [2] - X [1]$ (2.2)
Here P[I] is a array that is used for missing value Y their corresponding X value minus predecessor of missing
value in X[I] so , $P[I] = (X [I] - X[Pred]) / H$ (2.3)
At the next step make a pass and obtained the difference table. The differentiation's are $y1 - y0$,
$y^2 - y^1$, $y^3 - y^2$,, $y^n - y^{n-1}$ when denoted by dy^1 , dy^2 , dy^3 ,, dy^n are respectively, called the first
backward differences. At next step repeat a loop for $J = 1$ to $J < N$ then , Repeat for $I = 0$ to $I < (N-J)$ then
$Y[I][J] \leftarrow Y[I+1][J-1] - Y[I][J-1]$ (2.4)
Then make next iterations of I and J so , $I = I+1$, $J=J+1$
At next step, Perform Missing value Recovery using backward interpolation method. Now initialize temp
variable for predecessor data.
$Temp \leftarrow Pred(2.5)$
Now apply a Suit Approach of Newton Backward Interpolation method
Y[i] = Y[I][J] + (P[I] * Y[temp][J-1]) + (((P[I] * P[I]-1) (Y[temp][J-2]))/ (2 * 1)) + (((P[I] * P[I]-1) (Y[temp][J-2]))) + (((P[I] * P[I]-1) (Y[temp][J-2])))) + (((P[I] * P[I]-1) (Y[temp][J-2]))) + (((P[I] * P[I]-1) (Y[temp][J-2])))) + (((P[I] * P[I]-1) (Y[temp][J-2])))) + (((P[I] * P[I]-1) (Y[temp][J-2])))) + (((P[I] * P[I]-1) (Y[temp][J-2])))))))))
(((P[I] * P[I]-1 * P[I]-2) (Y[temp][J-3]))/ (3 * 2 * 1)) +
$(((P[I] * P[I]-1 * P[I]-2 * P[I]-3) (Y[temp][J-4]))/(4*3*2*1)) \dots (2.6)$

Display the Y value for the corresponding missing value for X.

The proposed method is based on the replacement of the missing random values for the values generated by an application of Newton Backward Interpolation method. This method is very useful for numeric attributes. In general, this method is the search for randomly missing values that is very close to the real mean of the attribute and closer to the value than the original value of missing values. The below table shows the overall idea of backward difference table.

Х	Y	∇Y	$\nabla^2 Y$	$\nabla^{3}Y$	$\nabla^4 Y$
Xo	Yo				
\mathbf{X}_1	Y1	∇Y_1			
X2	Y2	∇Y_2	$ abla^2 Y_2$		
X3	Y3	∇ Y ₃	$\nabla^2 Y_3$	$\nabla^3 Y_3$	
X4	Y4	∇ Y ₄	$\nabla^2 Y_4$	$ abla^3 m Y_4$	$ abla^4$ Y ₄

Table .1 Backward Difference table for calculating the Y values of the corresponding X values using formula.

III. A Suit Approach for Newton Backward Interpolation method algorithm

The intended method is based on replacing missing attribute values by an applied Newton Raphson method. This method is very much helpful for numerical attributes. In general, this method is search of missing values and after searching its value is replaced by recovered value of the attribute in arbitrarily missing database.

Introduction: Given an array X and Y are of size N, N= 50, this procedure replaces the missing values with the recovered data from data set. Here Prev is the predecessor of the missing data. Here two arrays are taken first is X[I] and Y[I][J] is two dimension array which is used for storing differences of table. The variable I is used to index elements from 1 to N in a given data. The variable J is used to index column elements from 1 to N in a given data Following are the steps of the algorithm in detail:

Step 1: Select a dataset on which Missing values recovery is to be performed from the database.

Step 2: [Initialize the variables]

I \leftarrow NULL, J \leftarrow NULL, N \leftarrow 50, H \leftarrow NULL, P[i]=NULL, Prev \leftarrow NULL, temp \leftarrow NULL.

Step 3: [Create a loop for N passes]

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Repeat for I = 0 to I < N.

Read X [I] and Y [I][0].

If (X [I] = = NULL) then Pred = X [I] - 1 // Predecessor value of missing value.

And H = X [2] - X [1] // Interval of successor and Predecessor value

P[I] = (X [I] - X[Pred]) / H // difference of X[I] of missing data and predecessor value.

Step 4: [Make a Pass and Obtained difference table]

Repeat for J = 1 to J < N then

Repeat for I = 0 to I < (N-J) then

Y[I][J] \leftarrow Y[I+1][J-1] - Y[I][J-1] then I \leftarrow I+1 , J\leftarrow J+1

Step 5: [Display Backward difference table]

Repeat for I = 0 to I < N then

Print X[I] and I \leftarrow I+1

Repeat for J = 0 to J < (N-J) then
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Print Y[I][J] and J= J+1
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Step 6: [Perform Missing value Recovery using backward interpolation method]

 $Y[i] \leftarrow Y[I][J] + (P[I] Y[temp][J-1]) + (((P[I] P[I]-1) (Y[temp][J-2]))/(2*1)) + (((P[I] P[I]-1) (Y[temp][J-2])) + (((P[I] P[I]-1) (Y[temp][J-2]))) + (((P[I] P[I]-1) (Y[temp][J-2]))/(2*1)) + (((P[I] P[I]-1) (Y[temp][J-2]))) + (((P[I] P[I]-1) (Y[temp][J-2])))) + (((P[I] P[I]-1) (Y[temp][J-2])))) + (((P[I] P[I]-1) (Y[temp][J-2])))) + (((P[I] P[I]-1) (Y[temp][J-2])))) + (((P[I] P[I]-1) (Y[temp][J-2]))) + (((P[I] P[I]-1) (Y[temp][J-2])))) + (((P[I] P[I]-$

(((P[I] * P[I]-1 * P[I]-2) (Y[temp][J-3]))/ (3*2*1)) +

(((P[I] * P[I]-1 * P[I]-2 * P[I]-3) (Y[temp][J-4]))/ (4*3*2*1))

Step 7: [Display the Y value for the corresponding missing value for X]

Print Y[i] **Step 8:** Finished. Stop.

IV. Discussion of Results

Measure of central tendency (mean): Table-1 shows the global carbon dioxide emissions from fossil fuel burning by fuel type coal, oil and natural gas from 1960-2009. The mean of global carbon dioxide emissions due to coal, oil and natural gas are 2109, 2262 and 879 respectively. After missing values at the randomly, the mean calculated from incomplete data sets are 2,106 for coal, 2,280 for oil and 886 for natural gas.

The proposed ratio based approach method is applied on the data sets of Table 1 to fill up the missing values. It is observed that mean values of coal, oil and natural gas are 2,100, 2,246 and 866 respectively. It is considerable that the mean values obtained after replacing the missing values by the proposed approach very close to the actual mean as given.

Standard Deviation: From the analysis of result of standard deviation it is found that after estimation of missing values, the values of standard deviation obtained are very similar to the standard deviation of standard dataset. On the basis of result we can say that proposed algorithm is appropriate for missing values estimation and recovery.

Coefficient of Variation: From the analysis of result of co-efficient of variation (CV) it is found that, after estimation of missing values, the values of co-efficient of variation is not significantly change or slightly decline which shows that the series is uniform now.

Analysis of Variance: We wish to test the hypothesis

H0: $\mu 1 = \mu 2 = \mu 3$ against the alternative

H1: at least two μ 's are different (i.e. at least one of the equalities does not hold).

For testing this hypothesis we setup the following analysis of variance for all the variables:

One Way ANOVA (COAL)

ANOVA

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	2153.033	2	1076.517	0.003231	0.996774	3.060292
Within Groups	46981137	141	333199.6			
Total	46983290	143				

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Table 1 Value :- F(2, 141) at 5% Level of Significance = 3.0718, 1% Level of Significance = 4.7865,

One Way	ANOVA	(OIL)
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Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	26340.47	2	13170.24	0.032878	0.967664	3.060292
Within Groups	56481620	141	400578.9			
Total	56507961	143				
Table 2 Value :- F(2, 141)	at 5% Level of Si	ignificance =	3.0718 , 1% Le	evel of Signific	ance = 4.7865,	
One Way ANOVA (NATU	JRAL GAS)					
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	9139.001	2	4569.5	0.027803	0.972585	3.060292
Within Groups	23173403	141	164350.4			

Table 3 Value :- F(2, 141) at 5% Level of Significance = 3.0718, 1% Level of Significance =

143

23182542

4.7865,

Total

Decision and Conclusion: Since F (Calculated) < 3.0781 so accept H0 at 5% level of significance and Hence conclude that there is no significant difference among groups of Coal, Oil and Gas regarding Mean value.

Table 4. Table for A Suit Approach of Newton backward Interpolation method for Arbitarily missing values of data. Dataset Global Carbon Dioxide Emissions from Fossil Fuel Burning by Fuel Type, 1960-2009 (In Million Tones of Carbon Missing).

Standard Data						Missing Values					Recovered Values		
S. N	YEAR	COAL	OIL	NATURL GAS		COAL	OIL	NATURAL GAS		COAL	OIL	NATURAL GAS	
	Million Tons of Carbon					М	illion Tons	of Carbon		Million Tons of Carbon			
1	1960	1,410	849	235		1,410	849	235		1,410	849	235	
2	1961	1349	904	254		1349	904	254		1349	904	254	
3	1962	1351	980	277		1351	980	277		1351	980	277	
4	1963	1396	1,052	300		1396	1,052	300		1396	1,052	300	
5	1964	1435	1,137	328		1435	1,137	328		1435	1,137	328	
6	1965	1460	1,219	351		1460		351		1460	<u>934</u>	351	
7	1966	1478	1,323	380		1478	1,323	380		1478	1,323	380	
8	1967	1448	1,423	410		1448	1,423	410		1448	1,423	410	
9	1968	1448	1,551	446		1448	1,551			1448	1,551	<u>330</u>	
10	1969	1486	1,673	487		1486	1,673	487		1486	1,673	487	
11	1970	1556	1,839	516		1556	1,839	516		1556	1,839	516	
12	1971	1559	1,946	554		1559		554		1559	<u>1489</u>	554	
13	1972	1576	2,055	583			2,055	583		<u>1451</u>	2,055	583	

14	1973	1581	2,240	608		1581	2,240	608		1581	2,240	608
15	1974	1579	2,244	618]	1579	2,244			1579	2,244	512
16	1975	1673	2,131	623		1673	2,131	623		1673	2,131	623
17	1976	1710	2,313	650		1710	2,313	650		1710	2,313	650
18	1977	1766	2,395	649		1766		649		1766	<u>2237</u>	649
19	1978	1793	2,392	677			2,392	677		<u>1637</u>	2,392	677
20	1979	1887	2,544	719		1887	2,544	719		1887	2,544	719
21	1980	1947	2,422	740		1947	2,422			1947	2,422	<u>665</u>
22	1981	1921	2,289	756		1921	2,289	756		1921	2,289	756
23	1982	1992	2,196	746		1992	2,196	746		1992	2,196	746
24	1983	1995	2,177	745		1995		745		1995	<u>2300</u>	745
25	1984	2094	2,202	808			2,202	808		<u>1960</u>	2,202	808
26	1985	2237	2,182	836		2237	2,182	836		2237	2,182	836
27	1986	2300	2,290	830		2300	2,290			2300	2,290	<u>784</u>
28	1987	2364	2,302	893		2364	2,302	893		2364	2,302	893
29	1988	2414	2,408	936		2414	2,408	936		2414	2,408	936
30	1989	2457	2,455	972		2457		972		2457	<u>2455</u>	972
31	1990	2409	2,517	1,026			2,517	1,026		<u>2280</u>	2,517	1,026
32	1991	2341	2,627	1,069		2341	2,627	1,069		2341	2,627	1,069
33	1992	2318	2,506	1,101		2318	2,506			2318	2,506	<u>936</u>
34	1993	2,265	2,537	1,119		2,265	2,537	1,119		2,265	2,537	1,119
35	1994	2,331	2,562	1,132		2,331	2,562	1,132		2,331	2,562	1,132
36	1995	2,414	2,586	1,153		2,414		1,153		2,414	<u>2586</u>	1,153
37	1996	2,451	2,624	1,208			2,624	1,208		<u>2424</u>	2,624	1,208
38	1997	2,480	2,707	1,211		2,480	2,707	1,211		2,480	2,707	1,211
39	1998	2,376	2,763	1,245		2,376	2,763			2,376	2,763	<u>1122</u>
40	1999	2,329	2,716	1,272		2,329	2,716	1,272		2,329	2,716	1,272
41	2000	2,342	2,831	1,291		2,342	2,831	1,291		2,342	2,831	1,291
42	2001	2,460	2,842	1,314		2,460	2,842	1,314		2,460	2,842	1,314
43	2002	2,487	2,819	1,349			2,819	1,349		<u>2598</u>	2,819	1,349
44	2003	2,638	2,928	1,399		2,638	2,928	1,399		2,638	2,928	1,399
45	2004	2,850	3,032	1,436		2,850	3,032	1,436		2,850	3,032	1,436
46	2005	3,032	3,079	1,479		3,032	3,079	1,479		3,032	3,079	1,479
47	2006	3,193	3,092	1,527		3,193	3,092	1,527		3,193	3,092	1,527
48	2007	3,295	3,087	1,551		3,295	3,087	1,551		3,295	3,087	1,551
49	2008	3,401	3,079	1,589		3,401	3,079	1,589		3,401	3,079	1,589
50	2009	3,393	3,019	1,552	ļ	3,393	3,019	1,552		3,393	3,019	1,552
Ν	MEAN	2,109	2,262	879		2,106	2,280	886		2,100	2,246	866
	S.D	567.89	621.13	400.27		591.97	638.59	414.50	5	73.39	639.55	402.42
	C.V	0.27	0.27	0.46		0.28	0.28	0.47		0.27	0.28	0.46

V. CONCLUSION

In general, there is no universal and absolute technique for managing the values of missing attributes. The closest fitting method proposed is useful for the numerical attribute, with a deviation lower than the average. This is the best way to recover arbitrarily missing values from the database. Accordingly, it is noted that the techniques for managing the values of missing attributes must be chosen individually or according to the nature and type of data.

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