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Consumer Credit analysis.docx



Assignment



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Frequently Asked Questions

What does the percentage mean?

The percentage shown in the AI writing detection indicator and in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was generated by AI.

Our testing has found that there is a higher incidence of false positives when the percentage is less than 20. In order to reduce the likelihood of misinterpretation, the AI indicator will display an asterisk for percentages less than 20 to call attention to the fact that the score is less reliable.



However, the final decision on whether any misconduct has occurred rests with the reviewer/instructor. They should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in greater detail according to their school's policies.

How does Turnitin's indicator address false positives?

Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be AI-generated will be highlighted blue on the submission text.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

What does 'qualifying text' mean?

Sometimes false positives (incorrectly flagging human-written text as AI-generated), can include lists without a lot of structural variation, text that literally repeats itself, or text that has been paraphrased without developing new ideas. If our indicator shows a higher amount of AI writing in such text, we advise you to take that into consideration when looking at the percentage indicated.

In a longer document with a mix of authentic writing and AI generated text, it can be difficult to exactly determine where the AI writing begins and original writing ends, but our model should give you a reliable guide to start conversations with the submitting student.

Disclaimer

Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (it may misidentify both human and AI-generated text) so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.





Consumer Credit analysis

Question a

Discriminant Analysis (DFA) analysis is mainly performed on a set of data to identify the linear functions existing in the data. In this case, Canonical Discriminant Analysis (DFA) was performed on the dataset "Ass2Credit" to identify a linear function of the variables that best discriminates between individuals who pay off their debt (TARGET = 0) and those who do not (TARGET = 1).

Table 1.0

Canonical Discriminant Analysis

The DISCRIM Procedure Canonical Discriminant Analysis													
	Can	Adju sted Can onic	Approxim	Squ ared Can onic	Eigenvalues of Inv(E)*H = CanRsq/(1-CanRsq)				Test of H0: The canonical correlations i n the current row and all that follow are zero				
	Corr Corr S elati elati d	ate al Stan Corr dard elati Error on	Eige nval ue	Diff ere nce	Pro port ion	Cum ulati ve	Likelih ood Ratio	Approxi mate F Value	Num DF	Den DF	Pr >		
1	0.45 0851	0.43 6162	0.036 790	0.20 3267	0.25 51		1.00	1.00 00	0.79673 341	13.04	9	460	<.00 01

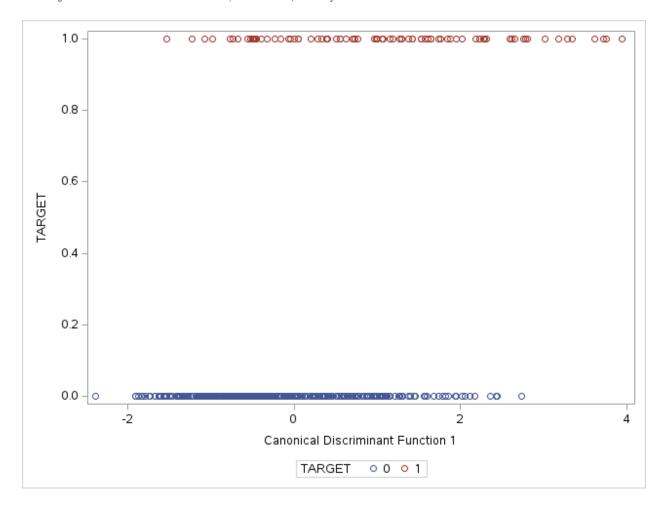
Only one discriminant function was identified in the data. The Canonical Discriminant
 Analysis table above provides different statistics and also identifies the number of linear functions in the data.



The below plot justifies the use of a single discriminant function in separating the two individual groups.

Figure 1.0

Plot of Canonical Discriminant (Function) Analysis



2) Identifying the most important variables that discriminate between the different classes in the data, can be achieved by critically analyzing the "Total-Sample Standardized Canonical Coefficients" and "Pooled Within-Class Standardized Canonical Coefficients" tables from the output of the PROC DISCRIM procedure allowing to determine which variables contribute the most to the discrimination between classes. The variables with the highest absolute coefficient are deemed the most important.





Table 2.0

Total-Sample Standardized Canonical Coefficients

Total-Sample Standardized Canonical Coefficients						
Variable	Label	Can1				
CollectCnt	Number Collections	0.0499636785				
InqFinanceCnt24	Number Finance Inquires 24 Months	0.5466558736				
InqTimeLast	Time Since Last Inquiry	0.1033763125				
TLTimeFirst	Time Since First Trade Line	1687640127				
TLBalHCPct	Percent Trade Line Balance to High Credit	0.3080052121				
TLSatPct	Percent Satisfactory to Total Trade Lines	7163946321				
TLSum	Total Balance All Trade Lines	0.0752990652				
TLOpenPct	Percent Trade Lines Open	0.3295953728				
TLDel60Cnt24	Number Trade Lines 60 Days or Worse 24 Months	0.3712633783				

Table 3.0Pooled Within Canonical Structure Coefficients

Pooled Within Canonical Structure						
Variable	Label	Can1				
CollectCnt	Number Collections	0.172287				
InqFinanceCnt24	Number Finance Inquires 24 Months	0.486341				
InqTimeLast	Time Since Last Inquiry	-0.083938				





Pooled Within Canonical Structure						
Variable	Label	Can1				
TLTimeFirst	Time Since First Trade Line	-0.181288				
TLBalHCPct	Percent Trade Line Balance to High Credit	0.401838				
TLSatPct	Percent Satisfactory to Total Trade Lines	-0.618060				
TLSum	Total Balance All Trade Lines	-0.029255				
TLOpenPct	Percent Trade Lines Open	-0.135203				
TLDel60Cnt24	Number Trade Lines 60 Days or Worse 24 Months	0.599692				

The most important variables from the data are TLSatPct, TLDel60Cnt24 and InqFinanceCnt24. These variables are the most critical in distinguishing between individuals who pay off their debt and those who do not.

3. I would consider reducing the variables in the data and focus on the most important variables as identified. Reducing the variables and focusing on the most important variables in the data will ensure the DFA methods sustains higher discriminative Power, Simplicity and increase classification accuracy.

Question b

Fisher Discriminant Analysis

Fisher Discriminant Analysis also know as Linear Discriminant Analysis (LDA) is a mathematical method used to classify data points based on their characteristics that separates the data distinctively. To classify the individuals, Fisher Discriminant Analysis method was applied. The method produced an overall classification accuracy of 68.40%. The method correctly classified 75.85% of class 0 and 67.44% of class 1 and had an error rate 28.36%.





Table 4.0Number of Observations and Percent Classified into TARGET

Number of Observations and Percent Classified into TARGET						
From TARGET	0	1	Total			
0	314	100	414			
	75.85	24.15	100.00			
1	28	58	86			
	32.56	67.44	100.00			
Total	342	158	500			
	68.40	31.60	100.00			
Priors	0.5	0.5				

Table 5.0Error Count Estimates for TARGET

Error Count Estimates for TARGET						
	0	1	Total			
Rate	0.2415	0.3256	0.2836			
Priors	0.5000	0.5000				

linear discriminant analysis is more preferable than the quadratic discriminant analysis method since the LDA results satisfies the assumption of equality of the covariance matrices of the two classes. The assumption of linearity holds for the data, this implies that the method finds a linear





combination of the predictor variables that best separates the classes. Based on the visual inspection, the assumption of linearity is reasonable for the most important variables. In practical applications, especially in financial and consumer credit analysis, simpler models that are easy to explain to stakeholders are often preferred. The performance difference between the two methods is not substantial enough to warrant the additional complexity of QDA.





References

Discriminant Function Analysis / SAS Data Analysis Examples. (2018).

https://stats.oarc.ucla.edu/sas/dae/discriminant-function-analysis/

Fisher's linear discriminant functions. (2018, April 6).

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functions/td-p/451752

