Journal of Advances and Scholarly Researches in Allied Education
Vol. 18, Issue No. 4, July-2021, ISSN 2230-7540

Model of Ordinal Regression with Flexible Parameters

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Abstract - Cluster randomization studies have become more common when traditional trials with individual random assignment are impractical for theoretical, ethical, or practical reasons. While there has been a lot of focus on developing methods for studying continuous or binary outcome data in clusters, the same cannot be said for ordinal data. Our empirical research is based on a database of s&p, moody's, and fitch ratings for U.S.-based corporations from 2016 to 2021. Because it was at that time frame that Fitch really started to make an impact in the American ratings industry, that's where our focus went. Credit rating sample size affects pairwise likelihood estimates: a multivariate approach The average root-mean-square errors (RMSEs) of the coefficients and the thresholds parameters are almost same across the several simulated data sets with different correlation structures.

Keywords - Ordinal Models, Ordinal, Cumulative Link Models, F Odds, Scale Effects

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INTRODUCTION

The study of ordinal outcomes, whether they be univariate or multivariate, plays a significant role in many different types of research, ranging from the social sciences to clinical medicine. Correlated ordinal outcomes sometimes occur in settings where many raters provide divergent assessments of the same set of subjects. Credit ratings are a common kind of ordinal data seen in articles on the financial markets. Ratings for creditworthiness, or the likelihood that a company will be unable to pay its debts when they become due, are ordinal scales. Banks may use their own internal rating models to generate such credit ratings, or they can get them from credit rating organizations (CRAs).

One of the most frequent and extensively utilized sources of information regarding credit quality is credit ratings from CRAs like Standard and Poor's (S&P), Moody's, and Fitch. Through their issuer ratings, CRAs provide a prognostic assessment of an organization's long-term creditworthiness. Quantitative and qualitative metrics are used in credit quality assessments. The financial and market situations evaluation is the backbone of the quantitative analysis. Using data from the market and the company's financial records, analysts may calculate key financial ratios to assess the effectiveness of various business operations

Literature on credit ratings to date has often addressed credit rating agency (CRA) models independently when discussing credit risk modeling. Ordinal regression models using financial ratios as explanatory variables are used by Blume et al. (1998) and Alp (2013), for instance, to better understand S&P's rating behavior. There are a number of factors that might cause a discrepancy in rating between the three major CRAs. To begin, Moody's uses a different scale than S&P and Fitch. Second, although default probabilities are the most important factor in determining creditworthiness according to S&P and Fitch, Moody's ratings also take into account recovery rates in the event of default.

Third, it is unclear if the CRAs place equal weight on all factors in their study since their rating and estimating technique is not fully published. Taking into account these facts, a multivariate analysis may shed light on the heterogeneity among raters and the drivers of such credit ratings by treating credit ratings as the dependent variable and firm-level and market information as the covariates.

Model While there are a variety of models available, cumulative link models are often used for analyzing ordinal data. The idea behind a cumulative link model is that the observed ordinal Y is a simplified representation of a latent continuous $\tilde{Y}$. Assume for the purpose at hand that one has a potentially imbalanced panel of businesses seen many times over a period of T years, yielding a total of n observations across n firms throughout that time period. Moreover, let's assume that in year t, CRAs indexed by $j \in J_{htj}$ issue ordinal ratings to firms h, where J_{ht} is a non-empty subset of the set J of all q =

|J | available raters, and the number of ratings for firm h in year t is provided by $q_{ht} = |J_{htj}|$. It is presumed that the ratings that are absent do not matter. Let's call the overall ranking, out of a potential K_j, that rater j gave to company h in year t as Y_{htj} . $\tilde{Y}_{htj}$ is a latent variable that is not directly observable, while Y_{htj} is an observed rating:

$$Y_{htj} = r_{htj} \quad \text{if } \theta_{j,r_{htj}-1} < \tilde{Y}_{htj} \le \theta_{j,r_{htj}}, \qquad r_{htj} \in \{1, \dots, K_j\},$$

where θ_j is a set of factors that, subject to the following constraint, provide an appropriate threshold for the j_{th} outcome: $-\infty \equiv \theta_{j,0} < \theta_{j,1} < \cdots < \theta_{j,K_j} \equiv \infty$. To accommodate for changes in rating behavior amongst raters, we let the thresholds to vary between outcomes.

LITERATURE REVIEW

Aya A. Mitani, (2019) For example, while analyzing dental data, the problem of informative cluster size (ICS) often occurs. ICS depicts a circumstance where the result of interest is connected to cluster size. In longitudinal research with possible ICS, most of the work on modeling marginal inference has concentrated on continuous outcomes. However, periodontal disease outcomes, including clinical attachment loss, are commonly measured using ordinal grading methods. In addition, as the patients' condition progresses, they may experience tooth loss. Here we develop longitudinal cluster-weighted generalized estimating equations (CWGEE) to model the association of ordinal clustered longitudinal outcomes with participant-level health-related covariates including metabolic syndrome and smoking status and potentially decreasing cluster size due to teeth-loss, by fitting a proportional odds logistic regression model. The within-teeth correlation coefficient over time is evaluated using the two-stage quasi-least squares approach. The impetus for our investigation derives from the Department of Veterans Affairs Dental Longitudinal Study in which participants routinely got general and oral health assessments. In an extended simulation analysis.

Rainer Hirk (2019) Multiple measurements on a group of participants often provide correlated ordinal data. Our interest in multivariate ordinal regression models with a latent variable specification and correlated error terms is inspired by their use in the field of credit risk, whereby a number of credit rating agencies assign a firm's creditworthiness on an ordinal scale. We use a multivariate normal distribution and a multivariate logistic distribution for the latent variables that underlie the ordinal outcomes, which lead us to use two distinct link functions. For parameter estimation, we use a composite likelihood technique, especially the pairwise and triplet wise likelihood approach. We examine the efficiency of the pairwise likelihood estimates using simulated data sets with varied numbers of participants and show that they are reliable for both link functions and a sufficient sample size. For the empirical application, we look at how Standard & Poor's, Moody's, and Fitch rank companies' financial stability. To demonstrate the usefulness of the proposed approach, we collect and analyze firm-level and stock price data for publicly listed US corporations, in addition to an imbalanced panel of issuer credit ratings.

Daniel Fernandez (2019) Many psychological and psychiatric investigations gather and utilize ordinal variables. While continuous variable models are comparable to ordinal variable models, there are benefits to using a model built for ordinal data, such as avoiding "floor" and "ceiling" effects and not having to give scores (which might lead to score-sensitive outcomes in continuous models). The ordered stereotype model, created for modeling ordinal outcomes but less well-known than alternatives like linear regression and proportional chances models, is the topic of this research. This paper's goal is to evaluate the ordered stereotype model next to several other popular models utilized in the academic and professional communities. Using three, four, and five levels of ordinal categories and sample sizes of 100, 500, and 1000, this article evaluates the stereotype model in comparison to the proportional odd and linear regression models. This article also uses a simulation study to talk about the issue of considering ordinal replies as continuous. The program also includes the trend odds model. According to the results, three distinct models—an ordered stereotype model, a proportional chances model, and a trend odds model—were all adapted to the same real-world data set. Regarding the importance of variables, they came to the same result. The ordered stereotype model's efficacy in four scenarios was analyzed in the simulation research.

Shubham Karnawat (2019) The inflexibility of Bayesian quantile regression for ordinal models with an asymmetric Laplace (AL) error distribution inspired us to write this piece. The distribution's skewness is totally determined when a quantile is selected, leading to the lack of flexibility. To address this shortcoming, we develop a practical likelihood for the ordinal quantile model by deriving the cumulative distribution function of the generalized asymmetric Laplace (GAL) distribution, a variant of the AL distribution that disentangles the skewness from the quantile parameter. Models based on this methodology are referred to as FBQROR. However, it is difficult to provide an accurate estimate. Using Gibbs sampling and the combined Metropolis-Hastings algorithm, we offer a fast and accurate Markov chain Monte Carlo (MCMC) approach for estimating unknown quantities. Multiple simulation experiments confirm the benefits of the suggested approach, and it has been put to use to examine how Americans feel about homeownership as a long-term investment in the wake of the Great Recession.

Pedro Antonio Gutiérrez (2015) Classifying patterns on a categorical scale when there is a clear hierarchy between the labels is the goal of ordinal regression issues in machine learning. This labeling structure is used in many practical applications, leading to a proliferation of related approaches and algorithms in recent years. Standard nominal classification approaches may be used to ordinal regression, but there are also a few algorithms that can make use of the ordering information. Therefore, the purpose of this research is to assess the current status of these methods and to propose a taxonomy based on the construction of the models that takes into consideration the hierarchy. As a further step, it is recommended to conduct a comprehensive experimental investigation to determine whether or not the incorporation of the order information enhances the performance of the produced models, taking into account some of the strategies included in the taxonomy. The findings show that ordinal models benefit from ordering information, which increases their accuracy and the proximity of their predictions to real objectives along the ordinal scale.

INVESTIGATING THE EFFECT OF THE SAMPLE SIZE ON THE PAIRWISE LIKELIHOOD ESTIMATES

Both the probit and logit pairwise likelihood estimates are studied here, along with their sensitivity to varying sample sizes. To do this, we simulate data sets with a sample size of S = 100 and a subject pool of progressively larger sizes (n = 75, 100, 200, 300, 400, 500, 700, 1000, 2000, 3000, 4000, 5000). High correlation is used (R_1; solid line), correlation strength: moderate (R_2; dashed line) with a correlation matrix that is low (R_3; dotted line). Correlation between the mean squared errors (MSEs) and sample size (n). Since we did not find any significant variations in the MSE curves for the individual parameters, we simply provide averaged MSEs for thresholds, coefficients, and correlation parameters.

There is no discernible variation in the average MSEs of the coefficients and the thresholds parameters across the simulated data sets with varied correlation topologies. However, the metric standard errors (MSEs) of the correlation parameters vary with correlation strength. We find that high correlation data sets' correlation parameters are more reliably retrieved than moderate and low correlation data sets.

Similarly, Bhat et al. (2010) reported same result in their simulation analysis of the multivariate probit model. Finally, the average MSEs of all estimated parameters are shown to illustrate that the MSE curves begin to flatten out at n = 500 patients. Smaller sample sizes (say n = 100) nevertheless provide respectable MSEs and outcomes. The average mean squared errors (MSEs) from the logit connection are somewhat larger than those from the probit link, but this trend does not seem to hold for the correlation parameters.

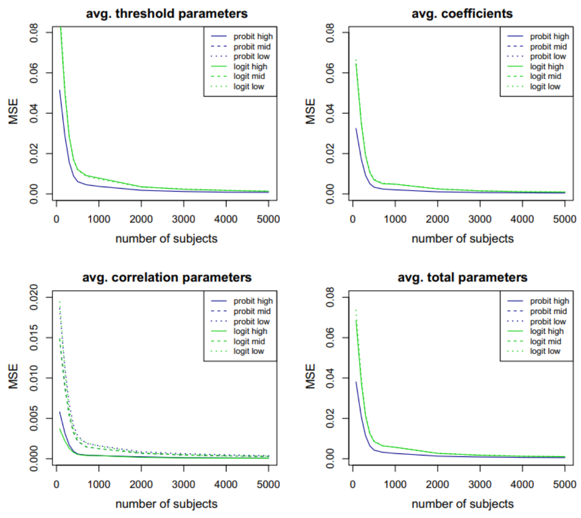

Figure 1 These plots display the averaged MSEs for increasing number of subjects

Because even the smallest commercial sector has around a thousand people in it, we report results for n = 1000 subjects per group in the paper's continuation. Furthermore, we simulate with n = 100, 200, and 500 and provide those results as well in the appendices. As expected, we find that both the bias and the standard errors go down as the sample size goes up. Both the probit and logit link functions exhibit this property. The absolute percentage bias of the pairwise likelihood estimates for the probit and logit did not exceed 6.79 and 5.29 percent, respectively, even in the study with n = 100 subjects.

MULTIVARIATE ANALYSIS OF CREDIT RATINGS

Our empirical research is predicated on a database of S&P, Moody's, and Fitch ratings for U.S. companies from 1999 through 2013. We zeroed in on this time range since it was approximately then that Fitch began making significant inroads into the US ratings business.

Data

Long-term issuer credit ratings are gathered from the three largest CRAs in the US market (S&P, Moody's, and Fitch). S&P domestic long-term issuer credit ratings are collected from the S&P Capital IQ's Compustat North America© Ratings file, while issuer credit ratings from Moody's and Fitch were given by the CRAs themselves. On an ordinal scale, CRAs will rate the performance of a given item. There are 21 nondefault categories that S&P and Fitch use to rank issuers. Moody's rating methodology for issuers has 20 non-default rating classes and employs distinct labels, where AAA and Aaa, respectively reflect the greatest credit quality and consequently lowest default risk.

Enterprises falling into the finest 10 categories (AAA/Aaa to BBB−/Baa3) are called investment grade (IG) firms, whereas those falling into B B+/Ba1 to C/Ca are speculative grade (SG) firms. In order to create the covariates, yearly financial statement data and daily stock prices from the Center of Research in Security Prices (CRSP) are obtained for the S&P Capital IQ's Compustat North America© universe of publicly listed US enterprises. We construct the following covariates in accordance with the available research and the CRAs' stated grading methodology: interest coverage ratio [earnings before interest and taxes (EBIT) and interest expenses]/interest expenses, tangibility measured as net property plant and equipment/assets, debt/assets, long-term debt to long-term capital, retained earnings/assets, return on capital (EBIT/equity and debt), earnings before interest, taxes, depreciation and amortization (EBITDA)/sales, research and development expenses (R&D)/ assets and capital expenditures/assets.

In addition, we calculate the following metrics using daily stock prices: Market capitalization is calculated by multiplying the stock price by the number of outstanding shares and dividing by the CRSP value weighted index. Relative size (RSIZE) is the logarithm of this ratio. The beta of a stock indicates its volatility in relation to the market as a whole and is thus a measure of systematic risk. Independent variables are quantified using the SIGMA index. We do a year-ahead regression using the daily stock price and the daily CRSP value weighted index.

The regression coefficient is denoted by BETA, whereas the residual standard deviation is denoted by SIGMA. Market equity plus book liabilities divided by book assets makes up the final metric, known as the market assets to book assets ratio (MB). Since financials (GICS code 40) and utilities (GICS code 55) are subject to a different reporting norm for their yearly financials, we follow accepted practice in the literature and exclude them from the sample. Through the use of CUSIPs, we are able to connect the ratings data with the financial statement data from CompStat.

We pair each rating with three-month-delayed data from the company's financial statements to make sure the information is readily available to the rating agencies at the time the rating is assigned. We opted for a three-month delay since annual reports must be submitted to the SEC by all publicly listed US companies within 90 days after the end of the fiscal year. There are 21,397 firm-year observations and 2,961 companies in the combined sample with at least one rating. A summary of the CRAs' co-ratings and missing ratings is provided in Table 1. S&P rates 95% of the firm-year data in the sample, whereas Moody's only rates 63% and Fitch only rates 22%.

Only 3,727 business years (17%) receive ratings from all three CRAs. Due to the nontrivial nature of describing a combined model for the observed and missing answers, we use the simplistic assumption that the missing data mechanism is ignorable to prevent an increase in model uncertainty. Investors often request ratings from CRAs. Companies will pay rating firms to evaluate their financial stability and publicize their findings. It's up to the company's discretion to determine whether to remove a rating as well. Companies have an incentive to shop around for the best rating since the main three CRAs operate on an "issuer-pays" approach, which has been the subject of criticism and research into whether or not it leads to sample selection bias.

Unfortunately, there is a lack of consensus in the literature. In their model, Cantor and Packer (1997), for instance, However, Bongaerts et al. (2012) state that companies are more likely to request a Fitch rating when Moody's and S&P rank at opposing ends of the investment-speculative grade frontier to explain why businesses seek out multiple ratings and how they weigh their options when deciding which agency to employ.

However, this is just a simple assumption, and we purposefully leave this area of study wide open. Figure 2 displays the rating distributions for all CRAs. We combine the middle rating from S&P and Fitch's "+" and "-" scales, and Moody's "1" and "3" scales, for further study. In addition, we aggregate S&P and Fitch classifications CCC to C, which is standard procedure for the CRAs throughout their report series. For a visual representation of the rating distribution on the combined scale, see Fig. 3. At the 99% quantile, we apply winsorization to all of the variables, and at the 1% quantile, we apply winsorization to the variables that potentially take on negative values.

If a ratio figure is missing for a given year, the median across industries is used as a replacement. Standardizing the variables to have a mean of zero and a variation of one makes the regression coefficients consistent across analyses. Firms are categorized into industry groups using the Global Industry Classification Standard so that a sector wise correlation study may be conducted (GICS). We use data from eight industries: energy (GICS code 10, 2683 observations), materials (GICS code 15, 2536 observations), industrials (GICS code 20, 3639 observations), consumer discretion (GICS code 25, 5282 observations), consumer staples health care (GICS code 35, 2031 observations), information technology (GICS code 45, 2294 observations), and telecommunications services.

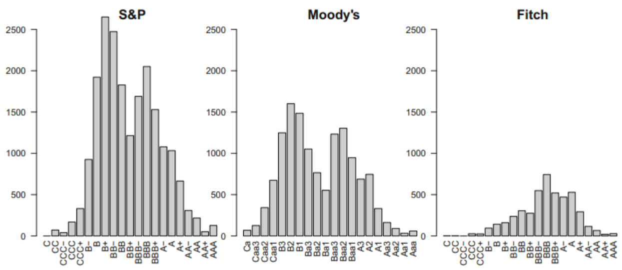

Figure 2 This figure displays the distribution of ratings on the original scale containing 21 rating

classes for S&P and Fitch and 20 rating classes for Moody's

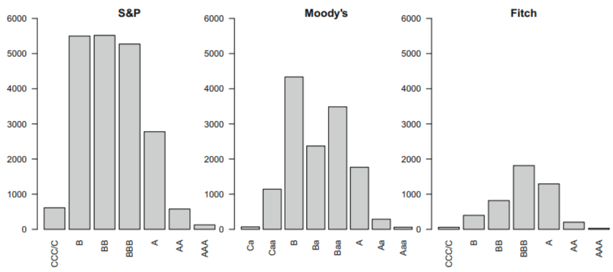

Figure 3 This figure displays the distribution of ratings on the aggregated scale containing 7 rating classes for S&P and Fitch and 8 rating classes for Moody's

Results

The ratings data set is used to fit model (1) and many subsidiary models. Ordinal models' logical framework, based on latent variables, makes the case study a breeze to work with. Consider a company's latent creditworthiness on a continuous scale as an example of a latent variable in the context of credit risk. Different authors have presented this latent variable with various labels and contexts.

The Z-score, for instance, was developed by Altman (1968) as a linear combination of many accounting criteria for use in predicting business failure. In addition, Merton (1974) uses the distance-to-default, which is the percentage difference between the firm's log asset value and its default threshold on the real line, as a proxy for creditworthiness. So, ratings might be thought of as a rough approximation of this hidden variable. If the latent creditworthiness is low, then the lowest ratings classes will be assigned, and the highest ratings classes will be assigned to the highest latent values.

There is a wide range of complexity in the models we fit. We employ criteria that are unique to each rater in each model. Here, we estimate models that include both shared and individual rater regression parameters. In addition, we take into account both a consistent generic correlation structure and a structure that is industry-specific. The models are estimated using both multivariate probit and multivariate logit connections. In all model assumptions, the CLIC-BIC indicates that the multivariate logit link outperforms the multivariate probit link. The model with a single set of regression parameters, adjustable threshold parameters, and a correlation structure tailored to the business sector performs best in comparison to the other models. Accordingly, we'll get to the model's results discussion below.

Table 1 This table displays the regression coefficients from the multivariate ordered logit model using the multiple corporate credit ratings data set

Covariate	Est.	SE
Interest coverage ratio	0.033^{*}	0.013
Net property plant & equipment/assets	0.080^{***}	0.019
Debt/assets	-0.522^{***}	0.028
Long term debt/long term capital	-0.333^{***}	0.027
Retained earnings/assets	0.572^{***}	0.018
Return on capital	0.481^{***}	0.018
EBITDA/sales	0.165^{***}	0.016
R&D/assets	0.232^{***}	0.015
Capital expenditures/assets	-0.098^{***}	0.017
RSIZE	0.978^{***}	0.018
BETA	-0.240^{***}	0.018
SIGMA	-0.675^{***}	0.022
MB	-0.211^{***}	0.017

Due to identifiability constraints, the estimated thresholds and coefficients in the flexible model are signal to noise ratios. Parameters cannot be compared directly because of the different measurement units used for the underlying latent processes. In contrast, the selected model has the benefit of allowing for an interpretation of variations in the threshold parameters across raters if the regression coefficients are the same for all raters.

Threshold parameters

displays the predicted threshold parameters and associated standard errors for the multivariate logit model. With the exception of the final threshold criteria, Moody's ratings are more cautious than those from the other two CRAs. Moody's looks to separate itself from S&P in the manner it assigns ratings and tends to be more cautious in the speculative grade rating classes, but the gap between their criteria is quite minimal for the investment grade classes. Fitch, on the other hand, has BBB|A and BB|BBB threshold criteria that are much lower than S&P's, which may lead to a more optimistic rating scale around the investment-speculative grade frontier.

Regression coefficients

Consistent with the aforementioned works, all coefficients take the form expected by the experts. Companies with higher ratios of retained earnings to assets, return on capital, and EBITDA to sales, as well as those that invest more in R&D and are larger in size, tend to have higher ratings. Credit ratings tend to decline for businesses that have higher debt to equity ratios, a greater share of long-term debt (which is riskier than short-term debt), greater capital expenditures, and a higher exposure to both idiosyncratic and systematic risk. Creditworthiness is inversely related to the market-to-book ratio (MB). High MB ratios are correlated with market overvaluation of a company, which can be a negative indicator of credit quality, as was also found by Campbell et al. (2008).

Year intercepts

Because the regression coefficients may be understood as marginal log odds ratios when utilizing the logit link, this is an obvious benefit. For the year intercepts, this indicates that, all else being equal, the probabilities of a business being assigned to rating class r or better rather than a poorer class than r, for allr, increase by the factor of exp (α_{tj}) times the odds in 1999 (the baseline year). These odds ratios are shown for each rating agency and year dummy coefficient in Figure 4. We find that the odds ratios go below 1 after the year 2000, suggesting that the likelihood of a business with consistent features receiving an upgrade in rating decreases after that year. This may suggest that rating requirements are becoming more stringent (also found by Alp 2013). An intriguing observation is that the odds start rising before the financial crisis, reaching a high in 2008. This may suggest that rating requirements have been relaxed in light of the current financial crisis. Once the financial crisis of 2008 passed, the chances essentially returned to where they had been before.

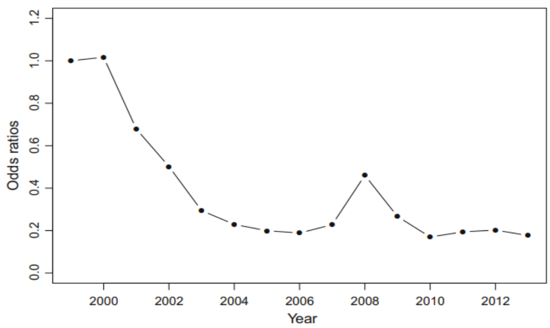

Figure 4 This figure displays the time dummy coefficients from 1999 to 2013 from the multivariate ordered logit model

CONCLUSIONS

Credit rating agencies are motivated to use this joint modelling approach when they analyses a company's credit quality using firm-level and market information and then offer ordinal credit ratings. Parameters of the model are estimated with the help of composite likelihood methods, and a wide range of questions are answered by means of a simulation study. First, we check whether the pairwise likelihood estimates are affected by a higher or fewer number of observations. Even with modest sample sizes we find that results are credible, and that level off with expansion Clustering based on multivariate models is a logical extension of the more common assumption of conditional independence for categorical data. Using it on real-world datasets, we were able to find clusters missed by its competitors' more conventional approaches. Effect of sample size on pairwise likelihood estimates, parameters of the cutoff, correlation coefficients

REFERENCES

1. Aya a. Mitani, (2019) “marginal analysis of ordinal clustered longitudinal data with informative cluster size” published in final edited form as: biometrics. 2019 september ; 75(3): 938–949. Doi:10.1111/biom.13050.

2. Rainer hirk (2019) “multivariate ordinal regression models: an analysis of corporate credit ratings” statistical methods & applications (2019) 28:507–539 https://doi.org/10.1007/s10260-018-00437-7

3. Daniel fernandez (2019) “a method for ordinal outcomes: the ordered stereotype model” received: 15 february 2019 revised: 23 may 2019 accepted: 6 july 2019 doi: 10.1002/mpr.1801

4. Matechou, eleni, ivy liu, daniel fernández, miguel farias, and bergljot gjelsvik. “biclustering models for two-mode ordinal data.” Psychometrika 81, no. 3 (2016): 611–24. Doi:10.1007/s11336-016-9503-3.

5. Pan zhang. Evaluating accuracy of community detection using the relative normalized mutual information. Journal of statistical mechanics: theory and experiment, 2015(11): p11006, 2015.

6. Simone romano, james bailey, vinh nguyen, and karin verspoor. Standardized mutual information for clustering comparisons: one step further in adjustment for chance. In proceedings of the 31st international conference on machine learning (icml-14), pages 1143–1151, 2014.

7. Jia, h., and cheung, y.-m. 2018. Subspace clustering of categorical and numerical data with an unknown number of clusters. Ieee transactions on neural networks and learning systems 29(8):3308–3325

8. Jia, h.; cheung, y.-m.; and liu, j. 2016. A new distance metric for unsupervised learning of categorical data. Ieee transactions on neural

networks and learning systems 27(5):1065–1079

9. Cheung, y.-m., and jia, h. 2013. Categorical-and numerical-attribute data clustering based on a unified similarity metric without knowing cluster number. Pattern recognition 46(8):2228–2238.

10. Ienco, d.; pensa, r. G.; and meo, r. 2012. From context to distance: learning dissimilarity for categorical data clustering. Acm transactions on knowledge discovery from data 6(1):1–22.

11. Hedeker, d. (2015). Methods for multilevel ordinal data in prevention research. Prevention science, 16(7), 997–1006.

12. Capuano, a. W., dawson, j. D., ramirez, m. R., wilson, r. S., barnes, l. L., & field, r. W. (2016). Modeling likert scale outcomes with trend-proportional odds with and without cluster data. Methodology

13. Shubham Karnawat, (2019), Flexible Bayesian Quantile Regression in Ordinal Models, arXiv:1609.00710

14. Gutiérrez, Pedro Antonio & Pérez-Ortiz, María & Sánchez-Monedero, Javier & Fernandez-Navarro, Francisco & Martínez, Cesar. (2015). Ordinal Regression Methods: Survey and Experimental Study. IEEE Transactions on Knowledge and Data Engineering. 28. 10.1109/TKDE.2015.2457911.

15. Bürkner, Paul-Christian & Vuorre, Matti. (2019). Ordinal Regression Models in Psychology: A Tutorial. Advances in Methods and Practices in Psychological Science. 2. 251524591882319. 10.1177/2515245918823199.

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