

Alternative Prediction-Interval Scaling Strategies for Regression Models

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Two prediction-interval scaling strategies are illustrated for a 10-point ordinal attribute: one strategy compresses the most extreme scores, and the other strategy compresses the least extreme scores on the scale.

Earlier research demonstrated how ODA may be used to identify threshold values which maximize ESS obtained in predicting ordered scores based on the observations' predicted response function values ("Y-hats") obtained by linear regression analysis.¹⁻⁴ For example, for a 10-point integer scale, to determine accuracy (and thus ESS) it is necessary to define ten prediction

intervals to transform the regression model Y-hats into predicted integer scores. The scaling strategy used in initial research is shown in Figure 1. As seen, the range on the scale used to define the two most extreme scores (1 and 10) is compressed (to half an integer) relative to less-extreme scores of 2 to 9, each defined using a full one-integer range on the scale.

Figure 1: Original Prediction-Interval Scaling Strategy Compressing the Most-Extreme Scores

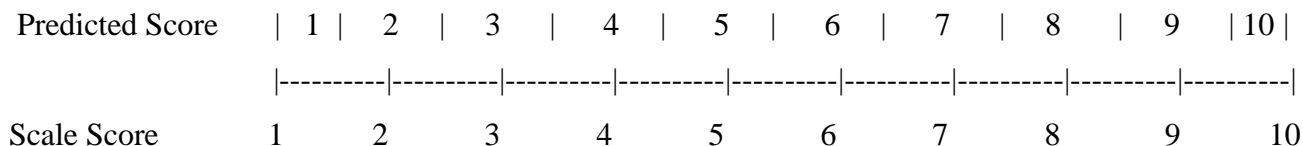
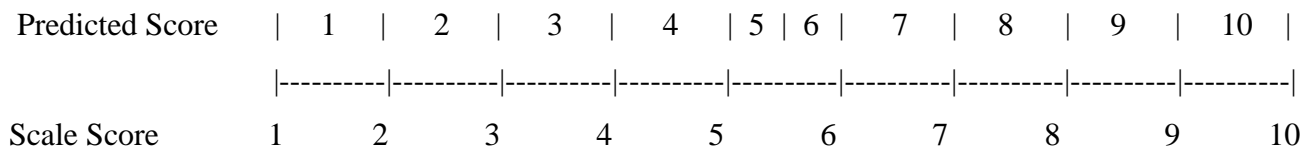


Figure 2 illustrates an alternative scaling strategy for which the range on the scale used to define the two least extreme scores (5 and 6) is

compressed (to half an integer) relative to more-extreme scores of 1-4 and 7-10, which each are defined by a one-integer range on the scale.

Figure 2: Alternative Prediction-Interval Scaling Strategy Compressing the Least-Extreme Scores



Of course, the wider prediction interval range at the scale poles in the alternative scaling strategy (Figure 2) only influences classification outcomes of linear models with nearly perfect R^2 values—otherwise the poles never come into consideration because Y-hats are insufficiently extreme.¹ Furthermore, because ODA operates only on Y-hats—identifying the optimal threshold values for assigning Y-hats to predicted scale scores, classification decisions made by the regression model are irrelevant.¹⁻⁴ Finally, compared to novometric methods, restricting solutions to fit the original scale architecture typically induces a suboptimal solution.⁵⁻¹⁰

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Author Notes

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