Corporate reputation model example of the cross-validated predictive ability test

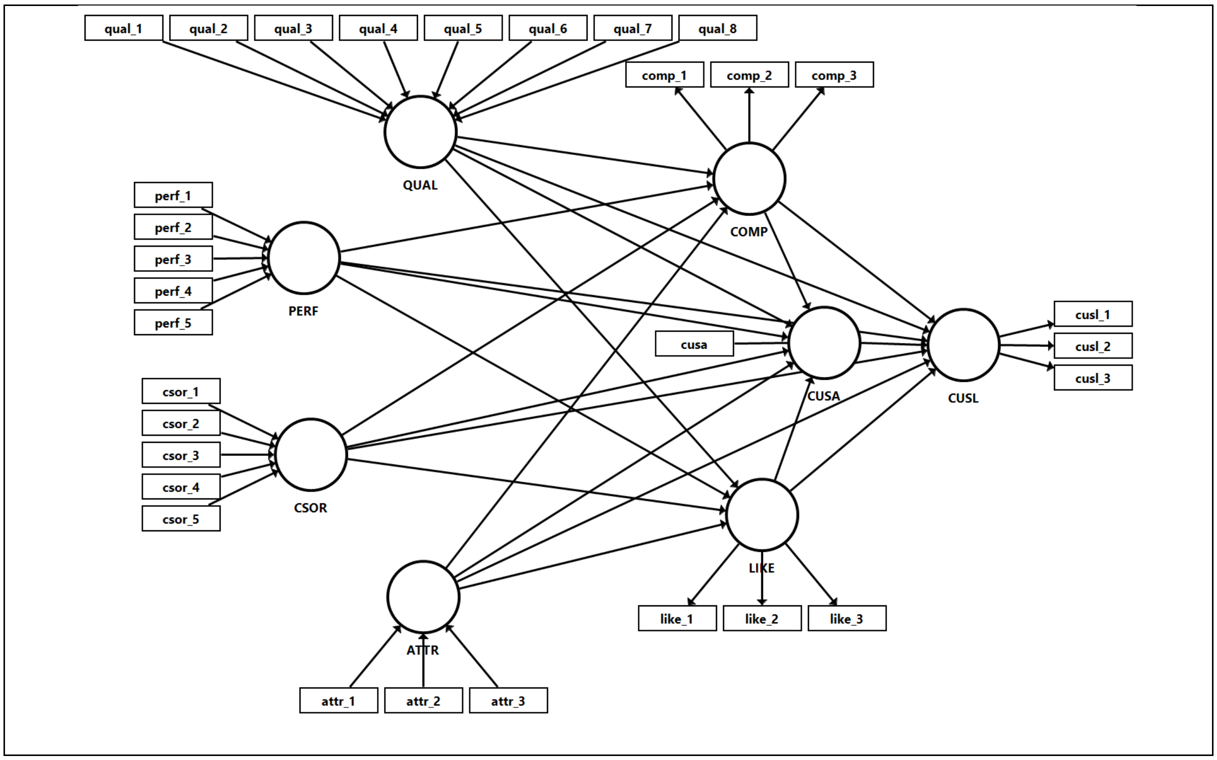
This example shows an application of the cross-validated predictive ability test (CVPAT; Liengaard et al., 2020) to the corporate reputation model (Schwaiger, 2004). The established model (EM) includes competence (COMP) and likeability (LIKE), which represent corporate reputation's two dimensions. These two constructs explain customer satisfaction (CUSA) and customer loyalty (CUSL), while the model also includes a direct relationship from CUSA to CUSL. Moreover, with quality of customer orientation (QUAL), economic and managerial performance (PERF), corporate social responsibility (CSOR), and attractiveness (ATTR) of a company, the model includes fours antecedents of the corporate reputation dimensions COMP and LIKE (for more details of this example, see Hair et al, 2017). This model does not include direct relationships form QUAL, PERF, CSOR, and ATTR to CUSA and CUSL. Therefore, it implicitly assumes a full mediation of these relationships by the two corporate reputation dimensions COMP and LIKE. The alternative model (AM) includes these direct relationships from QUAL, PERF, CSOR, and ATTR to CUSA and to CUSL.

In the "Results extraction" section, we show four ways to obtain results from the CVPAT function (all types of output from the CVPAT function is described in the README.txt file). The two first lines

- res_CVPAT$losses$avg_losses$avg_losses_M1
- res_CVPAT$losses$avg_losses$avg_losses_M2

provide the average losses for Model 1 and Model 2 respectively. The output gives the overall loss in the first column and the remaining columns are the average losses associated with specific dependent constructs in the PLS path model. Comparing average losses for specific constructs across the two models can give hints to which constructs is contributing most to the deviation between the models' overall loss. Notice that the AM is specified as Model 1 in the CVPAT function and the EM is specified as Model 2. Hence, when comparing the average model loss between the EM and AM, we find that the EM has a lower average loss than the AM.

Figure 1: Model 1 (i.e., the alternative model, AM)



- res_CVPAT$boot.p.values

gives the bootstrapped p-values, and shows no significant difference between the two models. The boot.p.values is described in the README file.

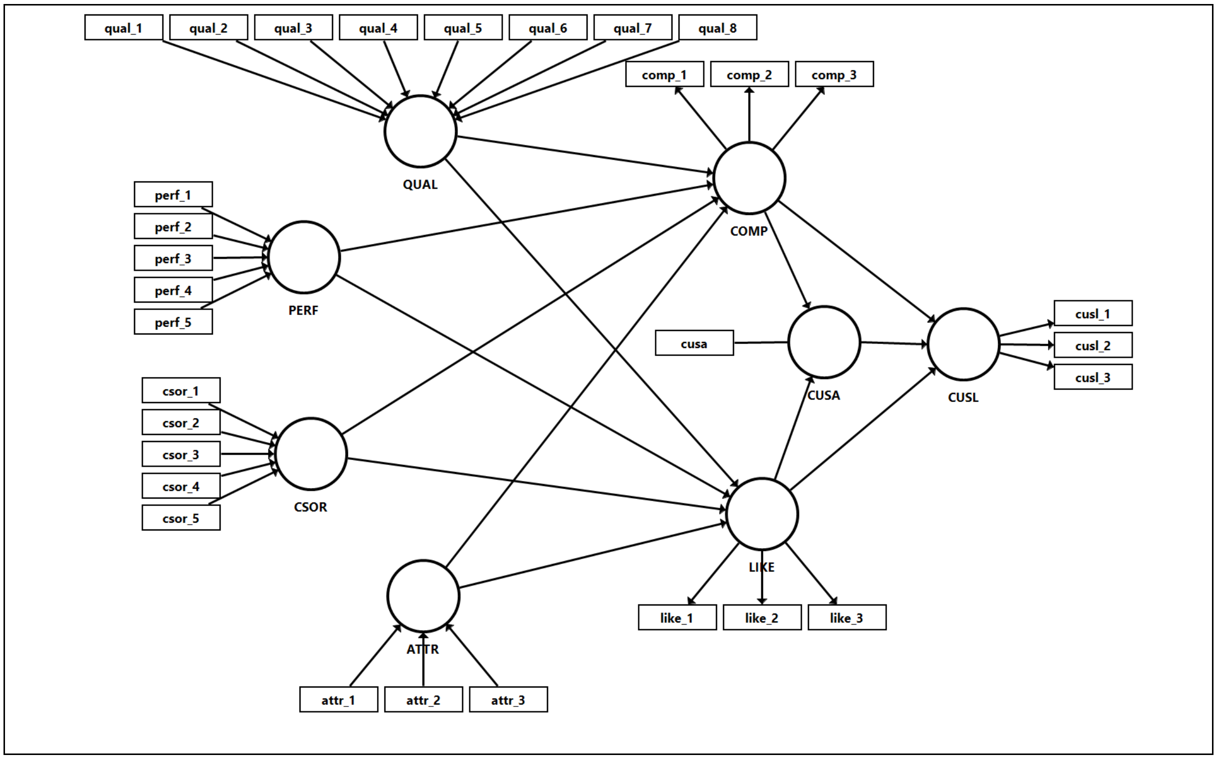
- res_CVPAT$p.value

is the non-bootstrapped p-value and is in line with the bootstrapped p-values.

- res_CVPAT$conf.int

gives the non-bootstrapped confidence interval, which is also yields the conclusion of no significant differences between the two models.

Figure 2: Model 2 (i.e., the proposed model, PM)



Overall there is no evidence in favor of the AM being the model with best out-of-sample performance, and we retain the EM as the best predictive model. When comparing the average losses between the AM and EM, we find that the EM has the lowest loss. For this reason, the statistical test shows that the out-of-sample prediction accuracy of AM is not significantly better than the EM.

References

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Thousand Oaks, CA: Sage.

Liengaard, B., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2020). Prediction: coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. Decision Sciences, forthcoming.

Schwaiger, M. (2004). Components and parameters of corporate reputation: An empirical study. Schmalenbach Business Review, 56(1), 46-71.