**Motivation**

*We use entropic relevance [ICPM2020] to quantify the quality of the discovered and forecasted DFGs with respect to the event logs they represent. Entropic relevance penalizes the discrepancies in the relative frequencies of traces recorded in the log and described by the DFG. Entropic relevance stands for the average number of bits used to encode a log trace using the DFG, with small values being preferable to large ones.*

*The entropic relevance of the forecasted DFG and the actual future DFG with respect to the test log is 4.64 and 4.63, respectively, suggesting that both DFGs represent the future behavior similarly well. The entropic relevance of the historical DFG derived from the training log with respect to the testing log is X, suggesting that the future behavior shifts and the historical DFG does not describe the testing log well enough. Finally, the DFG that describes all and only traces of the testing log with the relative frequencies as they are observed in the log has the entropic relevance with the testing log of Y, the best possible relevance value for this log. As the difference between 4.64 and Y is small, we conclude that the forecasted DFG approximates the actual future behavior well and much better than the historical DFG.*

**Discussion**

*The technique for forecasting DFGs presented in this paper can be seen as a process discovery technique [WIL’S BOOK]. Similar to the standard approaches in data mining and machine learning that construct a model from historical data that represents future data, in addition to representing historical log, the forecasted DFGs aims to achieve good generalization [GOOD REF ON GENERALIZATION], that is, the ability to represent traces observed in the future.*