for learning purpose goes beyond hyper-links and traditional metadata keywords. Consequently, we proposed an information model in which contents are qualified regarding the competencies they require and the competencies they provide. As latent factors, competencies are difficult to recognize even by knowledge domain experts. For this purpose we presented our results on automated competency extraction providing methods to name them and evaluate competency frameworks predictive quality. Among future developments, we envision the extension of our work on competency frameworks to multi-relational structures including the two types of competencies defined in our information model (competencies gain and required) while taking care as discussed in Section 4, of the scalability of proposed methods.

## 6. ACKNOWLEDGMENTS

This work is part of the National Research Council Canada program Learning and Performance Support Systems (LPSS), which addresses training, development and performance support in all industry sectors, including education, oil and gas, policing, military and medical devices.

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