**LEVEL 0 SUMMARY**

* **Name of student:** Reckia Jiffard
* **Name of your Level 1:** Mohamed Anissat
* **Source (e.g. scholars.google.com):** Google scholar
* **Paper title:** Using Artificial Neural Networks to Derive Process
* **Keywords specific to the paper:** “business process modeling”“deep learning”
* **Summary of the main contributions (Use text paragraphs, tables and if necessary, figures):**

The paper studies how deep learning techniques can be used to automatically generate activity labels for business process models from descriptive text documentation. Business process modeling is an important part of business process management but creating models from textual descriptions requires significant cognitive effort. Previous approaches to this problem have used rule-based natural language processing techniques but these can be inaccurate. Deep learning methods from natural language processing have achieved good results on related tasks like machine translation and text summarization.

The research aim to investigate whether these methods could effectively derive process model activity labels from descriptive text. As deep learning models require large annotated datasets for training, and publicly available pairs of process model descriptions and corresponding activity labels are scarce, the researchers employ a transfer learning approach. They train a neural network model on a large corpus of news headlines and sentence summarizations to perform a deletion-based sentence compression task.

This compression model is then fine-tuned on a smaller set of process model descriptions and manual activity labels. Two compression models are studied - a base model using only word embeddings as input, and a linguistic knowledge model which also incorporates part-of-speech tags and dependency labels. The models are evaluated on precision, recall, F1-score and compression rate for both the news corpus and process descriptions. Performance on the news corpus indicates the linguistic knowledge model learns syntactic patterns more effectively. When applied to the process description test data, both models achieve significantly higher recall than precision, indicating they retain most important terms but include additional unnecessary words. The compression rates are also higher for process data than news, showing more words are retained in the summaries.

These results suggest the domain shift between training and test data affects performance. Two output examples are provided where the model summaries fully contain the true activity labels but with extra words. While less concise than manual labels, the automated summaries could still help reduce the cognitive load for modelers by highlighting important terms to consider. To improve precision on the process domain, the researchers propose collecting a process-specific training corpus and applying online learning techniques to gradually introduce this new data during model training. Limitations included the small size of the process description dataset and requirement for manual post-processing to clean up generated labels. In conclusion, the transfer learning approach was able to leverage existing sentence compression techniques and general linguistic knowledge learned from large unlabeled datasets to derive process activity labels with high recall from descriptive text.

However, domain-specific data could help address precision issues and better adapt models to the process modeling context. With refinement, neural networks may assist in automating part of the business process modeling task. Moving forward, more extensive evaluations are needed using realistic process modeling scenarios and datasets. Collecting datasets pairing process documentation with annotated activity labels identified by experts would enable end-to-end training of compression models without transfer learning. User studies could explore how integrated tools impact modelers' productivity.

Overall, the study demonstrates the potential for deep learning to semi-automate knowledge extraction from unstructured process descriptions. With further work bridging domains and optimizing for precision in target applications, neural networks may take over more of the routine labeling work - freeing modelers to focus on the higher-level conceptual tasks. Continued research in this area holds promise for advancing the automation of business process modeling.

* **AI model used (e.g. Neural network, etc.)**

The document discusses the use of Artificial Neural Networks (ANNs).

* **Introduce the AI models**

The Artificial Neural Networks (ANNs) model is used to derive process model activity labels from process descriptions. It employs a transfer learning approach, where the model is initially trained on a large news corpus for sentence compression and then transferred to the task of labeling process descriptions. The model aims to address the scarcity of publicly available pairs of text and process models by leveraging transfer learning to adapt the pre-trained compression model to the task of deriving label descriptions from process descriptions.

* **How do they contribute the idea proposed by the paper?**

The AI model used in the paper, contribute to the proposed idea by providing a mechanism for deriving process model activity labels from process descriptions. The transfer learning approach allows the pre-trained compression model to be adapted to the specific task of labeling process descriptions, addressing the scarcity of publicly available pairs of text and process models. By leveraging ANNs and transfer learning, the paper aims to overcome the lack of domain-specific training data and achieve high recall in deriving label descriptions from process descriptions.

**Supported by a software application? (If yes, provide more details)**

No, it does not mention any specific software application that supports the AI model or the transfer learning approach discussed.