

AUTOMATIC AND INTERPRETABLE DREAM REPORTS ANNOTATION WITH TEXT-GENERATION LARGE LANGUAGE MODEL

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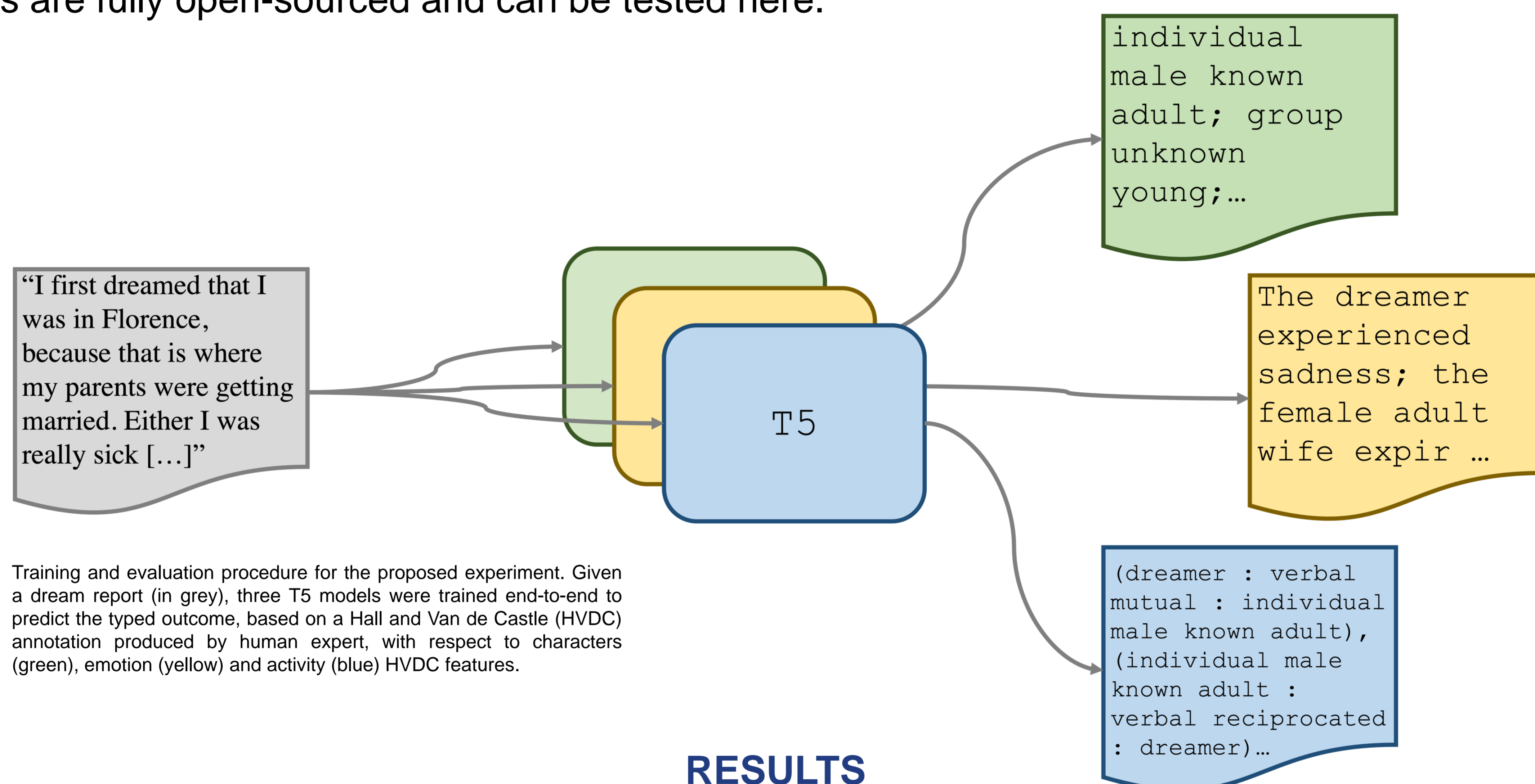
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INTRODUCTION

Dream and sleep researchers have shown great interest in adopting natural language processing (NLP) tools to automatically analyse and annotate dream reports [1,3]. However, current approaches are largely limited to dictionary-based and distributional semantic models, unable to analyse the full context of a report, requiring considerable data pre-processing, and producing poorly grounded annotations. These issues can be easily superseded by adopting pre-trained large language models (LLMs), like BERT and GPT, capable of learning new tasks even with little-to-no supervision [1,2]. In this work, I adopted T5, a text-to-text generation model, to train a series of LLMs that produce fully-interpretable Hall and Van de Castle (HVCD) annotations.

METHOD

Approximately 1.8k reports annotated by experts according to the HVDC system were obtained from DreamBank's team. Using 80% of the data, three T5 models were trained end-to-end for up to 10 epochs – using training loss as a selection metric – to (re-)produce spelt-out HVDC annotations. Given a full report, LLMs were trained to (re-)produce three HVDC features, namely characters (e.g., (individual female known adult; individual male stranger adult;)), emotions (e.g., (sadness, apprehension)), and activity (e.g., (dreamer : towards verbal : individual male stranger adult)), as identified by expert annotators. The remaining 20% of data was used to evaluate each model, via the Rouge-1 [0,1] metric. Obtained models are fully open-sourced and can be tested here.



RESULTS

All models easily learned to produce realistic and grammatically correct outputs. Out of the three tasks/features, the best performing one (in Rouge-1 [0,1] scores) was emotions (.81), followed by characters (.78), and activity (.47). Interestingly, using the LLM trained on character as a base, instead of only using a pretrained T5, boosted the performance on the other two tasks.

CONCLUSIONS

In this work, I propose a solution to tune pre-trained state-of-the-art LLMs to produce robust and transparent HVDC features annotations. LLMs represent a great opportunity for dream and sleep research, since they can require relatively little training to adapt to new tasks, need very little to-no data processing, and are widely available and open source, increasing replicability and usage.

REFERENCES

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