Generating Medical Prescriptions with Conditional Transformer

Motivations

► Access to real-world medication prescriptions is essential for medical research and healthcare quality improvement.

► This access is often limited due to the sensitive nature of the information expressed.

► Manually labelling these instructions for training and fine-tuning Natural Language Processing (NLP) models can be tedious and expensive.

LT3: Label to Text Transformer
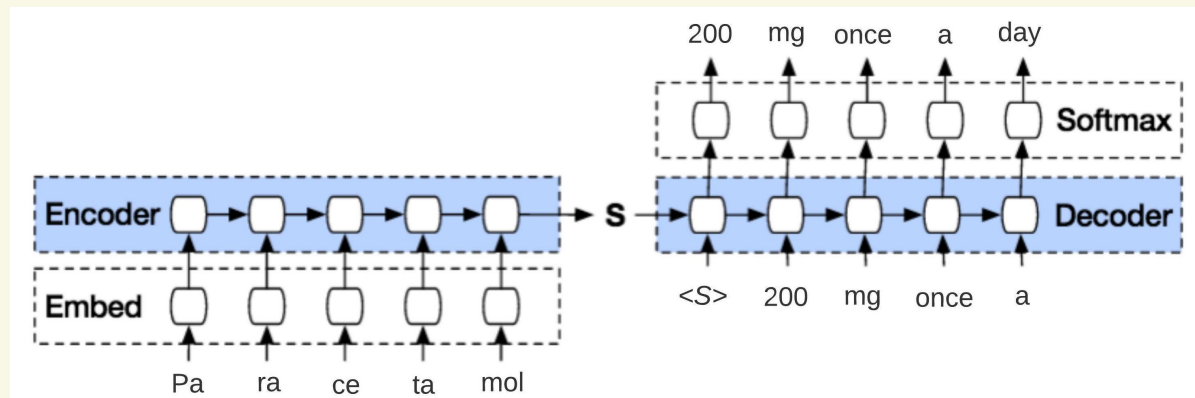
LT3 Architecture with input/output behaviour (this is a shortened example of a generated synthetic medical prescription.)

Methodology

► A novel task-specific model architecture, **LT3:** Label to Text Transformer

► Tailored to generate synthetic medication prescriptions based on provided labels, e.g. a vocabulary list of medications and their attributes.

► LT3 is trained on a set of around 2K lines of medication prescriptions from the MIMIC-III

► Evaluate LT3's performance by contrasting it with T5, analysing the quality and diversity of generated texts.

► Deploy the generated synthetic data to train the SpacyNER model over the n2c2-2018 dataset.

Quality Evaluation to Reference and Intra-Diversity

Models	BLEU	ROUGE-1	ROUGE-2	ROUGE-L	BERTScore
T5 Small	71.75	76.16	66.24	75.55	0.70
T5 Base	71.98	76.28	66.30	75.45	0.70
T5 Large	69.89	75.07	65.19	74.22	0.68
LT3	**78.52**	**78.16**	**68.72**	**77.55**	**0.72**

Table: Closeness to Reference Evaluation with Lexical and Embedding Metrics

	Median Jaccard Score	Average Jaccard Score
LT3	**0.650**	**0.652**
T5 Base	0.658	0.660

Table: Jaccard scores of LT3 and T5 on Intra-diversity of generated text (lower is better)

Conventional BSD vs B2SD

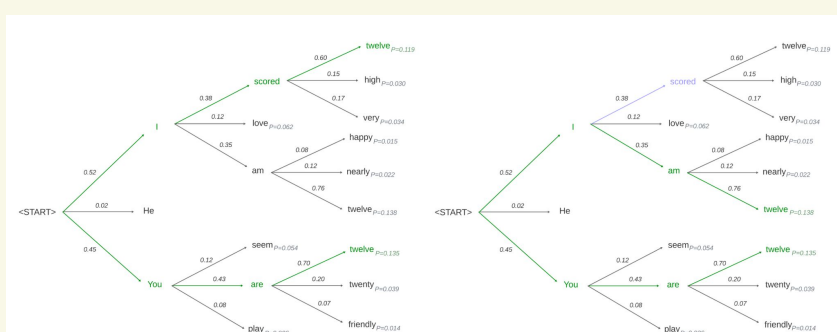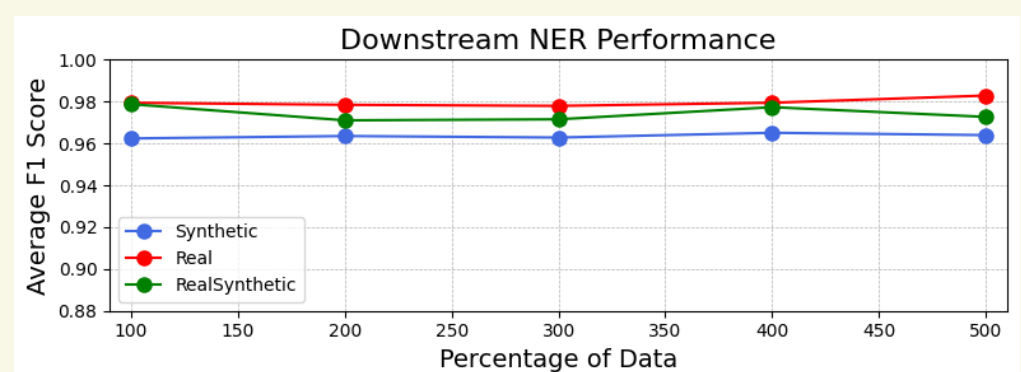(a) Original BSD ($n = 2$)   (b) B2SD ($n = 2, m = 2, p_b = 1$)

Figure 2: Execution Examples of Conventional Greedy BSD and B2SD Algorithms

► Beam Search Decoding using Backtracking (B2SD) to Transformers

► B2SD allows the model to find global optimised output instead of locally at each time step.

NER model training using real vs synthetic data

► Real data is over-sampled from 100 to 500%; RealSynthetic used 100% real plus synthetic data.

► The experiments show that the model trained on synthetic data can achieve a 96-98% F1 score at Label Recognition on Drug, Frequency, Route, Strength, and Form.

► **LT3** project including codes is **open-sourcely hosted** at `https://github.com/HECTA-UoM/Label-To-Text-Transformer`

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