Are we spreading Hate or Reach? Towards Generating Contextually Relevant Reactions for LinkedIn Data

Group 17

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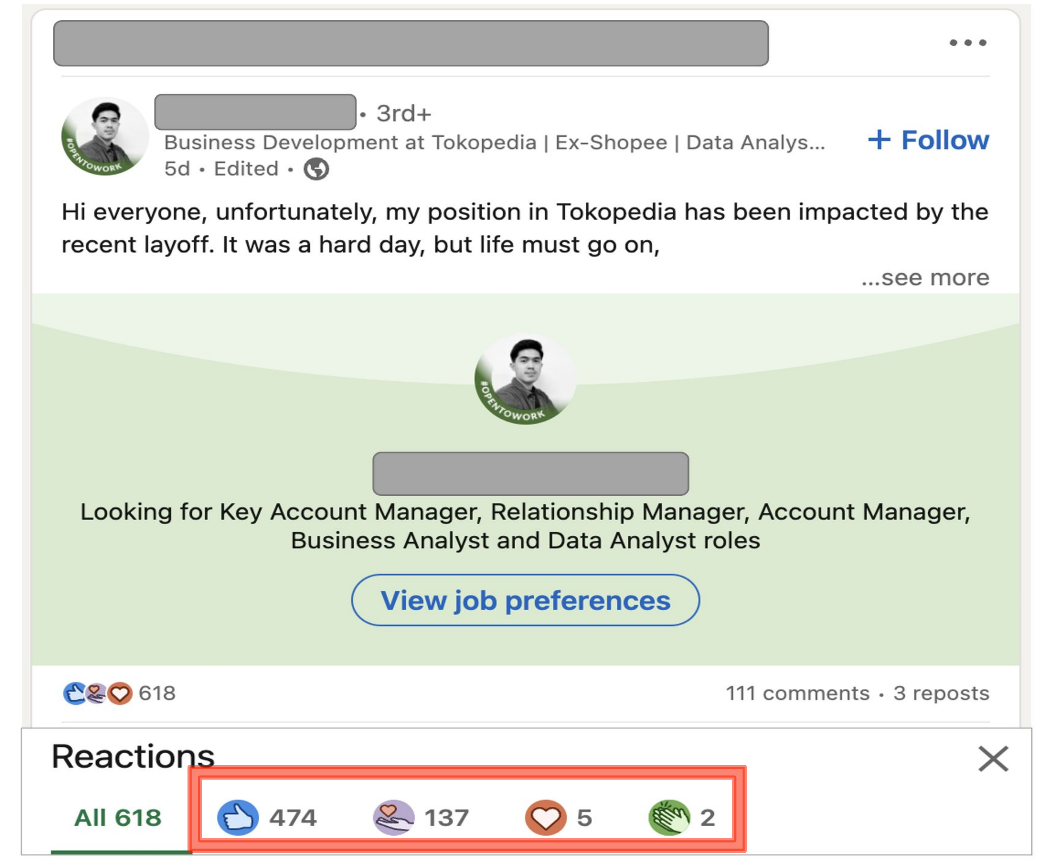
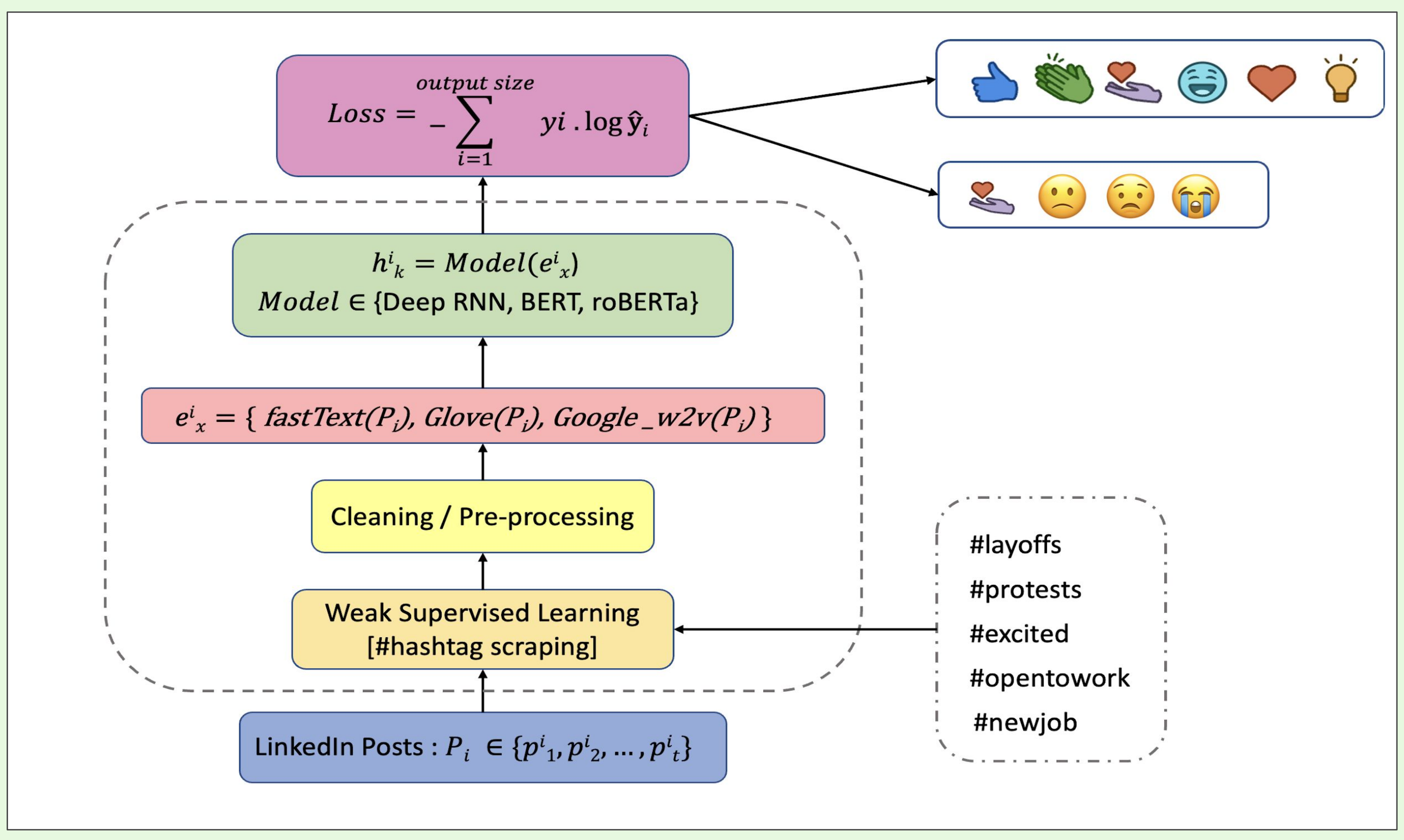
Motivation

- LinkedIn gets flooded with 1000s of **posts**, and there are **multiple reactions** to react to a post
- Most of the time, such **reactions** often tend to be **against the sentiment of the post**
- This **spreads negative sentiments** amongst the users creating a negative psychological impact on the user. (E.g., like/celebrate/funny reaction to a post related to unemployment/protests)
- **Novelty**: We propose a system that generates only contextually relevant reactions based on the sentiment.
- Our system aims to answer the following **research questions**:
  - How many people react with a reaction opposite to the LinkedIn post sentiment?
  - How can we generate contextually relevant reactions to restrict the negative hate spread?



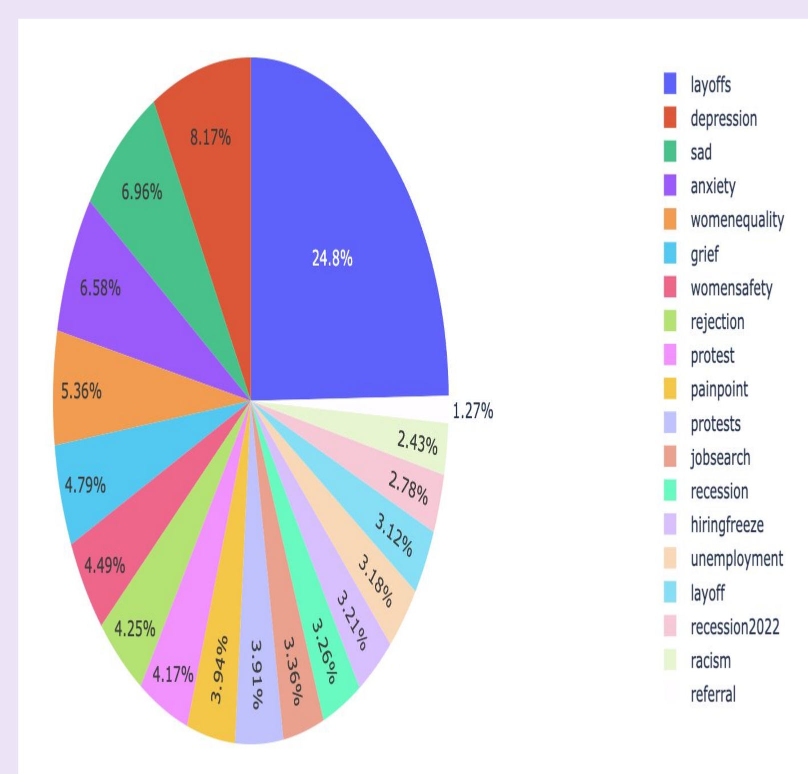
Design

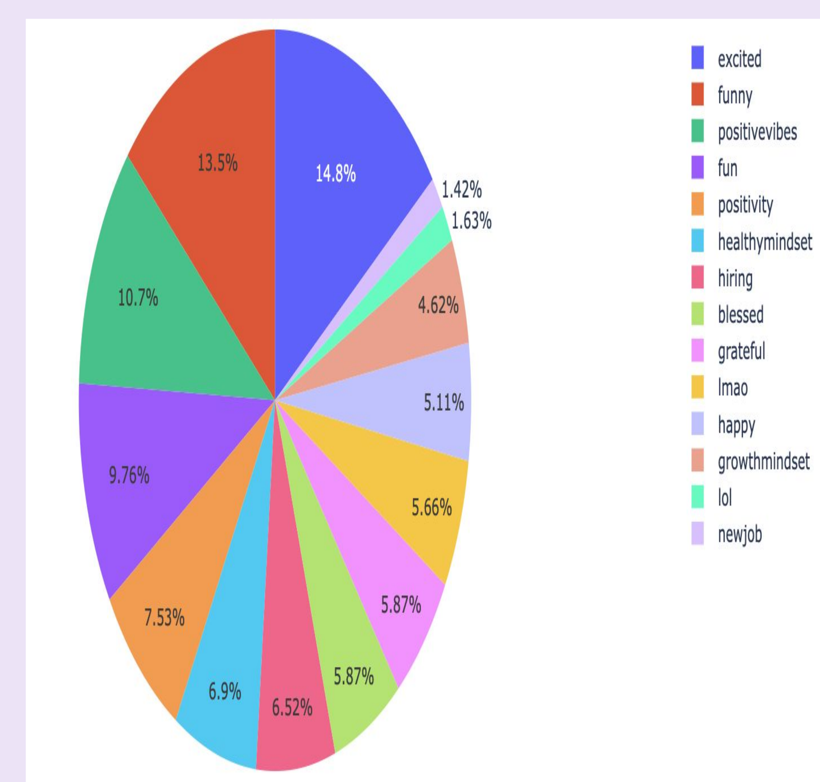
- Custom model architectures such as **Deep Bidirectional- LSTMs, GRUs** and **Stacked LSTM-GRUs** were trained on **20K posts.**
- **FastText, Google pre-trained w2v,** and **GloVe** were used to obtain vector representation for words.
- Pre-trained **BERT$_{BASE}$** and **RoBERTa$_{BASE}$** models were fine-tuned on our training data.



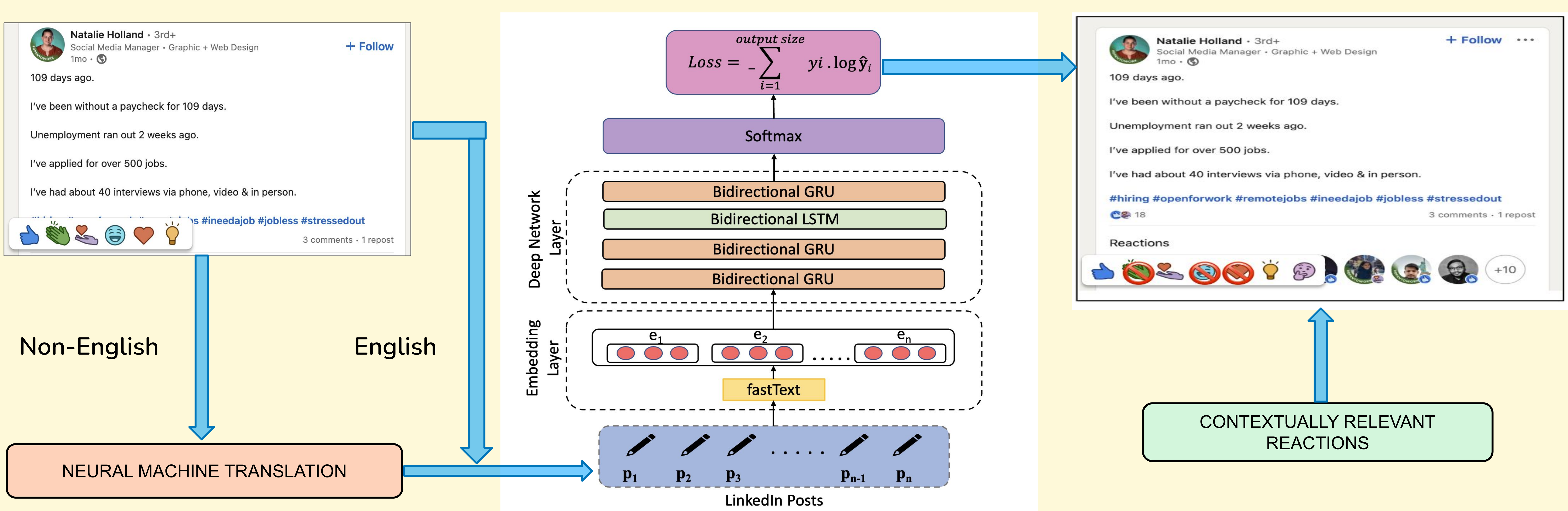
Dataset

- Used **Weak Supervised Learning** approach to generate and annotate data from raw LinkedIn posts
- Around **20K posts** were scraped using a **scraping script** and 30 different hashtags
- Posts were further classified into respective sentiments based on the hashtags (E.g., Neg sentiment for #layoffs, #protests, etc.)





Model Architecture & Pipeline



Analysis and Results

- Models were evaluated on **~3K test data posts.**
- **False positives** are of higher concern to us. Hence, we want **precision to be high.**
- **Stacked GRU-LSTM** performed better as compared to other custom models.
- Fine-tuned BERT$_{BASE}$ and RoBERTa$_{BASE}$ models were the **top performers.**

Model	Embedding	Avg. P	Avg. F1	Avg. Accuracy
Deep Bidirectional-GRUs	Fast Text	0.87	0.87	0.87
	Glove	0.85	0.85	0.85
	Google-W2V	0.86	0.86	0.86
Stacked GRU-LSTM	Fast Text	0.89	0.88	0.89
	Glove	0.86	0.85	0.85
	Google-W2V	0.87	0.87	0.87
BERT$_{BASE}$	Pre-trained	0.96	0.96	0.96
RoBERTa$_{BASE}$	Pre-trained	0.96	0.96	0.96