Programa de Pós-graduação em Sistemas de Informação

Enhancing LSTM-Based Sarcasm Detection on Social Media with LLM-Generated Sentences

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#1:

Such a wonderful day, I love hurricanes!

#2:

Seriously, Sherlock? You're such a smart guy!

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You can differentiate sarcasm from other types of rhetorical questions by identifying if the sentence has a target.

Nonetheless, it's safe to say that even humans may struggle to identify sarcasm in text.

How do machines learn sarcasm?

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Message: Oh, of course she believes the earth is round! She's so smart!

Answering to: Johnny anti-science

Community: Flat-earth society

The state-of-the-art

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Maynard and Greenwood (2014) propose a technique that utilizes hashtags inside the Tweets to improve model accuracy.

Using Reddit data, Hazarika et al. (2018) present a unique, still obvious approach: gather context from the user and use it to train the model. This technique is quite clever since the model can know infer based on the user's profile instead of only the sentence alone.

The hypothesis

LLMs as synthetic sentence generators

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If LLMs are effective in sarcasm detection tasks, can they be used as synthetic sentence generators?

Since we have a dataset of real sarcastic tweets (Abu Farha et al. 2022) for evaluation, can we use these generated synthetic sentences to train and enhance the model for contrast detection?

The training step

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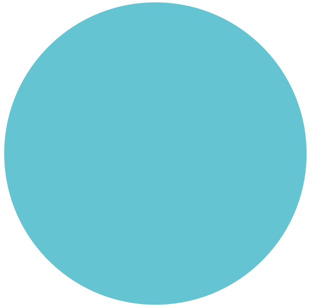
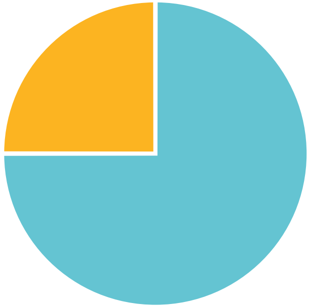
Only real tweets



50% of synthetic and 50% of real tweets

25% of synthetic and 75% of real tweets



75% of synthetic and 25% of real tweets

The training step

Since GPT-4o is the most advanced LLM as of the day I write this, it has been chosen as the synthetic sentence generator. (OpenAI 2024a)

Recurrent Neural Networks in a nutshell

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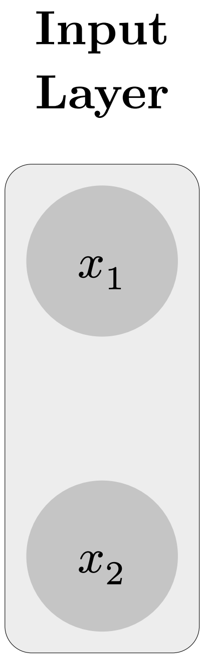

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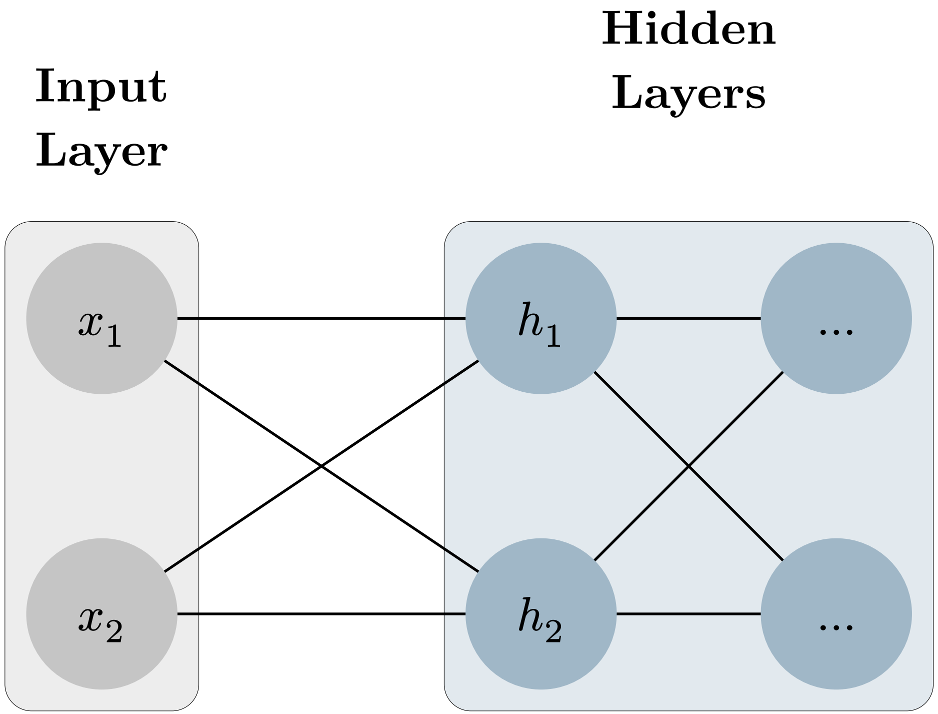

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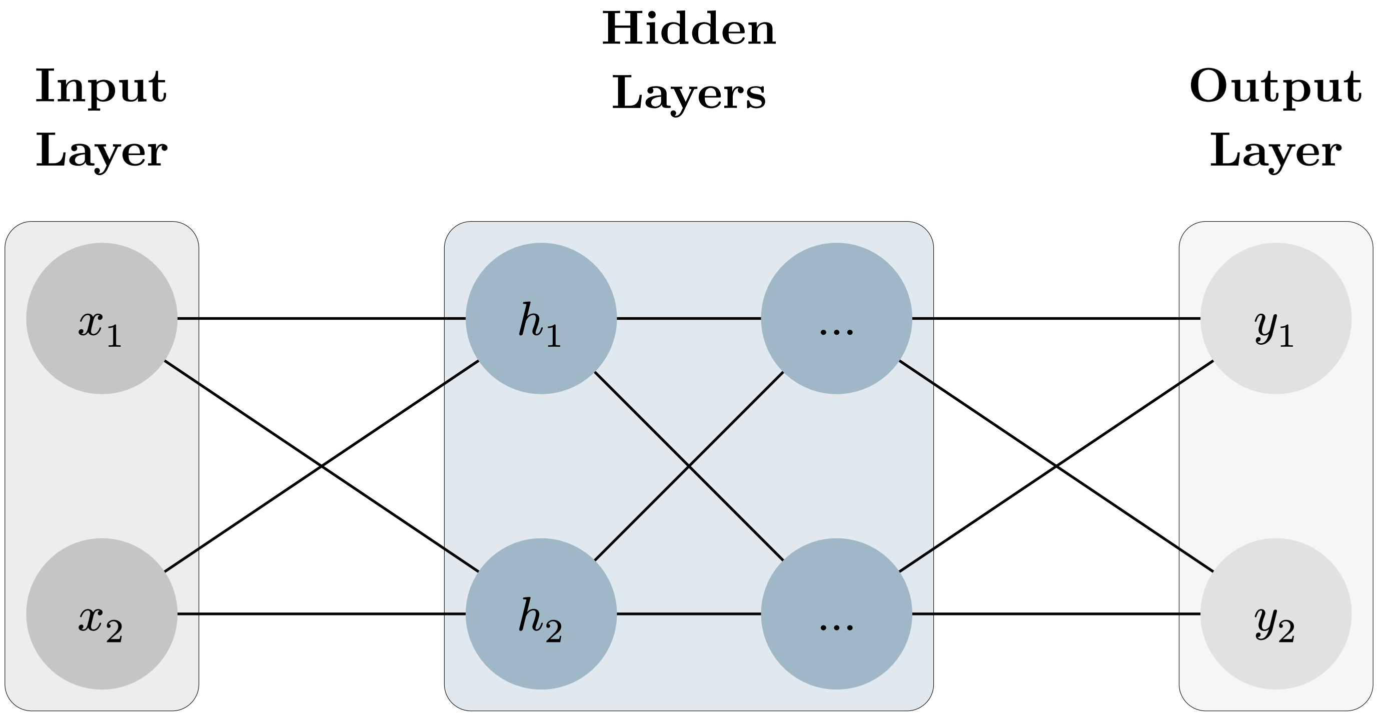

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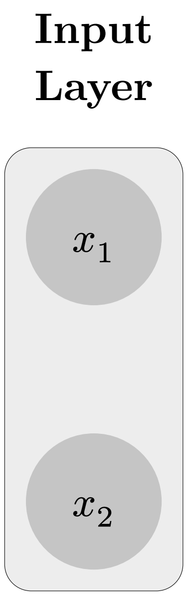

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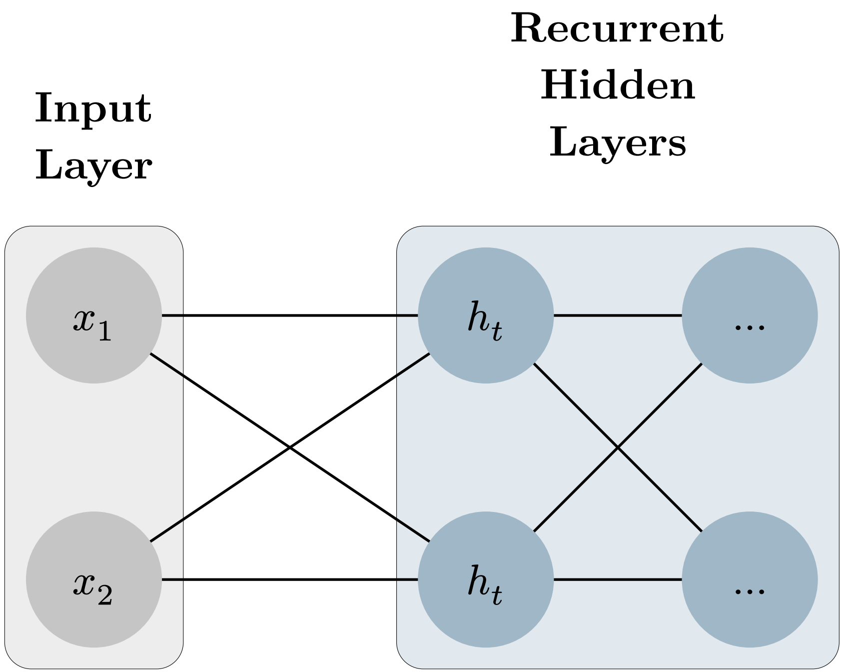

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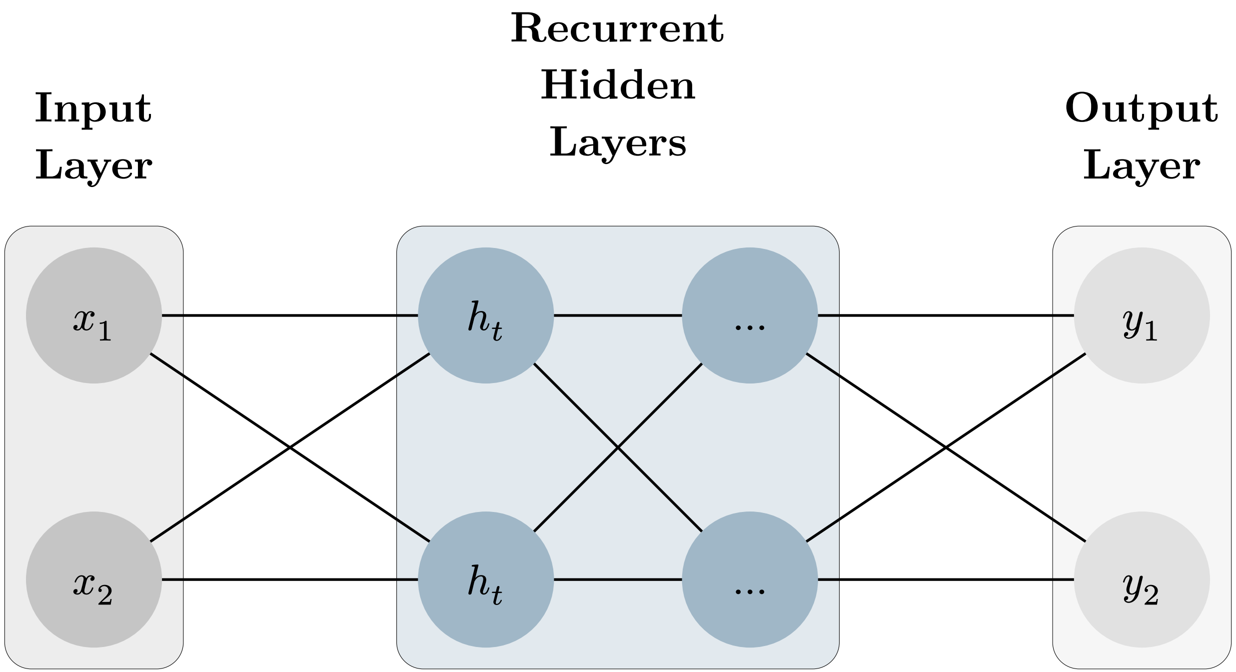
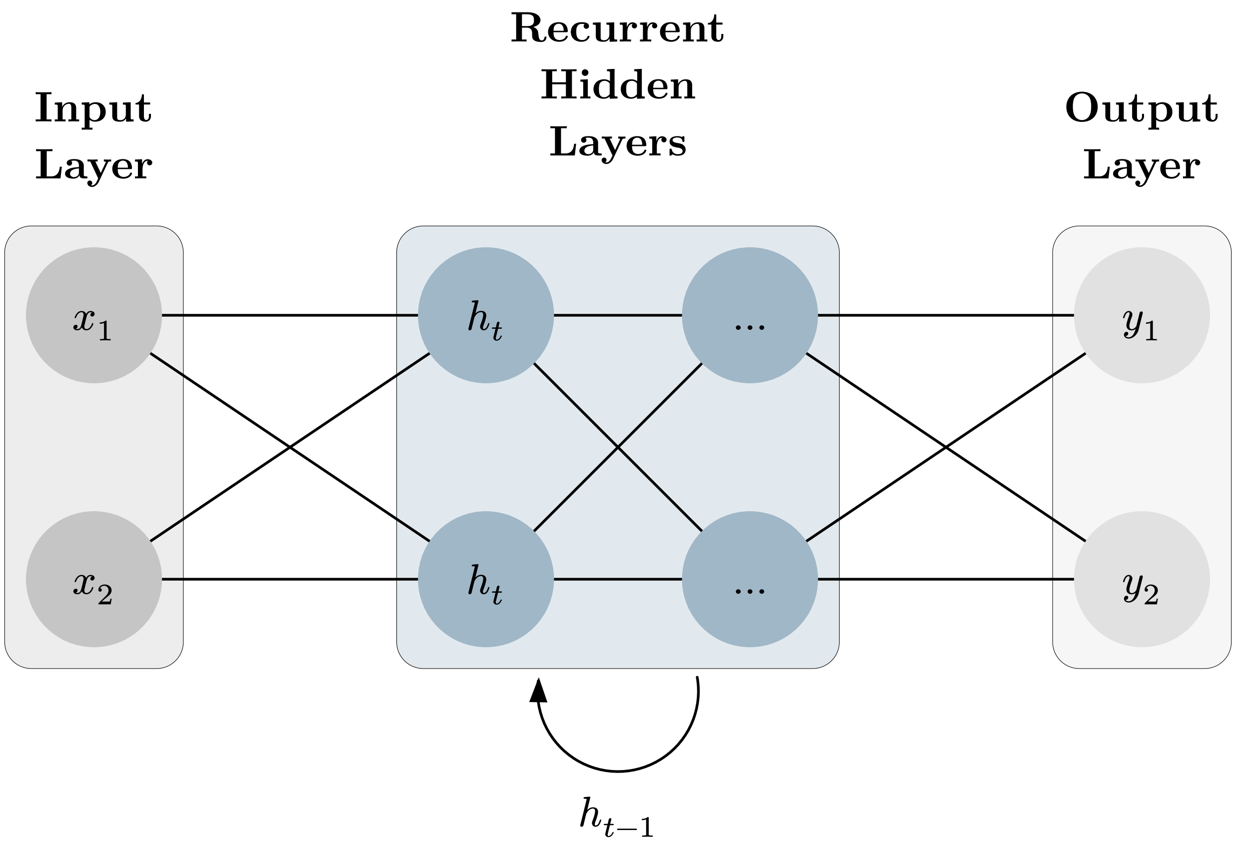


Recurrent Hidden Layers
Input Layer
Output Layer
x_1
x_2
h_t
h_t
...
...
y_1
y_2

RNNs, maybe?


Input
Layer
Recurrent
Hidden
Layers
Output
Layer
x_1
x_2
h_t
h_t
...
...
y_1
y_2
h_{t-1}

The vanishing gradient problem

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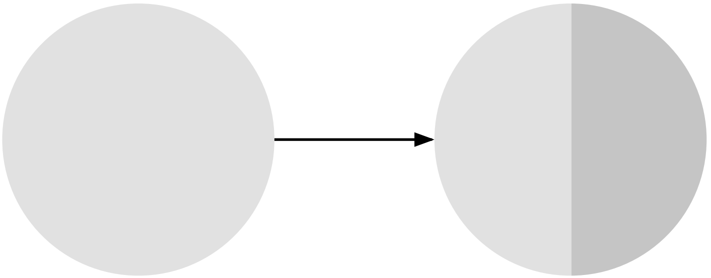

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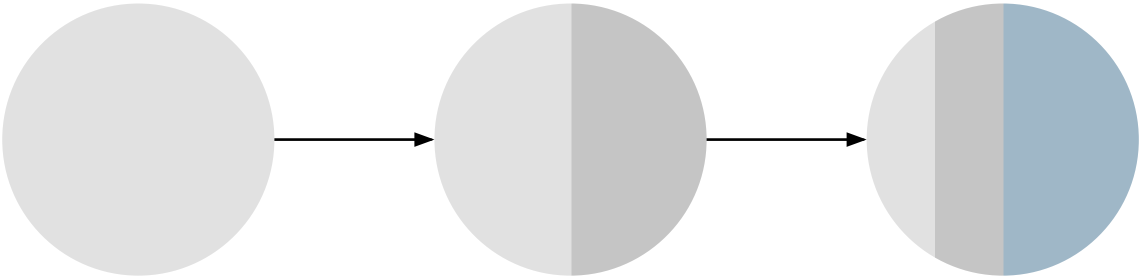

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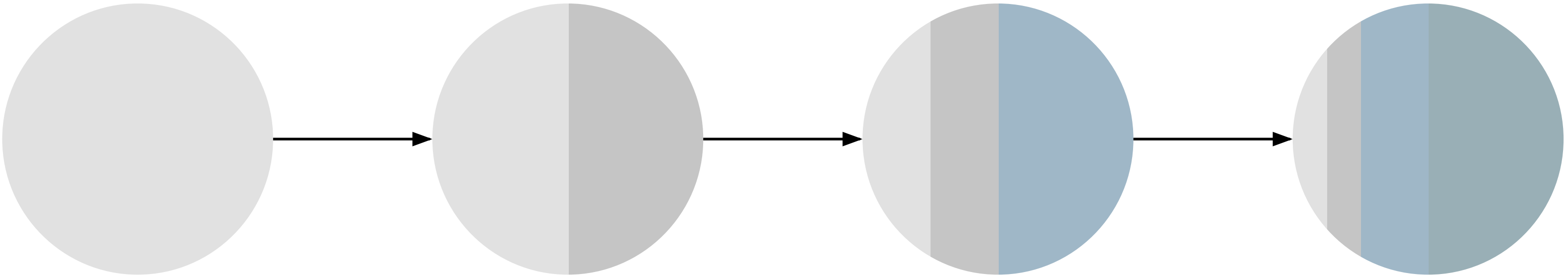

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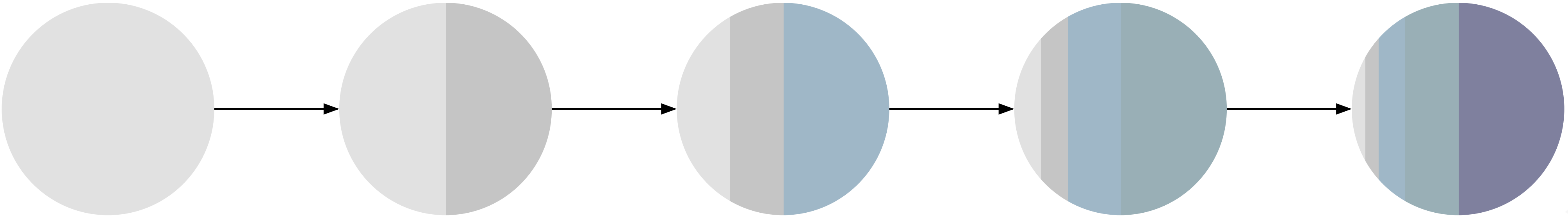

What about Long short-term memory neural networks?

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LSTMs implement a more robust mechanism that allows them to retain information over longer periods of time.

By maintaining the state C_t and using the input gate i_t, forget gate f_t, and output gate o_t, they can decide what to add or remove, as well as what to output for the next iteration.

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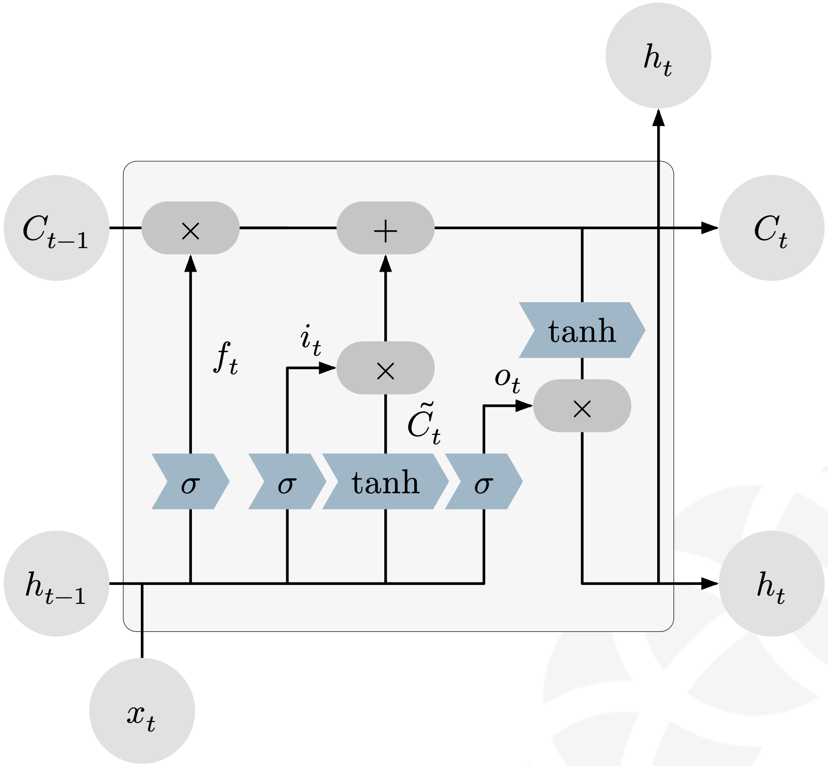

Evaluation

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The effectiveness of the model will be benchmarked against other models as well: GPT 4, GPT 4.0o, BERT, Llama 2 and Llama 3 (Achiam et al. 2023; OpenAI 2024b; Devlin et al. 2019; Touvron et al. 2023; Meta 2024).

Timeline

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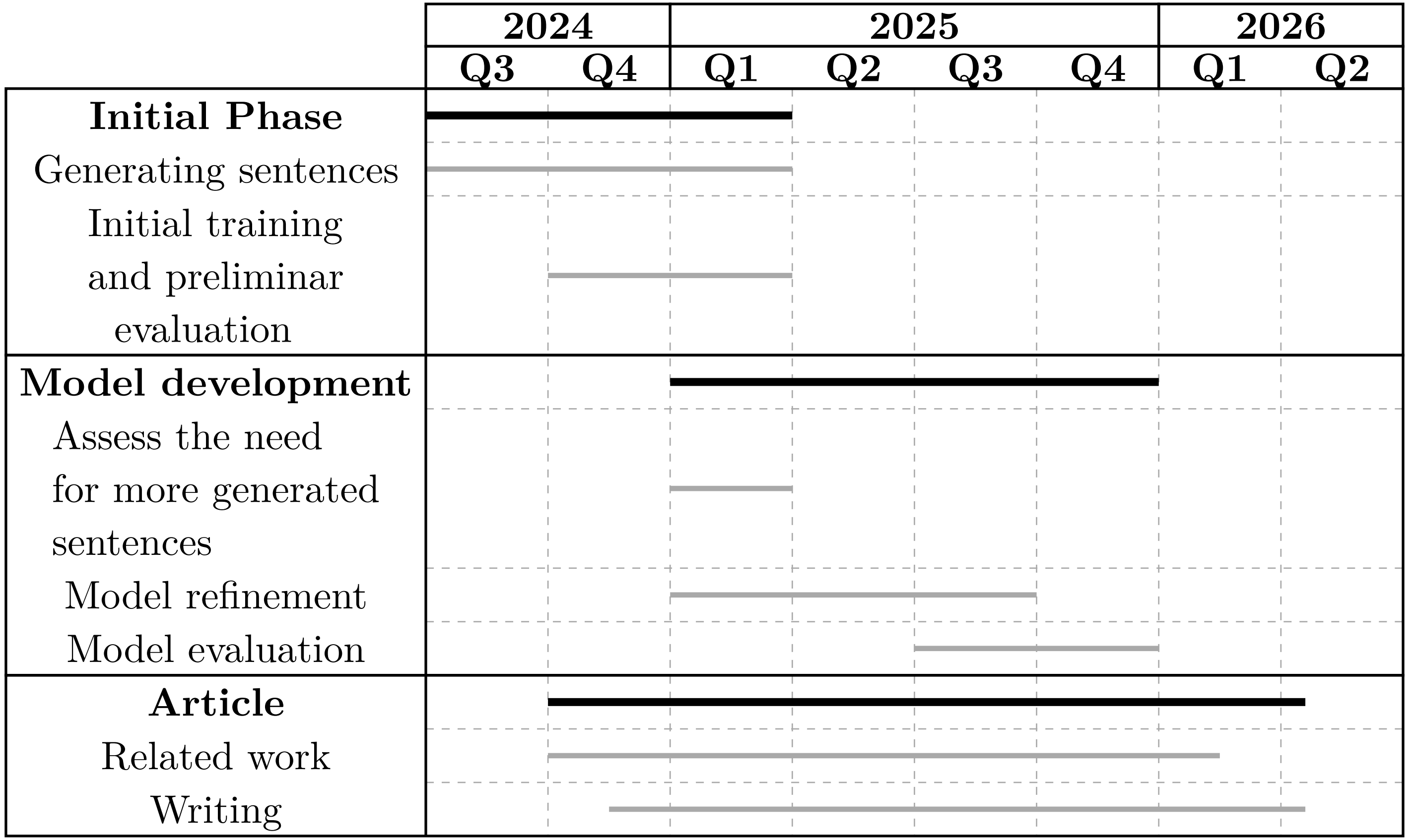
2024
2025
2026
Q3
Q4
Q1
Q2
Q3
Q4
Q1
Q2
Initial Phase
Generating sentences
Initial training and preliminar evaluation
Model development
Assess the need for more generated sentences
Model refinement
Model evaluation
Article
Related work
Writing

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Appendix

Long Short-Term Memory Networks

Cell state: This is the "memory" part of the LSTM, carrying relevant information throughout the processing of the sequence. Plays a major role in transferring past knowledge to future states.

Input gate: Decides how much of the newly computed state for the current input x_t should be added to the cell state.

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{1}$$

Forget gate: Decides how much of the current cell state should be kept. Anything that was not forgotten is passed along to the next step.

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \tag{2}$$

Update Cell State: This step combines the old state C_{t-1} and the new candidate values, modulated by the forget gate and the input gate.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{3}$$

Output: Decides what part of the cell state should be output at this step

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh(C_t) \end{aligned} \tag{4}$$

Evaluation metrics

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{5}$$

$$precision = \frac{TP}{TP + FP} \tag{6}$$

$$recall = \frac{TP}{TP + FN} \tag{7}$$

$$f1 = \frac{2 \cdot (precision \cdot recall)}{precision + recall} \tag{8}$$

Activation functions

Sigmoid:

$$\sigma(x) = \frac{1}{1} + e^{-x} \tag{9}$$

Tanh:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{10}$$

Cross Validation

A dataset D is split into k equal parts. The model is trained and validated k times, with one of the parts D_k being used as the validation set V_i in each iteration, while the other parts T_i are used for training. Performance metrics are calculated at each step. The overall error rate is the average of the error rates from each step, where e_i is the error rate in the i-th iteration:

$$E = \frac{1}{k} \cdot \sum_{i=1}^{k} e_i \tag{11}$$

Stratified Cross Validation

The dataset D is first stratified into k parts $(D_1, D_2, ..., D_k)$, ensuring that the sample ratio for each class in each part D_i is as close as possible to the ratio of that class in the complete dataset D. If C represents a class label, then the class ratio C in each D_i, denoted as p_{C_i}, should closely match p_C, the ratio of the class C throughout the dataset D:

$$p_{C_i} \approx p_C, \quad \forall i = 1, 2, ..., k \tag{12}$$

Once the data is stratified, cross validation proceeds as usual. Each part D_i is used once as a validation set V_i, while the remaining combined parts form the training set T_i.

Questions?