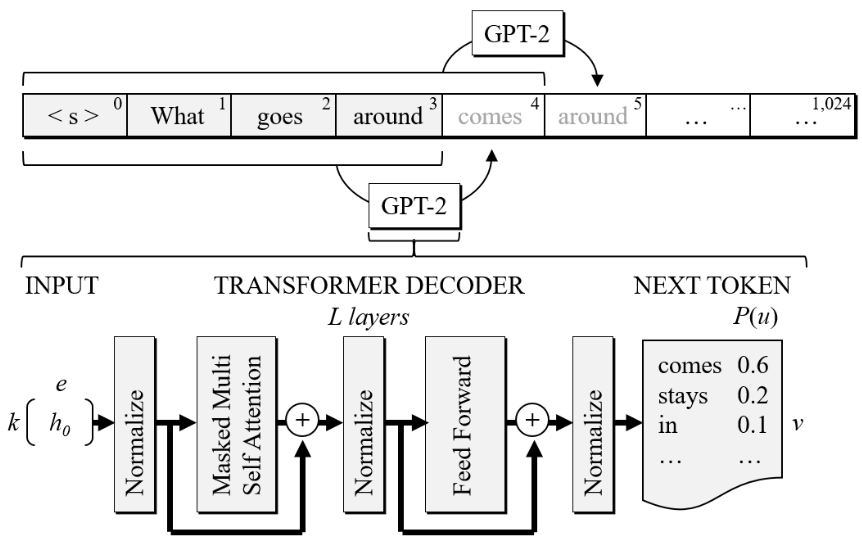
1.1 GPT-2 Model Description

To provide the intuition behind transformer-based NLG models, we briefly illustrate the mechanics of the popular GPT-2 model. Given a sequence of tokens with context window size k, $U=(u_{-k},\dots,u_{-1})$, the objective of the autoregressive model GPT-2 is to accurately "predict" the next likely word[1] (Figure W1.1) by sampling from a probability distribution over its entire learned vocabulary (consisting of 50,257 tokens) conditional on the given word sequence and on a pre-trained neural network with parameters Θ. Model pre-training tries to maximize the likelihood in equation (W1) for an unsupervised corpus of words ($\mathcal{U}$) (Radford et al. 2018).

Figure W1.1: The GPT-2 Model[2]



$$L_1(\mathcal{U}) = \sum_i logP(u_i|u_{i-k},\dots,u_{i-1};\Theta) \quad \text{(W1)}$$

$$h_0 = UW_e + W_p \quad \text{(W2)}$$

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[1] For ease of discussion, we describe the model in terms of "words." GPT-2 is derived using BPE (Byte Pair Encoding) and tokens (i.e., learned and encoded pieces of words).

[2] Visualization derived from Radford et al. (2018), and adapted to depict the updated GPT-2 architecture.

$$h_l = transformer\_block_{(h_{l-1})} \forall i \in [1, L] \quad \text{(W3)}$$

$$P(u) = softmax(h_L W_e^T) \quad \text{(W4)}$$

In essence, GPT-2 relies on word and given context meaning information to generate its output distribution over its vocabulary. More specifically, the data input consists of a matrix h_0 (W2), where the given word sequence U, word meaning information in terms of word embeddings W_e, and sequential word position information in terms of position embeddings W_p are combined. As illustrated in Figure W1.1, information from h_0 is extracted, transformed, added and normalized multiple times (to ease processing), and projected into the embedding space e by L layers of decoder transformer blocks (W3). This information includes the extent of putting attention on a given word sequence using multi-headed self attention (Vaswani et al. 2017), and high dimensional hidden language states to shift the focus in the embedding space e to recreate natural word sequences from position-wise feed forward neural networks. The output of the final block h_L projects all this information into the embedding space and is multiplied with GPT-2's original (unconditional) transposed word embeddings matrix W_e^T to assess which word from the GPT-2 vocabulary best matches the information contained in h_L (W4). The multiplication of h_L and W_e^T can be thought of as a similarity or matching between the embedding space distribution of the output of h_L (containing meaning, position, attention, and hidden language states information) and the unconditional embedding space distribution of each respective vocabulary word. More similarity of a vocabulary word in terms of its embedding to h_L will result in a higher probability in GPT-2's output distribution. GPT-2 then obtains a probability distribution over its vocabulary $P(u)$ (W4) and can sample the upcoming word in the sequence from the most likely words in $P(u)$.

Using the above procedure, GPT-2 learned and stored word probabilities for given word sequences represented in its 345 million parameters (including embeddings, attention weight matrices and Θ) using 8 million English text documents with a broad topical variety. Neural network parameters Θ were first initialized and then trained on batches of 512 sequences. The loss function refers to the language modeling cross entropy loss, where 1 is assigned to the word that appears next (u_i) in the training sequence (e.g., “comes” in Figure W1.1), and 0 to all other words in GPT-2’s vocabulary, and compare the log transformed GPT-2 softmaxed output probability value P_u for that respective word to appear next. A loss of 0 means the GPT-2 prediction was in perfect accordance with the actual next word (i.e., 1), the higher the deviation of the GPT-2 prediction (e.g., 1-0.6 = 0.4 for “comes” in Figure W1.1) to the actual word, the more the loss value increases. During training, GPT-2 performs this process on batches and mini-batches of several sequences before updating Θ.

Appendix References

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