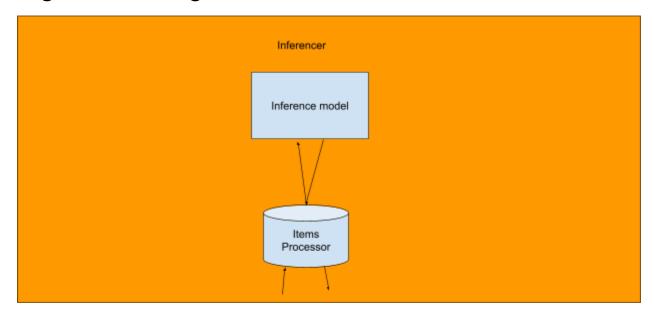
High level design



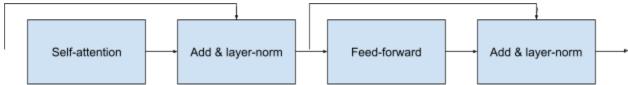
Detailed Design

Inferencer

This class receives one batch of tokens, and returns a batch of generated tokens.

Inference Model

We use pretty simple self-attention.



Self-attention

The basic formula of the self-attention is:

$$softmax(\frac{QK^T}{\sqrt{dim_k}}) * V$$

For the training case, Q, K, V are all [b, s, dim]. However, for inference, we actually only need to do the inference for the last sequence of each batch.

Meanwhile, we want to keep the cache for K, V.

We have 11 related tensors:

- inp: Input tensor of shape [b, s, inputDim]
- lengths: The sequence length of each batch. [b]
- wk, wq, wv: [InputDim, outputDim]
- new_batch_idx: the index of the new batches. -1 means this index is not new. [b]
- kt_cache: k cache. But we actually always use its transpose. [b, outputDim, s]
- v cahce: v cache. [b,, s, outputDim]
- q_output: The result of *inp* * wq. [b, outputDim]
- qkt_output: The result of QK^T . We also use it to store the softmax result. [b, s]
- attention_result: The result of the self-attention block. [b, outputDim]

We split the responsibilities into 5 cuda kernels.

```
fill new kt v cache
```

This kernel checks the new batch idx and inserts into the kt cache and v cache accordingly.

- Launch [b, s, outputDim] threads.
- If new_batch_idx[blockldx.z] is not -1, we use inp[i_batch, 1:lengths[i_batch], input_dim] to multiply with wk, wv.
- Update new batch idx[blockldx.z] to -1
- Insert the result into kt_cache and v_cache.

```
get latest kt q v
```

This kernel multiplies each batch's latest embedding with *wk*, *wq* and *wv*. And set to *kt_cache*, *v* cache and *q* output.

gkt

This kernel multiples *q* with *kt*. And the *lengths* is used to avoid necessary computation.

```
softmax_in_place_with_lengths
```

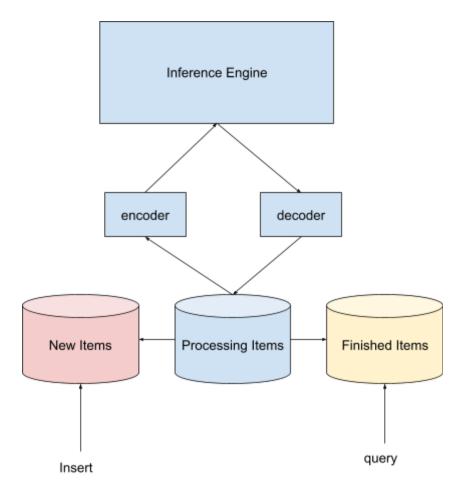
Apply softmax_in_place operation for *qkt_output*. Note any element exceeding the *lengths[i_batch]* should be 0.

```
softmax v
```

This kernel multiplies the qkt output with v cache, and saves into attention result.

Item Processor

The *ItemProcessor* manages the items from decoding and to be encoded.



Decoder

The decoder serves 2 tasks:

- On cuda kernels:
 - Given the embeddings of [b, outputDim]. The kernel multiplies it with the embedding_table to get similarity of [b, vocab].
 - Considering the *vocab* can be large. We use one block to handle per row, to find the maximum index. Here, we ignore the softmax operation. The result is of shape [b]. Meanwhile, in the same kernel, we can store the embedding of this token ([b, inputDim]) to the inp of shape [b, s, inputDim], given the lengths. This can work because we are using greedy sampling. We have to change this strategy if we use beam search in the future.
 - If *lengths[i_batch_index]* == 0, this is one invalid row. Return -1.

Processing Items

process decoder result

- 1. Copy the tokens of [b] to cpu. Find the corresponding tokens and append to pending results.
- 2. For each item, check
 - a. If the token_index is -1, this is one empty row. But still add it to *finished_indices* because we can add new items to this row.
 - b. If the token is <EOF> or the length exceeds the maximum, add to finished items and finished indices.

insert new items

- If finished_indices.size() > 0, try to fetch this amount of new_items.
- Clone the *new_items* and *new_lengths* to gpu. If we haven't filled every finished index, fill the remaining with *length* == 0.

Encoder

The encoder only encodes the new items of shape $[n_{newItems,} s]$ with lengths:

Calculates the embeddings of shape [n_{newItems}, s, inputDim] and clone to the corresponding new_batch_idx of inp.

Extend to other structures

This optimization idea can easily apply to any layer:

- Store the cache result for past sequences.
- For new items, with *new_items* and *new_lengths*, calculate the cache once, and add to the existing cache.

Future plans

• Inferencer can keep receiving new tokens. We can have a thread to put the new tokens to the **NewItems**.