Assessing incrementality in sequence-to-sequence models

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Abstract

Since their inception, encoder-decoder models have successfully been applied to a wide array of problems in computational linguistics. The most recent successes are predominantly due to the use of different variations of attention mechanisms, but their cognitive plausibility is questionable. In particular, because past representations can be revisited at any point in time, attention-centric methods seem to lack an incentive to build up incrementally more informative representations of incoming sentences. This way of processing stands in stark contrast with the way in which humans are believed to process language: continuously and rapidly integrating new information as it is encountered. In this work, we propose three novel metrics to assess the behavior of RNNs with and without an attention mechanism and identify key differences in the way the different model types process sentences.

1 Introduction

Incrementality – that is, building up representations "as rapidly as possible as the input is encountered" (Christiansen and Chater, 2016) – is considered one of the key ingredients for humans to process language efficiently and effectively.

Christiansen and Chater (2016) conjecture how this trait is realized in human cognition by identifying several components which either make up or are implications of their hypothesized *Now-or-Never bottleneck*, a set of fundamental constraints on human language processing, which include a limited amount of available memory and time pressure. First of all, one of the implications of the now-or-never bottleneck is anticipation, implemented by a mechanism called *predictive processing*. As humans have to process sequences of inputs fast, they already try to anticipate the next element before it is being uttered. This is hypothesized to be the reason why people struggle with so-called garden path sentences like "The horse race past the barn fell", where the last word encountered, "fell", goes against the representation of the sentence built up until this point. Secondly, another strategy being employed by humans in processing language seems to be *eager processing*: the cognitive system encodes new input into "rich" representations as fast as possible. These are build up in chunks and then processed into more and more abstract representations, an operation Christiansen and Chater (2016) call *Chunk-and-pass processing*.

In this paper, we aim to gain a better insight into the inner workings of recurrent models with respect to incrementality while taking inspiration from and drawing parallels to this psycholinguistic perspective. To ensure a successful processing of language, the human brain seems to be forced to employ an encoding scheme that seems highly reminiscent of the encoder in today's encoder-decoder architectures. Here, we look at differences between a recurrent-based encoder-decoder model with and without attention. We analyze the two model variants when tasked with a navigation instruction dataset designed to assess the compositional abilities of sequence-to-sequence models (Lake and Baroni, 2018).

The key contributions of this work can be summarized as follows:

- We introduce three new metrics for incrementality that help to understand the way that recurrent-based encoder-decoder models encode information;
- We conduct an in-depth analysis of how incrementally recurrent-based encoder-decoder models with and without attention encode sequential information;
- We confirm existing intuitions about

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attention-based recurrent models but also highlight some new aspects that explain their superiority over most attention-less recurrent models.

2 Related Work

Sequence-to-Sequence models that rely partly or fully on attention have gained much popularity in recent years (Bahdanau et al. (2015), Vaswani et al. (2017)). Although this concept can be related to the prioritisation of information in the human visual cortex (Hassabis et al., 2017), it seems contrary to the incremental processing of information in a language context, as for instance recently shown empirically for the understanding of conjunctive generic sentences (Tessler et al., 2019).

In machine learning, the idea of incrementality has already played a role in several problem statements, such as inferring the tree structure of a sentence (Jacob et al., 2018), parsing (Köhn and Menzel, 2014), or in other problems that are naturally equipped with time constraints like real-time neural machine translation (Neubig et al., 2017; Dalvi et al., 2018a), and speech recognition (Baumann et al., 2009; Jaitly et al., 2016; Graves, 2012). Other approaches try to encourage incremental behavior implictly by modifying the model architecture or the training objective: Guan et al. (2018) introduce an encoder with an incremental self-attention scheme for story generation. Wang (2019) try to encourage a more incremental attention behaviour through masking for text-to-speech, while Hupkes et al. (2018a) guide attention by penalizing deviation from a target pattern.

The significance of the encoding process in sequence-to-sequence models has also been studied extensively by Conneau et al. (2018). Proposals exploring how to improve the resulting approaches include adding additional loss terms (Serdyuk et al., 2018) or a second decoder (Jiang and Bansal, 2018; Korrel et al., 2019).

3 Metrics

In this section, we present three novel metrics called *Diagnostic Classifier Accuracy* (Section 3.1), *Integration Ratio* (Section 3.2) and *Representational Similarity* (Section 3.3) to assess the ability of models to process information incrementally. These metrics are later evaluated themselves in Section 5.2 and differ from traditional ones used to assess the incrementality of models, e.g. as the ones summarized by Köhn and Menzel (2014), as they focus on the role of the encoder in sequence-to-sequence models. It further should be noted that the "optimal" score of these measures with respect to downstream applications cannot defined explicity; they rather serve as a mean to uncover insights about the ways that attention changes a model's behavior, which might aid the development of new architectures.

3.1 Diagnostic Classifier Accuracy

Several works have utilized linear classifiers to predict the existence of certain features in the hidden activations[1] of deep neural networks (Hupkes et al., 2018b; Dalvi et al., 2018b; Conneau et al., 2018). Here we follow the nomenclature of Hupkes et al. (2018b) and call these models *Diagnostic Classifiers* (DCs).

We hypothesize that the hidden activations of an incremental model contain more information about previous tokens inside the sequence. This is based on the assumption that attention-based models have no incentive to encode inputs recurrently, as previous representations can always be revisited. To test this assumption, we train a DC on every time step $t > 1$ in a sequence $t \in [1, \dots T]$ to predict the k most frequently occuring input tokens for all time steps $t' < t$ (see Figure 1). For a sentence of length T, this results in $\sum_{t=2}^{T} \sum_{t'=t-1}^{t} k$ trained DCs. To then generate the corresponding training set for one of these classifiers, all activations from the network on a test set are extracted and the corresponding tokens recorded. Next, all activations from time step t are used as the training samples and all tokens to generate binary labels based on whether the target token x_k occured on target time step t'. As these data sets are highly unbalanced, class weights are also computed and used during training.

Applying this metric to a model, the accuracies of all classifiers after training are averaged on a given test set, which we call *Diagnostic Classifier Accuracy* (DC Accuracy). We can test this way how much information about specific inputs is lost and whether that even matters for successful model performance, should it employ an encoding procedure of increasing abstraction like in *Chunk-and-pass processing*. On the other hand, one might assume that a more powerful model

[1] In this work, the terms *hidden representation* and *hidden activations* are used synonymously.

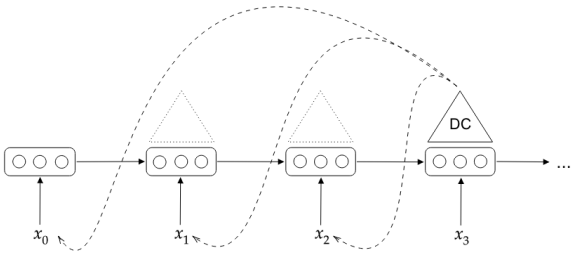


Figure 1: For the Diagnostic Classifier Accuracy, DCs are trained on the hidden activations to predict previously occuring tokens. The accuracies are averaged and potentially weighed by the distance between the hidden activations used for training the occurrence of the token to predict.

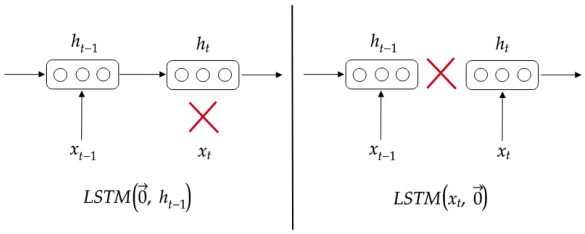


Figure 2: Illustration of a thought experiment about two types of extreme recurrent models. (*Left*) The model completely ignores the current token and bases its new hidden state entirely on the previous one. (*Right*) The model forgets the whole history and just encodes the current input.

might require to retain information about an input even if the same occured several time steps ago. To account for this fact, we introduce a modified version of this metric called *Weighed Diagnostic Classifier Accuracy* (Weighed DC Accuracy), where we weigh the accuracy of a classifier based on the distance $t - t'$.

3.2 Integration Ratio

Imagine an extreme attention-based model that does not encode information recurrently but whose hidden state $\mathbf{h}_t$ is solely based on the current token $\mathbf{x}_t$ (see right half of Figure 2). If we formalize an LSTM as a recurrent function $f_\theta : \mathbb{R}^n, \mathbb{R}^m \mapsto \mathbb{R}^m$ parameterized by weights θ that maps two continuous vector representations, in our case the n-dimensional representation of the current token $\mathbf{x}_t \in \mathbb{R}^n$ and the m-dimensional previous hidden state representation $\mathbf{h}_{t-1} \in \mathbb{R}^m$ to a new hidden state $\mathbf{h}_t \in \mathbb{R}^m$, we can formalize the mentioned scenario as a recurrent function that completely ignores the pevious hidden state, which we can denote using a zero-vector $\vec{0} \in \mathbb{R}^m$: $\mathbf{h}_t = f_\theta(\mathbf{x}_t, \vec{0})$.

In a more realistic setting, we can exploit this thought experiment to quantify the amount of new information that is integrated into the current hidden representation by subtracting this hypothetical value from the actual value at timestep t:

$$\Delta\mathbf{x}_t = ||\mathbf{h}_t - f_\theta(\mathbf{x}_t, \vec{0})||^2, \tag{1}$$

where $||\dots||^2$ denotes the l_2-norm. Conversely, we can quantify the amount of information that was lost from previous hidden states with:

$$\Delta\mathbf{h}_t = ||\mathbf{h}_t - f_\theta(\vec{0}, \mathbf{h}_{t-1})||^2. \tag{2}$$

In the case of the extreme attention-based model, we would expect $\Delta\mathbf{x}_t = 0$, as no information from $\mathbf{h}_{t-1}$ has been used in the transformation of $\mathbf{x}_t$ by f_θ. Likewise, the "ignorant" model would produce a value of $\Delta\mathbf{h}_t = 0$, as any new hidden representation completely originates from a transformation of the previous one.

Using these two quanitities, we can formulate a metric expressing the average ratio between them throughout a sequence which we call *Integration Ratio*:

$$\phi_{int} = \frac{1}{T-1}\sum_{t=2}^{T}\frac{\Delta\mathbf{x}_t}{\Delta\mathbf{h}_t} \tag{3}$$

This metric provides an intuitive insight into the (average) model behavior during the encoding process: For $\phi_{int} < 1$ it holds that $\Delta\mathbf{x}_t < \Delta\mathbf{h}_t$, signifying that the model prefers to integrate new information into the hidden state. Vice versa, $\phi_{int} > 1$ and therefore $\Delta\mathbf{x}_t > \Delta\mathbf{h}_t$ implies a preference to maintain a representation of preceding inputs, possibly at the cost of encoding the current token $\mathbf{x}_t$ in an incomplete manner.

To account for the fact that integrating new information is more important at the beginning of a sequence – as no inputs have been processed yet – and maintaining a representation of the sentence is more plausile towards the end of a sentence, we introduce two linear weighing terms with $\alpha_{\Delta\mathbf{x}_t} = \frac{T-t}{T}$ and $\alpha_{\Delta\mathbf{h}_t} = \frac{t}{T}$ for $\Delta\mathbf{x}_t$ and $\Delta\mathbf{h}_t$, respectively, which simplify to a single term α_t:

$$\phi_{int} = \frac{1}{Z}\sum_{t=2}^{T}\alpha_t\frac{\Delta\mathbf{x}_t}{\Delta\mathbf{h}_t} = \frac{1}{Z}\sum_{t=2}^{T}\frac{T-t}{t}\frac{\Delta\mathbf{x}_t}{\Delta\mathbf{h}_t}, \tag{4}$$

where Z corresponds to a new normalizing factor such that $Z = \sum_{t=2}^{T}\frac{T-t}{t}$. It should be noted that

the ideal score for this metric is unknown. The motivation for this score merely lies in gaining inside into a model's behaviour, showing us whether it engages in a similar kind of *eager processing* while having to handle memory constraints (in this case realized in the constant dimensionality of hidden representations) like in human cognition.

3.3 Representational Similarity

The sentences "I saw a cat" and "I saw a feline" only differ in terms of word choice, but essentially encode the same information. An incremental model, based on the Chunk-and-Pass processing described by Christiansen and Chater (2016), should arrive at the same or at least a similar, abstract encoding of these phrases.[2] While the exact wording might be lost in the process, the information encoded should still describe an encounter with a feline creature. We therefore hypothesize that an incremental model should map the hidden activations of similar sequences of tokens into similar regions of the hidden activation space. To test this assumption, we compare the representations produced by a model after encoding the same sequence of tokens - or *history* - using their average pairwise distance based on a distance measure like the l_2 norm or cosine similarity. We call the length of the history the *order* of the *Representational Similarity*.

To avoid models to score high on this model metric by substituting most or all of a hidden representation with an encoding of the current token,[3] we only gather the hidden states for comparison after encoding another, arbitrary token (see Figure 3). We can therefore interpret the score as the ability to "remember" the same sequence of tokens in the past through the encoding.

The procedure is repeated for the n most common histories of a specified order occuring in the test corpus over all time steps and, to obtain the final score, results are averaged.

4 Setup

We test our metric on two different architectures, trained on the SCAN dataset proposed by Lake and Baroni (2018). We explain both below.

[2]In fact, given that humans built up sentence representations in a compositional manner, the same should hold for sentence pairs like "I saw a cat" and "A feline was observed by me", which is beyond the limits of the metric proposed here.

[3]$\Delta \mathbf{x}_t = 0$ in the framework introduced in the previous Section 3.2.

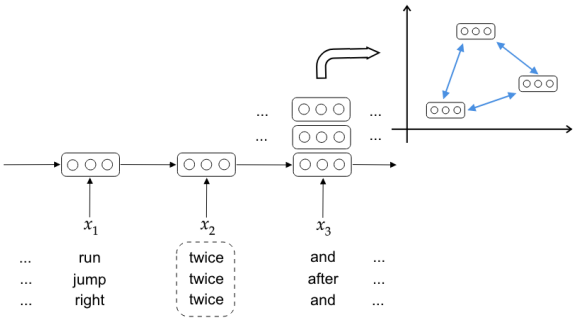


Figure 3: *Representational Similarity* measures the average pair-wise distance of hidden representations after encoding the same subsquence of tokens (in this case the history is only of first order, i.e. x_2) as well as one arbitrary token x_3.

4.1 Data

We use the SCAN data set proposed by Lake and Baroni (2018): It is a simplified version of the CommAI Navigation task, where the objective is to translate an order in natural language into a sequence of machine-readable commands, e.g. "jump thrice and look" into `I_JUMP I_JUMP I_JUMP I_LOOK`. We focus on the `add_prim_jump_split` (Loula et al., 2018), where the model has to learn to generalize from seeing a command like `jump` only in primitive forms (i.e. by itself) to seeing it in composite forms during test time (e.g. `jump twice`), where the remainder of the composite forms has been encountered in the context of other primitive commands during training.

The SCAN dataset has been proposed to assess the *compositional* abilities of a model, which we believe to be deeply related with the concept of *incrementality*, which is the target of our research.

4.2 Models

We test two seasoned architectures used in sequence processing, namely a Long-Short Term Memory (LSTM) network (Hochreiter and Schmidhuber, 1997) and an LSTM network with attention (Bahdanau et al., 2015). The attention mechanism creates a time-dependent context vector $\mathbf{c}_i$ for every decoder time step i that is used together with the previous decoder hidden state. This vector is a weighted average of the output of the encoder, where the weights are calculated based on some sort of similarity measure. More specifically, we first calculate the energy e_{it} between the last decoder hidden state $\mathbf{s}_{i-1}$ and

any encoder hidden state $\mathbf{h}_t$ using some function $a(\cdot)$

$$e_{it} = a(\mathbf{s}_{i-1}, \mathbf{h}_t) \tag{5}$$

We then normalize the energies using the softmax function and use the normalised attention weights α_{it} to create the context vector $\mathbf{c}_t$:

$$\mathbf{c}_i = \sum_{t=1}^{T} \alpha_{it} \mathbf{h}_t \tag{6}$$

In this work, we use a simple attention function, namely a dot product a_{dot}:

$$a_{dot}(\mathbf{s}_{i-1}, \mathbf{h}_t) = \mathbf{s}_{i-1}^T \mathbf{h}_t, \tag{7}$$

matching the setup originally introduced by Bahdanau et al. (2015).

4.3 Training

For both architectures, we train 15 single-layer uni-directional models, with an embedding and hidden layer size of 128. We use the same hyperparameters for both architectures, to ensure compatibility. More specifically, both models were trained for 50 epochs using the Adam optimizer (Kingma and Ba, 2015) with the AMSgrad correction (Reddi et al., 2018) and a learning rate of 0.001 and a batch size of 128.

5 Results

We compute metric values for all 30 models (15 per architecture) that resulted from the training procedure described above.[4] We plot the metric values, averaged over all runs for both models, in Figure 4. For the representational similarity score, we use all instances of the $n = 5$ most frequently occuring histories of length 2 at all available time steps. The unweighted DC accuracies are not depicted, as they do not differ substantially from their weighted counter part, for which we also try to detect the $k = 5$ most frequently occuring inputs at every time step.

5.1 Metric scores

As expected, the standard attention model significantly outperforms the vanilla model in terms of sequence accuracy. Surprisingly, both models perform very similarly in terms of weighed DC accuracy. While one possible conclusion is that both models display a similar ability to store information about past tokens, we instead hypothesize that this can be explained by the fact that all sequences in our test set are fairly short (6.8 tokens on average). Therefore, it is easy for both models to store information about tokens over the entire length of the input even under the constrained capacity of the hidden representations. Bigger differences might be observed on corpora that contain longer sequences.

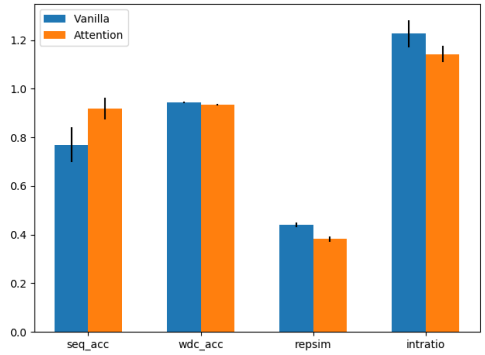


Figure 4: Results on SCAN `add_prim_left` with $n = 15$. Abbreviations stand for sequence accuracy, weighed diagnostic classifier accuracy, integration ratio and representational similarity, respectively. All differences are statistically significant (using a Student's t-test with $p = 0.05$).

From the integration ratio scores (last column in Figure 4), it seems that, while both models prefer to maintain a history of previous tokens, the attention-based model contains a certain bias to add new information about the current input token. This supports our suspicion that this model is less incentivized to build up expressive representations over entire sequences, as the encoder representation can always be revisited later via the attention mechanism. Counterintuitively and perhaps surprisingly, it appears that the attention model produces representations that are more similar than the vanilla model, judging from the representational similarity score. To decode successfully, the vanilla model has to include information about the entire input sequence in the last encoder hidden state, making the encodings of similar subsequences more distinct because of their different prefixes.[5] In contrast, the representations of the at-

[4] The code used in this work is available online under https://github.com/i-machine-think/incremental_encoding.

[5] Remember that to obtain these scores, identical subsequences of only length 2 were considered.

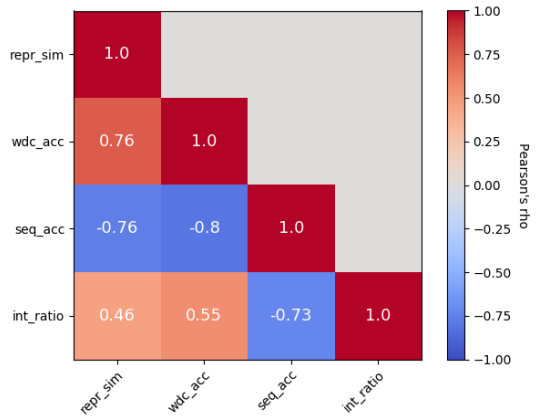


Figure 5: Correlations between metrics as heatmap of Pearson's rho values. 1 indicates a strong positive correlation, -1 a negative one. Abbreviations correspond to the same metrics as in Figure 4. Best viewed in color.

tention model is able to only contain information about the most recent tokens, exclusively encoding the current input at a given time step in the extreme case, as the attention mechanism can select the required representations on demand. These results will be revisited in more detail in section 5.3.

5.2 Metrics Comparison

To further understand the salience of our new metrics, we use *Pearson's correlation coefficient* to show their correlation with each other and with sequence accuracy. A heat map showing Pearson's ρ values between all metric pairs is given in Figure 5.

We can observe that representational similarity and weighed DC accuracy display a substantial negative correlation with sequence accuracy. In the first case, this implies that the more similar representations of the same subsequences produced by the model's encoder are, the better the model itself performs later.[6] Surprisingly, we can infer from the latter case that storing more information about the previous inputs does not lead to better performance. At this point we should disentangle correlation from causation, as it is to be assumed that our hypothesis about the attention mechanism applies here as well: The attention is always able to revisit the encodings later during the decoding process, thus a hidden representation does not need to contain information about all previous tokens and the weighed DC accuracy suffers. Therefore, as the attention model performs better in terms of sequence accuracy, a negative correlation score is observed. The same trend can be observed for the sequence accuracy - integration ratio pair, where the better performance of the attention model creates a significant negative correlation.

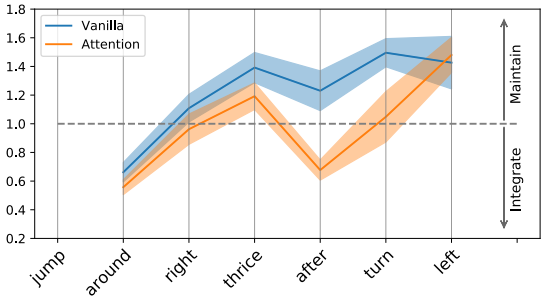
The last noteworthy observation can be found looking at the high positive correlation between the weighed DC accuracy and representational similarity, which follows from the line of thought in Section 5.1: As the vanilla model has to squeeze information about the whole history into the hidden representation at every time step, encodings for a shorter subsequence become more distinct, while the attention model only encodes the few most recent inputs and are therefore able to produce more homogenous representations.

5.3 Qualitative Analysis

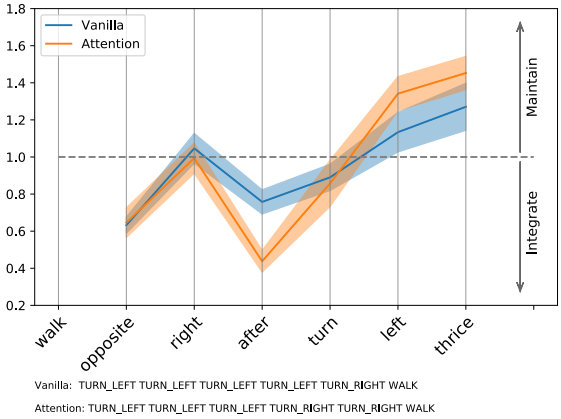
We scrutinize the models' behavior when processing the same sequence by recording the integration ratio per time step and contrasting them in plots, which are shown in Figure 6. Figure 6a and 6b are thereby indicative of a trend which further reinforces our hypothesis about the behavior of attention-based models: As the orange curve lies below the vanilla model's blue curve in the majority of cases, we can even infer on a case by case basis that these models tend to integrate more information at every time step than a vanilla LSTM. Interestingly, these distinct behaviors when processing information do not always lead to the models finding different solutions. In Figure 6 however, we present three error cases in which the models' results do diverge.

In Figure 6a, we can see that the vanilla model decodes a second and redundant `TURN-LEFT` in the beginning of the sequence. Although this happens right at the start, the corresponding part in the input sequence is actually encountered right at the end of the encoding process in the form of "turn left", where "after" in front of it constitutes an inversion of the sequence of operations. Therefore, when the vanilla model starts decoding based on the last encoder hidden state, "left" is actually the most recently encoded token. We might assume that, due to this reason, the vanilla model might contain some sort of recency bias, which seems to corrupt some count information and leads

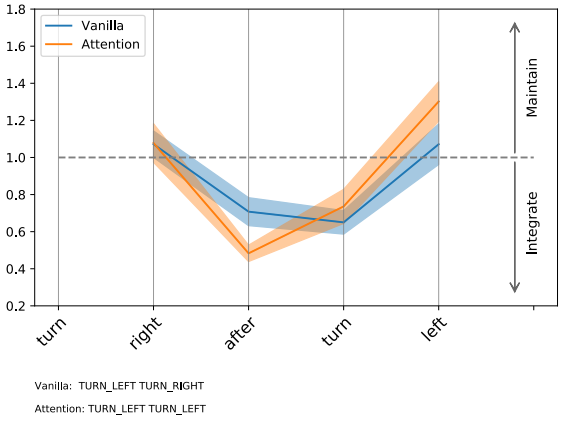
[6] The representational similarity score actually expresses a degree of dissimilarity, i.e. a lower score results from more similar representations, therefore we identify a negative correlation here.



(a) The vanilla model adds a redundant TURN-LEFT in the beginning.



(b) The vanilla model confuses left and right when decoding opposite.



(c) The attention model fails on a trivial sequence.

Figure 6: Qualitative analysis about the models' encoding behavior. Bounds show the standard deviation of integration ratio scores per time step. Decoded sentences are produced by having each model decode the sequence individually and then consolidating the solution via a majority vote. Resulting sequences have been slightly simplified for readability. Best viewed in color.

to a duplicate in the output sequence. The attention model seems to be able to avoid this issue by erasing a lot of its prior encoded information when processing "after", as signified by the drop in the graph. Afterwards, only very little information seems to be integrated by the model.

The vanilla model commits a slightly different error in Figure 6b: After both models decode three TURN-LEFT correctly, it choses to decode "opposite" as TURN-LEFT TURN-RIGHT in contrast to the corect TURN-RIGHT TURN-RIGHT supplied by the attention model. It is to be assumed here that the last half of the input, "turn left thrice" had the vanilla model overwrite some critical information about the initial command. Again, the attention model is able to evade this problem by erasing a lot of its representation when encoding "after" and can achieve a correct decoding this critical part by attending to the representation produced at "right" later. "turn left thrice" can followingly be encoded without having to loose any past information.

Lastly, we want to shed some light on one of the rare failure cases of the *attention model*, as given in Figure 6c. Both models display very similar behavior when encoding this trivial sequence, yet only the vanilla model is able to decode it correctly. A possible reason for this could be found in the model's energy function: When deciding which encoded input to attend to for the next decoding step, the model scores potential candidates based on the last decoder hidden state (see eq. 7), which was decoded as TURN-LEFT. Therefore the most similar inputs token might appear to be TURN-LEFT as well. Notwithstanding this explanation, it falls short of giving a conclusive reason why the model does not err in similar ways in other examples.

Looking at all three examples, it should furthermore be noted that the encoder of the attention model seems to anticipate the mechanism's behavior and learns to erase much of its representation after encoding one contiguous chunk of information, as exemplified by the low integration ratio after finishing the first block of commands in an input sequence. This freedom seems to enable the encoder to come up with more homogenous representations, i.e. that no information has to be overwritten and possibly being corrupted to process later, less related inputs, which also explains the lower representational similarity score in 5.1.

6 Conclusion

In this work, we introduced three novel metrics that try to shine a light on the incremental abilities of the encoder in a sequence-to-sequence model and tested them on a LSTM-RNN with and without an attention mechanism. We showed how these metrics relate to each other and how they can be employed to better understand the encoding behavior of models and how these difference lead to performance improvements in the case of the attention-based model.

We confirm the general intuition that using an attention mechanism, due to its ability to operate on the whole encoded input sequence, prefers to integrate new information about the current token and is less pressured to maintain a representation for the whole input sequence, which seems to lead to some corruptions of the encoded information in case of the vanilla model. Moreover, our qualitative analysis suggests that the encoder of the attention model learns to chunk parts of the input sequence into salient blocks, a behavior that is reminiscent of the Chunk-and-Pass processing described by Christiansen and Chater (2016) and one component that is hypothesized to enable incremental processing in humans. In this way, the attention model most surprisingly seems to display a more incremental way of processing than the vanilla model.

These results open up several lines of future research: Although we tried to assess incrementality in sequence-to-sequence models in a quantitative manner, the notion of incremental processing lacks a formal definition within this framework. Thus, such definition could help to confirm our findings and aid in developing more incremental architectures. It furthermore appears consequential to extend this methodology to deeper models and other RNN-variants as well as other data sets in order to confirm this work's findings.

Although we were possibly able to identify one of the components that build the foundation of human language processing (as defined by Christiansen and Chater, 2016) in attention models, more work needs to be done to understand how these dynamics play out in models that solely rely on attention like the Transformer (Vaswani et al., 2017) and how the remaining components could be realized in future models.

Based on these reflections, future work should attack this problem from a solid foundation: A formalization of incrementality in the context of sequence-to-sequence modelling could help to develop more expressive metrics. These metrics in turn could then be used to assess possible incremental models in a more unbiased way. Further thought should also be given to a fairer comparison of candidate models to existing baselines: The attention mechanism by Bahdanau et al. (2015) and models like the Transformer operate without the temporal and memory pressure that is claimed to fundamentally shape human cognition Christiansen and Chater (2016). Controlling for this factor, it can be better judged whether incremental processing has a positive impact on the model's performance. We hope that these steps will lead to encoders that create richer representations that can followingly be used back in regular sequence-to-sequence modelling tasks.

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