The Referential Reader: A Recurrent Entity Network for Anaphora Resolution

Fei Liu
The University of Melbourne
Victoria, Australia

Luke Zettlemoyer
Facebook AI Research
University of Washington
Seattle, USA

Jacob Eisenstein
Facebook AI Research
Seattle, USA

Abstract

We present a new architecture for storing and accessing entity mentions during online text processing. While reading the text, entity references are identified, and may be stored by either updating or overwriting a cell in a fixed-length memory. The update operation implies coreference with the other mentions that are stored in the same cell; the overwrite operations causes these mentions to be forgotten. By encoding the memory operations as differentiable gates, it is possible to train the model end-to-end, using both a supervised anaphora resolution objective as well as a supplementary language modeling objective. Evaluation on a dataset of pronoun-name anaphora demonstrates that the model achieves state-of-the-art performance with purely left-to-right processing of the text.

1 Introduction

Reference resolution is a fundamental problem in language understanding. Many systems employ the mention-pair model, in which a classifier is applied to all pairs of spans (e.g., Lee et al., 2017). While this model performs well in some settings, it is expensive in both computation and labeled data. Furthermore, a new challenge set of pronoun-name references shows that the best supervised systems are outperformed by a simple baseline that links pronouns to names with the same syntactic function, e.g., subject or object (Webster et al., 2018). The mention-pair model is also cognitively implausible: human readers must interpret text in a nearly online fashion.

In this paper, we present a new method for reference resolution, which reads the text left-to-right while storing entities in a fixed-size working memory (Figure 1). As each token is encountered, the reader must decide whether to: (a) link the token to an existing memory, thereby creating a coreference link, (b) overwrite an existing memory and store a new entity, or (c) disregard the token and move ahead. As memories are reused, they receive increasing salience, making them less likely to be overwritten.

This online model for coreference resolution is based on the memory network architecture (Weston et al., 2015), in which memory operations are differentiable, enabling end-to-end training from gold anaphora resolution data. Furthermore, the memory can be combined with a recurrent hidden state, enabling prediction of the next student, and a corresponding language modeling objective. An evaluation on the GAP dataset of pronoun-name anaphora resolution yields promising results. To summarize the contributions of this paper:

- We present a generative model for coreference resolution which can be trained on labeled and unlabeled data.
- Our model is end-to-end differentiable, supporting efficient training without inference over discrete entity assignments.
- Unlike state-of-the-art coreference resolution...
hidden state

memory unit

pre-recurrent

input embeddings

\[
\begin{align*}
&h_t \leftarrow \text{GRU}(x_t, h_{t-1} + c_t) \\
&h_{t+1} \leftarrow \text{pre-recurrent}(h_t) \\
&c_t = \min(\sigma(W_\epsilon h_t + b_\epsilon), \sum_i s_t(i))
\end{align*}
\]

where \(W_\epsilon\) and \(b_\epsilon\) are learned parameters. Finally, the hidden state is computed as:

\[
h_t = \text{GRU}(x_t, (1 - c_t) \times h_{t-1} + c_t \times m_t),
\]

where \(x_t\) is the embedding of token \(t\).

2.2 Memory Unit

Pre-recurrent update. The memory gates are controlled by a vector \(\tilde{h}_t\), which combines the input \(x_t\) with the previous hidden state \(h_{t-1}\). Because this vector is computed before applying the GRU recurrence, we call it the pre-recurrent state, and define it as:

\[
\tilde{h}_t = \tanh(W h_{t-1} + U x_t),
\]

where \(W \in \mathbb{R}^{D_h \times D_h}\) and \(U \in \mathbb{R}^{D_h \times D_t}\) are learned parameters.

Detecting entity mentions. The memory gates are a collection of scalars \(\{w_t(i), o_t(i)\}^N_{i=1}\). To compute these gates, we first determine whether the token \(w_t\) is an entity mention. This decision is controlled by a sigmoid activation:

\[
\epsilon_t = \sigma(\phi_e \cdot \tilde{h}_t),
\]

where \(\phi_e \in \mathbb{R}^{D_h}\) is a learnable vector. Next, we must decide whether \(w_t\) refers to a previously mentioned entity:

\[
r_t = \sigma(\phi_r \cdot \tilde{h}_t) \times \epsilon_t,
\]

where \(\phi_r \in \mathbb{R}^{D_h}\) is a learnable vector.

Updating existing entities. If \(w_t\) is a referential entity mention \((r_t \approx 1)\), it may refer to an entity in the memory. To compute the compatibility between \(w_t\) and each memory, we first summarize the current state as a query vector:

\[
q_t = f_q(\tilde{h}_t),
\]

where \(f_q\) is a two-layer feed-forward network.

The query vector is then combined with the memory keys to obtain attention scores:

\[
\alpha_t(i) = r_t \times \text{SoftMax}(k_t^{(i)} \cdot q_t + b),
\]

where the softmax is computed over all cells \(i\) and \(b\) is a learnable bias term, inversely proportional to the likelihood of introducing a new entity. The gate \(r_t \in [0, 1]\) determines whether \(w_t\) is referential, as defined above.

The update gate is then set equal to the query match \(\alpha_t(i)\), gated by the salience \(s_{t-1}(i)\):

\[
u_t(i) = \min(\alpha_t(i), 2s_{t-1}(i)).
\]

The upper bound of \(2s_{t-1}\) ensures that an update can at most triple the salience of a memory.

Storing new entities. Overwrite operations are used to store new entities. The total amount to overwrite is \(\delta_t = c_t - \sum_i s_{t-1}(i)\), which is the difference between the entity gate and the sum of the update gates. We prefer to overwrite the memory with the lowest salience. This decision
is made differentiable using the Gumbel-softmax distribution (GSM; Jang et al., 2017), $o_t^{(i)} = e_t^{(i)} \times \text{GSM}^{(i)}(s_{t-1}, \tau).$\(^1\)

**Memory salience.** To the extent that each memory is not updated or overwritten, it is copied along to the next timestep. The weight of this copy operation is:

$$r_t^{(i)} = \max(0, 1 - u_t^{(i)} - o_t^{(i)}).$$

The salience is updated by exponential decay,

$$\lambda_t = (e_t \times \gamma_e + (1 - e_t) \times \gamma_n) \quad (1)$$

$$s_t^{(i)} = \lambda_t \times s_t^{(i)} + u_t^{(i)} + o_t^{(i)} \quad (2)$$

where $\gamma_e$ and $\gamma_n$ represent the salience decay rate upon seeing an entity or non-entity.\(^2\)

**Memory state.** To update the memory states, we first transform the hidden state $h_t$ to the next timestep. The weight of this copy operation is

$$\tilde{w}_t = \left( \tilde{u}_t \times \tilde{\gamma}_e + (1 - \tilde{u}_t) \times \tilde{\gamma}_n \right)$$

$$s_t^{(i)} = \tilde{\lambda}_t \times s_t^{(i)} + \tilde{u}_t^{(i)} + \tilde{o}_t^{(i)}$$

where $\tilde{g}_t$ ($\tilde{g}_o$) is a recurrent GRU update on the key (value) of the memory cell.

### 2.3 Coreference Chains

To compute the probability of coreference between the mentions $w_{t_1}$ and $w_{t_2}$, we first compute the probability that each cell $i$ refers to the same entity at both of those times,

$$\omega_{t_1, t_2}^{(i)} = \prod_{t=t_1}^{t_2} (1 - \tilde{o}_t^{(i)})$$

where $\tilde{o}_t^{(i)}$ is the overwrite gate for token $t$ into memory $i$. Furthermore, the probability that mention $t_1$ is stored in memory $i$ is $u_t^{(i)} + \tilde{o}_t^{(i)}$. Therefore, the log probability that two mentions corefer is,

$$\tilde{w}_{t_1, t_2} = \log \sum_{i=1}^{N} (u_{t_1}^{(i)} + o_{t_1}^{(i)}) \times u_{t_2}^{(i)} \times \omega_{t_1, t_2}^{(i)} \quad (5)$$

\(^1\)Here $\tau$ is the “temperature” of the distribution, which is gradually decreased over the training period, until the distribution approaches a one-hot vector indicating the argmax.

\(^2\)We set $\gamma_e = \exp(\log(0.5)/\ell_e)$ with $\ell_e = 4$ denoting the entity half-life, which is the number of entity mentions before the salience decreases by half. The non-entity halflife $\gamma_n$ is computed analogously, with $\ell_n = 30$.

### 2.4 Training

The coreference probability defined in Equation 5 is a differentiable function of the gates, which in turn are computed from the inputs $w_1, w_2, \ldots w_T$. We can therefore train the entire network end-to-end from a cross-entropy objective, where a loss is incurred for incorrect decisions on the level of token pairs. Specifically, we set $y_{i,j} = 1$ when $w_i$ and $w_j$ corefer, and also when both $w_i$ and $w_j$ are part of the same mention span. The coreference loss is then the cross-entropy.

$$\sum_{t=1}^{T} \sum_{j=i+1}^{T} H(\psi_{i,j}, y_{i,j}).$$

Since the hidden state $h_t$ is computed recurrently from $w_{1:t}$, the reader can also be trained from a language modeling objective. Word probabilities are computed by projecting the hidden state $h_t$ by a matrix of output embeddings, and applying the softmax operation. This objective can be used even when coreference annotations are unavailable.

### 3 Experiments

As a preliminary evaluation of the ability of the referential reader to correctly track entity references in text, we evaluate against the GAP dataset, recently introduced by Webster et al. (2018). Each instance consists of: (1) a sequence of tokens $\{w_1, \ldots, w_T\}$ extracted from Wikipedia biographical pages; (2) two person names ($A$ and $B$), whose token index spans are denoted $s_A$ and $s_B$; (3) a single-token pronoun ($P$ with the token index $s_P$); and (4) two binary labels ($y_A$ and $y_B$) indicating whether $P$ is referring to $A$ or $B$. The task is then to identify the coreferential relationship between $P$ and $A$ or $B$ given $\{w_1, \ldots, w_T\}$.

**Language modeling.** Given the limited size of GAP, it is difficult for the model to learn a good representation of text. We therefore consider the task of language modeling as a pre-training step. We make use of the page text of the original Wikipedia articles from GAP, the URLs to which are included as part of the data release.\(^3\) This results in a corpus of 3.8 million tokens. We pretrain the referential reader on this data. The reader is free to use the memory to improve its language modeling performance, but it receives no supervision on the coreference links that might be imputed on this unlabeled data.

\(^3\)Page text downloaded with the Python Wikipedia API v1.4.0: https://pypi.org/project/wikipedia/.
As required by Webster et al. (2018), the model is responsible for detecting mentions; only the scoring function accesses labeled spans.
required for inference, and the model cannot be trained on unlabeled data.

5 Conclusion

This paper demonstrates the viability of anaphora resolution in an online framework, using an end-to-end differentiable memory network architecture. This enables semi-supervised learning from a language modeling objective, which substantially improves performance on the GAP dataset. A key question for future work is the performance on longer texts, such as the full-length news articles encountered in OntoNotes, which would presumably require a larger memory. Another interesting direction is to further explore semi-supervised learning, by reducing the amount of training data.

References

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. In Proceedings of the NIPS 2014 Deep Learning and Representation Learning Workshop.

Kevin Clark and Christopher D. Manning. 2015. Entity-centric coreference resolution with model stacking. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1405–1415. Association for Computational Linguistics.

Bhuwan Dhingra, Qiao Jin, Zhilin Yang, William Cohen, and Ruslan Salakhutdinov. 2018. Neural models for reasoning over multiple mentions using coreference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 42–48. Association for Computational Linguistics.

Barbara J Grosz, Scott Weinstein, and Aravind K Joshi. 1995. Centering: A framework for modeling the local coherence of discourse. Computational linguistics, 21(2):203–225.

Mikael Henaff, Jason Weston, Arthur Szlam, Antoine Bordes, and Yann LeCun. 2017. Tracking the world state with recurrent entity networks. In Proceedings of the 5th International Conference on Learning Representations, Toulon, France.

Eric Jang, Shixiang Gu, and Ben Poole. 2017. Categorical reparameterization with gumbel-softmax. In Proceedings of the 5th International Conference on Learning Representations.

Yangfeng Ji, Chenhao Tan, Sebastian Martenschat, Yejin Choi, and Noah A. Smith. 2017. Dynamic entity representations in neural language models. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1830–1839. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Sosuke Kobayashi, Naoaki Okazaki, and Kentaro Inui. 2017. A neural language model for dynamically representing the meanings of unknown words and entities in a discourse. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 473–483. Asian Federation of Natural Language Processing.

Heeyoung Lee, Angel Chang, Yves Peirson, Nathanael Chambers, Mihai Surdeanu, and Dan Jurafsky. 2013. Deterministic coreference resolution based on entity-centric, precision-ranked rules. Computational Linguistics, 39(4).

Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. 2017. End-to-end neural coreference resolution. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 188–197. Association for Computational Linguistics.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543. Association for Computational Linguistics.

Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. 2015. End-to-end memory networks. In Proceedings of Advances in Neural Information Processing Systems, pages 2440–2448, Montréal, Canada.

Kellie Webster, Marta Recasens, Vera Axelrod, and Jason Baldridge. 2018. Mind the gap: A balanced corpus of gendered ambiguous pronouns. In Transactions of the ACL, page to appear.

Jason Weston, Sumit Chopra, and Antoine Bordes. 2015. Memory networks. In Proceedings of the 3rd International Conference on Learning Representations, San Diego, USA.

Sam Wiseman, Alexander M. Rush, and Stuart M. Shieber. 2016. Learning global features for coreference resolution. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 994–1004. Association for Computational Linguistics.
Zichao Yang, Phil Blunsom, Chris Dyer, and Wang Ling. 2017. Reference-aware language models. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1850–1859. Association for Computational Linguistics.

A Supplemental information

Model configuration. Training is carried on the development set of GAP with the Adam optimizer (Kingma and Ba, 2014) and a learning rate of 0.001. Early stopping is applied based on the performance on the validation set. We use the following model hyper-parameters: embedding size $D_x = 300$, memory key and value size $D_k = 16$, $D_v = 300$, number of memory cells $N = 2$, the size of both the pre-recurrent and hidden states is set to $D_h = 300$, halflife and entity halflife is 30 and 4 respectively, the dimensions of the hidden layers in $f_k/GRU_k$ and $f_v/GRU_v$ are the same as $D_k = 16, D_v = 300$. Gumbel softmax starts at temperature $\tau = 1.0$ with an exponential decay rate of 0.5 applied every 10 epochs. Dropout is applied to the embedding layer, pre-recurrent state $\tilde{h}_t$, and GRU hidden state $h_t$, with a rate of 0.5. Embeddings are not updated during training (for +LM, initialized with GloVe (Pennington et al., 2014); for +LM+Coref, inherited from the pre-trained language model embeddings).

Language modeling pre-training is carried out using the same set of hyper-parameters with embedding update and early stopping based on perplexity on the validation set.

B Example

Figure 3 gives an example of the behavior of the referential reader, as applied to a concatenation of two instances from GAP. The top panel shows the salience of each entity as each token is consumed, with the two memory cells distinguished by color. The figure elides long spans of tokens whose gate activations are nearly zero. These tokens are indicated in the x-axis by ellipsis; the corresponding decrease in salience is larger, because it represents a longer span of text. The bottom panel shows the gate activations for each token, with memory cells again distinguished by color, and operations distinguished by line style. The gold token-entity assignments are indicated with color.

The reader essentially ignores the first name, Braylon Edwards, making a very weak overwrite to memory 0 ($m0$). It then makes a large overwrite to $m0$ on the pronoun *his*. When encountering the token *Avant*, the reader makes an update to the same memory cell, creating a cataphoric link between *Avant* and *his*. The name Padbury appears much later (as indicated by the ellipsis), and at this point, $m0$ has lower salience than $m1$. For this reason, the reader chooses to overwrite $m0$ with this name. The reader ignores the name Cathy Vespers and overwrites $m1$ with the adverb coincidentally. On encountering the final pronoun *she*, the reader is conflicted, and makes a partial overwrite to $m0$, a partial update (indicating coreference with Padbury), and a weaker update to $m1$. If the update to $m0$ is above the threshold, then the reader may receive credit for this coreference edge, which would otherwise be scored as a false negative.

The reader ignores the names Braylon Edwards, Piers Haggard, and Cathy Vespers, leaving them out of the memory. Edwards and Vespers appear in prepositional phrases, while Haggard is a possessive determiner of the object of a prepositional phrase. Centering theory argues that these syntactic positions have low salience in comparison with subject and object position (Grosz et al., 1995). It is possible that the reader has learned this principle, and that this is why it chooses not to store these names in memory. However, the reader also learns from the GAP supervision that pronouns are important, and therefore stores the pronoun *his* even though it is also a possessive determiner.
Figure 3: An example of the referential reader, as applied to a concatenation of two instances from GAP. The ground truth is indicated by the color of each token on the x-axis.