Neural Language Modeling with Visual Features

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Abstract

Multimodal language models attempt to incorporate non-linguistic features for the language modeling task. In this work, we extend a standard recurrent neural network (RNN) language model with features derived from videos. We train our models on data that is two orders-of-magnitude bigger than datasets used in prior work. We perform a thorough exploration of model architectures for combining visual and text features. Our experiments on two corpora (YouCookII and 20bn-something-something-v2) show that the best performing architecture consists of middle fusion of visual and text features, yielding over 25% relative improvement in perplexity. We report analysis that provides insights into why our multimodal language model improves upon a standard RNN language model.

1 Introduction

Language models are vital components of a wide variety of systems for Natural Language Processing (NLP) including Automatic Speech Recognition, Machine Translation, Optical Character Recognition, Spelling Correction, etc. However, most language models are trained and applied in a manner that is oblivious to the environment in which human language operates (Ororbia et al., 2018). These models are typically trained only on sequences of words, ignoring the physical context in which the symbolic representations are grounded, or ignoring the social context that could inform the semantics of an utterance.

For incorporating additional modalities, the NLP community has typically used datasets such as MS COCO (Lin et al., 2014) and Flickr (Rashtchian et al., 2010) for image-based tasks, while several datasets (Chen and Dolan, 2011; Yeung et al., 2014; Das et al., 2013; Rohrbach et al., 2013; Hendricks et al., 2017) have been curated for video-based tasks. Despite the lack of big datasets, researchers have started investigating language grounding in images (Plummer et al., 2015; Rohrbach et al., 2016; Socher et al., 2014) and to lesser extent in videos (Regneri et al., 2013; Lin et al., 2014). However, language grounding has focused more on obtaining better word and sentence representations or other downstream tasks, and to lesser extent on language modeling.

In this paper, we examine the problem of incorporating temporal visual context into a recurrent neural language model (RNNLM). Multimodal Neural Language Models were introduced in (Kiros et al., 2014), where log-linear LMs (Mnih and Hinton, 2007) were conditioned to handle both image and text modalities. Notably, this work did not use the recurrent neural model paradigm which has now become the de facto way of implementing neural LMs.

The closest work to ours is that of Ororbia et al. (2018), who report perplexity gains of around 5–6% on three languages on the MS COCO dataset (with an English vocabulary of only 16K words). Our work is distinguishable from previous work with respect to three dimensions:

1. We train our model on video transcriptions comprised of text and visual features. Thus, both modalities of our model are temporal, in contrast to most previous work which uses static images. At the same time, our model respects the temporal alignment between the two modalities, combining the text with its concurrent visual context, mimicking a real natural language understanding situation.

2. We explore several architectures for combining the two modalities, and our best model reduces perplexity by more than 25% relative to a text-only baseline.

\*Work performed while the author was an intern at Google.
3. The scale of our experiments is unprecedented: we train our models on two orders of magnitude more data than any previous work. This results in quite strong, hard-to-beat baselines.

2 Model

A language model assigns to a sentence $W = w_1 \ldots w_M$ the probability:

$$ p(W) = \prod_{m=1}^{M} p(w_m | w_{<m}) $$

where each word is assigned a probability given the previous word history.

For a given video segment, we assume that there is a sequence of $N$ video frames represented by features $V = v_1 \ldots v_N$, and the corresponding transcription $W = w_1 \ldots w_M$. In practice, we assume $N = M$ since we can always assign a video frame to each word by replicating the video frames the requisite number of times. Thus, our visually-grounded language model models the probability of the next word given the history of previous words as well as video frames:

$$ p(W) = \prod_{m=1}^{M} p(w_m | w_{<m}, v_{<m}) $$

2.1 Combining the text and video modalities

There are several options for combining the text and video modalities. We opt for the simplest strategy, which concatenates the representations. For a word embedding $w_i$ and corresponding visual representation $v_i$, the input to our RNNLM will be the concatenated vector $e_i = [w_i ; v_i]$. For the examples where we were unable to compute visual features (see Section §3), we set $v_i$ to be a zero-vector.

In addition to concatenating the word and visual embedding, we explore two variants of our model that allow for a finer-grained integration of the two modalities:

a. Learning a linear combination of the two modalities

In this case, the RNNLM is given as input a vector $e_i$ that is a weighted sum of the two embeddings:

$$ e_i = K^w w_i + K^v v_i $$

where $K^w, K^v$ are learned matrices.

b. Weighting the visual embedding conditioned on the word

Here, we apply the intuition that some words could provide information as to whether or not the visual context is helpful. In a simplistic example, if the word history is the article “the,” then the visual context could provide relevant information needed for predicting the next word. For other word histories, though, the visual context might not be needed or be even irrelevant for the next word prediction: if the previous word is “carpe”, the next word is very likely to be “diem”, regardless of visual context. We implement a simple weighting mechanism that learns
| Model               | Perplexity (Reduction) | YouCook2 | sth-sth |
|---------------------|------------------------|----------|---------|
| text-only           | 89.8                   | 513.6    |         |
| Linear Comb. Weighting | 84.8 (6%)              | 580.8 (–) |         |
| Early Fusion        | 76.8 (14%)             | 538.8 (–) |         |
| Middle Fusion       | 93.7 (–)               | 611.3 (–) |         |
| Late Fusion         | 79.3 (12%)             | 485.5 (5%)|         |
| text + video        | 64.9                   | 411.4    |         |
| text + zero vectors | 99.0                   | 537.7    |         |

Table 1: Middle Fusion of text and frame-level visual features leads to significant reductions in perplexity on two multimodal datasets.

| Inputs to | Perplexity |
|-----------|------------|
| Middle Fusion | YouCook2 | sth-sth |
| text + video | 64.9 | 411.4 |
| text + zero vectors | 99.0 | 537.7 |

Table 2: Withholding visual context from our best model leads to worse performance (similar to an RNNLM trained only on text).

YouCookII dataset: The YouCookII dataset (YouCook2) (Das et al., 2013; Zhou et al., 2018) consists of 2,000 instructional cooking videos, each annotated with steps localized in video. An example annotation could be that of a video segment between 00:53–01:03 with the recipe step “cook bacon until crispy, then drain on paper towel.” The dataset was manually created, so that for each textual recipe segment the corresponding as a word-level model (Mielke and Eisner, 2018). For about 75% of the segments, we were able to obtain visual features at the frame level. The features are 1500-dimensional vectors, extracted from the video frames at 1-second intervals, similar to those used for large scale image classification tasks (Varadarajan et al., 2015; Abu-El-Haija et al., 2016). For a $K$-second video and $N > K$ wordpieces, each feature is uniformly allocated to $N/K$ wordpieces.

Our RNNLM models consist of 2 LSTM layers, each containing 2048 units which are linearly projected to 512 units (Sak et al., 2014). The word-piece and video embeddings are of size 512 each. We do not use dropout. During training, the batch size per worker is set to 256, and we perform full length unrolling to a max length of 70. The $l_2$-norms of the gradients are clipped to a max norm of 1.0 for the LSTM weights and to 10,000 for all other weights. We train with Synchronous SGD with the Adafactor optimizer (Shazeer and Stern, 2018) until convergence on a development set, created by randomly selecting 1% of all utterances.

4 Experiments

For evaluation we used two datasets, YouCook2 and sth-sth, allowing us to evaluate our models in cases where the visual context is relevant to the modelled language. Note that no data from these datasets are present in the YouTube videos used for training. The perplexity of our models is shown in Table 1.

This approach does not add any new parameters to the model, but since the word representations $w_i$ are learned, this mechanism has the potential to learn word embeddings that are also appropriate for weighting the visual context.

2.2 Location of combination

We explore three locations for fusing visual features in an RNNLM (Figure 1). Our Early Fusion strategy merges the text and the visual features at the input to the LSTM cells. This embodies the intuition that it is best to do feature combination at the earliest possible stage. The Middle Fusion merges the visual features at the output of the 1st LSTM layer while the Late Fusion strategies merges the two features after the final LSTM layer. The idea behind the Middle and Late fusion is that we would like to minimize changes to the regular RNNLM architecture at the early stages and still be able to benefit from the visual features.

3 Data and Experimental Setup

Our training data consist of about 64M segments from YouTube videos comprising a total of 1.2B tokens (Soltan et al., 2017). We tokenize the training data using a vocabulary of 66K wordpieces (Schuster and Nakajima, 2012). Thus, the input to the model is a sequence of wordpieces. Using wordpieces allows us to address out-of-vocabulary (OOV) word issues that would arise from having a fixed word vocabulary. In practice, a wordpiece RNNLM gives similar performance...
a) Our multimodal model has significantly lower word-level perplexity on word-pieces that correspond to items shown in the video (“spray, pan”).

| text-only | spray the pan with cooking spray | Total Score |
|-----------|----------------------------------|-------------|
|           | 10.2 2.9 5.6 1.4 7.5 0.2         | 27.8        |
| Middle Fusion | 8.9 2.6 3.5 1.8 7.7 0.5           | 24.8        |

b) A rare example where the text-only model is overall better than the multimodal one. Still, though, entities (“cucumber”) that appear in the video receive better scores from the multimodal system.

| text-only | place cucumber salad and then the hot dog on the bun | Total Score |
|-----------|------------------------------------------------------|-------------|
|           | 7.7 14.5 4.8 1.9 2.9 3.3 6.6 3.1 4.5 0.9 5.0 | 55.1 |
| Middle Fusion | 6.6 11.9 5.3 2.0 4.0 3.5 6.1 4.6 4.0 1.3 7.7 | 57.0 |

Table 3: Two sentences from YouCook2 with wordpiece-level negative log likelihood scores. Most gains (highlighted) of our Middle Fusion model come from word-pieces corresponding to entities that appear in the videos.

The domain shift between training and the sth-sth dataset is reflected in quite high PPL scores. The videos are also much shorter (typically a few seconds) than the average YouTube video. We speculate that the length mismatch between training and test is responsible for the lower performance of the fine-grained approaches on sth-sth.

Does our model really use the visual features?
In order to confirm that our model does utilize the visual modality, we perform a simple experiment of blinding it: we deprive the RNNLM of the visual context, substituting the video embeddings with zero vectors. The the results shown in Table 2. The performance is worse, but it is in fact comparable to a model trained only on the text modality on YouCook2. This confirms that our model indeed uses the visual context in a productive way. Furthermore, it shows that our model is somewhat robust to the absence of visual context; this is the result of training with 25% of our instances lacking visual features.

Where do the improvements come from? We obtained wordpiece-level negative log likelihoods for 50 randomly chosen sentences from the YouCook2 dataset. For the majority (88% of the sentences), the Middle Fusion model had better sentence-level scores than the text-only model. We show two examples in Table 3. We find that the largest improvements are due to the added visual information: the highest reductions are found on word-pieces corresponding to entities that appear in the video.

video frame provides related context. Therefore, this constrained scenario allows us to explicitly test whether our language models indeed manage to take advantage of the visual context.

20BN-Something-Something dataset v2: (Goyal et al., 2017): This dataset (henceforth sth-sth) consists of about 220K short videos of actions performed by humans with every day objects, annotated with text descriptions of the actions. Each description follows a template e.g. “Taking something out of something.” This is a very constrained scenario, where the objects (“something”) mentioned in the text definitely appear in the video. We evaluate on the predefined validation set (25K videos) computing perplexity (PPL) on the textual action descriptions.

Out of all the architectures we consider, only two lead to consistently better performance on both datasets: Middle and Late Fusion. Late Fusion leads to modest improvements (12% and 5% relative on the two datasets), but Middle Fusion is able to take better advantage of both modalities, leading to 28% and 20% relative reductions in perplexity. In contrast, Early Fusion performs worse than the baseline. We suspect that the crucial factor for success with such architectures is allowing at least one lower layer of the RNNLM to be dedicated to text-only modeling.

The variants that do not simply concatenate the word and video embeddings, but perform a finer-grainer integration, yield improvements on only one dataset (YouCook2). The linear combination approach leads to 6% relative reduction, while the learned weighting of the video embedding reduces perplexity by 14%.
5 Conclusion

We present a simple strategy to augment a standard recurrent neural network language model with temporal visual features. Through an exploration of candidate architectures, we show that the Middle Fusion of visual and textual features leads to a 20–28% reduction in perplexity relative to a text only baseline. These experiments were performed using datasets of unprecedented scale, with more than 1.2 billion tokens—two orders of magnitude more than any previously published work. Our work is a first step towards creating and deploying large-scale multimodal systems that properly situate themselves into a given context, by taking full advantage of every available signal.

References

Sami Abu-El-Haija, Nisarg Kothari, Joonseok Lee, Apostol (Paul) Natsev, George Toderici, Balkrishnan Varadarajan, and Sudheendra Vijayanarasimhan. 2016. Youtube-8m: A large-scale video classification benchmark. In arXiv:1609.08675.

David L. Chen and William B Dolan. 2011. Collecting highly parallel data for paraphrase evaluation. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 190–200. Association for Computational Linguistics.

Pradipto Das, Chenliang Xu, Richard F Doell, and Jason J Corso. 2013. A thousand frames in just a few words: Lingual description of videos through latent topics and sparse object stitching. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2634–2641.

Raghav Goyal, Samira Ebrahimi Kahou, Vincent Michalski, Joanna Materzyńska, Susanne Westphal, Heuna Kim, Valentín Haenel, Ingo Freund, Peter Yianilos, Moritz Mueller-Freitag, et al. 2017. The something something video database for learning and evaluating visual common sense. In The IEEE International Conference on Computer Vision (ICCV), volume 1, page 3.

Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. 2017. Localizing moments in video with natural language. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), pages 5803–5812.

Ryan Kiros, Ruslan Salakhutdinov, and Rich Zemel. 2014. Multimodal neural language models. In International Conference on Machine Learning, pages 595–603.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer.

Sebastian J Mielke and Jason Eisner. 2018. Spell once, summon anywhere: A two-level open-vocabulary language model. arXiv preprint arXiv:1804.08205.

Andriy Mnih and Geoffrey Hinton. 2007. Three new graphical models for statistical language modelling. In Proceedings of the 24th international conference on Machine learning, pages 641–648. ACM.

Alexander G Ororbia, Ankur Mali, Matthew A Kelly, and David Reitter. 2018. Visually grounded, situated learning in neural models. arXiv preprint arXiv:1805.11546.

Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. 2015. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In Proceedings of the IEEE international conference on computer vision, pages 2641–2649.

Cyrus Rashtchian, Peter Young, Micah Hodosh, and Julia Hockenmaier. 2010. Collecting image annotations using amazon’s mechanical turk. In Proceedings of the NAACL HLT 2010 Workshop on Creating Speech and Language Data with Amazon’s Mechanical Turk, pages 139–147. Association for Computational Linguistics.

Michaela Regneri, Marcus Rohrbach, Dominikus Wetzel, Stefan Thater, Bernt Schiele, and Manfred Pinkal. 2013. Grounding action descriptions in videos. Transactions of the Association of Computational Linguistics, 1:25–36.

Anna Rohrbach, Marcus Rohrbach, Ronghang Hu, Trevor Darrell, and Bernt Schiele. 2016. Grounding of textual phrases in images by reconstruction. In European Conference on Computer Vision, pages 817–834. Springer.

Marcus Rohrbach, Wei Qiu, Ivan Titov, Stefan Thater, Manfred Pinkal, and Bernt Schiele. 2013. Translating video content to natural language descriptions. In Proceedings of the IEEE International Conference on Computer Vision, pages 433–440.

Hasim Sak, Andrew W. Senior, and François Beaufays. 2014. Long short-term memory recurrent neural network architectures for large scale acoustic modeling. In Proc. INTERSPEECH.

Mike Schuster and Kaisuke Nakajima. 2012. Japanese and korean voice search. In Proc. of ICASSP.

Noam Shazeer and Mitchell Stern. 2018. Adafactor: Adaptive learning rates with sublinear memory cost. arXiv preprint arXiv:1804.04235.
Richard Socher, Andrej Karpathy, Quoc V Le, Christopher D Manning, and Andrew Y Ng. 2014. Grounded compositional semantics for finding and describing images with sentences. *Transactions of the Association of Computational Linguistics*, 2(1):207–218.

Hagen Soltau, Hank Liao, and Hasim Sak. 2017. Neural speech recognizer: Acoustic-to-word lstm model for large vocabulary speech recognition. In *Proc. Interspeech*, pages 3707–3711.

Balakrishnan Varadarajan, George Toderici, Sudheendra Vijayanarasimhan, and Apostol Natsev. 2015. Efficient large scale video classification. *arXiv preprint arXiv:1505.06250*.

Serena Yeung, Alireza Fathi, and Li Fei-Fei. 2014. Videoset: Video summary evaluation through text. *arXiv preprint arXiv:1406.5824*.

Luowei Zhou, Chenliang Xu, and Jason J Corso. 2018. Towards automatic learning of procedures from web instructional videos. In *AAAI Conference on Artificial Intelligence*. 