Table 6: Standard deviation of attended subsequences

Sentiment	Porosity						Cut					
	gr	rop	c1	c2	c3	c4	gr	rop	c1	c2	c3	c4
Good	3.27	2.78	29.25	12.08	2.20	8.36	4.97	0.97	7.85	38.87	10.03	0.31
Neutral	4.41	6.33	29.53	8.56	4.59	94.03	3.93	15.63	22.99	10.14	3.04	5.00
Negative	4.01	0.28	232.16	11.97	54.87	43.32	5.45	1.10	11.22	10.34	5.53	6.11

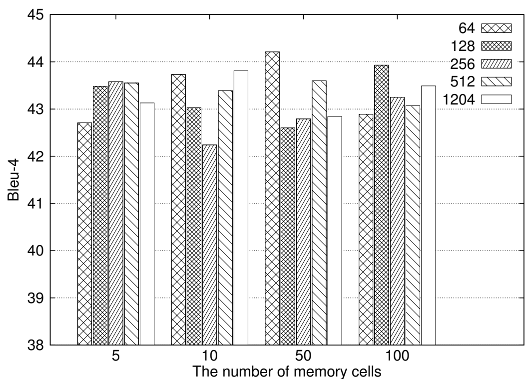

Figure 8: Performance change in different parameters of external memory

in the range between 42 and 44. It can also be seen that the performance with the dimension of memory cells, such as 64, increases when the number of memory cells increases from 5 to 50. Given the number of memory cells, the dimension of the memory cells, such as 512, seems not be able to achieve the best performances compared with other dimensions.

9 CONCLUSIONS

In this paper, we presented the problem in oil & gas industry of generating rock descriptions in human-readable text from multiple well logs automatically. Our approach can reduce the cost and time required by engineers to write such reports. To the best of our knowledge, this is the first work to methodically study this problem. Our experiments conducted on real well data from North Dakota in the United States give significant insight into this problem. The experiment results show that our models with a hierarchical decoder and techniques such as the two forms of attention and external memory are effective in generating rock descriptions.

For future work, we would like to explore three possible paths. First, we will try different addressing methods to read and write the external memory, and determine which kind of addressing method is most suitable for this task. Second, the metric used for model optimization is different from the metric used for evaluating the quality of the generated text. We would like to use reinforcement learning to directly optimize the metrics of interest [16]. Third, even the metrics used in this paper are widely applied in machine translation and image captioning tasks, it can not evaluate the quality of generated text thoroughly. Therefore, how to design a metric for our specific domain is another interesting work.

REFERENCES

[1] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. In *ICLR*, 2015.
[2] K. Cho, B. van Merrienboer, Ç. Gülçehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *EMNLP*, pages 1724–1734, 2014.
[3] A. Graves, G. Wayne, and I. Danihelka. Neural turing machines. *arXiv:1410.5401*, 2014.
[4] K. Holdaway. *Harness Oil and Gas Big Data with Analytics: Optimize Exploration and Production with Data Driven Models*. Wiley, 2014.
[5] A. Karpathy, A. Joulin, and F. Li. Deep fragment embeddings for bidirectional image sentence mapping. In *NIPS*, pages 1889–1897, 2014.
[6] A. Karpathy and F. Li. Deep visual-semantic alignments for generating image descriptions. In *CVPR*, pages 3128–3137, 2015.
[7] J. Krause, J. Johnson, R. Krishna, and F. Li. A hierarchical approach for generating descriptive image paragraphs. In *arXiv:1611.06607*, 2016.
[8] A. Lavie and A. Agarwal. Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments. In *StatMT*, pages 228–231, 2007.
[9] J. Li, M. Luong, and D. Jurafsky. A hierarchical neural autoencoder for paragraphs and documents. In *ACL*, pages 1106–1115, 2015.
[10] C.-Y. Lin. Rouge: A package for automatic evaluation of summaries. In *ACL Workshop*, pages 74–81, 2004.
[11] M. Luong, H. Pham, and C. D. Manning. Effective approaches to attention-based neural machine translation. In *EMNLP*, pages 1412–1421, 2015.
[12] S. D. Mohaghegh. Reservoir simulation and modeling based on pattern recognition. In *SPE*, 2011.
[13] F. J. O. Morales and D. Roggen. Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. *Sensors*, 16(1):115, 2016.
[14] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu. Bleu: a method for automatic evaluation of machine translation. In *ACL*, pages 311–318, 2002.
[15] S. Pirson. *Handbook of Well Log Analysis for Oil and Gas Formation Evaluation*. Prentice-Hall, 1963.
[16] M. Ranzato, S. Chopra, M. Auli, and W. Zaremba. Sequence level training with recurrent neural networks. In *ICLR*, 2016.
[17] A. Scollard. Petrel shale-engineered for exploiting shale resources. In *URTec*, 2014.
[18] I. Sutskever, O. Vinyals, and Q. V. Le. Sequence to sequence learning with neural networks. In *NIPS*, pages 3104–3112, 2014.
[19] B. Tong, M. Klinkigt, M. Iwayama, Y. Kobayashi, A. Sahu, and R. Vennelakanti. Deep match between geology reports and well logs using spatial information. In *CIKM*, pages 1833–1842, 2016.
[20] B. Tong, H. Ozaki, M. Iwayama, Y. Kobayashi, A. Sahu, and R. Vennelakanti. Production Estimation for Shale Wells with Sentiment-Based Features from Geology Reports. In *ICDM Workshop*, pages 1310–1317, 2015.
[21] S. Venugopalan, M. Rohrbach, J. Donahue, R. J. Mooney, T. Darrell, and K. Saenko. Sequence to sequence - video to text. In *ICCV*, pages 4534–4542, 2015.
[22] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In *CVPR*, pages 3156–3164, 2015.
[23] M. Wang, Z. Lu, H. Li, and Q. Liu. Memory-enhanced decoder for neural machine translation. In *EMNLP*, pages 278–286, 2016.
[24] K. Xu, J. Ba, R. Kiros, K. Cho, A. C. Courville, R. Salakhutdinov, R. S. Zemel, and Y. Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *ICML*, pages 2048–2057, 2015.
[25] L. Yao, A. Torabi, K. Cho, N. Ballas, C. J. Pal, H. Larochelle, and A. C. Courville. Describing videos by exploiting temporal structure. In *ICCV*, pages 4507–4515, 2015.