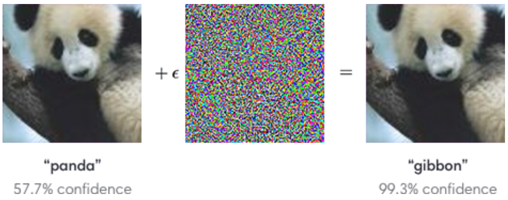
Chapter 9: (Need for) Sanity

The Paradox of Deep Learning

Why does deep learning work so well despite



[a] https://arxiv.org/pdf/1710.05468.pdf

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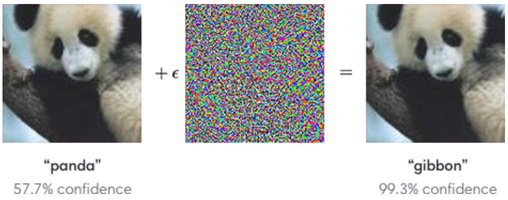

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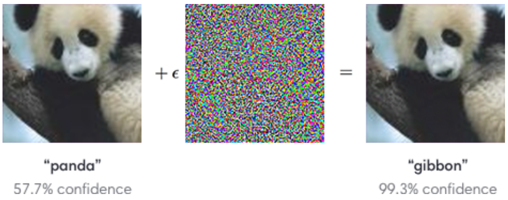

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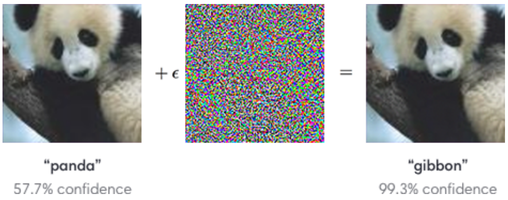

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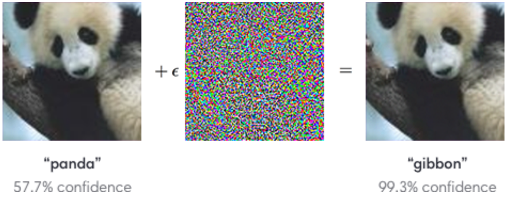

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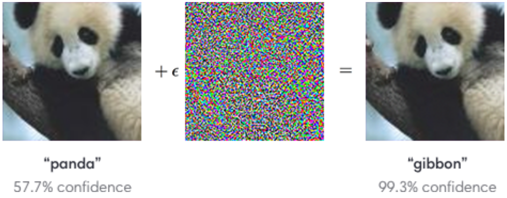
No clear answers yet but ...



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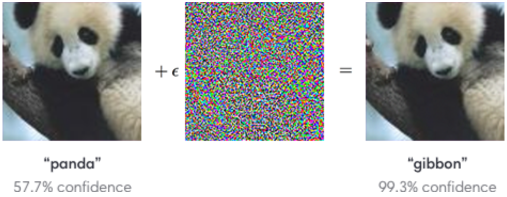

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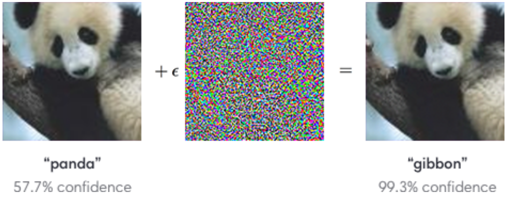

No clear answers yet but ...

- Slowly but steadily there is increasing emphasis on explainability and theoretical justifications! [a]
- Hopefully this will bring sanity to the proceedings !

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References I

[1] Tomas Mikolov, Martin Karafiát, Lukás Burget, Jan Cernocký, and Sanjeev Khudanpur. Recurrent neural network based language model. In *INTERSPEECH 2010, 11th Annual Conference of the International Speech Communication Association, Makuhari, Chiba, Japan, September 26-30, 2010*, pages 1045–1048, 2010.

[2] Aaron van den Oord, Nal Kalchbrenner, and Koray Kavukcuoglu. Pixel recurrent neural networks. *arXiv preprint arXiv:1601.06759*, 2016.

[3] Tim Salimans, Andrej Karpathy, Xi Chen, and Diederik P Kingma. Pixelcnn++: Improving the pixelcnn with discretized logistic mixture likelihood and other modifications. *arXiv preprint arXiv:1701.05517*, 2017.

[4] Ryan Kiros, Yukun Zhu, Ruslan Salakhutdinov, Richard S. Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. Skip-thought vectors. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 3294–3302, 2015.

[5] Yoon Kim, Yacine Jernite, David Sontag, and Alexander M. Rush. Character-aware neural language models. *CoRR*, abs/1508.06615, 2015.

[6] Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Process. Mag.*, 29(6):82–97, 2012.

[7] Alex Graves, Abdel-rahman Mohamed, and Geoffrey E. Hinton. Speech recognition with deep recurrent neural networks. In *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2013, Vancouver, BC, Canada, May 26-31, 2013*, pages 6645–6649, 2013.

[8] Jan Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, Kyunghyun Cho, and Yoshua Bengio. Attention-based models for speech recognition. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 577–585, 2015.

[9] Hasim Sak, Andrew W. Senior, Kanishka Rao, and Françoise Beaufays. Fast and accurate recurrent neural network acoustic models for speech recognition. In *INTERSPEECH 2015, 16th Annual Conference of the International Speech Communication Association, Dresden, Germany, September 6-10, 2015*, pages 1468–1472, 2015.

[10] Nal Kalchbrenner and Phil Blunsom. Recurrent continuous translation models. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, EMNLP 2013, 18-21 October 2013, Grand Hyatt Seattle, Seattle, Washington, USA, A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1700–1709, 2013.

References II

[11] Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1724–1734, 2014.

[12] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473, 2014.

[13] Sébastien Jean, KyungHyun Cho, Roland Memisevic, and Yoshua Bengio. On using very large target vocabulary for neural machine translation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pages 1–10, 2015.

[14] Çaglar Gülçehre, Orhan Firat, Kelvin Xu, Kyunghyun Cho, Loïc Barrault, Huei-Chi Lin, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. On using monolingual corpora in neural machine translation. *CoRR*, abs/1503.03535, 2015.

[15] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 3104–3112, 2014.

[16] Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 1412–1421, 2015.

[17] Hao Zheng, Yong Cheng, and Yang Liu. Maximum expected likelihood estimation for zero-resource neural machine translation. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 4251–4257, 2017.

[18] Yong Cheng, Qian Yang, Yang Liu, Maosong Sun, and Wei Xu. Joint training for pivot-based neural machine translation. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 3974–3980, 2017.

References III

[19] Yun Chen, Yang Liu, Yong Cheng, and Victor O. K. Li. A teacher-student framework for zero-resource neural machine translation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 1925–1935, 2017.

[20] Orhan Firat, Baskaran Sankaran, Yaser Al-Onaizan, Fatos T. Yarman-Vural, and Kyunghyun Cho. Zero-resource translation with multi-lingual neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016*, pages 268–277, 2016.

[21] Lifeng Shang, Zhengdong Lu, and Hang Li. Neural responding machine for short-text conversation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pages 1577–1586, 2015.

[22] Oriol Vinyals and Quoc V. Le. A neural conversational model. *CoRR*, abs/1506.05869, 2015.

[23] Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *Proceedings of the SIGDIAL 2015 Conference, The 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2-4 September 2015, Prague, Czech Republic*, pages 285–294, 2015.

[24] Jesse Dodge, Andreea Gane, Xiang Zhang, Antoine Bordes, Sumit Chopra, Alexander H. Miller, Arthur Szlam, and Jason Weston. Evaluating prerequisite qualities for learning end-to-end dialog systems. *CoRR*, abs/1511.06931, 2015.

[25] Jason Weston, Antoine Bordes, Sumit Chopra, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. *CoRR*, abs/1502.05698, 2015.

[26] Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. A hierarchical latent variable encoder-decoder model for generating dialogues. *CoRR*, abs/1605.06069, 2016.

[27] Antoine Bordes and Jason Weston. Learning end-to-end goal-oriented dialog. *CoRR*, abs/1605.07683, 2016.

[28] Iulian Vlad Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarath Chandar, Nan Rosemary Ke, Sai Mudumba, Alexandre de Brébisson, Jose Sotelo, Dendi Suhubdy, Vincent Michalski, Alexandre Nguyen, Joelle Pineau, and Yoshua Bengio. A deep reinforcement learning chatbot. *CoRR*, abs/1709.02349, 2017.

References IV

[29] Karl Moritz Hermann, Tomás Kociský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 1693–1701, 2015.

[30] Danqi Chen, Jason Bolton, and Christopher D. Manning. A thorough examination of the cnn/daily mail reading comprehension task. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers*, 2016.

[31] Caiming Xiong, Victor Zhong, and Richard Socher. Dynamic coattention networks for question answering. *CoRR*, abs/1611.01604, 2016.

[32] Min Joon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension. *CoRR*, abs/1611.01603, 2016.

[33] Bhuwan Dhingra, Hanxiao Liu, Zhilin Yang, William W. Cohen, and Ruslan Salakhutdinov. Gated-attention readers for text comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 1832–1846, 2017.

[34] Wenhui Wang, Nan Yang, Furu Wei, Baobao Chang, and Ming Zhou. Gated self-matching networks for reading comprehension and question answering. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 189–198, 2017.

[35] Minghao Hu, Yuxing Peng, and Xipeng Qiu. Mnemonic reader for machine comprehension. *CoRR*, abs/1705.02798, 2017.

[36] Junhua Mao, Wei Xu, Yi Yang, Jiang Wang, and Alan L. Yuille. Deep captioning with multimodal recurrent neural networks (m-rnn). *CoRR*, abs/1412.6632, 2014.

[37] Ryan Kiros, Ruslan Salakhutdinov, and Richard S. Zemel. Unifying visual-semantic embeddings with multimodal neural language models. *CoRR*, abs/1411.2539, 2014.

[38] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Trevor Darrell, and Kate Saenko. Long-term recurrent convolutional networks for visual recognition and description. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 2625–2634, 2015.

References V

[39] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3156–3164, 2015.

[40] Andrej Karpathy and Fei-Fei Li. Deep visual-semantic alignments for generating image descriptions. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3128–3137, 2015.

[41] Hao Fang, Saurabh Gupta, Forrest N. Iandola, Rupesh Kumar Srivastava, Li Deng, Piotr Dollár, Jianfeng Gao, Xiaodong He, Margaret Mitchell, John C. Platt, C. Lawrence Zitnick, and Geoffrey Zweig. From captions to visual concepts and back. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 1473–1482, 2015.

[42] Kan Chen, Jiang Wang, Liang-Chieh Chen, Haoyuan Gao, Wei Xu, and Ram Nevatia. ABC-CNN: an attention based convolutional neural network for visual question answering. *CoRR*, abs/1511.05960, 2015.

[43] Muhammad Ajmal, Muhammad Husnain Ashraf, Muhammad Shakir, Yasir Abbas, and Faiz Ali Shah. Video summarization: Techniques and classification. In *Computer Vision and Graphics - International Conference, ICCVG 2012, Warsaw, Poland, September 24-26, 2012. Proceedings*, pages 1–13, 2012.

[44] Ke Zhang, Wei-Lun Chao, Fei Sha, and Kristen Grauman. Video summarization with long short-term memory. In *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VII*, pages 766–782, 2016.

[45] Zhong Ji, Kailin Xiong, Yanwei Pang, and Xuelong Li. Video summarization with attention-based encoder-decoder networks. *CoRR*, abs/1708.09545, 2017.

[46] Rameswar Panda, Niluthpol Chowdhury Mithun, and Amit K. Roy-Chowdhury. Diversity-aware multi-video summarization. *IEEE Trans. Image Processing*, 26(10):4712–4724, 2017.

[47] Janghoon Choi, Junseok Kwon, and Kyoung Mu Lee. Visual tracking by reinforced decision making. *CoRR*, abs/1702.06291, 2017.

[48] Sangdoo Yun, Jongwon Choi, Youngjoon Yoo, Kimin Yun, and Jin Young Choi. Action-decision networks for visual tracking with deep reinforcement learning. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1349–1358, 2017.

References VI

[49] Albert Haque, Michelle Guo, Alexandre Alahi, Serena Yeung, Zelun Luo, Alisha Rege, Jeffrey Jopling, N. Lance Downing, William Beninati, Amit Singh, Terry Platchek, Arnold Milstein, and Li Fei-Fei. Towards vision-based smart hospitals: A system for tracking and monitoring hand hygiene compliance. *CoRR*, abs/1708.00163, 2017.

[50] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3431–3440, 2015.

[51] Ming Liang and Xiaolin Hu. Recurrent convolutional neural network for object recognition. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3367–3375, 2015.

[52] Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun. Faster R-CNN: towards real-time object detection with region proposal networks. *IEEE Trans. Pattern Anal. Mach. Intell.*, 39(6):1137–1149, 2017.

[53] Sean Bell, C. Lawrence Zitnick, Kavita Bala, and Ross B. Girshick. Inside-outside net: Detecting objects in context with skip pooling and recurrent neural networks. *CoRR*, abs/1512.04143, 2015.

[54] Joseph Redmon and Ali Farhadi. YOLO9000: better, faster, stronger. *CoRR*, abs/1612.08242, 2016.

[55] Jifeng Dai, Yi Li, Kaiming He, and Jian Sun. R-FCN: object detection via region-based fully convolutional networks. In *Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain*, pages 379–387, 2016.

[56] Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, and Yichen Wei. Deformable convolutional networks. *CoRR*, abs/1703.06211, 2017.

[57] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross B. Girshick. Mask R-CNN. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2980–2988, 2017.

[58] Sergi Caelles, Kevis-Kokitsi Maninis, Jordi Pont-Tuset, Laura Leal-Taixé, Daniel Cremers, and Luc Van Gool. One-shot video object segmentation. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 5320–5329, 2017.

[59] Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. *CoRR*, abs/1312.6114, 2013.

References VII

[60] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 2672–2680, 2014.

[61] Anh Nguyen, Jason Yosinski, Yoshua Bengio, Alexey Dosovitskiy, and Jeff Clune. Plug & play generative networks: Conditional iterative generation of images in latent space. *CoRR*, abs/1612.00005, 2016.

[62] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *CoRR*, abs/1710.10196, 2017.

[63] Adam Santoro, David Raposo, David G. T. Barrett, Mateusz Malinowski, Razvan Pascanu, Peter Battaglia, and Tim Lillicrap. A simple neural network module for relational reasoning. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA*, pages 4974–4983, 2017.

[64] Ronghang Hu, Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Kate Saenko. Learning to reason: End-to-end module networks for visual question answering. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 804–813, 2017.

[65] Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C. Lawrence Zitnick, and Ross B. Girshick. CLEVR: A diagnostic dataset for compositional language and elementary visual reasoning. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1988–1997, 2017.

[66] Hedi Ben-younes, Rémi Cadène, Matthieu Cord, and Nicolas Thome. MUTAN: multimodal tucker fusion for visual question answering. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2631–2639, 2017.

[67] Mateusz Malinowski, Marcus Rohrbach, and Mario Fritz. Ask your neurons: A neural-based approach to answering questions about images. In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 1–9, 2015.

[68] Vahid Kazemi and Ali Elqursh. Show, ask, attend, and answer: A strong baseline for visual question answering. *CoRR*, abs/1704.03162, 2017.

[69] Makarand Tapaswi, Yukun Zhu, Rainer Stiefelhagen, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. Movieqa: Understanding stories in movies through question-answering. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 4631–4640, 2016.

References VIII

[70] Kuo-Hao Zeng, Tseng-Hung Chen, Ching-Yao Chuang, Yuan-Hong Liao, Juan Carlos Niebles, and Min Sun. Leveraging video descriptions to learn video question answering. *CoRR*, abs/1611.04021, 2016.

[71] Tegan Maharaj, Nicolas Ballas, Anna Rohrbach, Aaron C. Courville, and Christopher Joseph Pal. A dataset and exploration of models for understanding video data through fill-in-the-blank question-answering. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 7359–7368, 2017.

[72] Zhou Zhao, Qifan Yang, Deng Cai, Xiaofei He, and Yueting Zhuang. Video question answering via hierarchical spatio-temporal attention networks. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 3518–3524, 2017.

[73] Youngjae Yu, Hyungjin Ko, Jongwook Choi, and Gunhee Kim. End-to-end concept word detection for video captioning, retrieval, and question answering. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 3261–3269, 2017.

[74] Hongyang Xue, Zhou Zhao, and Deng Cai. The forgettable-watcher model for video question answering. *CoRR*, abs/1705.01253, 2017.

[75] Amir Mazaheri, Dong Zhang, and Mubarak Shah. Video fill in the blank with merging lstms. *CoRR*, abs/1610.04062, 2016.

[76] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, and Trevor Darrell. Long-term recurrent convolutional networks for visual recognition and description. *CoRR*, abs/1411.4389, 2014.

[77] Subhashini Venugopalan, Huijuan Xu, Jeff Donahue, Marcus Rohrbach, Raymond J. Mooney, and Kate Saenko. Translating videos to natural language using deep recurrent neural networks. In *NAACL HLT 2015, The 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado, USA, May 31 - June 5, 2015*, pages 1494–1504, 2015.

[78] Anna Rohrbach, Marcus Rohrbach, Wei Qiu, Annemarie Friedrich, Manfred Pinkal, and Bernt Schiele. Coherent multi-sentence video description with variable level of detail. In *Pattern Recognition - 36th German Conference, GCPR 2014, Münster, Germany, September 2-5, 2014, Proceedings*, pages 184–195, 2014.

[79] Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher J. Pal, Hugo Larochelle, and Aaron C. Courville. Describing videos by exploiting temporal structure. In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 4507–4515, 2015.

References IX

[80] Yingwei Pan, Tao Mei, Ting Yao, Houqiang Li, and Yong Rui. Jointly modeling embedding and translation to bridge video and language. *CoRR*, abs/1505.01861, 2015.

[81] Linchao Zhu, Zhongwen Xu, Yi Yang, and Alexander G. Hauptmann. Uncovering temporal context for video question and answering. *CoRR*, abs/1511.04670, 2015.

[82] Amir Sadeghian, Alexandre Alahi, and Silvio Savarese. Tracking the untrackable: Learning to track multiple cues with long-term dependencies. *CoRR*, abs/1701.01909, 2017.

[83] Junhua Mao, Xu Wei, Yi Yang, Jiang Wang, Zhiheng Huang, and Alan L. Yuille. Learning like a child: Fast novel visual concept learning from sentence descriptions of images. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2015.

[84] Jürgen Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, 61:85–117, 2015.

[85] Tommy Chheng. Video summarization using clustering.

[86] Aäron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alexander Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio. In *Arxiv*, 2016.

[87] Aaron van den Oord, Nal Kalchbrenner, Lasse Espeholt, koray kavukcuoglu, Oriol Vinyals, and Alex Graves. Conditional image generation with pixelcnn decoders. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 4790–4798. Curran Associates, Inc., 2016.

[88] Y. LeCun, I. Kanter, and S. A. Solla. Second order properties of error surfaces: Learning time and generalization. In D. S. Lippman, J. E. Moody, and D. S. Touretzky, editors, *Advances in Neural Information Processing Systems 3*, pages 918–924. Morgan Kaufmann, 1991.

[89] Vinod Nair and Geoffrey E. Hinton. Rectified linear units improve restricted Boltzmann machines. In *International Conference on Machine Learning (ICML)*, 2010.

[90] Alex Krizhevsky, I Sutskever, and G. E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NIPS 2012)*, page 4, 2012.

[91] Andrew L. Maas, Awni Y. Hannun, and Andrew Y. Ng. Rectifier nonlinearities improve neural network acoustic models. In *International Conference on Machine Learning (ICML)*, 2013.

References X

[92] W.S.McCulloch and W.Pitts. A logival calculus of the ideas imminent in nervous activity. 1943.

[93] P. J. Werbos. Applications of advances in nonlinear sensitivity analysis. In *Proceedings of the 10th IFIP Conference, 31.8 - 4.9, NYC*, pages 762–770, 1981.

[94] A.G. Ivakhnenko and V.G. Lapa. Cybernetic predicting devices. 1965.

[95] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning internal representations by error propagation. In D. E. Rumelhart and J. L. McClelland, editors, *Parallel Distributed Processing*, volume 1, pages 318–362. MIT Press, 1986.

[96] M.Minsky and S.Papert. Perceptrons. 1969.

[97] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. Back-propagation applied to handwritten zip code recognition. *Neural Computation*, 1(4):541–551, 1989.

[98] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, November 1998.

[99] K. Fukushima. Neocognitron: A self-organizing neural network for a mechanism of pattern recognition unaffected by shift in position. *Biological Cybernetics*, 36(4):193–202, 1980.

[100] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proc. of the National Academy of Sciences*, 79:2554–2558, 1982.

[101] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *ICML*, volume 37 of *JMLR Workshop and Conference Proceedings*, pages 448–456. JMLR.org, 2015.

[102] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15:1929–1958, 2014.

[103] Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. *CoRR*, abs/1207.0580, 2012.

[104] Kurt Hornik, Maxwell Stinchcombe, and Halbert White. Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5):359–366, 1989.

References XI

[105] D. H. Wiesel and T. N. Hubel. Receptive fields of single neurones in the cat's striate cortex. *J. Physiol.*, 148:574–591, 1959.

[106] Ruslan Salakhutdinov and Geoffrey Hinton. An efficient learning procedure for deep boltzmann machines. *Neural Comput.*, 24(8):1967–2006, August 2012.

[107] Alex Graves and Jürgen Schmidhuber. Offline handwriting recognition with multidimensional recurrent neural networks. In D. Koller, D. Schuurmans, Y. Bengio, and L. Bottou, editors, *Advances in Neural Information Processing Systems 21*, pages 545–552. Curran Associates, Inc., 2009.

[108] G. E. Dahl, Dong Yu, Li Deng, and A. Acero. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. *Trans. Audio, Speech and Lang. Proc.*, 20(1):30–42, January 2012.

[109] Dan Claudiu Ciresan, Ueli Meier, Luca Maria Gambardella, and Jürgen Schmidhuber. Deep big simple neural nets excel on handwritten digit recognition. *CoRR*, abs/1003.0358, 2010.

[110] Dan C. Ciresan, Ueli Meier, and Jürgen Schmidhuber. Multi-column deep neural networks for image classification. *CoRR*, abs/1202.2745, 2012.

[111] Jayanth Koushik and Hiroaki Hayashi. Improving stochastic gradient descent with feedback. *CoRR*, abs/1611.01505, 2016.

[112] Matthew D. Zeiler. ADADELTA: an adaptive learning rate method. *CoRR*, abs/1212.5701, 2012.

[113] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014.

[114] Anonymous. On the convergence of adam and beyond. *International Conference on Learning Representations*, 2018.

[115] John C. Duchi, Elad Hazan, and Yoram Singer. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12:2121–2159, 2011.

[116] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

[117] Matthew D. Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. *CoRR*, abs/1311.2901, 2013.

References XII

[118] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[119] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott E. Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. *CoRR*, abs/1409.4842, 2014.

[120] T. Tieleman and G. Hinton. Lecture 6.5—RmsProp: Divide the gradient by a running average of its recent magnitude. COURSERA: Neural Networks for Machine Learning, 2012.

[121] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.