

Important Papers

February 3, 2025

1 Language Model

1. A. Aghajanyan, L. Zettlemoyer, and S. Gupta. Intrinsic dimensionality explains the effectiveness of language model fine-tuning, 2020.
2. Y. Bengio, R. Ducharme, P. Vincent, and C. Janvin. A Neural Probabilistic Language Model. *Journal of Machine Learning Research*, 3:1137–1155, Mar. 2003.
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4. J. Chung, C. Gulcehre, K. Cho, and Y. Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling, 2014.
5. Claude <https://www.anthropic.com/news/claude-3-family>
6. G. Team, R. Anil, and S. et al. Gemini: A family of highly capable multimodal models, 2024.
7. J. Gehring, M. Auli, D. Grangier, D. Yarats, and Y. N. Dauphin. Convolutional sequence to sequence learning. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 1243–1252, 2017.
8. OpenAI, J. Achiam, S. Adler, et al. Gpt-4 technical report, 2024.
9. A. Graves. Generating sequences with recurrent neural networks, 2014.
10. E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.
11. D. Jurafsky and J. H. Martin. *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. 3rd edition, 2025. Online manuscript released January 12, 2025.

12. W. Lai, H. Xie, G. Xu, and Q. Li. Multi-task learning with llms for implicit sentiment analysis: Data- level and task-level automatic weight learning, 2024.
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15. A. Mnih and G. Hinton. A scalable hierarchical distributed language model. In Proceedings of the 21st International Conference on Neural Information Processing Systems, NIPS’08, pages 1081–1088, USA, 2008. Curran Associates Inc.
16. F. Morin and Y. Bengio. Hierarchical probabilistic neural network language model. In R. G. Cowell and Z. Ghahramani, editors, Proceedings of the Tenth International Workshop on Artificial Intelligence and Statistics, volume R5 of Proceedings of Machine Learning Research, pages 246–252. PMLR, 06–08 Jan 2005. Reissued by PMLR on 30 March 2021.
17. F. Morin and Y. Bengio. Hierarchical probabilistic neural network language model. In Aistats, volume 5, pages 246–252. Citeseer, 2005.
18. P. Nguyen, S. Sengupta, G. Malik, A. Gupta, and B. Min. Install: Context-aware instructional task assistance with multi-modal large language models, 2025.
19. M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer. Deep contextualized word representations. CoRR, abs/1802.05365, 2018.[17] L. Shang, Z. Lu, and H. Li. Neural responding machine for short-text conversation. CL, 2015.
20. I. Sutskever, J. Martens, G. Dahl, and G. Hinton. On the importance of initialization and momentum in deep learning. In S. Dasgupta and D. McAllester, editors, Proceedings of the 30th International Conference on Machine Learning, volume 28 of Proceedings of Machine Learning Research, pages 1139–1147, Atlanta, Georgia, USA, 17–19 Jun 2013. PMLR.
21. I. Sutskever, J. Martens, G. Dahl, and G. Hinton. On the importance of initialization and momentum in deep learning, 2013.
22. I. Sutskever, O. Vinyals, and Q. V. Le. Sequence to sequence learning with neural networks. In Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, NIPS’14, pages 3104–3112, Cambridge, MA, USA, 2014. MIT Press.

23. H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, B. Rozière, N. Goyal, E. Hambro, F. Azhar, A. Rodriguez, A. Joulin, E. Grave, and G. Lample. Llama: Open and efficient foundation language models, 2023.
24. Y. Wang, X. Li, Z. Yan, Y. He, J. Yu, X. Zeng, C. Wang, C. Ma, H. Huang, J. Gao, M. Dou, K. Chen, W. Wang, Y. Qiao, Y. Wang, and L. Wang. Internvideo2.5: Empowering video mllms with long and rich context modeling, 2025.
25. S. Zhang, L. Dong, X. Li, S. Zhang, X. Sun, S. Wang, J. Li, R. Hu, T. Zhang, F. Wu, and G. Wang. Instruction tuning for large language models: A survey, 2024.

2 Sentiment Analysis

1. G. Brauwers and F. Frasincar. A survey on aspect-based sentiment classification. *ACM Comput. Surv.*, 55(4), Nov. 2022.
2. N. C. Dang, M. N. Moreno-García, and F. De la Prieta. Sentiment analysis based on deep learning: A comparative study. *Electronics*, 9(3):483, Mar. 2020.
3. Q. Gu, Z. Wang, H. Zhang, S. Sui, and R. Wang. Aspect-level sentiment analysis based on syntax-aware and graph convolutional networks. *Applied Sciences*, 14(2), 2024.
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- and S. Bethard, editors, Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1631–1642, Seattle, Washington, USA, Oct. 2013. Association for Computational Linguistics.
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 13. T. Zhu, L. Li, J. Yang, S. Zhao, H. Liu, and J. Qian. Multimodal sentiment analysis with image-text interaction network. *Trans. Multi.*, 25:3375–3385, Jan. 2023.

3 Machine Comprehension

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2. K. M. Hermann, T. Kociský, E. Grefenstette, L. Espeholt, W. Kay, M. Suleyman, and P. Blunsom. Teaching machines to read and comprehend, 2015.
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4. M. Seo, A. Kembhavi, A. Farhadi, and H. Hajishirzi. Bidirectional attention flow for machine comprehension, 2018.
5. S. Wang and J. Jiang. Machine comprehension using match-lstm and answer pointer, 2016.

4 Multimodal Learning

1. T. Baltrušaitis, C. Ahuja, and L.-P. Morency. Multimodal machine learning: A survey and taxonomy, 2017.
2. F. Dipaola, M. Gatti, A. Gaj Levra, R. Men'e, D. Shiffer, R. Faccincani, Z. Raouf, A. Secchi, P. Rovere Querini, A. Voza, S. Badalamenti, M. Solbiati, G. Costantino, V. Savevski, and R. Furlan. Multi-modal deep learning for covid-19 prognosis prediction in the emergency department: a bi-centric study. *Scientific Reports*, 13(1):10868, 2023.
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5. S. Jabeen, X. Li, M. S. Amin, O. Bourahla, S. Li, and A. Jabbar. A review on methods and applications in multimodal deep learning. *ACM Trans. Multimedia Comput. Commun. Appl.*, 19(2s), Feb. 2023.
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7. P. Nguyen, S. Sengupta, G. Malik, A. Gupta, and B. Min. Install: Context-aware instructional task assistance with multi-modal large language models, 2025.
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9. Y. Wang, X. Li, Z. Yan, Y. He, J. Yu, X. Zeng, C. Wang, C. Ma, H. Huang, J. Gao, M. Dou, K. Chen, W. Wang, Y. Qiao, Y. Wang, and L. Wang. Internvideo2.5: Empowering video mllms with long and rich context modeling, 2025.
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5 Attention

1. G. Brauwiers and F. Frasincar. A survey on aspect-based sentiment classification. *ACM Comput. Surv.*, 55(4), Nov. 2022.

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6 Question Answering

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2. T. Kwiatkowski, J. Palomaki, O. Redfield, M. Collins, A. Parikh, C. Alberti, D. Epstein, I. Polosukhin, J. Devlin, K. Lee, K. Toutanova, L. Jones, M. Kelcey, M.-W. Chang, A. M. Dai, J. Uszkoreit, Q. Le, and S. Petrov. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:452–466, 2019.
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7 Instruction Tuning

1. S. Min, M. Lewis, L. Zettlemoyer, and H. Hajishirzi. Metaicl: Learning to learn in context, 2022.
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- Yong, H. Pandey, R. Bawden, T. Wang, T. Neeraj, J. Rozen, A. Sharma, A. Santilli, T. Fevry, J. A. Fries, R. Teehan, T. Bers, S. Biderman, L. Gao, T. Wolf, and A. M. Rush. Multitask prompted training enables zero-shot task generalization, 2022.
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 5. C. Xu, Q. Sun, K. Zheng, X. Geng, P. Zhao, J. Feng, C. Tao, and D. Jiang. Wizardlm: Empowering large language models to follow complex instructions, 2023.
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8 Prompt Engineering

1. Prompt engineering guide, <https://www.promptingguide.ai/introduction/basics>.
2. H. He, H. Zhang, and D. Roth. Rethinking with retrieval: Faithful large language model inference, 2022.
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- T. Wolf, and A. M. Rush. Multitask prompted training enables zero-shot task generalization, 2022.
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9 Distillation

10 Quantization

11 Pruning