高级机器学习课程参考文献

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参考文献按照课程进展进行整理，共有 130 篇参考文献

其中前半部分加了中文概述，后面还没来得及加上，持续更新中~

# 课程介绍

### A1.1 - Overview.pdf

### A1.2 - chatglm.pdf

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| 1. Du and Qian et al. All NLP Tasks are Generation Tasks. ACL’22. arxiv: 2103.10360   目前已经有各种类型的预训练架构，包括BERT、GPT和编码器-解码器模型（例如 T5）。但是，没有一种预训练框架能够在自然语言理解 (NLU)、无条件生成和条件生成这三大类任务的所有任务中表现最佳。为了应对这一挑战，该论文提出了一种基于自回归空白填充的通用语言模型 (GLM)。GLM 通过添加 2D 位置编码并允许任意顺序预测跨度来改进空白填充预训练，从而使其在 NLU 任务上的性能优于 BERT 和 T5。   1. Liang et al., Holistic Evaluation of Language Models. arXiv: 2211.09110   语言模型 (LM) 正在成为几乎所有主要语言技术的基础，但它们的功能、局限性和风险尚未得到很好的理解。我们提出了语言模型整体评估框架 (HELM)，以提高语言模型的透明度。 |

# 深度学习基础

### A2.1 - DNN.pdf

### A2.2 - CNN.pdf

### A2.3 - RNN.pdf

# Transformer基础

### A3 - Transformer Basics.pdf

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| 1. https://lilianweng.github.io/ 2. Irsoy et al. A Corrected CBOW Implementation. 2020.   Mikolov 等人 (2013a) 观察到CBOW词嵌入的表现往往不如 Skip-gram (SG) 嵌入。我们发现这些观察结果并非由训练目标的根本差异所致，而更可能是由流行库（例如官方实现、word2vec.c 和 Gensim）中错误的负采样 CBOW 实现所致。我们表明，在纠正 CBOW 梯度更新中的错误后，CBOW 词嵌入在很多任务上的表现可以和SG 竞争，同时训练速度要快很多倍。   1. https://www.cnblogs.com/baobaotql/p/11662720.html 2. https://spaces.ac.cn/archives/8823/comment-page-1 3. Image (left) source: Transformer: A General Framework from Machine Translation to Others   机器翻译是一项重要且具有挑战性的任务，旨在自动将自然语言句子从一种语言翻译成另一种语言。最近，基于 Transformer 的神经机器翻译 (NMT) 取得了重大突破，已成为方法论和应用领域的新主流方法。在本文中，我们概述了基于 Transformer 的 NMT 及其在其他任务中的扩展。   1. Language Models are Unsupervised Multitask Learners. (OpenAI, Radford et al.)   自然语言处理任务，例如问答、机器翻译、阅读理解和总结，通常采用监督学习的方式在特定任务的数据集上进行。我们证明，当在名为 WebText 的包含数百万个网页的新数据集上进行训练时，语言模型无需任何明确的监督即可开始学习这些任务。   1. Language Models are Few-Shot Learners. (NeurIPS 2020, Brown et al.)   我们证明，扩展语言模型可以极大地提高与任务无关的少样本性能，有时甚至可以与之前最先进的微调方法相媲美。具体来说，我们训练了 GPT-3，这是一个具有 1750 亿个参数的自回归语言模型。   1. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. (NAACL 2019, Devlin et al.)   这是一种新的语言表示模型，称为 BERT，代表来自 Transformers 的双向编码器表示。只需一个额外的输出层即可对预训练的 BERT 模型进行微调，从而为各种任务（例如问答和语言推理）创建最先进的模型，而无需对特定任务的架构进行大量修改。   1. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. (JMLR, Raffel et al.)   迁移学习是先在数据丰富的任务上对模型进行预训练，然后在下游任务上进行微调，它已成为自然语言处理 (NLP) 中的一种强大技术。在本文中，我们通过引入一个统一的框架来探索 NLP 迁移学习技术的前景，该框架将所有基于文本的语言问题转换为文本到文本的格式。   1. GLM: General Langauge Model Pretraining with Autoregressive Blank Infilling. (ACL 2022, Du et al.)   目前已经有各种类型的预训练架构，包括BERT、GPT和编码器-解码器模型（例如 T5）。但是，没有一种预训练框架能够在自然语言理解 (NLU)、无条件生成和条件生成这三大类任务的所有任务中表现最佳。为了应对这一挑战，该论文提出了一种基于自回归空白填充的通用语言模型 (GLM)。GLM 通过添加 2D 位置编码并允许任意顺序预测跨度来改进空白填充预训练，从而使其在 NLU 任务上的性能优于 BERT 和 T5。 |

# 语境学习与模型预训练

### A5.1 - In-context-v2.pdf

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| 1. UW, Meta, Allen4AI. Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?   大语言模型能够进行上下文学习——仅通过推理来执行新任务，只需对一些输入标签对进行条件设置并对新输入进行预测即可。然而，人们对模型如何学习以及演示的哪些方面有助于最终任务性能的理解甚少。在本文中，我们表明，真实例子的演示实际上并不是必需的。   1. Wei et al, Chain-of-Thought Prompting Elicits Reasoning in Large Language Models   我们探索如何生成思路链（一系列中间推理步骤）来显著提高大型语言模型执行复杂推理的能力。   1. Kojima et al, Large Language Models are Zero-Shot Reasoners   思路链 (CoT) 提示是一种通过分步答案示例引出复杂多步骤推理的最新技术，它在算术和符号推理中取得了最先进的性能，虽然这些成功通常归因于 LLM 的小样本学习能力，但我们通过在每个答案前添加“让我们一步一步思考”来表明 LLM 是不错的零样本推理器。   1. Qin et al, Is ChatGPT a General-Purpose Natural Language Processing Task Solver?   目前尚不清楚 ChatGPT 是否可以作为一个通用模型，以零样本执行许多 NLP 任务。在这项工作中，我们通过在 20 个流行的 NLP 数据集上对 ChatGPT 进行评估来实证分析其零样本学习能力。通过大量的实证研究，我们证明了当前版本 ChatGPT 的有效性和局限性。   1. Von Oswald, Johannes, et al. "Transformers learn in-context by gradient descent." International Conference on Machine Learning. PMLR, 2023.   目前，Transformers 中的上下文学习机制尚不明确，大多仍是一种直觉。在本文中，我们认为在自回归目标上训练 Transformers 与基于梯度的元学习公式密切相关。   1. Ramsauer, Hubert, et al. "Hopfield networks is all you need." arXiv preprint arXiv:2008.02217 (2020).   我们引入了具有连续状态和相应更新规则的现代 Hopfield 网络。新的 Hopfield 网络可以以指数方式存储许多模式，通过一次更新检索模式，检索误差呈指数级减小。新的现代 Hopfield 网络可以作为层集成到深度学习架构中，以允许存储和访问原始输入数据、中间结果。   1. Olsson, Catherine, et al. "In-context learning and induction heads." arXiv preprint arXiv:2209.11895 (2022).   “Induction heads”是注意力头，它实现一种简单的算法来完成像 [A][B] ... [A] -> [B] 这样的标记序列。在这项工作中，我们为以下假设提供了初步和间接证据：Induction heads可能构成大型 Transformer 模型中大多数“上下文内学习”的机制（即随着标记索引的增加而损失减少）。   1. Dai et al, Why Can GPT Learn In-Context? Language Models Implicitly Perform Gradient Descent as Meta-Optimizers   大型预训练语言模型已经展现出令人惊叹的上下文学习 (ICL) 能力。通过一些演示输入标签对，它们可以在不更新参数的情况下预测未见过的输入的标签。尽管在性能上取得了巨大的成功，但其工作机制仍然是一个悬而未决的问题。在本文中，我们将语言模型解释为元优化器，将上下文学习理解为隐式微调。   1. J Wei, et al. Emergent Abilities of Large Language Models. arXiv: 2206.07682   事实证明，扩大语言模型规模可以可预测地提高各种下游任务的性能和采样效率。本文讨论了一种不可预测的现象，我们称之为大型语言模型的突发能力。如果一种能力在较小的模型中不存在，但在较大的模型中存在，我们就认为这种能力是突发的。因此，不能简单地通过推断较小模型的性能来预测突发能力。   1. Rylan Schaeffer, Brando Miranda, Sanmi Koyejo. Are Emergent Abilities of Large Language Models a Mirage? NeurIPS’23.   最近的研究表明，大型语言模型表现出突发能力 {新兴能力}，即规模较小的模型中不存在但规模较大的模型中存在的能力。新兴能力之所以引人入胜，有两个原因：其突发度 {敏锐度}，似乎瞬间从不存在转变为存在，出现在看似不可预见的模型规模上。在这里，我们为新兴能力提出了另一种解释：对于特定任务和模型系列，在分析固定模型输出时，新兴能力的出现是由于研究人员对度量的选择，而不是由于模型行为随规模而发生的根本变化。 |

### A5.2 - Pretrain-llm-v2.pdf

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| 1. http://keg.cs.tsinghua.edu.cn/glm-130b/ 2. Xiong, Ruibin, et al. "On layer normalization in the transformer architecture." International Conference on Machine Learning. PMLR, 2020   Transformer 广泛应用于自然语言处理任务。然而，要训练 Transformer，通常需要精心设计的学习率预热阶段，这对最终性能至关重要，但会减慢优化速度并带来更多的超参数调整。在本文中，我们首先从理论上研究了学习率预热阶段为何必不可少，并表明层归一化的位置很重要。   1. Ding, Ming, et al. "Cogview: Mastering text-to-image generation via transformers." Advances in Neural Information Processing Systems 34 (2021).   文本到图像生成在通用领域长期以来一直是一个悬而未决的问题，它既需要强大的生成模型，也需要跨模态理解。我们提出了 CogView，这是一个带有 VQ-VAE 标记器的 40 亿参数 Transformer，以推进这一问题。我们还展示了各种下游任务的微调策略，例如风格学习、超分辨率以及稳定预训练的方法，   1. Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." NAACL, 2019   这是一种新的语言表示模型，称为 BERT，代表来自 Transformers 的双向编码器表示。只需一个额外的输出层即可对预训练的 BERT 模型进行微调，从而为各种任务（例如问答和语言推理）创建最先进的模型，而无需对特定任务的架构进行大量修改。   1. He, Ruining, et al. "Realformer: Transformer likes residual attention." arXiv preprint arXiv:2012.11747 (2020).   Transformer 是现代 NLP 模型的支柱。在本文中，我们提出了 RealFormer，这是一种简单而通用的技术，用于创建残差注意力层 Transformer 网络，   1. Wang, Hongyu, et al. "Deepnet: Scaling transformers to 1,000 layers." arXiv preprint arXiv:2203.00555 (2022).   在本文中，我们提出了一种简单而有效的方法来让层数很深的 Transformers训练稳定收敛。具体来说，我们引入了一个新的规范化函数（DeepNorm）来修改 Transformer 中的残差连接，并给出了理论推导的初始化。   1. Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).   主要的序列传导模型基于复杂的RNN或卷积神经网络，包括编码器和解码器。性能最佳的模型还通过注意机制连接编码器和解码器。我们提出了一种新的简单网络架构 Transformer，它完全基于注意机制，完全省去了RNN和卷积。   1. Shaw, Peter, Jakob Uszkoreit, and Ashish Vaswani. "Self-attention with relative position representations." arXiv preprint arXiv:1803.02155 (2018).   Vaswani 等人 (2017) 提出的 Transformer 完全依赖于注意力机制，在机器翻译方面取得了最先进的成果。与循环神经网络和卷积神经网络相比，Transformer 的结构中没有明确地模拟相对或绝对位置信息。相反，它需要在其输入中添加绝对位置的表示。在这项工作中，我们提出了一种替代方法，扩展了自注意力机制，以有效地考虑相对位置的表示，即序列元素之间的距离。   1. Dai, Zihang, et al. "Transformer-XL: Attentive Language Models beyond a Fixed-Length Context." Proceedings of the 57th Annual Meeting of the Association for Computational   Transformer 具有学习长期依赖关系的潜力，但在语言建模设置中受到固定长度上下文的限制。我们提出了一种新颖的神经架构 Transformer-XL，它能够在不破坏时间连贯性的情况下学习超过固定长度的依赖关系。它由段级递归机制和新颖的位置编码方案组成。我们的方法不仅能够捕获长期依赖关系，而且还解决了上下文碎片化问题。   1. Press, Ofir, Noah A. Smith, and Mike Lewis. "Train short, test long: Attention with linear biases enables input length extrapolation." arXiv preprint arXiv:2108.12409 (2021).   自从 Vaswani 等人 (2017) 提出 Transformer 模型以来，一个基本问题仍未得到解答：模型如何在推理时实现比训练时更长的序列的外推？我们首先表明，只需改变位置表示方法即可实现外推，但我们发现当前方法无法实现有效的外推。因此，我们引入了一种更简单、更高效的定位方法，即具有线性偏差的注意力 (ALiBi)。ALiBi 不会将位置嵌入添加到词嵌入中；相反，它会对查询关键注意力分数施加与距离成比例的惩罚   1. Su, Jianlin, et al. "Roformer: Enhanced transformer with rotary position embedding." arXiv preprint arXiv:2104.09864 (2021).   最近，位置编码已被证明在 Transformer 架构中是有效的。它为序列中不同位置的元素之间的依赖关系建模提供了有价值的监督。在本文中，我们首先研究了将位置信息集成到基于 Transformer 的语言模型的学习过程中的各种方法。然后，我们提出了一种名为旋转位置嵌入 (RoPE) 的新方法来有效地利用位置信息。具体而言，所提出的 RoPE 使用旋转矩阵对绝对位置进行编码，同时在自注意力公式中结合显式相对位置依赖性.   1. Micikevicius, Paulius, et al. "Mixed Precision Training." International Conference on Learning Representations. 2018.   增加神经网络的大小通常会提高准确性。随着模型大小的增加，训练这些模型的内存和计算要求也会增加。我们引入了一种使用半精度浮点数训练深度神经网络的技术。在我们的技术中，权重、激活和梯度以 IEEE 半精度格式存储。   1. Aohan Zeng, Xiao Liu, et al., GLM-130B: An open bilingual pre-trained models. arXiv: 2010.02414   深度卷积神经网络显著提高了超分辨率 (SR) 的峰值信噪比。然而，图像查看器应用程序通常允许用户将图像缩放到任意放大倍数，从而导致计算成本巨大。为了获得用于任意尺度 SR 的计算效率更高的模型，本文采用拉普拉斯金字塔方法，使用拉普拉斯频率表示中的高频图像细节重建任意尺度的高分辨率 (HR) 图像。 |

# 后训练：监督式微调

### A6 - PostTraining-v2.pdf

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| 1. Devlin J, et al. Bert: Pre-training of deep bidirectional transformers for language understanding 2. Jason Wei, et al. Finetuned language models are zero-shot learners 3. Armen Aghajanyan et al, Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning. ACL 2021. Meta. 4. Chunyuan Li, Heerad Farkhoor, Rosanne Liu, Jason Yosinski. Measuring the Intrinsic Dimension of Objective Landscapes. ICLR’18 5. Picture from Ding et al, Delta Tuning: A Comprehensive Study of Parameter Efficient Methods for Pre-trained Language Models 6. 1. Google. Parameter-Efficient Transfer Learning for NLP, ICML 2019. 7. Hu et al. LORA: Low-Rank Adaption of Large Language Models. ICLR’22. Microsoft. 8. Hu et al. LORA: Low-Rank Adaption of Large Language Models. 2021 9. Tim Dettmers et al. QLORA: Efficient Finetuning of Quantized LLMs. 2023 10. Liu X\*, Zheng Y\*, et al. GPT Understands, Too 11. Wei et al., Fine-tuned Language Models are Zero-shot Learner 12. Sanh et al., Multitask Prompted Training Enables Zero-Shot Task Generalization (2021) 13. Chung et al., Scaling Instruction-Finetuned Language Models (2022) 14. https://ai4comm.media.mit.edu/slides/emergence.pdf |

# 后训练：基于人类反馈的强化学习

### A7.1 - AIntro2RL.pdf

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| 1. David Silver, “Model-Free Prediction” 2. David Silver, “Introduction to RL” 3. <https://en.wikipedia.org/wiki/Go_and_mathematics> |

### A7.2 - Reinforce Learning from Human Feedback.pdf

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| 1. Long Ouyang, Jeff Wu, Xu Jiang…, Jan Leike and Ryan Lowe. Training language models to follow instructions with human feedback. 2022. 2. Jason Wei, et al. Finetuned language models are zero-shot learners 3. Gekhman Z, Yona G, Aharoni R, et al. Does Fine-Tuning LLMs on New Knowledge Encourage Hallucinations? 2024. 4. Chung H W, Hou L, Longpre S, et al. Scaling instruction-finetuned language models. 2024. 5. Ouyang L, Wu J, Jiang X, et al. Training language models to follow instructions with human feedback. 2022. 6. An Introduction to Training LLMs Using Reinforcement Learning From Human Feedback (RLHF) 7. <https://openai.com/blog/chatgpt> |

### A9.1 - Reinforce Learning from Human Feedback\_PPO&DPO.pdf

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| 1. Ouyang L, Wu J, Jiang X, et al. Training language models to follow instructions with human feedback. 2022. 2. Schulman J, Wolski F, Dhariwal P, et al. Proximal policy optimization algorithms. 2017. 3. Rafailov R, Sharma A, Mitchell E, et al. Direct preference optimization: Your language model is secretly a reward model. 2024. 4. Yuan W, Pang R Y, Cho K, et al. Self-rewarding language models. 2024. 5. Ethayarajh K, Xu W, Muennighoff N, et al. Kto: Model alignment as prospect theoretic optimization. 2024. 6. Yuan Z, Yuan H, Tan C, et al. Rrhf: Rank responses to align language models with human feedback without tears. 2023. 7. <https://www.youtube.com/watch?v=kYWUEV_e2ss> 8. <https://jonathan-hui.medium.com/rl-proximal-policy-optimization-ppo-explained-77f014ec3f12> |

# 大语言模型的科学评估与对齐

### A8 - LLM\_Evaluation\_and\_alignment\_LiLei.pdf

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| 1. Ouyang et al. Training language models to follow instructions with human feedback. 2022 2. Aman Madaan, Niket Tandon …, and Peter Clark. 2023. Self-refine: Iterative refinement with self-feedback 3. Xinyun Chen, Maxwell Lin, Nathanael Schärli, and Denny Zhou. 2023. Teaching large language models to self-debug 4. Liu et al. G-EVAL: NLG Evaluation using GPT-4 with Better Human Alignment. 2023 5. Chen et al. Exploring the Use of Large Language Models for Reference-Free Text Quality Evaluation: An Empirical Study. 2023 6. Xu, Wang, Pan, Song, Freitag, Wang, Li. INSTRUCTSCORE: Explainable Text Generation Evaluation with Finegrained Feedback. EMNLP 2023 7. Wenda Xu, Guanglei Zhu, Xuandong Zhao, Liangming Pan, Lei Li, William Yang Wang. Pride and Prejudice: LLM Amplifies Self-Bias in Self-Refinement. ACL 2024 8. Dong et al. Statistical Knowledge Assessment for LLMs. NeurIPS 2023 9. Nicola De Cao, Wilker Aziz, and Ivan Titov. Editing factual knowledge in language models. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, 2021 10. Qingxiu Dong, Jingjing Xu, Lingpeng Kong, Zhifang Sui, Lei Li. StaAsAcal Knowledge Assessment for LLMs. Neurips 2023 11. Wenda Xu, Jiachen Li, William Yang Wang, Lei Li. BPO: Staying Close to the Behavior LLM Creates Better Online LLM Alignment. EMNLP 2024 12. Pinzhen Chen, Zhicheng Guo, Barry Haddow, and Kenneth Heafield. 2023. Iterative translation refinement with large language models 13. Wenda Xu, Daniel Deutsch, Mara Finkelstein, Juraj Juraska, Biao Zhang, Zhongtao Liu, William Yang Wang, Lei Li, and Markus Freitag. LLMRefine: Pinpointing and Refining Large Language Models via Fine-Grained Actionable Feedback. NAACL 2024 |

# 智能体

### A9.2 - AutoGLM&Agent.pdf

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| 1. LeCun, Yann. "A path towards autonomous machine intelligence version 0.9. 2, 2022 - 06 - 27." Open Review 62.1 (2022). |

# 大模型的安全与评估

### A10.1 - Safety.pdf

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| 1. Wei, Alexander, Nika Haghtalab, and Jacob Steinhardt. "Jailbroken: How does llm safety training fail?." arXiv preprint arXiv:2307.02483 (2023). |

### A10.2 - LLM Evaluation.pdf

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| 1. Hendrycks, Dan, et al. "Measuring Massive Multitask Language Understanding. International Conference on Learning Representations. 2. Hendrycks, Dan, et al. "Measuring Mathematical Problem Solving With the MATH Dataset." Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2). 3. Zhang, Shudan, et al. "NaturalCodeBench: Examining Coding Performance Mismatch on HumanEval and Natural User Queries." Findings of the Association for Computational Linguistics ACL 2024.2024. 4. Zhou, Jeffrey, et al. "Instruction-following evaluation for large language models." arXiv preprint arXiv:2311.07911 (2023). 5. Liu, Xiao, et al. "Alignbench: Benchmarking chinese alignment of large language models." Findings of the Association for Computational Linguistics ACL 2024. 6. ZLiu, Xiao, et al. "Alignbench: Benchmarking chinese alignment of large language models." Findings of the Association for Computational Linguistics ACL 2024. |

# 项目提案

# 多模态语言模型

### A11.1 - Collaboration\_and\_Evolution\_of\_Foundation\_and\_Specialized\_Models.pdf

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# 专用模型协作与语音模型，数据与TTC

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