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Here is what was submitted on January 11, 2024.

ConcEPT: Concept-Enhanced Pre-Training for Language Models

by Xintao Wang, Zhouhong Gu, Jiaqing Liang, Dakuan Lu, Yanghua Xiao, Wei Wang

Pre-trained language models (PLMs) have been prevailing in state-of-the-art methods for natural language processing, and knowledge-enhanced PLMs are further proposed to promote model performance in knowledge-intensive tasks. However, conceptual knowledge, one essential kind of knowledge for human cognition, still remains understudied in this line of research. This limits PLMs' performance in scenarios requiring human-like cognition, such as understanding long-tail entities with concepts. In this paper, we propose ConcEPT, which stands for Concept-Enhanced Pre-Training for language models, to infuse conceptual knowledge into PLMs. ConcEPT exploits external taxonomies with entity concept prediction, a novel pre-training objective to predict the concepts of entities mentioned in the pre-training contexts. Unlike previous concept-enhanced methods, ConcEPT can be readily adapted to various downstream applications without entity linking or concept mapping. Results of extensive experiments show the effectiveness of ConcEPT in four tasks such as entity typing, which validates that our model gains improved conceptual knowledge with concept-enhanced pre-training.

UCorrect: An Unsupervised Framework for Automatic Speech Recognition Error Correction

by Jiaxin Guo, Minghan Wang, Xiaosong Qiao, Daimeng Wei, Hengchao Shang, Zongyao Li, Zhengzhe Yu, Yinglu Li, Chang Su, Min Zhang, Shimin Tao, Hao Yang

Error correction techniques have been used to refine the output sentences from automatic speech recognition (ASR) models and achieve a lower word error rate (WER). Previous works usually adopt end-to-end models and has strong dependency on Pseudo Paired Data and Original Paired Data. But when only pre-training on Pseudo Paired Data, previous models have negative effect on correction. While fine-tuning on Original Paired Data, the source side data must be transcribed by a well-trained ASR model, which takes a lot of time and not universal. In this paper, we propose UCorrect, an unsupervised Detector-Generator-Selector framework for ASR Error Correction. UCorrect has no dependency on the training data mentioned before. The whole procedure is first to detect whether the character is erroneous, then to generate some candidate characters and finally to select the most confident one to replace the error character. Experiments on the public AISHELL-1 dataset and WenetSpeech dataset show the effectiveness of UCorrect for ASR error correction: 1) it achieves significant WER reduction, achieves 6.83\% even without fine-tuning and 14.29\% after fine-tuning; 2) it outperforms the popular NAR correction models by a large margin with a competitive low latency; and 3) it is an universal method, as it reduces all WERs of the ASR model with different decoding strategies and reduces all WERs of ASR models trained on different scale datasets.

Integrating Physician Diagnostic Logic into Large Language Models: Preference Learning from Process Feedback

by Chengfeng Dou, Zhi Jin, Wenpin Jiao, Haiyan Zhao, Yongqiang Zhao, Zhenwei Tao

The use of large language models in medical dialogue generation has garnered significant attention, with a focus on improving response quality and fluency. While previous studies have made progress in optimizing model performance for single-round medical Q&A tasks, there is a need to enhance the model's capability for multi-round conversations to avoid logical inconsistencies. To address this, we propose an approach called preference learning from process feedback~(PLPF), which integrates the doctor's diagnostic logic into LLMs. PLPF involves rule modeling, preference data generation, and preference alignment to train the model to adhere to the diagnostic process. Experimental results using Standardized Patient Testing show that PLPF enhances the diagnostic accuracy of the baseline model in medical conversations by 17.6%, outperforming traditional reinforcement learning from human feedback. Additionally, PLPF demonstrates effectiveness in both multi-round and single-round dialogue tasks, showcasing its potential for improving medical dialogue generation.

R-BI: Regularized Batched Inputs enhance Incremental Decoding Framework for Low-Latency Simultaneous Speech Translation

by Jiaxin Guo, Zhanglin Wu, Zongyao Li, Hengchao Shang, Daimeng Wei, Xiaoyu Chen, Zhiqiang Rao, Shaojun Li, Hao Yang

Incremental Decoding is an effective framework that enables the use of an offline model in a simultaneous setting without modifying the original model, making it suitable for Low-Latency Simultaneous Speech Translation. However, this framework may introduce errors when the system outputs from incomplete input. To reduce these output errors, several strategies such as Hold-n, LA-n, and SP-n can be employed, but the hyper-parameter n needs to be carefully selected for optimal performance. Moreover, these strategies are more suitable for end-to-end systems than cascade systems. In our paper, we propose a new adaptable and efficient policy named "Regularized Batched Inputs". Our method stands out by enhancing input diversity to mitigate output errors. We suggest particular regularization techniques for both end-to-end and cascade systems. We conducted experiments on IWSLT Simultaneous Speech Translation (SimulST) tasks, which demonstrate that our approach achieves low latency while maintaining no more than 2 BLEU points loss compared to offline systems. Furthermore, our SimulST systems attained several new state-of-the-art results in various language directions.

CAT-LLM: Prompting Large Language Models with Text Style Definition for Chinese Article-style Transfer

by Zhen Tao, Dinghao Xi, Zhiyu Li, Liumin Tang, Wei Xu

Text style transfer is increasingly prominent in online entertainment and social media. However, existing research mainly concentrates on style transfer within individual English sentences, while ignoring the complexity of long Chinese texts, which limits the wider applicability of style transfer in digital media realm. To bridge this gap, we propose a Chinese Article-style Transfer framework (CAT-LLM), leveraging the capabilities of Large Language Models (LLMs). CAT-LLM incorporates a bespoke, pluggable Text Style Definition (TSD) module aimed at comprehensively analyzing text features in articles, prompting LLMs to efficiently transfer Chinese article-style. The TSD module integrates a series of machine learning algorithms to analyze article-style from both words and sentences levels, thereby aiding LLMs thoroughly grasp the target style without compromising the integrity of the original text. In addition, this module supports dynamic expansion of internal style trees, showcasing robust compatibility and allowing flexible optimization in subsequent research. Moreover, we select five Chinese articles with distinct styles and create five parallel datasets using ChatGPT, enhancing the models' performance evaluation accuracy and establishing a novel paradigm for evaluating subsequent research on article-style transfer. Extensive experimental results affirm that CAT-LLM outperforms current research in terms of transfer accuracy and content preservation, and has remarkable applicability to various types of LLMs.

Zero Resource Cross-Lingual Part Of Speech Tagging

by Sahil Chopra

Part of speech tagging in zero-resource settings can be an effective approach for low-resource languages when no labeled training data is available. Existing systems use two main techniques for POS tagging i.e. pretrained multilingual large language models(LLM) or project the source language labels into the zero resource target language and train a sequence labeling model on it. We explore the latter approach using the off-the-shelf alignment module and train a hidden Markov model(HMM) to predict the POS tags. We evaluate transfer learning setup with English as a source language and French, German, and Spanish as target languages for part-of-speech tagging. Our conclusion is that projected alignment data in zero-resource language can be beneficial to predict POS tags.

Cross-modal Retrieval for Knowledge-based Visual Question Answering

by Paul Lerner, Olivier Ferret, Camille Guinaudeau

Knowledge-based Visual Question Answering about Named Entities is a challenging task that requires retrieving information from a multimodal Knowledge Base. Named entities have diverse visual representations and are therefore difficult to recognize. We argue that cross-modal retrieval may help bridge the semantic gap between an entity and its depictions, and is foremost complementary with mono-modal retrieval. We provide empirical evidence through experiments with a multimodal dual encoder, namely CLIP, on the recent ViQuAE, InfoSeek, and Encyclopedic-VQA datasets. Additionally, we study three different strategies to fine-tune such a model: mono-modal, cross-modal, or joint training. Our method, which combines mono-and cross-modal retrieval, is competitive with billion-parameter models on the three datasets, while being conceptually simpler and computationally cheaper.

A Shocking Amount of the Web is Machine Translated: Insights from Multi-Way Parallelism

by Brian Thompson, Mehak Preet Dhaliwal, Peter Frisch, Tobias Domhan, Marcello Federico

We show that content on the web is often translated into many languages, and the low quality of these multi-way translations indicates they were likely created using Machine Translation (MT). Multi-way parallel, machine generated content not only dominates the translations in lower resource languages; it also constitutes a large fraction of the total web content in those languages. We also find evidence of a selection bias in the type of content which is translated into many languages, consistent with low quality English content being translated en masse into many lower resource languages, via MT. Our work raises serious concerns about training models such as multilingual large language models on both monolingual and bilingual data scraped from the web.

Probing Structured Semantics Understanding and Generation of Language Models via Question Answering

by Jinxin Liu, Shulin Cao, Jiaxin Shi, Tingjian Zhang, Lei Hou, Juanzi Li

Recent advancement in the capabilities of large language models (LLMs) has triggered a new surge in LLMs' evaluation. Most recent evaluation works tends to evaluate the comprehensive ability of LLMs over series of tasks. However, the deep structure understanding of natural language is rarely explored. In this work, we examine the ability of LLMs to deal with structured semantics on the tasks of question answering with the help of the human-constructed formal language. Specifically, we implement the inter-conversion of natural and formal language through in-context learning of LLMs to verify their ability to understand and generate the structured logical forms. Extensive experiments with models of different sizes and in different formal languages show that today's state-of-the-art LLMs' understanding of the logical forms can approach human level overall, but there still are plenty of room in generating correct logical forms, which suggest that it is more effective to use LLMs to generate more natural language training data to reinforce a small model than directly answering questions with LLMs. Moreover, our results also indicate that models exhibit considerable sensitivity to different formal languages. In general, the formal language with the lower the formalization level, i.e. the more similar it is to natural language, is more LLMs-friendly.

Risk Taxonomy, Mitigation, and Assessment Benchmarks of Large Language Model Systems

by Tianyu Cui, Yanling Wang, Chuanpu Fu, Yong Xiao, Sijia Li, Xinhao Deng, Yunpeng Liu, Qinglin Zhang, Ziyi Qiu, Peiyang Li, Zhixing Tan, Junwu Xiong, Xinyu Kong, Zujie Wen, Ke Xu, Qi Li

Large language models (LLMs) have strong capabilities in solving diverse natural language processing tasks. However, the safety and security issues of LLM systems have become the major obstacle to their widespread application. Many studies have extensively investigated risks in LLM systems and developed the corresponding mitigation strategies. Leading-edge enterprises such as OpenAI, Google, Meta, and Anthropic have also made lots of efforts on responsible LLMs. Therefore, there is a growing need to organize the existing studies and establish comprehensive taxonomies for the community. In this paper, we delve into four essential modules of an LLM system, including an input module for receiving prompts, a language model trained on extensive corpora, a toolchain module for development and deployment, and an output module for exporting LLM-generated content. Based on this, we propose a comprehensive taxonomy, which systematically analyzes potential risks associated with each module of an LLM system and discusses the corresponding mitigation strategies. Furthermore, we review prevalent benchmarks, aiming to facilitate the risk assessment of LLM systems. We hope that this paper can help LLM participants embrace a systematic perspective to build their responsible LLM systems.

Evidence to Generate (E2G): A Single-agent Two-step Prompting for Context Grounded and Retrieval Augmented Reasoning

by Md Rizwan Parvez

While chain-of-thought (CoT) prompting has revolutionized how LLMs perform reasoning tasks, its current methods and variations (e.g, Self-consistency, ReACT, Reflexion, Tree-of-Thoughts (ToT), Cumulative Reasoning (CR)) suffer from limitations like slowness, limited context grounding, hallucination and inconsistent outputs. To overcome these challenges, we introduce Evidence to Generate (E2G), a novel single-agent, two-step prompting framework. Instead of unverified reasoning claims, this innovative approach leverages the power of "evidence for decision making" by first focusing exclusively on the thought sequences (the series of intermediate steps) explicitly mentioned in the context which then serve as extracted evidence, guiding the LLM's output generation process with greater precision and efficiency. This simple yet powerful approach unlocks the true potential of chain-of-thought like prompting, paving the way for faster, more reliable, and more contextually aware reasoning in LLMs. \tool achieves remarkable results robustly across a wide range of knowledge-intensive reasoning and generation tasks, surpassing baseline approaches with state-of-the-art LLMs. For example, (i) on LogiQA benchmark using GPT-4 as backbone model, \tool achieves a new state-of-the Accuracy of 53.8% exceeding CoT by 18%, ToT by 11%, CR by 9% (ii) a variant of E2G with PaLM2 outperforms the variable-shot performance of Gemini Ultra by 0.9 F1 points, reaching an F1 score of 83.3 on a subset of DROP.

Discovering Low-rank Subspaces for Language-agnostic Multilingual Representations

by Zhihui Xie, Handong Zhao, Tong Yu, Shuai Li

Large pretrained multilingual language models (ML-LMs) have shown remarkable capabilities of zero-shot cross-lingual transfer, without direct cross-lingual supervision. While these results are promising, follow-up works found that, within the multilingual embedding spaces, there exists strong language identity information which hinders the expression of linguistic factors shared across languages. For semantic tasks like cross-lingual sentence retrieval, it is desired to remove such language identity signals to fully leverage semantic information. In this work, we provide a novel view of projecting away language-specific factors from a multilingual embedding space. Specifically, we discover that there exists a low-rank subspace that primarily encodes information irrelevant to semantics (e.g., syntactic information). To identify this subspace, we present a simple but effective unsupervised method based on singular value decomposition with multiple monolingual corpora as input. Once the subspace is found, we can directly project the original embeddings into the null space to boost language agnosticism without finetuning. We systematically evaluate our method on various tasks including the challenging language-agnostic QA retrieval task. Empirical results show that applying our method consistently leads to improvements over commonly used ML-LMs.

Designing Heterogeneous LLM Agents for Financial Sentiment Analysis

by Frank Xing

Large language models (LLMs) have drastically changed the possible ways to design intelligent systems, shifting the focuses from massive data acquisition and new modeling training to human alignment and strategical elicitation of the full potential of existing pre-trained models. This paradigm shift, however, is not fully realized in financial sentiment analysis (FSA), due to the discriminative nature of this task and a lack of prescriptive knowledge of how to leverage generative models in such a context. This study investigates the effectiveness of the new paradigm, i.e., using LLMs without fine-tuning for FSA. Rooted in Minsky's theory of mind and emotions, a design framework with heterogeneous LLM agents is proposed. The framework instantiates specialized agents using prior domain knowledge of the types of FSA errors and reasons on the aggregated agent discussions. Comprehensive evaluation on FSA datasets show that the framework yields better accuracies, especially when the discussions are substantial. This study contributes to the design foundations and paves new avenues for LLMs-based FSA. Implications on business and management are also discussed.

Tuning LLMs with Contrastive Alignment Instructions for Machine Translation in Unseen, Low-resource Languages

by Zhuoyuan Mao, Yen Yu

This article introduces contrastive alignment instructions (AlignInstruct) to address two challenges in machine translation (MT) on large language models (LLMs). One is the expansion of supported languages to previously unseen ones. The second relates to the lack of data in low-resource languages. Model fine-tuning through MT instructions (MTInstruct) is a straightforward approach to the first challenge. However, MTInstruct is limited by weak cross-lingual signals inherent in the second challenge. AlignInstruct emphasizes cross-lingual supervision via a cross-lingual discriminator built using statistical word alignments. Our results based on fine-tuning the BLOOMZ models (1b1, 3b, and 7b1) in up to 24 unseen languages showed that: (1) LLMs can effectively translate unseen languages using MTInstruct; (2) AlignInstruct led to consistent improvements in translation quality across 48 translation directions involving English; (3) Discriminator-based instructions outperformed their generative counterparts as cross-lingual instructions; (4) AlignInstruct improved performance in 30 zero-shot directions.

Hallucination Benchmark in Medical Visual Question Answering

by Jinge Wu, Yunsoo Kim, Honghan Wu

The recent success of large language and vision models on vision question answering (VQA), particularly their applications in medicine (Med-VQA), has shown a great potential of realizing effective visual assistants for healthcare. However, these models are not extensively tested on the hallucination phenomenon in clinical settings. Here, we created a hallucination benchmark of medical images paired with question-answer sets and conducted a comprehensive evaluation of the state-of-the-art models. The study provides an in-depth analysis of current models limitations and reveals the effectiveness of various prompting strategies.

Towards Boosting Many-to-Many Multilingual Machine Translation with Large Language Models

by Pengzhi Gao, Zhongjun He, Hua Wu, Haifeng Wang

The training paradigm for machine translation has gradually shifted, from learning neural machine translation (NMT) models with extensive parallel corpora to instruction finetuning on pretrained multilingual large language models (LLMs) with high-quality translation pairs. In this paper, we focus on boosting the many-to-many multilingual translation performance of LLMs with an emphasis on zero-shot translation directions. We demonstrate that prompt strategies adopted during instruction finetuning are crucial to zero-shot translation performance and introduce a cross-lingual consistency regularization, XConST, to bridge the representation gap among different languages and improve zero-shot translation performance. XConST is not a new method, but a version of CrossConST (Gao et al., 2023a) adapted for multilingual finetuning on LLMs with translation instructions. Experimental results on ALMA (Xu et al., 2023) and LLaMA-2 (Touvron et al., 2023) show that our approach consistently improves translation performance. Our implementations are available at https://github.com/gpengzhi/CrossConST-LLM.

Enhancing Personality Recognition in Dialogue by Data Augmentation and Heterogeneous Conversational Graph Networks

by Yahui Fu, Haiyue Song, Tianyu Zhao, Tatsuya Kawahara

Personality recognition is useful for enhancing robots' ability to tailor user-adaptive responses, thus fostering rich human-robot interactions. One of the challenges in this task is a limited number of speakers in existing dialogue corpora, which hampers the development of robust, speaker-independent personality recognition models. Additionally, accurately modeling both the interdependencies among interlocutors and the intra-dependencies within the speaker in dialogues remains a significant issue. To address the first challenge, we introduce personality trait interpolation for speaker data augmentation. For the second, we propose heterogeneous conversational graph networks to independently capture both contextual influences and inherent personality traits. Evaluations on the RealPersonaChat corpus demonstrate our method's significant improvements over existing baselines.

Generative Deduplication For Socia Media Data Selection

by Xianming Li, Jing Li

Social media data is plagued by the redundancy problem caused by its noisy nature, leading to increased training time and model bias. To address this issue, we propose a novel approach called generative duplication. It aims to remove duplicate text from noisy social media data and mitigate model bias. By doing so, it can improve social media language understanding performance and save training time. Extensive experiments demonstrate that the proposed generative deduplication can effectively reduce training samples while improving performance. This evidence suggests the effectiveness of generative deduplication and its importance in social media language understanding.

EpilepsyLLM: Domain-Specific Large Language Model Fine-tuned with Epilepsy Medical Knowledge

by Xuyang Zhao, Qibin Zhao, Toshihisa Tanaka

With large training datasets and massive amounts of computing sources, large language models (LLMs) achieve remarkable performance in comprehensive and generative ability. Based on those powerful LLMs, the model fine-tuned with domain-specific datasets posseses more specialized knowledge and thus is more practical like medical LLMs. However, the existing fine-tuned medical LLMs are limited to general medical knowledge with English language. For disease-specific problems, the model's response is inaccurate and sometimes even completely irrelevant, especially when using a language other than English. In this work, we focus on the particular disease of Epilepsy with Japanese language and introduce a customized LLM termed as EpilepsyLLM. Our model is trained from the pre-trained LLM by fine-tuning technique using datasets from the epilepsy domain. The datasets contain knowledge of basic information about disease, common treatment methods and drugs, and important notes in life and work. The experimental results demonstrate that EpilepsyLLM can provide more reliable and specialized medical knowledge responses.

Prompt-based mental health screening from social media text

by Wesley Ramos dos Santos, Ivandre Paraboni

This article presents a method for prompt-based mental health screening from a large and noisy dataset of social media text. Our method uses GPT 3.5. prompting to distinguish publications that may be more relevant to the task, and then uses a straightforward bag-of-words text classifier to predict actual user labels. Results are found to be on pair with a BERT mixture of experts classifier, and incurring only a fraction of its computational costs.

How Teachers Can Use Large Language Models and Bloom's Taxonomy to Create Educational Quizzes

by Sabina Elkins, Ekaterina Kochmar, Jackie C. K. Cheung, Iulian Serban

Question generation (QG) is a natural language processing task with an abundance of potential benefits and use cases in the educational domain. In order for this potential to be realized, QG systems must be designed and validated with pedagogical needs in mind. However, little research has assessed or designed QG approaches with the input from real teachers or students. This paper applies a large language model-based QG approach where questions are generated with learning goals derived from Bloom's taxonomy. The automatically generated questions are used in multiple experiments designed to assess how teachers use them in practice. The results demonstrate that teachers prefer to write quizzes with automatically generated questions, and that such quizzes have no loss in quality compared to handwritten versions. Further, several metrics indicate that automatically generated questions can even improve the quality of the quizzes created, showing the promise for large scale use of QG in the classroom setting.

Mitigating Unhelpfulness in Emotional Support Conversations with Multifaceted AI Feedback

by Jiashuo Wang, Chunpu Xu, Chak Tou Leong, Wenjie Li, Jing Li

An emotional support conversation system aims to alleviate users' emotional distress and assist them in addressing their challenges. To generate supportive responses, it is critical to consider multiple factors such as empathy, support strategies, and response coherence, as established in prior methods. Nonetheless, previous models occasionally generate unhelpful responses, which intend to provide support but display counterproductive effects. According to psychology and communication theories, poor performance in just one contributing factor might cause a response to be unhelpful. From the model training perspective, since these models have not been exposed to unhelpful responses during their training phase, they are unable to distinguish if the tokens they generate might result in unhelpful responses during inference. To address this issue, we introduce a novel model-agnostic framework named mitigating unhelpfulness with multifaceted AI feedback for emotional support (Muffin). Specifically, Muffin employs a multifaceted AI feedback module to assess the helpfulness of responses generated by a specific model with consideration of multiple factors. Using contrastive learning, it then reduces the likelihood of the model generating unhelpful responses compared to the helpful ones. Experimental results demonstrate that Muffin effectively mitigates the generation of unhelpful responses while slightly increasing response fluency and relevance.

SH2: Self-Highlighted Hesitation Helps You Decode More Truthfully

by Jushi Kai, Tianhang Zhang, Hai Hu, Zhouhan Lin

Large language models (LLMs) demonstrate great performance in text generation. However, LLMs are still suffering from hallucinations. In this work, we propose an inference-time method, Self-Highlighted Hesitation (SH2), to help LLMs decode more truthfully. SH2 is based on a simple fact rooted in information theory that for an LLM, the tokens predicted with lower probabilities are prone to be more informative than others. Our analysis shows that the tokens assigned with lower probabilities by an LLM are more likely to be closely related to factual information, such as nouns, proper nouns, and adjectives. Therefore, we propose to "highlight" the factual information by selecting the tokens with the lowest probabilities and concatenating them to the original context, thus forcing the model to repeatedly read and hesitate on these tokens before generation. During decoding, we also adopt contrastive decoding to emphasize the difference in the output probabilities brought by the hesitation. Experimental results demonstrate that our SH2, requiring no additional data or models, can effectively help LLMs elicit factual knowledge and distinguish hallucinated contexts. Significant and consistent improvements are achieved by SH2 for LLaMA-7b and LLaMA2-7b on multiple hallucination tasks.

Universal Vulnerabilities in Large Language Models: In-context Learning Backdoor Attacks

by Shuai Zhao, Meihuizi Jia, Luu Anh Tuan, Jinming Wen

In-context learning, a paradigm bridging the gap between pre-training and fine-tuning, has demonstrated high efficacy in several NLP tasks, especially in few-shot settings. Unlike traditional fine-tuning methods, in-context learning adapts pre-trained models to unseen tasks without updating any parameters. Despite being widely applied, in-context learning is vulnerable to malicious attacks. In this work, we raise security concerns regarding this paradigm. Our studies demonstrate that an attacker can manipulate the behavior of large language models by poisoning the demonstration context, without the need for fine-tuning the model. Specifically, we have designed a new backdoor attack method, named ICLAttack, to target large language models based on in-context learning. Our method encompasses two types of attacks: poisoning demonstration examples and poisoning prompts, which can make models behave in accordance with predefined intentions. ICLAttack does not require additional fine-tuning to implant a backdoor, thus preserving the model's generality. Furthermore, the poisoned examples are correctly labeled, enhancing the natural stealth of our attack method. Extensive experimental results across several language models, ranging in size from 1.3B to 40B parameters, demonstrate the effectiveness of our attack method, exemplified by a high average attack success rate of 95.0% across the three datasets on OPT models. Our findings highlight the vulnerabilities of language models, and we hope this work will raise awareness of the possible security threats associated with in-context learning.

LLM-as-a-Coauthor: The Challenges of Detecting LLM-Human Mixcase

by Chujie Gao, Dongping Chen, Qihui Zhang, Yue Huang, Yao Wan, Lichao Sun

With the remarkable development and widespread applications of large language models (LLMs), the use of machine-generated text (MGT) is becoming increasingly common. This trend brings potential risks, particularly to the quality and completeness of information in fields such as news and education. Current research predominantly addresses the detection of pure MGT without adequately addressing mixed scenarios including AI-revised Human-Written Text (HWT) or human-revised MGT. To confront this challenge, we introduce mixcase, a novel concept representing a hybrid text form involving both machine-generated and human-generated content. We collected mixcase instances generated from multiple daily text-editing scenarios and composed MixSet, the first dataset dedicated to studying these mixed modification scenarios. We conduct experiments to evaluate the efficacy of popular MGT detectors, assessing their effectiveness, robustness, and generalization performance. Our findings reveal that existing detectors struggle to identify mixcase as a separate class or MGT, particularly in dealing with subtle modifications and style adaptability. This research underscores the urgent need for more fine-grain detectors tailored for mixcase, offering valuable insights for future research. Code and Models are available at https://github.com/Dongping-Chen/MixSet.

Block-Diagonal Orthogonal Relation and Matrix Entity for Knowledge Graph Embedding

by Yihua Zhu, Hidetoshi Shimodaira

The primary aim of Knowledge Graph embeddings (KGE) is to learn low-dimensional representations of entities and relations for predicting missing facts. While rotation-based methods like RotatE and QuatE perform well in KGE, they face two challenges: limited model flexibility requiring proportional increases in relation size with entity dimension, and difficulties in generalizing the model for higher-dimensional rotations. To address these issues, we introduce OrthogonalE, a novel KGE model employing matrices for entities and block-diagonal orthogonal matrices with Riemannian optimization for relations. This approach enhances the generality and flexibility of KGE models. The experimental results indicate that our new KGE model, OrthogonalE, is both general and flexible, significantly outperforming state-of-the-art KGE models while substantially reducing the number of relation parameters.

Combating Adversarial Attacks with Multi-Agent Debate

by Steffi Chern, Zhen Fan, Andy Liu

While state-of-the-art language models have achieved impressive results, they remain susceptible to inference-time adversarial attacks, such as adversarial prompts generated by red teams arXiv:2209.07858. One approach proposed to improve the general quality of language model generations is multi-agent debate, where language models self-evaluate through discussion and feedback arXiv:2305.14325. We implement multi-agent debate between current state-of-the-art language models and evaluate models' susceptibility to red team attacks in both single- and multi-agent settings. We find that multi-agent debate can reduce model toxicity when jailbroken or less capable models are forced to debate with non-jailbroken or more capable models. We also find marginal improvements through the general usage of multi-agent interactions. We further perform adversarial prompt content classification via embedding clustering, and analyze the susceptibility of different models to different types of attack topics.

LinguAlchemy: Fusing Typological and Geographical Elements for Unseen Language Generalization

by Muhammad Farid Adilazuarda, Samuel Cahyawijaya, Alham Fikri Aji, Genta Indra Winata, Ayu Purwarianti

Pretrained language models (PLMs) have shown remarkable generalization toward multiple tasks and languages. Nonetheless, the generalization of PLMs towards unseen languages is poor, resulting in significantly worse language performance, or even generating nonsensical responses that are comparable to a random baseline. This limitation has been a longstanding problem of PLMs raising the problem of diversity and equal access to language modeling technology. In this work, we solve this limitation by introducing LinguAlchemy, a regularization technique that incorporates various aspects of languages covering typological, geographical, and phylogenetic constraining the resulting representation of PLMs to better characterize the corresponding linguistics constraints. LinguAlchemy significantly improves the accuracy performance of mBERT and XLM-R on unseen languages by ~18% and ~2%, respectively compared to fully finetuned models and displaying a high degree of unseen language generalization. We further introduce AlchemyScale and AlchemyTune, extension of LinguAlchemy which adjusts the linguistic regularization weights automatically, alleviating the need for hyperparameter search. LinguAlchemy enables better cross-lingual generalization to unseen languages which is vital for better inclusivity and accessibility of PLMs.

Investigating Data Contamination for Pre-training Language Models

by Minhao Jiang, Ken Ziyu Liu, Ming Zhong, Rylan Schaeffer, Siru Ouyang, Jiawei Han, Sanmi Koyejo

Language models pre-trained on web-scale corpora demonstrate impressive capabilities on diverse downstream tasks. However, there is increasing concern whether such capabilities might arise from evaluation datasets being included in the pre-training corpus – a phenomenon known as data contamination – in a manner that artificially increases performance. There has been little understanding of how this potential contamination might influence LMs' performance on downstream tasks. In this paper, we explore the impact of data contamination at the pre-training stage by pre-training a series of GPT-2 models from scratch. We highlight the effect of both text contamination (i.e.\ input text of the evaluation samples) and ground-truth contamination (i.e.\ the prompts asked on the input and the desired outputs) from evaluation data. We also investigate the effects of repeating contamination for various downstream tasks. Additionally, we examine the prevailing n-gram-based definitions of contamination within current LLM reports, pinpointing their limitations and inadequacy. Our findings offer new insights into data contamination's effects on language model capabilities and underscore the need for independent, comprehensive contamination assessments in LLM studies.

DeepSeekMoE: Towards Ultimate Expert Specialization in Mixture-of-Experts Language Models

by Damai Dai, Chengqi Deng, Chenggang Zhao, R. X. Xu, Huazuo Gao, Deli Chen, Jiashi Li, Wangding Zeng, Xingkai Yu, Y. Wu, Zhenda Xie, Y. K. Li, Panpan Huang, Fuli Luo, Chong Ruan, Zhifang Sui, Wenfeng Liang

In the era of large language models, Mixture-of-Experts (MoE) is a promising architecture for managing computational costs when scaling up model parameters. However, conventional MoE architectures like GShard, which activate the top-K out of N experts, face challenges in ensuring expert specialization, i.e. each expert acquires non-overlapping and focused knowledge. In response, we propose the DeepSeekMoE architecture towards ultimate expert specialization. It involves two principal strategies: (1) finely segmenting the experts into mN ones and activating mK from them, allowing for a more flexible combination of activated experts; (2) isolating K\_s experts as shared ones, aiming at capturing common knowledge and mitigating redundancy in routed experts. Starting from a modest scale with 2B parameters, we demonstrate that DeepSeekMoE 2B achieves comparable performance with GShard 2.9B, which has 1.5 times the expert parameters and computation. In addition, DeepSeekMoE 2B nearly approaches the performance of its dense counterpart with the same number of total parameters, which set the upper bound of MoE models. Subsequently, we scale up DeepSeekMoE to 16B parameters and show that it achieves comparable performance with LLaMA2 7B, with only about 40% of computations. Further, our preliminary efforts to scale up DeepSeekMoE to 145B parameters consistently validate its substantial advantages over the GShard architecture, and show its performance comparable with DeepSeek 67B, using only 28.5% (maybe even 18.2%) of computations.

Improving Large Language Models via Fine-grained Reinforcement Learning with Minimum Editing Constraint

by Zhipeng Chen, Kun Zhou, Wayne Xin Zhao, Junchen Wan, Fuzheng Zhang, Di Zhang, Ji-Rong Wen

Reinforcement learning (RL) has been widely used in training large language models~(LLMs) for preventing unexpected outputs, \eg reducing harmfulness and errors. However, existing RL methods mostly adopt the instance-level reward, which is unable to provide fine-grained supervision for complex reasoning tasks, and can not focus on the few key tokens that lead to the incorrectness. To address it, we propose a new RL method named RLMEC that incorporates a generative model as the reward model, which is trained by the erroneous solution rewriting task under the minimum editing constraint, and can produce token-level rewards for RL training. Based on the generative reward model, we design the token-level RL objective for training and an imitation-based regularization for stabilizing RL process. And the both objectives focus on the learning of the key tokens for the erroneous solution, reducing the effect of other unimportant tokens. The experiment results on mathematical tasks and question-answering tasks have demonstrated the effectiveness of our approach. Our code and data are available at https://github.com/RUCAIBox/RLMEC.

Autocompletion of Chief Complaints in the Electronic Health Records using Large Language Models

by K M Sajjadul Islam, Ayesha Siddika Nipu, Praveen Madiraju, Priya Deshpande

The Chief Complaint (CC) is a crucial component of a patient's medical record as it describes the main reason or concern for seeking medical care. It provides critical information for healthcare providers to make informed decisions about patient care. However, documenting CCs can be time-consuming for healthcare providers, especially in busy emergency departments. To address this issue, an autocompletion tool that suggests accurate and well-formatted phrases or sentences for clinical notes can be a valuable resource for triage nurses. In this study, we utilized text generation techniques to develop machine learning models using CC data. In our proposed work, we train a Long Short-Term Memory (LSTM) model and fine-tune three different variants of Biomedical Generative Pretrained Transformers (BioGPT), namely microsoft/biogpt, microsoft/BioGPT-Large, and microsoft/BioGPT-Large-PubMedQA. Additionally, we tune a prompt by incorporating exemplar CC sentences, utilizing the OpenAI API of GPT-4. We evaluate the models' performance based on the perplexity score, modified BERTScore, and cosine similarity score. The results show that BioGPT-Large exhibits superior performance compared to the other models. It consistently achieves a remarkably low perplexity score of 1.65 when generating CC, whereas the baseline LSTM model achieves the best perplexity score of 170. Further, we evaluate and assess the proposed models' performance and the outcome of GPT-4.0. Our study demonstrates that utilizing LLMs such as BioGPT, leads to the development of an effective autocompletion tool for generating CC documentation in healthcare settings.

Patchscope: A Unifying Framework for Inspecting Hidden Representations of Language Models

by Asma Ghandeharioun, Avi Caciularu, Adam Pearce, Lucas Dixon, Mor Geva

Inspecting the information encoded in hidden representations of large language models (LLMs) can explain models' behavior and verify their alignment with human values. Given the capabilities of LLMs in generating human-understandable text, we propose leveraging the model itself to explain its internal representations in natural language. We introduce a framework called Patchscopes and show how it can be used to answer a wide range of research questions about an LLM's computation. We show that prior interpretability methods based on projecting representations into the vocabulary space and intervening on the LLM computation, can be viewed as special instances of this framework. Moreover, several of their shortcomings such as failure in inspecting early layers or lack of expressivity can be mitigated by a Patchscope. Beyond unifying prior inspection techniques, Patchscopes also opens up new possibilities such as using a more capable model to explain the representations of a smaller model, and unlocks new applications such as self-correction in multi-hop reasoning.

Transformers are Multi-State RNNs

by Matanel Oren, Michael Hassid, Yossi Adi, Roy Schwartz

Transformers are considered conceptually different compared to the previous generation of state-of-the-art NLP models - recurrent neural networks (RNNs). In this work, we demonstrate that decoder-only transformers can in fact be conceptualized as infinite multi-state RNNs - an RNN variant with unlimited hidden state size. We further show that pretrained transformers can be converted into finite multi-state RNNs by fixing the size of their hidden state. We observe that several existing transformers cache compression techniques can be framed as such conversion policies, and introduce a novel policy, TOVA, which is simpler compared to these policies. Our experiments with several long range tasks indicate that TOVA outperforms all other baseline policies, while being nearly on par with the full (infinite) model, and using in some cases only 1{8} of the original cache size. Our results indicate that transformer decoder LLMs often behave in practice as RNNs. They also lay out the option of mitigating one of their most painful computational bottlenecks - the size of their cache memory. We publicly release our code at https://github.com/schwartz-lab-NLP/TOVA.

Axis Tour: Word Tour Determines the Order of Axes in ICA-transformed Embeddings

by Hiroaki Yamagiwa, Yusuke Takase, Hidetoshi Shimodaira

Word embedding is one of the most important components in natural language processing, but interpreting high-dimensional embeddings remains a challenging problem. To address this problem, Independent Component Analysis (ICA) is identified as an effective solution. ICA-transformed word embeddings reveal interpretable semantic axes; however, the order of these axes are arbitrary. In this study, we focus on this property and propose a novel method, Axis Tour, which optimizes the order of the axes. Inspired by Word Tour, a one-dimensional word embedding method, we aim to improve the clarity of the word embedding space by maximizing the semantic continuity of the axes. Furthermore, we show through experiments on downstream tasks that Axis Tour constructs better low-dimensional embeddings compared to both PCA and ICA.

That's all for today, thank you for listening. If you found the podcast helpful, please leave a comment, like, or share it with a friend. See you tomorrow!