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Here is what was submitted on January 10, 2024.

Can AI Write Classical Chinese Poetry like Humans? An Empirical Study Inspired by Turing Test

by Zekun Deng, Hao Yang, Jun Wang

Some argue that the essence of humanity, such as creativity and sentiment, can never be mimicked by machines. This paper casts doubt on this belief by studying a vital question: Can AI compose poetry as well as humans? To answer the question, we propose ProFTAP, a novel evaluation framework inspired by Turing test to assess AI's poetry writing capability. We apply it on current large language models (LLMs) and find that recent LLMs do indeed possess the ability to write classical Chinese poems nearly indistinguishable from those of humans. We also reveal that various open-source LLMs can outperform GPT-4 on this task.

Whose wife is it anyway? Assessing bias against same-gender relationships in machine translation

by Ian Stewart, Rada Mihalcea

Machine translation often suffers from biased data and algorithms that can lead to unacceptable errors in system output. While bias in gender norms has been investigated, less is known about whether MT systems encode bias about social relationships, e.g. sentences such as "the lawyer kissed her wife." We investigate the degree of bias against same-gender relationships in MT systems, using generated template sentences drawn from several noun-gender languages (e.g. Spanish). We find that three popular MT services consistently fail to accurately translate sentences concerning relationships between nouns of the same gender. The error rate varies considerably based on the context, e.g. same-gender sentences referencing high female-representation occupations are translated with lower accuracy. We provide this work as a case study in the evaluation of intrinsic bias in NLP systems, with respect to social relationships.

Bootstrapping LLM-based Task-Oriented Dialogue Agents via Self-Talk

by Dennis Ulmer, Elman Mansimov, Kaixiang Lin, Justin Sun, Xibin Gao, Yi Zhang

Large language models (LLMs) are powerful dialogue agents, but specializing them towards fulfilling a specific function can be challenging. Instructing tuning, i.e. tuning models on instruction and sample responses generated by humans (Ouyang et al., 2022), has proven as an effective method to do so, yet requires a number of data samples that a) might not be available or b) costly to generate. Furthermore, this cost increases when the goal is to make the LLM follow a specific workflow within a dialogue instead of single instructions. Inspired by the self-play technique in reinforcement learning and the use of LLMs to simulate human agents, we propose a more effective method for data collection through LLMs engaging in a conversation in various roles. This approach generates a training data via "self-talk" of LLMs that can be refined and utilized for supervised fine-tuning. We introduce an automated way to measure the (partial) success of a dialogue. This metric is used to filter the generated conversational data that is fed back in LLM for training. Based on our automated and human evaluations of conversation quality, we demonstrate that such self-talk data improves results. In addition, we examine the various characteristics that showcase the quality of generated dialogues and how they can be connected to their potential utility as training data.

Generating Diverse and High-Quality Texts by Minimum Bayes Risk Decoding

by Yuu Jinnai, Ukyo Honda, Tetsuro Morimura, Peinan Zhang

One of the most important challenges in text generation systems is to produce outputs that are not only correct but also diverse. Recently, Minimum Bayes-Risk (MBR) decoding has gained prominence for generating sentences of the highest quality among the decoding algorithms. However, existing algorithms proposed for generating diverse outputs are predominantly based on beam search or random sampling, thus their output quality is capped by these underlying methods. In this paper, we investigate an alternative approach – we develop diversity-promoting decoding algorithms by enforcing diversity objectives to MBR decoding. We propose two variants of MBR, Diverse MBR (DMBR) and k-medoids MBR (KMBR), methods to generate a set of sentences with high quality and diversity. We evaluate DMBR and KMBR on a variety of directed text generation tasks using encoder-decoder models and a large language model with prompting. The experimental results show that the proposed method achieves a better trade-off than the diverse beam search and sampling algorithms.

Aligning Translation-Specific Understanding to General Understanding in Large Language Models

by Yichong Huang, Xiaocheng Feng, Baohang Li, Chengpeng Fu, Wenshuai Huo, Ting Liu, Bing Qin

Although large language models (LLMs) have shown surprising language understanding and generation capabilities, they have yet to gain a revolutionary advancement in the field of machine translation. One potential cause of the limited performance is the misalignment between the translation-specific understanding and general understanding inside LLMs. To align the translation-specific understanding to the general one, we propose a novel translation process xIoD (Cross-Lingual Interpretation of Difficult words), explicitly incorporating the general understanding on the content incurring inconsistent understanding to guide the translation. Specifically, xIoD performs the cross-lingual interpretation for the difficult-to-translate words and enhances the translation with the generated interpretations. Furthermore, we reframe the external tools of QE to tackle the challenges of xIoD in the detection of difficult words and the generation of helpful interpretations. We conduct experiments on the self-constructed benchmark ChallengeMT, which includes cases in which multiple SOTA translation systems consistently underperform. Experimental results show the effectiveness of our xIoD, which improves up to +3.85 COMET.

BELHD: Improving Biomedical Entity Linking with Homonoym Disambiguation

by Samuele Garda, Ulf Leser

Biomedical entity linking (BEL) is the task of grounding entity mentions to a knowledge base (KB). A popular approach to the task are name-based methods, i.e. those identifying the most appropriate name in the KB for a given mention, either via dense retrieval or autoregressive modeling. However, as these methods directly return KB names, they cannot cope with homonyms, i.e. different KB entities sharing the exact same name. This significantly affects their performance, especially for KBs where homonyms account for a large amount of entity mentions (e.g. UMLS and NCBI Gene). We therefore present BELHD (Biomedical Entity Linking with Homonym Disambiguation), a new name-based method that copes with this challenge. Specifically, BELHD builds upon the BioSyn (Sung et al.,2020) model introducing two crucial extensions. First, it performs a preprocessing of the KB in which it expands homonyms with an automatically chosen disambiguating string, thus enforcing unique linking decisions. Second, we introduce candidate sharing, a novel strategy to select candidates for contrastive learning that enhances the overall training signal. Experiments with 10 corpora and five entity types show that BELHD improves upon state-of-the-art approaches, achieving the best results in 6 out 10 corpora with an average improvement of 4.55pp recall@1. Furthermore, the KB preprocessing is orthogonal to the core prediction model and thus can also improve other methods, which we exemplify for GenBioEL (Yuan et al, 2022), a generative name-based BEL approach. Code is available at: link added upon publication.

Can ChatGPT Rival Neural Machine Translation? A Comparative Study

by Zhaokun Jiang, Ziyin Zhang

Inspired by the increasing interest in leveraging large language models for translation, this paper evaluates the capabilities of large language models (LLMs) represented by ChatGPT in comparison to the mainstream neural machine translation (NMT) engines in translating Chinese diplomatic texts into English. Specifically, we examine the translation quality of ChatGPT and NMT engines as measured by four automated metrics and human evaluation based on an error-typology and six analytic rubrics. Our findings show that automated metrics yield similar results for ChatGPT under different prompts and NMT systems, while human annotators tend to assign noticeably higher scores to ChatGPT when it is provided an example or contextual information about the translation task. Pairwise correlation between automated metrics and dimensions of human evaluation produces weak and non-significant results, suggesting the divergence between the two methods of translation quality assessment. These findings provide valuable insights into the potential of ChatGPT as a capable machine translator, and the influence of prompt engineering on its performance.

Divide and Conquer for Large Language Models Reasoning

by Zijie Meng, Yan Zhang, Zhaopeng Feng, Yang Feng, Gaoang Wang, Joey Tianyi Zhou, Jian Wu, Zuozhu Liu

Large language models (LLMs) have shown impressive performance in various reasoning benchmarks with the emergence of Chain-of-Thought (CoT) and its derivative methods, particularly in tasks involving multi-choice questions (MCQs). However, current works all process data uniformly without considering the problem-solving difficulty, which means an excessive focus on simple questions while insufficient to intricate ones. To address this challenge, we inspired by humans using heuristic strategies to categorize tasks and handle them individually, propose to apply the Divide and Conquer to LLMs reasoning. First, we divide questions into different subsets based on the statistical confidence score (CS), then fix nearly resolved sets and conquer demanding nuanced process ones with elaborately designed methods, including Prior Knowledge based Reasoning (PKR) and Filter Choices based Reasoning (FCR), as well as their integration variants. Our experiments demonstrate that this proposed strategy significantly boosts the models' reasoning abilities across nine datasets involving arithmetic, commonsense, and logic tasks. For instance, compared to baseline, we make a striking improvement on low confidence subsets of 8.72\% for AQuA, 15.07\% for ARC Challenge and 7.71\% for RiddleSense. In addition, through extensive analysis on length of rationale and number of options, we verify that longer reasoning paths in PKR could prevent models from referring infer-harmful shortcuts, and also find that removing irrelevant choices in FCR would substantially avoid models' confusion. The code is at https://github.com/AiMijie/Divide-and-Conquer

Monte Carlo Tree Search for Recipe Generation using GPT-2

by Karan Taneja, Richard Segal, Richard Goodwin

Automatic food recipe generation methods provide a creative tool for chefs to explore and to create new, and interesting culinary delights. Given the recent success of large language models (LLMs), they have the potential to create new recipes that can meet individual preferences, dietary constraints, and adapt to what is in your refrigerator. Existing research on using LLMs to generate recipes has shown that LLMs can be finetuned to generate realistic-sounding recipes. However, on close examination, these generated recipes often fail to meet basic requirements like including chicken as an ingredient in chicken dishes. In this paper, we propose RecipeMC, a text generation method using GPT-2 that relies on Monte Carlo Tree Search (MCTS). RecipeMC allows us to define reward functions to put soft constraints on text generation and thus improve the credibility of the generated recipes. Our results show that human evaluators prefer recipes generated with RecipeMC more often than recipes generated with other baseline methods when compared with real recipes.

A Novel Prompt-tuning Method: Incorporating Scenario-specific Concepts into a Verbalizer

by Yong Ma, Senlin Luo, Yu-Ming Shang, Zhengjun Li, Yong Liu

The verbalizer, which serves to map label words to class labels, is an essential component of prompt-tuning. In this paper, we present a novel approach to constructing verbalizers. While existing methods for verbalizer construction mainly rely on augmenting and refining sets of synonyms or related words based on class names, this paradigm suffers from a narrow perspective and lack of abstraction, resulting in limited coverage and high bias in the label-word space. To address this issue, we propose a label-word construction process that incorporates scenario-specific concepts. Specifically, we extract rich concepts from task-specific scenarios as label-word candidates and then develop a novel cascade calibration module to refine the candidates into a set of label words for each class. We evaluate the effectiveness of our proposed approach through extensive experiments on {five} widely used datasets for zero-shot text classification. The results demonstrate that our method outperforms existing methods and achieves state-of-the-art results.

Pre-trained Large Language Models for Financial Sentiment Analysis

by Wei Luo, Dihong Gong

Financial sentiment analysis refers to classifying financial text contents into sentiment categories (e.g. positive, negative, and neutral). In this paper, we focus on the classification of financial news title, which is a challenging task due to a lack of large amount of training samples. To overcome this difficulty, we propose to adapt the pretrained large language models (LLMs) [1, 2, 3] to solve this problem. The LLMs, which are trained from huge amount of text corpora,have an advantage in text understanding and can be effectively adapted to domain-specific task while requiring very few amount of training samples. In particular, we adapt the open-source Llama2-7B model (2023) with the supervised fine-tuning (SFT) technique [4]. Experimental evaluation shows that even with the 7B model (which is relatively small for LLMs), our approach significantly outperforms the previous state-of-the-art algorithms.

CASA: Causality-driven Argument Sufficiency Assessment

by Xiao Liu, Yansong Feng, Kai-Wei Chang

The argument sufficiency assessment task aims to determine if the premises of a given argument support its conclusion. To tackle this task, existing works often train a classifier on data annotated by humans. However, annotating data is laborious, and annotations are often inconsistent due to subjective criteria. Motivated by the probability of sufficiency (PS) definition in the causal literature, we propose CASA, a zero-shot causality-driven argument sufficiency assessment framework. PS measures how likely introducing the premise event would lead to the conclusion, when both the premise and conclusion events are absent. To estimate this probability, we propose to use large language models (LLMs) to generate contexts that are inconsistent with the premise and conclusion, and revise them by injecting the premise event. Experiments on two logical fallacy detection datasets demonstrate that CASA accurately identifies insufficient arguments. We further deploy CASA in a writing assistance application, and find that suggestions generated by CASA enhance the sufficiency of student-written arguments. Code and data are available at https://github.com/xxxiaol/CASA.

AUTOACT: Automatic Agent Learning from Scratch via Self-Planning

by Shuofei Qiao, Ningyu Zhang, Runnan Fang, Yujie Luo, Wangchunshu Zhou, Yuchen Eleanor Jiang, Chengfei Lv, Huajun Chen

Language agents have achieved considerable performance on various complex tasks. Despite the incessant exploration in this field, existing language agent systems still struggle with costly, non-reproducible data reliance and face the challenge of compelling a single model for multiple functions. To this end, we introduce AutoAct, an automatic agent learning framework that does not rely on large-scale annotated data and synthetic trajectories from closed-source models (e.g., GPT-4). Given limited data with a tool library, AutoAct first automatically synthesizes planning trajectories without any assistance from humans or strong closed-source models. Then, AutoAct leverages a division-of-labor strategy to automatically differentiate based on the target task information and synthesized trajectories, producing a sub-agent group to complete the task. We conduct comprehensive experiments with different LLMs, which demonstrates that AutoAct yields better or parallel performance compared to various strong baselines. We even notice that AutoAct, when using the Llama-2-13b model, can achieve performance comparable to that of the GPT-3.5-Turbo agent. Code will be available at https://github.com/zjunlp/AutoAct.

INACIA: Integrating Large Language Models in Brazilian Audit Courts: Opportunities and Challenges

by Jayr Pereira, Andre Assumpcao, Julio Trecenti, Luiz Airosa, Caio Lente, Jhonatan Cléto, Guilherme Dobins, Rodrigo Nogueira, Luis Mitchell, Roberto Lotufo

This paper introduces INACIA (Instruc\~ao Assistida com Intelig\^encia Artificial), a groundbreaking system designed to integrate Large Language Models (LLMs) into the operational framework of Brazilian Federal Court of Accounts (TCU). The system automates various stages of case analysis, including basic information extraction, admissibility examination, Periculum in mora and Fumus boni iuris analyses, and recommendations generation. Through a series of experiments, we demonstrate INACIA's potential in extracting relevant information from case documents, evaluating its legal plausibility, and generating judicial recommendations. Utilizing a validation dataset alongside LLMs, our evaluation methodology presents an innovative approach to assessing system performance, correlating highly with human judgment. The results highlight INACIA's proficiency in handling complex legal tasks, indicating its suitability for augmenting efficiency and judicial fairness within legal systems. The paper also discusses potential enhancements and future applications, positioning INACIA as a model for worldwide AI integration in legal domains.

I am a Strange Dataset: Metalinguistic Tests for Language Models

by Tristan Thrush, Jared Moore, Miguel Monares, Christopher Potts, Douwe Kiela

Statements involving metalinguistic self-reference ("This paper has six sections.") are prevalent in many domains. Can large language models (LLMs) handle such language? In this paper, we present "I am a Strange Dataset", a new dataset for addressing this question. There are two subtasks: generation and verification. In generation, models continue statements like "The penultimate word in this sentence is" (where a correct continuation is "is"). In verification, models judge the truth of statements like "The penultimate word in this sentence is sentence." (false). We also provide minimally different metalinguistic non-self-reference examples to complement the main dataset by probing for whether models can handle metalinguistic language at all. The dataset is hand-crafted by experts and validated by non-expert annotators. We test a variety of open-source LLMs (7B to 70B parameters) as well as closed-source LLMs through APIs. All models perform close to chance across both subtasks and even on the non-self-referential metalinguistic control data, though we find some steady improvement with model scale. GPT 4 is the only model to consistently do significantly better than chance, and it is still only in the 60% range, while our untrained human annotators score well in the 89-93% range. The dataset and evaluation toolkit are available at https://github.com/TristanThrush/i-am-a-strange-dataset.

Leveraging Print Debugging to Improve Code Generation in Large Language Models

by Xueyu Hu, Kun Kuang, Jiankai Sun, Hongxia Yang, Fei Wu

Large language models (LLMs) have made significant progress in code generation tasks, but their performance in tackling programming problems with complex data structures and algorithms remains suboptimal. To address this issue, we propose an in-context learning approach that guides LLMs to debug by using a "print debugging" method, which involves inserting print statements to trace and analysing logs for fixing the bug. We collect a Leetcode problem dataset and evaluate our method using the Leetcode online judging system. Experiments with GPT-4 demonstrate the effectiveness of our approach, outperforming rubber duck debugging in easy and medium-level Leetcode problems by 1.5% and 17.9%.

InfiAgent-DABench: Evaluating Agents on Data Analysis Tasks

by Xueyu Hu, Ziyu Zhao, Shuang Wei, Ziwei Chai, Guoyin Wang, Xuwu Wang, Jing Su, Jingjing Xu, Ming Zhu, Yao Cheng, Jianbo Yuan, Kun Kuang, Yang Yang, Hongxia Yang, Fei Wu

In this paper, we introduce "InfiAgent-DABench", the first benchmark specifically designed to evaluate LLM-based agents in data analysis tasks. This benchmark contains DAEval, a dataset consisting of 311 data analysis questions derived from 55 CSV files, and an agent framework to evaluate LLMs as data analysis agents. We adopt a format-prompting technique, ensuring questions to be closed-form that can be automatically evaluated. Our extensive benchmarking of 23 state-of-the-art LLMs uncovers the current challenges encountered in data analysis tasks. In addition, we have developed DAAgent, a specialized agent trained on instruction-tuning datasets. Evaluation datasets and toolkits for InfiAgent-DABench are released at https://github.com/InfiAgent/InfiAgent.

CodePrompt: Improving Source Code-Related Classification with Knowledge Features through Prompt Learning

by Yong Ma, Senlin Luo, Yu-Ming Shang, Yifei Zhang, Zhengjun Li

Researchers have explored the potential of utilizing pre-trained language models, such as CodeBERT, to improve source code-related tasks. Previous studies have mainly relied on CodeBERT's text embedding capability and the `[CLS]' sentence embedding information as semantic representations for fine-tuning downstream source code-related tasks. However, these methods require additional neural network layers to extract effective features, resulting in higher computational costs. Furthermore, existing approaches have not leveraged the rich knowledge contained in both source code and related text, which can lead to lower accuracy. This paper presents a novel approach, CodePrompt, which utilizes rich knowledge recalled from a pre-trained model by prompt learning and an attention mechanism to improve source code-related classification tasks. Our approach initially motivates the language model with prompt information to retrieve abundant knowledge associated with the input as representative features, thus avoiding the need for additional neural network layers and reducing computational costs. Subsequently, we employ an attention mechanism to aggregate multiple layers of related knowledge for each task as final features to boost their accuracy. We conducted extensive experiments on four downstream source code-related tasks to evaluate our approach and our results demonstrate that CodePrompt achieves new state-of-the-art performance on the accuracy metric while also exhibiting computation cost-saving capabilities.

Useful Blunders: Can Automated Speech Recognition Errors Improve Downstream Dementia Classification?

by Changye Li, Weizhe Xu, Trevor Cohen, Serguei Pakhomov

Objectives: We aimed to investigate how errors from automatic speech recognition (ASR) systems affect dementia classification accuracy, specifically in the "Cookie Theft" picture description task. We aimed to assess whether imperfect ASR-generated transcripts could provide valuable information for distinguishing between language samples from cognitively healthy individuals and those with Alzheimer's disease (AD). Methods: We conducted experiments using various ASR models, refining their transcripts with post-editing techniques. Both these imperfect ASR transcripts and manually transcribed ones were used as inputs for the downstream dementia classification. We conducted comprehensive error analysis to compare model performance and assess ASR-generated transcript effectiveness in dementia classification. Results: Imperfect ASR-generated transcripts surprisingly outperformed manual transcription for distinguishing between individuals with AD and those without in the "Cookie Theft" task. These ASR-based models surpassed the previous state-of-the-art approach, indicating that ASR errors may contain valuable cues related to dementia. The synergy between ASR and classification models improved overall accuracy in dementia classification. Conclusion: Imperfect ASR transcripts effectively capture linguistic anomalies linked to dementia, improving accuracy in classification tasks. This synergy between ASR and classification models underscores ASR's potential as a valuable tool in assessing cognitive impairment and related clinical applications.

TrustLLM: Trustworthiness in Large Language Models

by Lichao Sun, Yue Huang, Haoran Wang, Siyuan Wu, Qihui Zhang, Chujie Gao, Yixin Huang, Wenhan Lyu, Yixuan Zhang, Xiner Li, Zhengliang Liu, Yixin Liu, Yijue Wang, Zhikun Zhang, Bhavya Kailkhura, Caiming Xiong, Chao Zhang, Chaowei Xiao, Chunyuan Li, Eric Xing, Furong Huang, Hao Liu, Heng Ji, Hongyi Wang, Huan Zhang, Huaxiu Yao, Manolis Kellis, Marinka Zitnik, Meng Jiang, Mohit Bansal, James Zou, Jian Pei, Jian Liu, Jianfeng Gao, Jiawei Han, Jieyu Zhao, Jiliang Tang, Jindong Wang, John Mitchell, Kai Shu, Kaidi Xu, Kai-Wei Chang, Lifang He, Lifu Huang, Michael Backes, Neil Zhenqiang Gong, Philip S. Yu, Pin-Yu Chen, Quanquan Gu, Ran Xu, Rex Ying, Shuiwang Ji, Suman Jana, Tianlong Chen, Tianming Liu, Tianyi Zhou, Willian Wang, Xiang Li, Xiangliang Zhang, Xiao Wang, Xing Xie, Xun Chen, Xuyu Wang, Yan Liu, Yanfang Ye, Yinzhi Cao, Yue Zhao

Large language models (LLMs), exemplified by ChatGPT, have gained considerable attention for their excellent natural language processing capabilities. Nonetheless, these LLMs present many challenges, particularly in the realm of trustworthiness. Therefore, ensuring the trustworthiness of LLMs emerges as an important topic. This paper introduces TrustLLM, a comprehensive study of trustworthiness in LLMs, including principles for different dimensions of trustworthiness, established benchmark, evaluation, and analysis of trustworthiness for mainstream LLMs, and discussion of open challenges and future directions. Specifically, we first propose a set of principles for trustworthy LLMs that span eight different dimensions. Based on these principles, we further establish a benchmark across six dimensions including truthfulness, safety, fairness, robustness, privacy, and machine ethics. We then present a study evaluating 16 mainstream LLMs in TrustLLM, consisting of over 30 datasets. Our findings firstly show that in general trustworthiness and utility (i.e., functional effectiveness) are positively related. Secondly, our observations reveal that proprietary LLMs generally outperform most open-source counterparts in terms of trustworthiness, raising concerns about the potential risks of widely accessible open-source LLMs. However, a few open-source LLMs come very close to proprietary ones. Thirdly, it is important to note that some LLMs may be overly calibrated towards exhibiting trustworthiness, to the extent that they compromise their utility by mistakenly treating benign prompts as harmful and consequently not responding. Finally, we emphasize the importance of ensuring transparency not only in the models themselves but also in the technologies that underpin trustworthiness. Knowing the specific trustworthy technologies that have been employed is crucial for analyzing their effectiveness.

POMP: Probability-driven Meta-graph Prompter for LLMs in Low-resource Unsupervised Neural Machine Translation

by Shilong Pan, Zhiliang Tian, Liang Ding, Zhen Huang, Zhihua Wen, Dongsheng Li

Low-resource languages (LRLs) face challenges in supervised neural machine translation due to limited parallel data, prompting research into unsupervised methods. Unsupervised neural machine translation (UNMT) methods, including back-translation, transfer learning, and pivot-based translation, offer practical solutions for LRL translation, but they are hindered by issues like synthetic data noise, language bias, and error propagation, which can potentially be mitigated by Large Language Models (LLMs). LLMs have advanced NMT with in-context learning (ICL) and supervised fine-tuning methods, but insufficient training data results in poor performance in LRLs. We argue that LLMs can mitigate the linguistic noise with auxiliary languages to improve translations in LRLs. In this paper, we propose Probability-driven Meta-graph Prompter (POMP), a novel approach employing a dynamic, sampling-based graph of multiple auxiliary languages to enhance LLMs' translation capabilities for LRLs. POMP involves constructing a directed acyclic meta-graph for each source language, from which we dynamically sample multiple paths to prompt LLMs to mitigate the linguistic noise and improve translations during training. We use the BLEURT metric to evaluate the translations and back-propagate rewards, estimated by scores, to update the probabilities of auxiliary languages in the paths. Our experiments show significant improvements in the translation quality of three LRLs, demonstrating the effectiveness of our approach.

REBUS: A Robust Evaluation Benchmark of Understanding Symbols

by Andrew Gritsevskiy, Arjun Panickssery, Aaron Kirtland, Derik Kauffman, Hans Gundlach, Irina Gritsevskaya, Joe Cavanagh, Jonathan Chiang, Lydia La Roux, Michelle Hung

We propose a new benchmark evaluating the performance of multimodal large language models on rebus puzzles. The dataset covers 333 original examples of image-based wordplay, cluing 13 categories such as movies, composers, major cities, and food. To achieve good performance on the benchmark of identifying the clued word or phrase, models must combine image recognition and string manipulation with hypothesis testing, multi-step reasoning, and an understanding of human cognition, making for a complex, multimodal evaluation of capabilities. We find that proprietary models such as GPT-4V and Gemini Pro significantly outperform all other tested models. However, even the best model has a final accuracy of just 24%, highlighting the need for substantial improvements in reasoning. Further, models rarely understand all parts of a puzzle, and are almost always incapable of retroactively explaining the correct answer. Our benchmark can therefore be used to identify major shortcomings in the knowledge and reasoning of multimodal large language models.

Scaling Laws for Forgetting When Fine-Tuning Large Language Models

by Damjan Kalajdzievski

We study and quantify the problem of forgetting when fine-tuning pre-trained large language models (LLMs) on a downstream task. We find that parameter-efficient fine-tuning (PEFT) strategies, such as Low-Rank Adapters (LoRA), still suffer from catastrophic forgetting. In particular, we identify a strong inverse linear relationship between the fine-tuning performance and the amount of forgetting when fine-tuning LLMs with LoRA. We further obtain precise scaling laws that show forgetting increases as a shifted power law in the number of parameters fine-tuned and the number of update steps. We also examine the impact of forgetting on knowledge, reasoning, and the safety guardrails trained into Llama 2 7B chat. Our study suggests that forgetting cannot be avoided through early stopping or by varying the number of parameters fine-tuned. We believe this opens up an important safety-critical direction for future research to evaluate and develop fine-tuning schemes which mitigate forgetting

The Benefits of a Concise Chain of Thought on Problem-Solving in Large Language Models

by Matthew Renze, Erhan Guven

In this paper, we introduce Concise Chain-of-Thought (CCoT) prompting. We compared standard CoT and CCoT prompts to see how conciseness impacts response length and correct-answer accuracy. We evaluated this using GPT-3.5 and GPT-4 with a multiple-choice question-and-answer (MCQA) benchmark. CCoT reduced average response length by 48.70% for both GPT-3.5 and GPT-4 while having a negligible impact on problem-solving performance. However, on math problems, GPT-3.5 with CCoT incurs a performance penalty of 27.69%. Overall, CCoT leads to an average per-token cost reduction of 22.67%. These results have practical implications for AI systems engineers using LLMs to solve real-world problems with CoT prompt-engineering techniques. In addition, these results provide more general insight for AI researchers studying the emergent behavior of step-by-step reasoning in LLMs.

Natural Language Processing for Dialects of a Language: A Survey

by Aditya Joshi, Raj Dabre, Diptesh Kanojia, Zhuang Li, Haolan Zhan, Gholamreza Haffari, Doris Dippold

State-of-the-art natural language processing (NLP) models are trained on massive training corpora, and report a superlative performance on evaluation datasets. This survey delves into an important attribute of these datasets: the dialect of a language. Motivated by the performance degradation of NLP models for dialectic datasets and its implications for the equity of language technologies, we survey past research in NLP for dialects in terms of datasets, and approaches. We describe a wide range of NLP tasks in terms of two categories: natural language understanding (NLU) (for tasks such as dialect classification, sentiment analysis, parsing, and NLU benchmarks) and natural language generation (NLG) (for summarisation, machine translation, and dialogue systems). The survey is also broad in its coverage of languages which include English, Arabic, German among others. We observe that past work in NLP concerning dialects goes deeper than mere dialect classification, and . This includes early approaches that used sentence transduction that lead to the recent approaches that integrate hypernetworks into LoRA. We expect that this survey will be useful to NLP researchers interested in building equitable language technologies by rethinking LLM benchmarks and model architectures.

On Detecting Cherry-picking in News Coverage Using Large Language Models

by Israa Jaradat, Haiqi Zhang, Chengkai Li

Cherry-picking refers to the deliberate selection of evidence or facts that favor a particular viewpoint while ignoring or distorting evidence that supports an opposing perspective. Manually identifying instances of cherry-picked statements in news stories can be challenging, particularly when the opposing viewpoint's story is absent. This study introduces Cherry, an innovative approach for automatically detecting cherry-picked statements in news articles by finding missing important statements in the target news story. Cherry utilizes the analysis of news coverage from multiple sources to identify instances of cherry-picking. Our approach relies on language models that consider contextual information from other news sources to classify statements based on their importance to the event covered in the target news story. Furthermore, this research introduces a novel dataset specifically designed for cherry-picking detection, which was used to train and evaluate the performance of the models. Our best performing model achieves an F-1 score of about %89 in detecting important statements when tested on unseen set of news stories. Moreover, results show the importance incorporating external knowledge from alternative unbiased narratives when assessing a statement's importance.

Unveiling the Tapestry of Automated Essay Scoring: A Comprehensive Investigation of Accuracy, Fairness, and Generalizability

by Kaixun Yang, Mladen Raković, Yuyang Li, Quanlong Guan, Dragan Gašević, Guanliang Chen

Automatic Essay Scoring (AES) is a well-established educational pursuit that employs machine learning to evaluate student-authored essays. While much effort has been made in this area, current research primarily focuses on either (i) boosting the predictive accuracy of an AES model for a specific prompt (i.e., developing prompt-specific models), which often heavily relies on the use of the labeled data from the same target prompt; or (ii) assessing the applicability of AES models developed on non-target prompts to the intended target prompt (i.e., developing the AES models in a cross-prompt setting). Given the inherent bias in machine learning and its potential impact on marginalized groups, it is imperative to investigate whether such bias exists in current AES methods and, if identified, how it intervenes with an AES model's accuracy and generalizability. Thus, our study aimed to uncover the intricate relationship between an AES model's accuracy, fairness, and generalizability, contributing practical insights for developing effective AES models in real-world education. To this end, we meticulously selected nine prominent AES methods and evaluated their performance using seven metrics on an open-sourced dataset, which contains over 25,000 essays and various demographic information about students such as gender, English language learner status, and economic status. Through extensive evaluations, we demonstrated that: (1) prompt-specific models tend to outperform their cross-prompt counterparts in terms of predictive accuracy; (2) prompt-specific models frequently exhibit a greater bias towards students of different economic statuses compared to cross-prompt models; (3) in the pursuit of generalizability, traditional machine learning models coupled with carefully engineered features hold greater potential for achieving both high accuracy and fairness than complex neural network models.

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!