

# 星火科研助手使用说明

## 一、登录系统

在浏览器地址栏中输入：<https://paperlogin.iflytek.com>，输入用户名和密码，进入科研助手系统，也可以注册账号免费试用。



## 二、成果调研

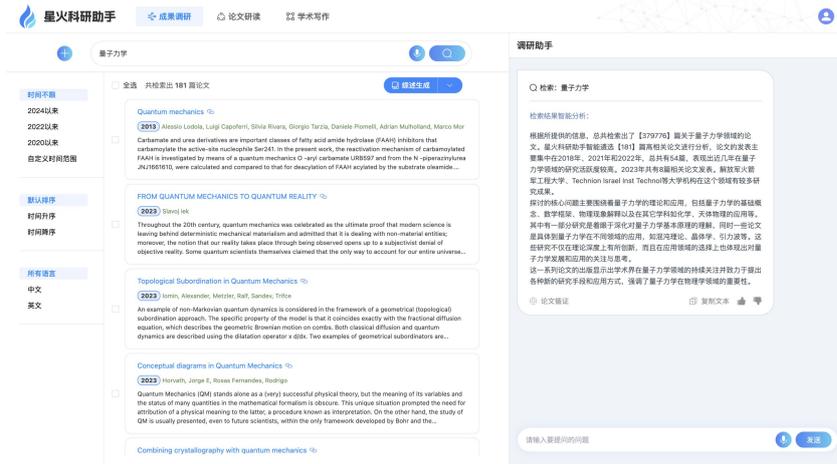
### (一) 搜索

在搜索栏输入关键词或内容描述，点击【检索】按钮，系统会根据输入的内容进行检索，并返回相关的结果。支持关键词检索、自然语言检索、语音检索；

鼠标 hover 至【检索历史】可以查看历史检索记录，点击记录跳转至历史检索结果页面；鼠标 hover 至【综述生成】可以查看历史综述生成列表，点击列表可跳转至综述详情页面；



根据检索内容生成检索结果，结果以列表的形式呈现，可以在左侧点击切换列表排序方式；同时会在右侧调研助手生成智能总结，可在对话框中对调研结果进行 AI 问答。



## (二) 综述生成

在检索结果列表页，选择一篇或多篇，最多支持选择 30 篇，点击【综述生成】可生成综述，点击【查看】可以在线查看 pdf 综述报告，综述报告支持下载；支持查看综述生成历史，综述生成历史显示名称、时间信息；点击【删除】可以删除历史综述报告。





### 三、论文研读

#### (一) 文件管理

论文研读模块，左侧为自定义文件夹，可以【添加】和【删除】文件夹，可以将文献文件按分类放至不同的文件夹内，右侧为文件夹内的文献列表，点击【上传文献】可以上传本地 pdf 格式文献到指定文件夹内，文献可以【下载】、【移动】和【删除】；在顶部搜索框中输入文献标题进行文献搜索；选择文献列表，点击【综述生成】可一键生成综述。



#### (二) 论文研读

点击文献列表中的论文标题，进入论文研读页面，AI 自动生成论文的摘要、方法和结论的总结，通过问答助手可针对论文内容进行 AI 问答；



选择论文中的文本内容，可以进行快捷【提取摘要】、【翻译文本】、【引用文本】和【添加笔记】：

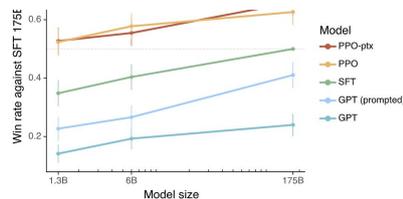


Figure 1: Human evaluations of various models on the API prompt distribution, evaluated by how often outputs from each model were preferred to those from the 175B SFT model. Our InstructGPT models (PPO-ptx) as well as its variant trained without pretraining mix (PPO) significantly outperform the GPT-3 baselines (GPT, GPT prompted); outputs from our 1.3B PPO-ptx model are preferred to those from the 175B GPT-3. Error bars throughout the paper are 95% confidence intervals.

used for many recent large LMs—predicting the next token on a webpage from different from the objective “follow the user’s instructions helpfully and safely” (Rai Brown et al., 2020; Fedus et al., 2021; Rae et al., 2021; Thoppilan et al., 2022). The language modeling objective is *misaligned*. Averting these unintended behaviors is important for language models that are deployed and used in hundreds of applications. We make progress on aligning language models by training them to act in accordance with human intent (Léke et al., 2018). This encompasses both explicit intentions such as following and implicit intentions such as staying truthful, and not being biased, toxic, or otherwise harmful. Using the language of Askell et al. (2021), we want language models to be *helpful* (they should help the user solve their task), *honest* (they shouldn’t fabricate information or mislead the user), and *harmless* (they should not cause physical, psychological, or social harm to people or the environment). We elaborate on the evaluation of these criteria in Section 3.3. We focus on *fine-tuning* approaches to aligning language models. Specifically, we use reinforcement learning from human feedback (RLHF; Christiano et al., 2017; Stiennon et al., 2020) to fine-tune GPT-3 to follow a broad class of written instructions (see Figure 2). This technique uses human preferences as a reward signal to fine-tune our models. We first hire a team of 40 contractors to label our data, based on their performance on a screening test (see Section 3.3 and Appendix B.1) for more details. We then collect a dataset of human-written demonstrations of the desired output behavior

- 提取摘要
- 翻译文本
- 引用文本
- 添加笔记

点击【提取摘要】，会右侧对话框中生成选中段落的摘要总结：

Our models generalize to the preferences of “held-out” labelers that did not produce any training data. Held-out labelers have similar ranking preferences as workers who we used to produce training data (see Figure 2). In particular, according to held-out workers, all of our InstructGPT models still greatly outperform the GPT-3 baselines. Thus, our InstructGPT models aren’t simply overfitting to the preferences of our training labelers.

Public NLP datasets are not reflective of how our language models are used. In Figure 5, we also compare InstructGPT to our 175B GPT-3 baselines fine-tuned on the FLAN (Wei et al., 2021) and T0 (Sanh et al., 2021) datasets (see Appendix D for details). We find that these models perform better than GPT-3, on par with GPT-3 with a well-chosen prompt, and worse than our SFT baseline. This indicates that these datasets are not sufficiently diverse to improve performance on our API prompt distribution. We believe this is partly because academic datasets focus on tasks where performance is easily measured, like classification and QA, while our API distribution consists of mostly (about 57%) open-ended generation tasks.

#### 4.2 Results on public NLP datasets

InstructGPT models show improvements in truthfulness over GPT-3. As measured by human evaluations on the TruthfulQA dataset, our PPO models show small but significant improvements in generating truthful and informative outputs compared to GPT-3 (see Figure 2). This behavior is the default: our models do not have to be specifically instructed to tell the truth to exhibit improved truthfulness. Interestingly, the exception is our 1.3B PPO-ptx model, which performs slightly worse than a GPT-3 model of the same size. Our improvements in truthfulness are also evidenced by the fact that our PPO models hallucinate less often on closed-domain tasks (Figure 4).

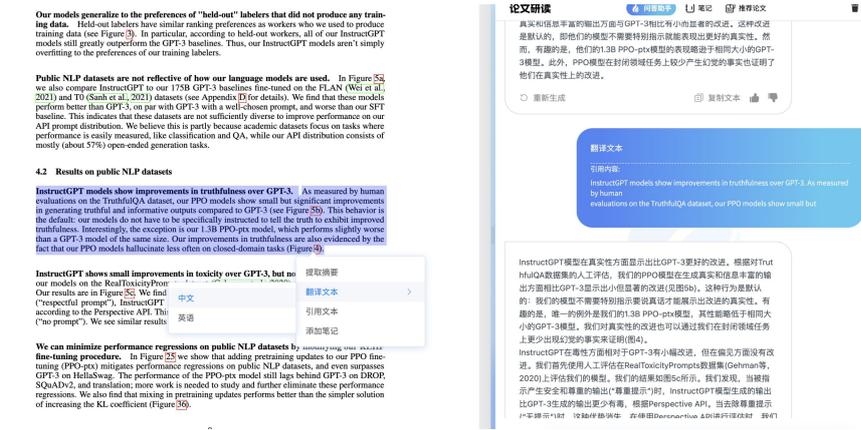
InstructGPT shows small improvements in toxicity over GPT-3, but not bias. We first evaluate our models on the RealToxicityPrompts dataset (Gehrmann et al., 2020) using human evaluations. Our results are in Figure 5. We find that, when instructed to produce a safe and respectful output (“respectful prompt”), InstructGPT models generate less toxic outputs than those from GPT-3 according to the Perspective API. This advantage disappears when the respectful prompt is removed (“no prompt”). We see similar results when evaluating using the Perspective API (Appendix E.7).

We can minimize performance regressions on public NLP datasets by modifying our RLHF fine-tuning procedure. In Figure 2, we show that adding pretraining updates to our PPO fine-tuning (PPO-ptx) mitigates performance regressions on public NLP datasets, and even surpasses GPT-3 on HellaSwag. The performance of the PPO-ptx model still lags behind GPT-3 on DROP, SQuADv2, and translation; more work is needed to improve performance on these tasks. We also find that mixing of increasing the KL coefficient (Fig

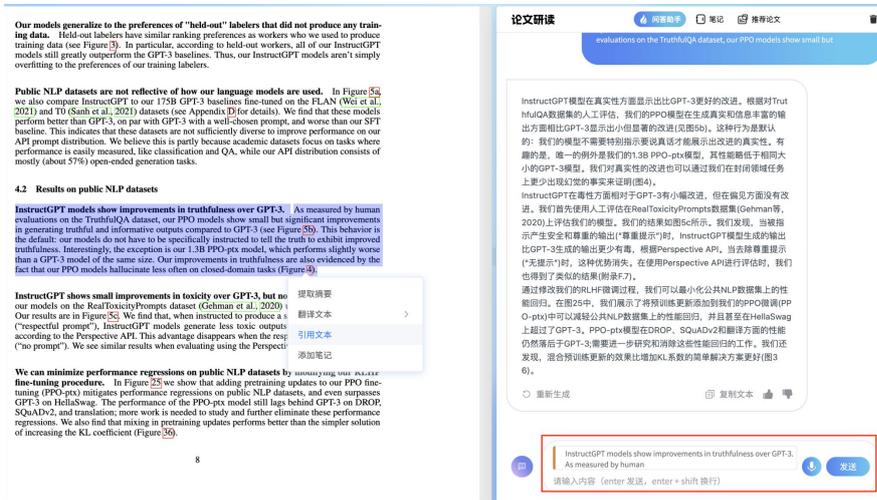
- 提取摘要
- 翻译文本
- 引用文本
- 添加笔记



点击【翻译文本】，会右侧对话框中生成翻译后的内容：



点击【引用文本】，会右侧对话框中自用引用选中内容，可以对选中内容进行问答：

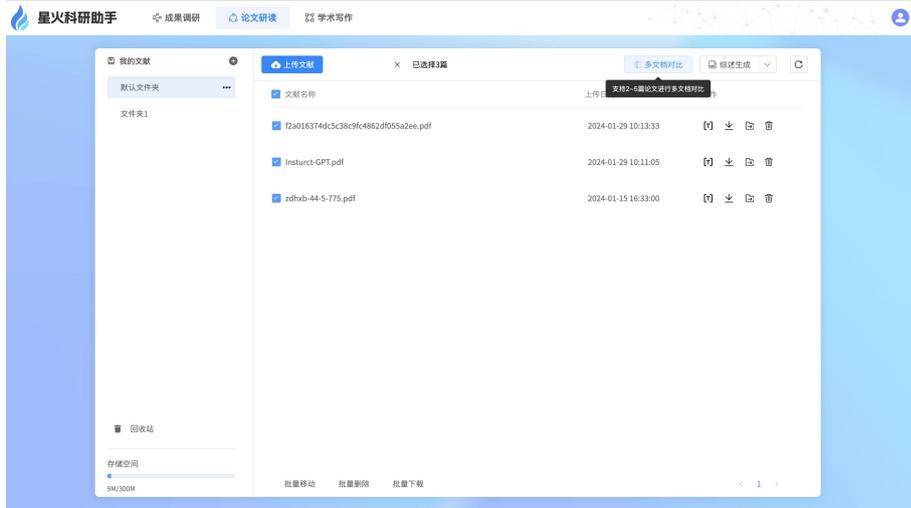


点击【添加笔记】，可将选中内容添加为笔记方便对重点内容进行查看：



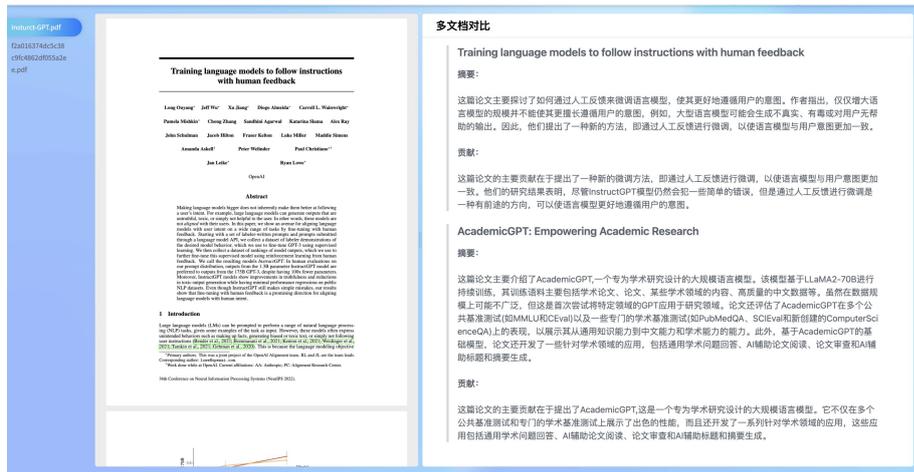
### (三) 多文档对比

在文献列表中选择 2~5 篇论文，点击【多文档对比】进行多文档对比研读页面：



多文档对比研读页面左侧为文献列表，点击可切换查看不同论文内容；

页面右侧为 AI 自动生成的多篇文档的摘要和贡献总结、优点与提出方法对比、以及相同点与不同点总结。



### 多文档对比

#### 多文档对比

对比分析表：

| 论文标题  | 提出的方法                      | 优点   |
|---|----------------------------|--|
| Training language models to follow instructions with human feedback | 通过人类反馈进行微调，使语言模型与用户意图对齐。   | 1. 在提示分布的人类评估中，InstructGPT模型的输出优于GPT-3模型的输出。2. InstructGPT模型在真实性上有所改进，并减少了有毒输出的生成，同时在公共NLP数据集上的性能回归最小。 |
| AcademicGPT: Empowering Academic Research                           | 引入AcademicGPT，专门为学术研究提供支持。 | 1. AcademicGPT在多个公共基准测试和一些专门的学术基准测试上表现出良好的能力。2. 基于AcademicGPT的基础模型，还开发了几个针对学术领域的应用。                    |

相同点和不同点：

相同点：

1. 两篇论文都提出了使用大型语言模型来解决特定领域的问题。
2. 两篇论文都通过实验验证了所提出方法的有效性。

不同点：

1. 第一篇论文主要关注如何通过人类反馈来训练语言模型以更好地遵循用户的意图，而第二篇论文则专注于为学术研究提供支持。
2. 第一篇论文使用了监督学习和强化学习相结合的方法，而第二篇论文则使用了特定的训练语料库和领域相关的应用。
3. 第一篇论文的实验结果表明，通过人类反馈进行微调可以提高语言模型的真实性和减少有毒输出，而第二篇论文的实验结果展示了AcademicGPT在多个基准测试和学术领域应用中的有效性。

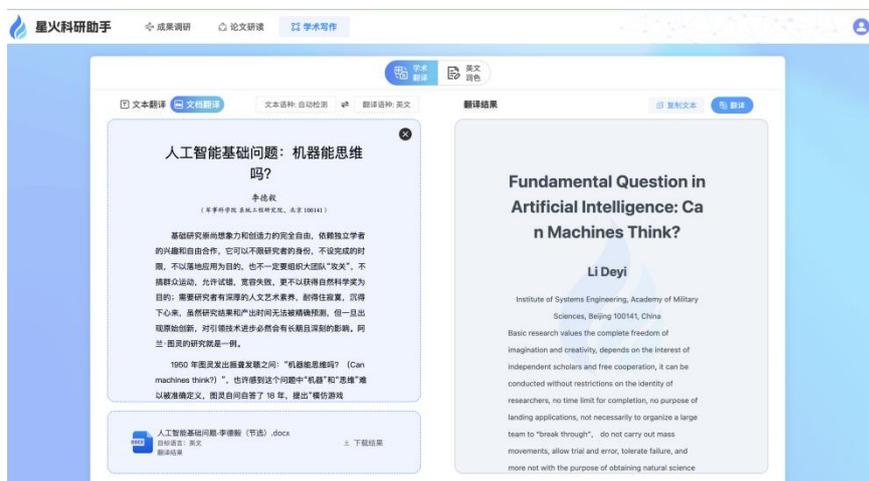
## 四、学术写作

### (一) 学术翻译

默认为【文本翻译】，输入要翻译的文本，最多输入 2000 字符，支持英译中、中译英，输入文本后自动检测语种，点击右侧【翻译】按钮进行翻译，右侧文本框中展示翻译结果；



点击【文档翻译】切换为文档翻译，



### (二) 英文润色

在左侧文本框中输入要润色的文本内容，最多输入 2000 字符，点击【润色】按钮进行英文润色，点击【对比展示】按钮，可以看到润色前后的文本对比。

英文润色

In recent years, WaveNet-based neural vocoder can achieve high quality of reconstructed speech. However, it depends on the amount of speech data because of the speaker-dependent model training method. In this paper, we study the training method of neural vocoders with limited target speaker data. In our proposed method, a speaker-independent WaveNet vocoder is first trained using a multi-speaker speech corpus. Then, the parameters of the speaker-independent model are adaptively updated to obtain the neural vocoder of the target speaker. In our experiments, we compare local updating strategy with global updating strategy in adaptive training, then compare adaptive training method with speaker-dependent training method on the same training data. Experiments show that the neural vocoder constructed by our proposed method can achieve better reconstructed speech quality than STRAIGHT, and the method can achieve better objective and subjective performance than speaker-dependent training with limited target speaker data.

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润色结果

对比展示

In recent years, WaveNet-based neural vocoder vocoders can achieve based on WaveNet have demonstrated the capacity to reconstruct speech with high quality quality. However, their performance is contingent upon the volume of available reconstructed speech. However, it depends on the amount of speech data because of due to the speaker-dependent model training approach, method. In the This paper, paper explores, we study the training method of for neural vocoders with that utilizes limited target speaker data. Our in our proposed method, methodology involves primarily training a speaker-independent WaveNet vocoder is first trained using a multi-speaker speech corpus. Then, Subsequently, the parameters of the this speaker-independent model are adaptively updated to obtain yield the neural vocoder of for the target speaker. In our experiments, we experimental compare comparisons, we juxtapose local updating strategy strategies with global updating strategy strategies in adaptive training, training and

点 对比: 展示

复制文本

润色

润色