AI大模型颠覆程序员的价值

个人简介

崔超 知乎教育生态合作负责人

毕业于北航数学系，曾经是数学竞赛冠军、NOI竞赛保送、ACM亚洲区铜牌

国内最早一批使用NVIDIA显卡和CUDA进行并行计划的程序员

三星综合技术研究院最年轻的算法工程师，在CV方向曾设计出世界排名第一的算法

入选福布斯中国 30 岁以下精英榜单

创业10年，管理过400人的研发团队，2000人的业务团队

为什么投身AGI的方向

table1 table2

世界排名	学校名称	地区	综合得分	学术声誉	雇主声誉	每位教员引用率	师生比
1	麻省理...	美国	100	100	100	100	100
2	剑桥大学	英国	98.8	100	100	92.3	100
3	斯坦福...	美国	98.5	100	100	99.9	100
4	牛津大学	英国	98.4	100	100	90	100
5	哈佛大学	美国	97.6	100	100	100	99.4
6	加州理...	美国	97	96.5	87.1	100	100

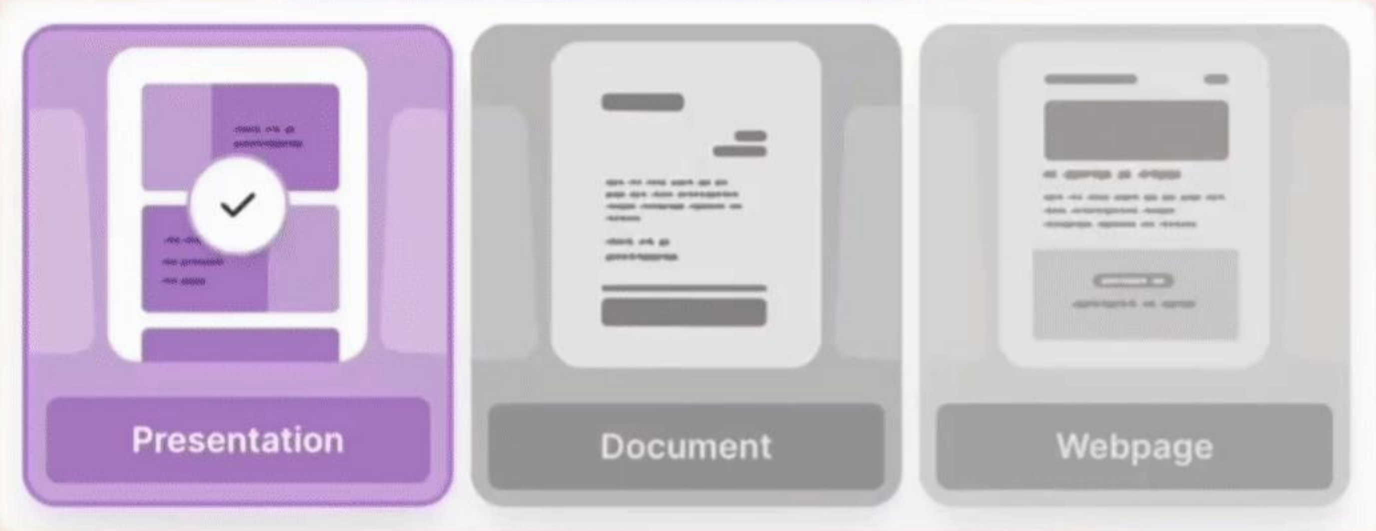
Query

将表一和表二中排名都在前10的学校名字后面加'*'

25/50

CHECK ▷ UNDO

👋 Hi Li, I'm your AI design partner. What would you like to create today?



Sounds good! What would you like the presentation to be about?

Tip: You can enter your own topic, or use one of our suggestions to get started quickly.

新产品策划方案

7/300

0 credits

记下一些文字

他们像往常一样发现 Mario 深入研究低音和人性，他们有一些摘录值得赞赏，还有一些陈旧的道德观察值得倾听。Kelly 和 David 有一些不同的信息要告诉他们。

制作待办事项清单

- [ ] 起床
- [ ] 吃早餐
- [x] ~~刷牙~~

创建子页面

子页面

图 AI 表格 AI 写作 AI 聊天

质量 × 详细 × 多层级 × 多分支 × 清晰 × +

深色 历史

新产品市场推广流程

余: 5次 (每日刷新)

编辑 保存

模板库 新产品市场推广流程 生成

再不投身进入 感觉要无路可走了

早一点进入 说不定我能享受到一些红利

今日课程内容

1、企业借助大模型获得业务增长的可能性

2、过去驾驭AI技术到底都要掌握些什么

3、现在驾驭AI技术门槛低到了什么程度

完课福利

1、无需翻墙的好用AI工具名称和网址

2、购买知乎AGI课程的课程优惠

企业是如何衡量程序员的收入

人才：人只有被企业争抢的时候，价格才会上涨

争抢：只有新技术能给企业带来增长的时候，相关人才才会被争抢

未来的哪些程序员收入会提高

这一轮AI技术的变革，真的能给企业带来增长么？

有句很著名的话：所有生意都可以用xxxxxx重做一遍

互联网 -》移动互联网

AI、AGI、AIGC ？

未来的哪些程序员收入会提高

只有很少的生意、业务，可以重做一遍

但有一些新的生意和业务，过去没得做，现在有的做了

过去我们互联网公司，做一个新业务，都要几十个程序员起，

所以业务规模小的、赛道小的，根本没法做

现在不一样了。

		消费与零售	生命科学与医疗	银行与金融服务	科技	传媒与电信	工业制造	政府与公共服务
新兴的	垂直	个性化对话式零售体验	数字化治疗AR/VR内容生成	欺诈模拟和模式检测	个性化AR/ VR体验生成	原创游戏创作	地质学评估和石油勘探	学术领域的全天候虚拟助理
	垂直	定制化产品设计和推荐	预测性和虚拟患者分诊	税务和合规审计与情景测试	自动化产品和硬件设计	预告片和简介生成	生成式模拟和安全测试	基础设施映射和规划
	垂直	产品细节和摄影生成	用于教育的人体解剖学三维图像	零售银行交易支持	个性化和自动化的UI/UX设计	剧本/配乐设计和字幕生成	三维环境渲染：油井、管道等	灾难恢复模拟
	垂直	时尚服装搭配策划	健康和福祉计划的创建	个性化虚拟财务顾问	产品测试和反馈生成	个性化新闻和内容生成	自动化技术设备培训	欺诈、浪费和滥用预防报告
	垂直	个人艺术创作和编辑	通过分子模拟进行药物研发	生成财务报告分析和洞察力	软件销售、客户体验和留存支持	原创虚拟短篇小说生成	智能工厂生成自动化	附有引文和解释的研究
成熟的	横向	个性化对话式零售体验	自助式人力资源和信息技术功能	端到端自动化客户服务	客户反馈情感分类		自动化代码调试和问题解决	虚拟助手对话生成
	横向	企业搜索和知识管理	3D环境渲染：元宇宙	营销/销售内容生成	无障碍支持（文字转语音和语音转文字）		自主代码生成和补全	跨平台个性化定向广告

借助大模型技术提高收入的可行性

驾驭AI有多难？

我们来直接上一套难的：AI算法论文

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com
Noam Shazeer* Google Brain noam@google.com
Niki Parmar* Google Research nikip@google.com
Jakob Uszkoreit* Google Research usz@google.com
Llion Jones* Google Research llion@google.com
Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu
Łukasz Kaiser* Google Brain lukaszkaiser@google.com
Illia Polosukhin* ‡ illia.polosukhin@gmail.com

谷歌2017年发表

在注意力机制的使用方面取得了很大的进步，对Transformer模型做出了重大改进

3 Model Architecture

Most competitive neural sequence transduction models have an encoder-decoder structure [5, 2, 35]. Here, the encoder maps an input sequence of symbol representations $(x_1, ..., x_n)$ to a sequence of continuous representations $\mathbf{z} = (z_1, ..., z_n)$. Given $\mathbf{z}$, the decoder then generates an output sequence $(y_1, ..., y_m)$ of symbols one element at a time. At each step the model is auto-regressive [10], consuming the previously generated symbols as additional input when generating the next.

The Transformer follows this overall architecture using stacked self-attention and point-wise, fully connected layers for both the encoder and decoder, shown in the left and right halves of Figure 1, respectively.

3 模型体系结构

最有竞争力的神经序列转导模型的编码器-解码器结构[5,2,35],在这里，编码器映射符号表示的输入序列(x_1，...，x_n)转换成一系列连续表示Z= (z_1，...，z_n)。给定Z，解码器然后生成输出序列(y_1，....y_m)的符号，一次一个元素。模型在每一步都是自回归的[10]，在生成下一个符号时，使用先前生成的符号作为附加输入。

Transformer遵循这一总体架构，编码器和解码器都使用堆叠的自我关注和逐点全连接层，分别如图1的左半部分和右半部分所示。

结构巨简单

但完全不知道在干啥

一张图讲清楚Transformer框架

左边是一个编码器模型，右边是一个解码器模型

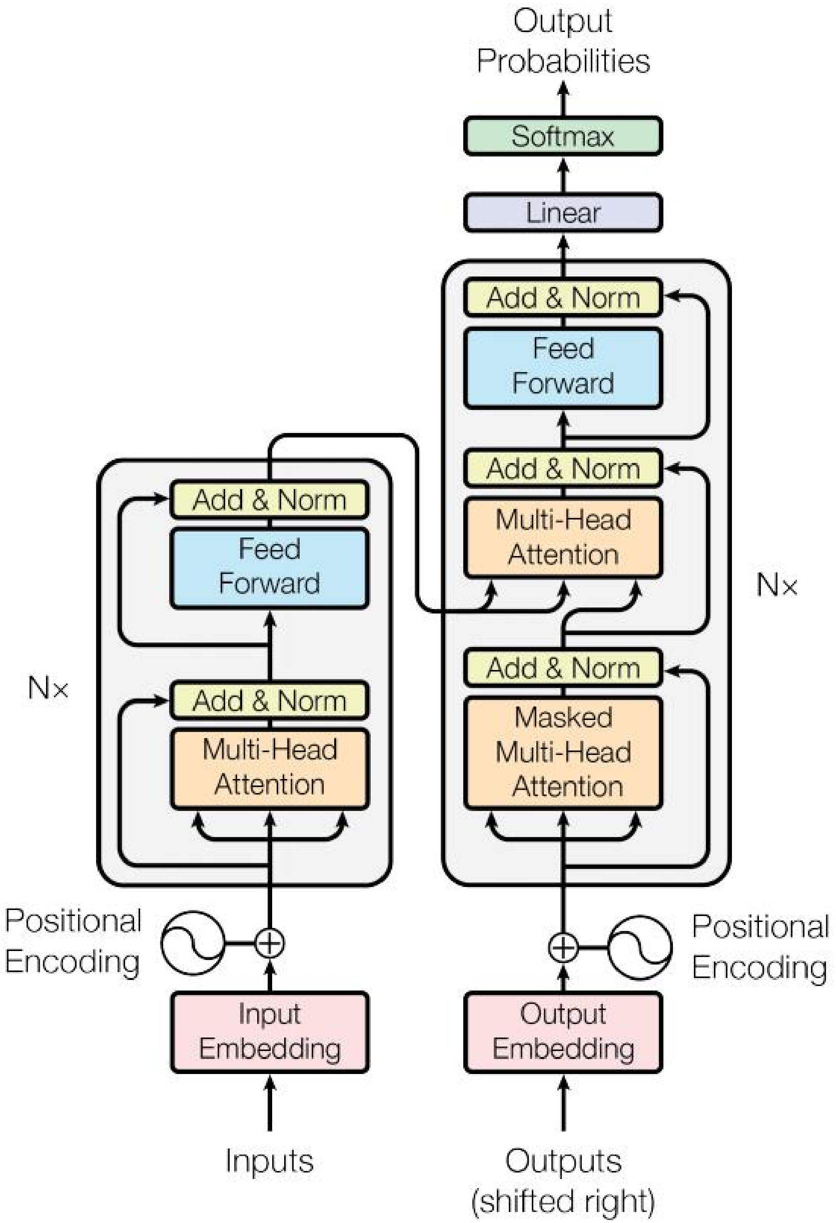


Figure 1: The Transformer - model architecture.

3.1 Encoder and Decoder Stacks

Encoder: The encoder is composed of a stack of $N = 6$ identical layers. Each layer has two sub-layers. The first is a multi-head self-attention mechanism, and the second is a simple, position-wise fully connected feed-forward network. We employ a residual connection [11] around each of the two sub-layers, followed by layer normalization [1]. That is, the output of each sub-layer is $\mathrm{LayerNorm}(x + \mathrm{Sublayer}(x))$, where $\mathrm{Sublayer}(x)$ is the function implemented by the sub-layer itself. To facilitate these residual connections, all sub-layers in the model, as well as the embedding layers, produce outputs of dimension $d_{\text{model}} = 512$.

3.1编码器和解码器栈

编码器由N＝6个相同层的堆栈组成。每层有两个编码器。第一种是多头自注意机制，第二种是简单的、位置上完全连接的前馈网络。我们在两个子层的每一个周围使用残差连接[11]，然后进行层归一化。也就是说，每个子层的输出是LayerNorm（x+Sublayer（x）），
其中Sublayer（x）是子层自身实现的函数。
为了促进这些剩余连接，模型中的所有子层以及嵌入层
都产生维度d_{model}=512的输出。

Decoder: The decoder is also composed of a stack of $N = 6$ identical layers. In addition to the two sub-layers in each encoder layer, the decoder inserts a third sub-layer, which performs multi-head attention over the output of the encoder stack. Similar to the encoder, we employ residual connections around each of the sub-layers, followed by layer normalization. We also modify the self-attention sub-layer in the decoder stack to prevent positions from attending to subsequent positions. This masking, combined with fact that the output embeddings are offset by one position, ensures that the predictions for position i can depend only on the known outputs at positions less than i.

解码器：解码器也由N=6个相同层的堆栈组成。除了每个编码器层中的两个子层外，解码器还插入了第三个子层，该子层对编码器堆栈的输出执行多头关注。与编码器类似，我们在每个子层周围使用残差连接，然后进行层规范化，我们还修改了解码器堆栈中的自注意子层，以防止位置关注后续位置。这种掩蔽，再加上输出嵌入偏移一个位置的事实，
确保了位置的预测只能取决于小于i的位置上的已知输出。

借助大模型技术提高收入的可行性

现在我们驾驭AI需要学会什么？

Fine-tune

原理就只剩一张图

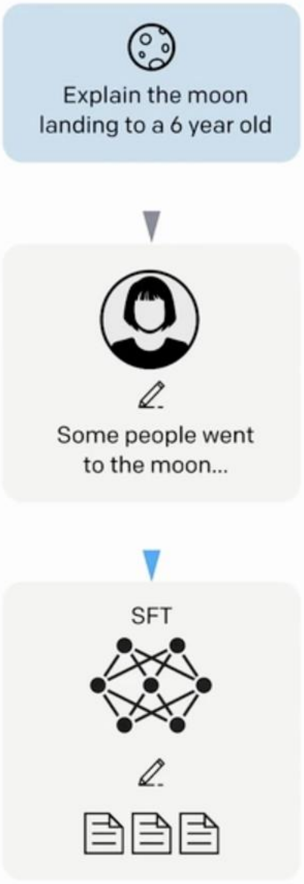
Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.



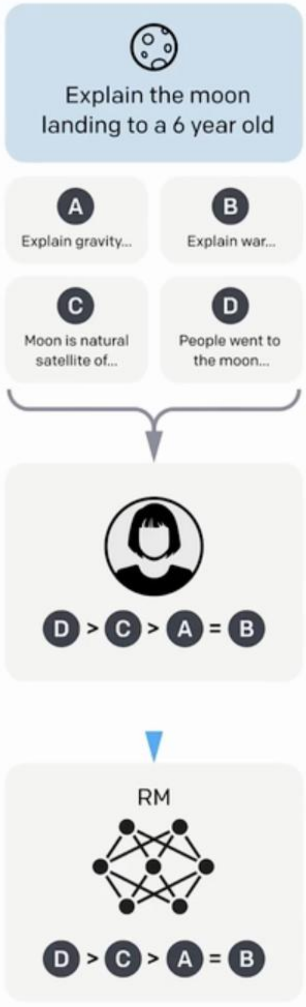
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using reinforcement learning.

第一步：收集示范数据，并制定监督政策。--准备了很多prompt

第二步：收集比较数据，并训练奖励模型。--Fine-tuning

第三步：使用强化学习针对奖励模型优化策略。

2.2 Training Dataset

Datasets for language models have rapidly expanded, culminating in the Common Crawl dataset[2] [RSR+19] constituting nearly a trillion words. This size of dataset is sufficient to train our largest models without ever updating on the same sequence twice. However, we have found that unfiltered or lightly filtered versions of Common Crawl tend to have lower quality than more curated datasets. Therefore, we took 3 steps to improve the average quality of our datasets: (1) we downloaded and filtered a version of CommonCrawl based on similarity to a range of high-quality reference corpora, (2) we performed fuzzy deduplication at the document level, within and across datasets, to prevent redundancy and preserve the integrity of our held-out validation set as an accurate measure of overfitting, and (3) we also added known high-quality reference corpora to the training mix to augment CommonCrawl and increase its diversity.

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

Table 2.2: Datasets used to train GPT-3. "Weight in training mix" refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen up to 3.4 times during training while other datasets are seen less than once.

To train the very first InstructGPT models, we asked labelers to write prompts themselves. This is because we needed an initial source of instruction-like prompts to bootstrap the process, and these kinds of prompts weren't often submitted to the regular GPT-3 models on the API. We asked labelers to write three kinds of prompts:

- **Plain:** We simply ask the labelers to come up with an arbitrary task, while ensuring the tasks had sufficient diversity.
- **Few-shot:** We ask the labelers to come up with an instruction, and multiple query/response pairs for that instruction.
- **User-based:** We had a number of use-cases stated in waitlist applications to the OpenAI API. We asked labelers to come up with prompts corresponding to these use cases.

From these prompts, we produce three different datasets used in our fine-tuning procedure: (1) our SFT dataset, with labeler demonstrations used to train our SFT models, (2) our RM dataset, with labeler rankings of model outputs used to train our RMs, and (3) our PPO dataset, without any human labels, which are used as inputs for RLHF fine-tuning. The SFT dataset contains about 13k training prompts (from the API and labeler-written), the RM dataset has 33k training prompts (from the API and labeler-written), and the PPO dataset has 31k training prompts (only from the API). More details on dataset sizes are provided in Table 6.

Fine-tuning models

Create your own custom models by fine-tuning our base models with your training data. Once you fine-tune a model, you'll be billed only for the tokens you use in requests to that model.

Learn more about fine-tuning ↗

Model	Training	Usage
Ada	$0.0004 / 1K tokens	$0.0016 / 1K tokens
Babbage	$0.0006 / 1K tokens	$0.0024 / 1K tokens
Curie	$0.0030 / 1K tokens	$0.0120 / 1K tokens
Davinci	$0.0300 / 1K tokens	$0.1200 / 1K tokens

Embedding models

Build advanced search, clustering, topic modeling, and classification functionality with our embeddings offering.

Learn more about embeddings ↗

没错，Alpaca是由Meta的LLaMA 7B微调而来的全新模型，仅用了52k数据，性能约等于GPT-3.5。

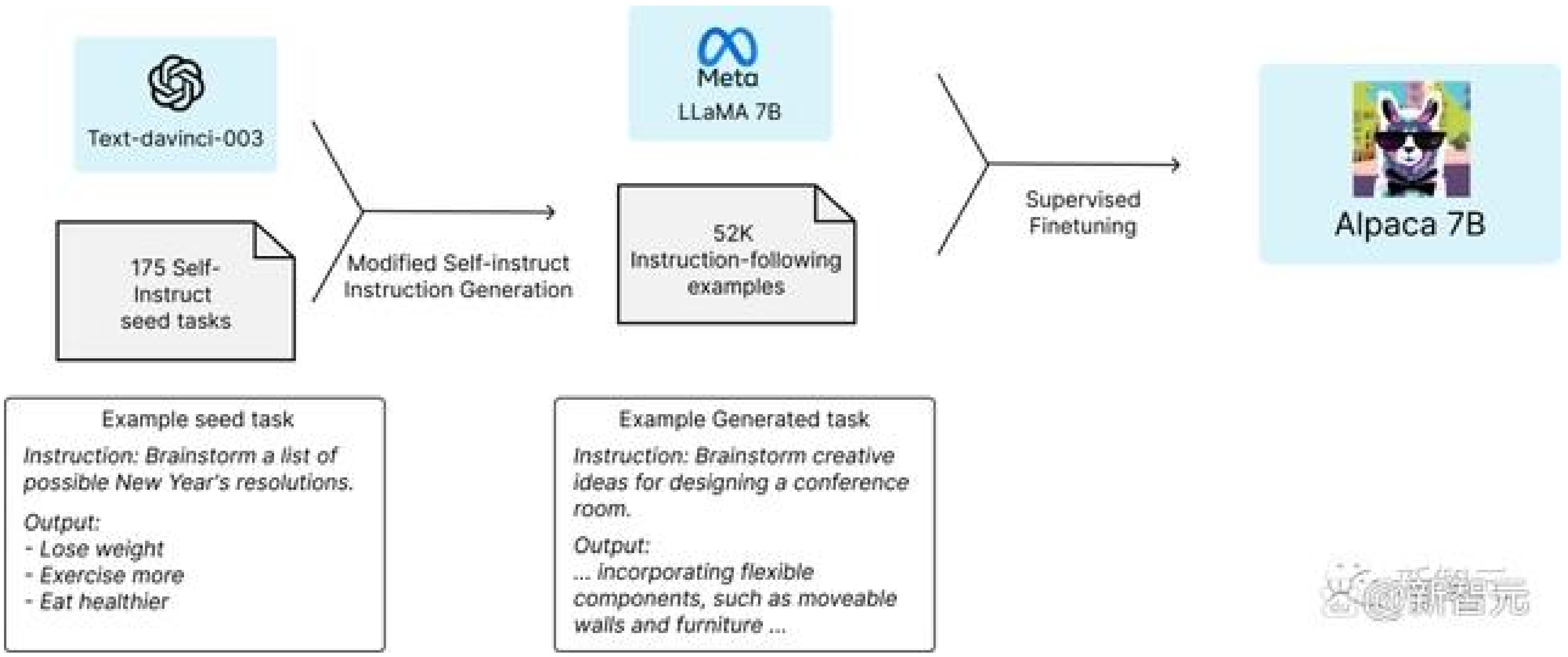
关键是训练成本奇低，不到600美元。具体花费如下：

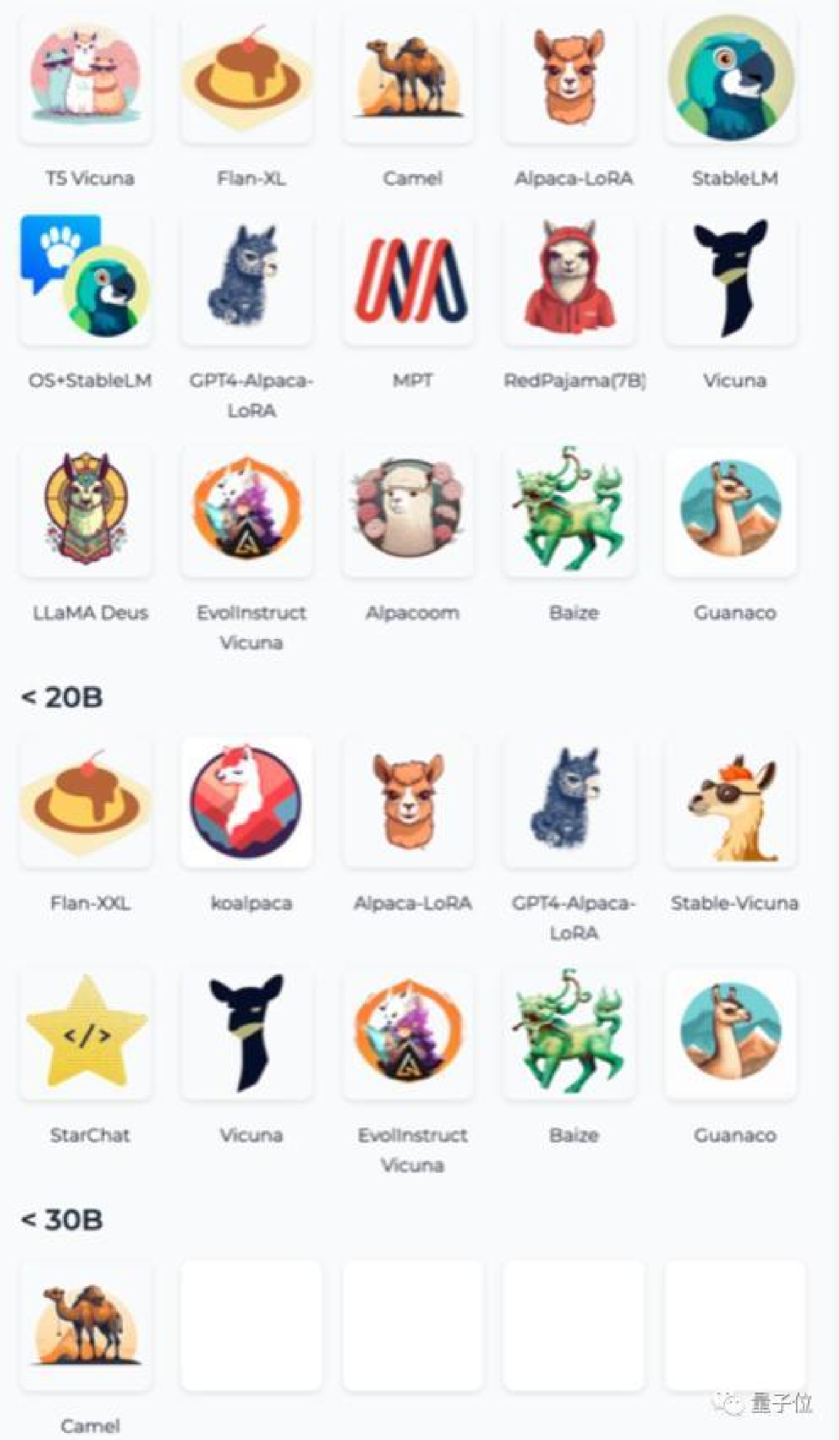
在8个80GB A100上训练了3个小时，不到100美元；

生成数据使用OpenAI的API，500美元。

「Self-Instruct: Aligning Language Model with Self Generated Instructions」

利用Hugging Face的训练框架对LLaMA模型进行微调




T5 Vicuna
Flan-XL
Camel
Alpaca-LoRA
StableLM
OS+StableLM
GPT4-Alpaca-LoRA
MPT
RedPajama(7B)
Vicuna
LLaMA Deus
EvolInstruct Vicuna
Alpacoom
Baize
Guanaco
< 20B
Flan-XXL
koalpaca
Alpaca-LoRA
GPT4-Alpaca-LoRA
Stable-Vicuna
StarChat
Vicuna
EvolInstruct Vicuna
Baize
Guanaco
< 30B
Camel
量子位

扫描上方二维码，
抢占福利名额