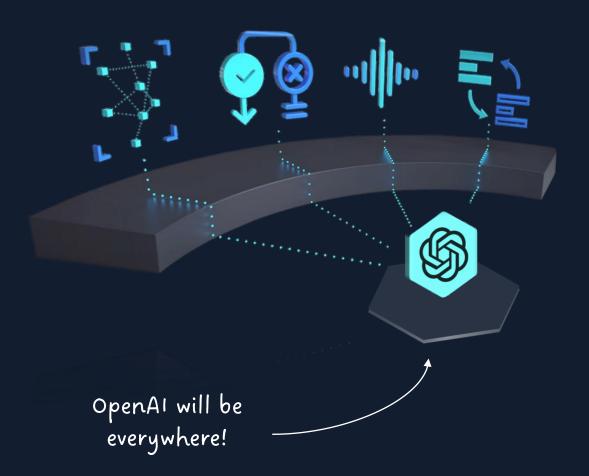


# **Enablement Session GCR**

听过这集,你就是 OpenAI 专家!





### OpenAl

它是什么,它不是什么?

#### With or without Azure

有什么区别,我们的价值如何体现?

#### GPT的限制

Be realistic

#### **Best Practices**

如何显得我们很专业!

#### 各种花式应用

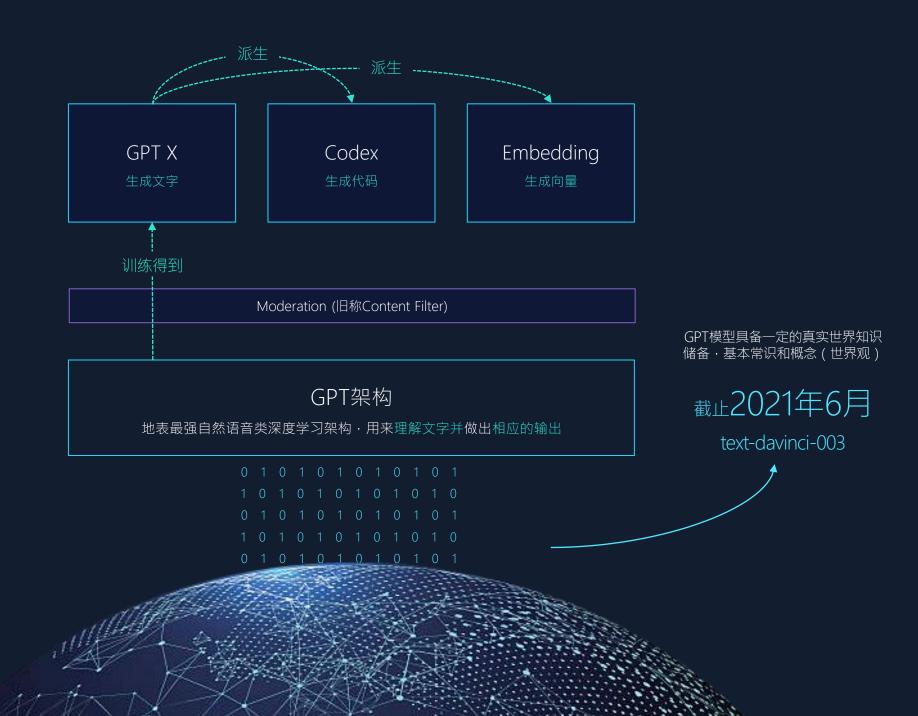
来自世界各地能说的,和不能说的应用案例!

# Open Al 它是...

预训练模型家族 (俗称大模型)

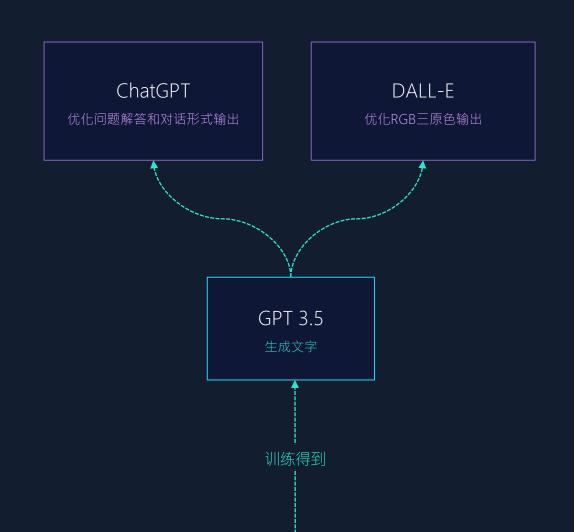
学习方法

学习内容 (文字类素材)



# Open AI 它不是...

- Chat GPT 和 DALL-E 是以GPT3.5为基础衍生 出来的应用
- 目的用来展示GPT可以做到什么程度
- 它不是模型服务,不能直接售卖
- 我们会有对应服务推出,暂定2月28日名为 Enterprise ChatGPT



# OpenAI能做什么?

GPT X

生成文字

#### 1.生成文章 (Completion)

- a. Conversational AI (客服Bot)
- b. 疑难解答 (QA)\*
- C. 翻译
- d. 根据语言理解生成文字
- e. 因果关系推理
- f. 语句/语法/词汇改善
- 2. 归纳/总结 (Summarization)
- 3. 分类 (Classification)
  - a. 情緒分析 (Sentiment Analysis)
  - b. 打标签 / 分类

#### Codex

生成代码

#### 1.文字转程序

- a. Auto testing
- b. Debugging
- c. Coding Quality Check
- d. 代写代码\*
- e. 代码生成文档\* (Reverse coding)

#### Embedding

生成向量

#### 1.文字转矢量

- a. 语义匹配\*
  (Vectorized Semantic Search)
- b. 疑难解答 (QA) \*
- c. 建立更强大的知识库 (KB)

# 和Cognitive Service 怎样区别?

解決方案类 (Pre-built) 泛应用领域 (原子能力) 视频分析/打标签 医学文档解析 分类 生成文字 对话类 语言分析 归纳/总结 翻译 视觉类 语音类 Pre-built OCR方案 NLP / 语言类 发票/小票/收据识别 • 名片识别



- 底层结构差异导致OpenAl各方面碾压传统DNN
- GPT本身丰富的语言理解能力和知识储备可实现零学习或Few-shot learning (举一反三)
- 未来Cognitive Services的底层会被GPT或其它
  Transfer架构取代(比如 Florence)



- OpenAI不具备的能力
- 商用成熟,包括定制化在内的 业务支援丰富

搜索

- 表单解析&识别
- 名片识别



认知服务

• 客戶寻求的解決方案级別的应用 (开箱即用)

### 不是对抗,而是联合!

• Cog Service本身的多元性 + 配合GPT强大的语言能力 = 提升现有能力或打造全新体验



# 那问题来了,Azure OpenAl是干嘛的?

打一个比喻...



### 商务价值





- 私有网络(vNet)
- Private Endpoint/Link
- Custom Domain
- CMK
- RBAC/IAM 权限管理
- Azure AD集成
- 托管身份 (Managed ID)
- 企业合规 ( SOC2 · HIPAA · ISO · GDPR Data Privacy etc. )
- 企业伦理审查 ( RAI )
- 企业级有偿Support
- 多区域可用/容灾
- 保证SLA 99.9%
- 更高Rate Limit (TPM/QPM)
- 更高Token上限 (Fine Tuning)
- Endpoint部署管理和监控
- 基于Azure的API扩充:
- Token监控
- 更好的Error & debug支持
- 集成现有Cognitive Service的服务架构
- 集成资源监控 (Monitor / Log Analytics )
- 集成自动化 ( Automation Task · ARM部署 )
- 集成Express Route
- 集成密匙管理 (AKV)
- 集成数据加密 (Azure Storage)



成果发布
公开测试
正式发布

A
Azure

独家授权

- - API 文档
  - Fine-tuningAPI发布/管控
  - Endpoint hosting

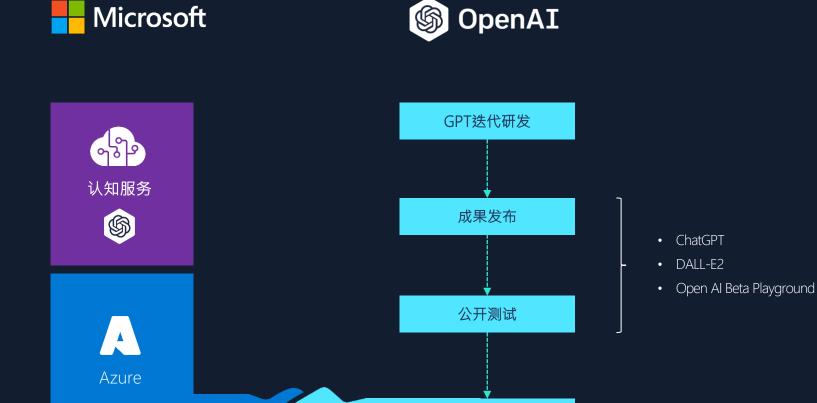
所有在 OpenAl.com 上产生的公共用量,全都是Azure的投资回报

### 模型服务

- AOAI PG有计划两边能力完全平等 (最快3月开始)
- 未来正式模型,两者间会同步发布

#### 但是

- 两边的gap不会完全消除
- 由于两边企业性质导致
- 客户用OpenAl作为early preview, 然后再挪到Azure



正式发布

## 解题思路1 - 如何实现属于我的ChatGPT ?

因为前述GPT的学习特性,Customize的方法也和传统思路不太一样

### 以客服QA Bot为例

- 1. 使用Embedding模型把知识库(KM)转为矢量,并保存到Vector Database做匹配和搜索
- 2. 用戶对Bot输入一段自然语言
- 3. 对其做同样的矢量转换 (一样的Embedding模型)
- 4. 將输入的矢量和Vector Database做近似度计算(=语义匹配),抽取出关联度最高的条目/文章。這部分建议搭配Open Source (比如 Redis, FAISS)
- 5. 返回文章給GPT 作为prompt engineering的一部分,得到自然语言形式的回答
- 6. 返回结果給用戶

# 解题思路2 - Embedding还能怎么玩?

Embedding不支持Fine-Tuning,但是它的应用最为广泛,手法也需要结合传统Machine Learning。 思路如下:

#### 以舆情分析为例

- 1. 使用Embedding模型把评论数据转为矢量 ,并保存到Vector Database
- 2. 对每一个Review人工标注(Positive, Negative等)
- 3. 使用传统ML分类算法学习标注
- 4. 对新的评论,同样用Embedding转换为矢量。
- 5. 用3学习到的模型进行预测,得到标签。

同样适用于其他类型的 Machine Learning手法

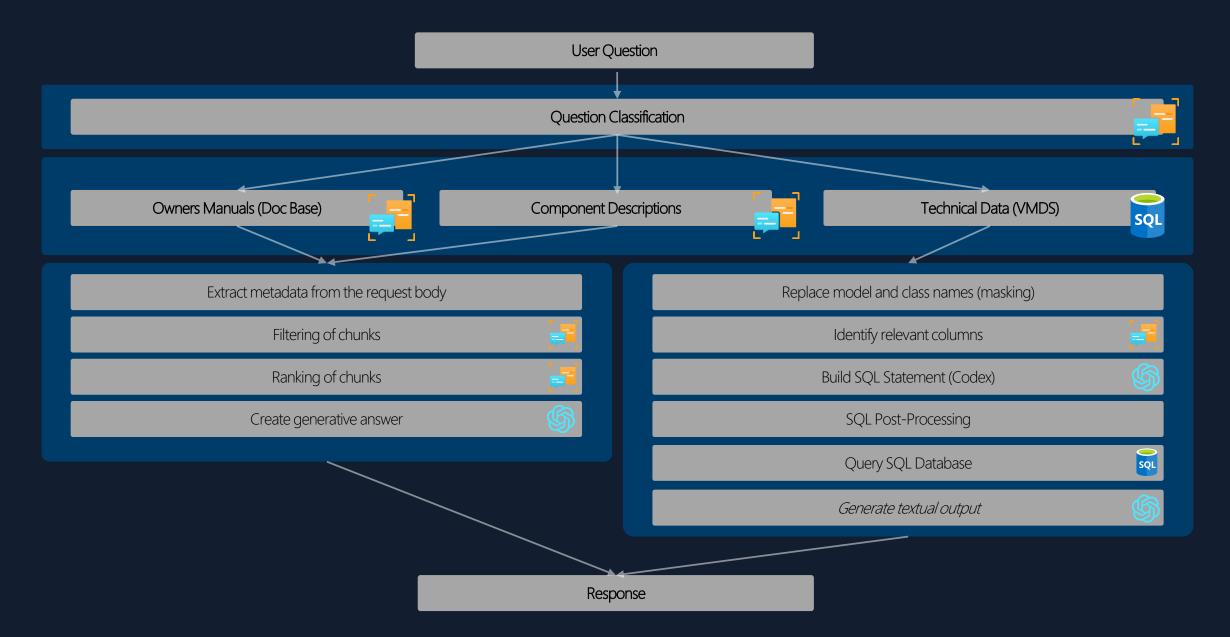
# 解题思路3 - 怎么应用到你的领域? (Data Grounding)

OpenAI的解决方案从来都不应是单独的,它在实际应用中需要结合多个其它服务构成完整方案:

#### 常见的经典构成

- 1. 分类 + (Codex) + GPT (根据不同场景,做不同处理)
- 2. Azur Bot + Embedding + Semantic Similarity + GPT (经典KB/QA, Virtual Agent)
- 3. LUIS/CLU 提取intent 转对应prompt + GPT (意图分类,限制不相干内容扩散)
- 4. GPT提取NER + Search Expansion + GPT (KG search的加强版应用)
- 5. Meta-prompt engineering 定型文做整体指引 (例如:总结对话·抽取大意, Call Center 合规检查)
- 6. 推荐场景新体验 (Search + 客户资料 作为 context + GPT)

## 某汽车客户QA GPT应用流程



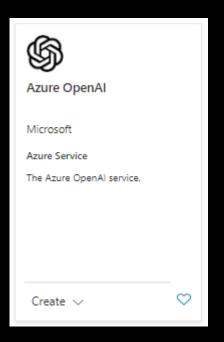


实战经验

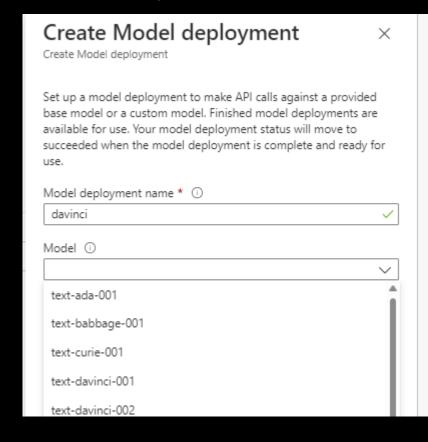
Best Practices

# Azure OpenAl 测试体验: Azure Open Al Studio

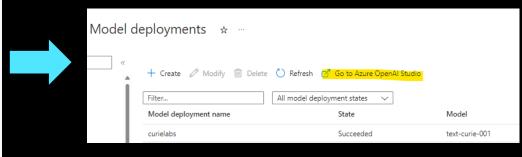
Azure Marketplace & create AOAI resource



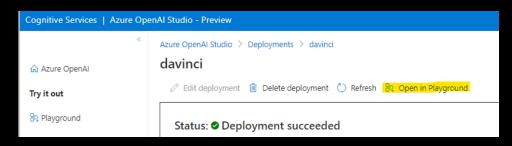
Create your base model



Azure Open Al Studio

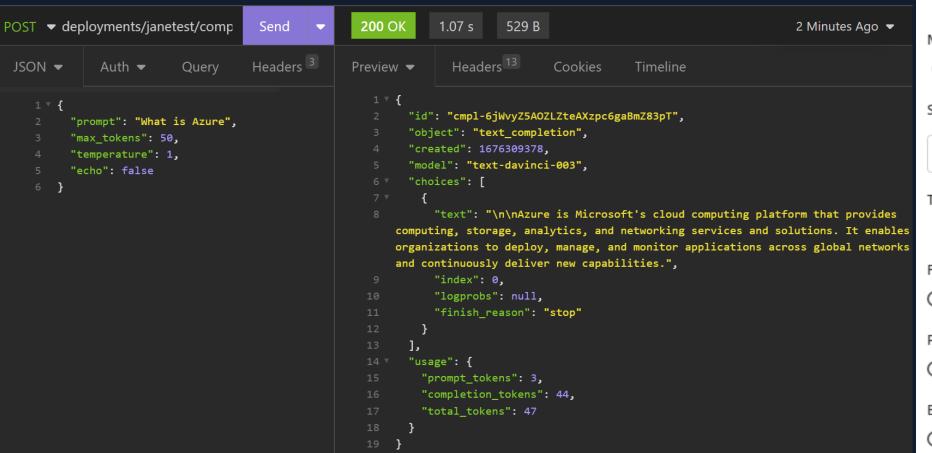


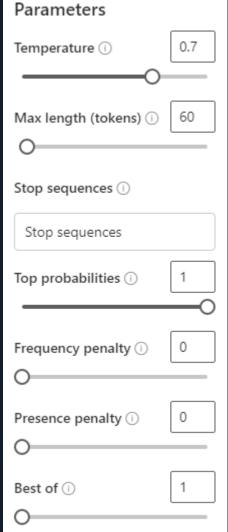
Open playground in your deployments & model to check this out



### 重点理解这些最常用的参数

- · Parameters 参数
  - Temperature Randomness / Creativity slider
  - · Max tokens After Max Tokens are reached, stop the completion.
  - Freq penalty Don't repeat words in your completions
  - Presence penalty Don't use language that has already appeared in the prompt





# 如何评估Completion调用费用

- 英文750~800 words = 1000 token (1.33倍率), input+output 两侧token都要计费
- 中文以及其它全角字符token倍率差异比较大,难在纸面上预测。越是生僻复杂结构的字,token消耗越多。
- 最好方法是测试一些接近真实用例的情景,衡量token消耗情况。

估算方式\*: OpenAl API (官方) or Token estimator (gpttools.com)

Sentence:

• Azure OpenAI service is General Available now!

Tokens:

• [AZ]-[ure] [Open]-[Al] [service] [is] [General] [Available] [now][!]

Azure OpenAI service is General Available now!

## In-context 调用可能可以满足部分定制化需求

Zero-shot - Predicting with no sample provided

One-shot - Predicting with one sample provided

Few-shot – Predicting with a few samples provided

#### Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.



#### **One-shot**

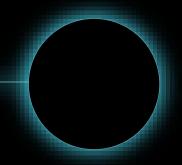
In addition to the task description, the model sees a single example of the task. No gradient updates are performed.



#### Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed





# 正确理解Fine Tuning

如果有客户抱怨怎么我越Tune越差??

Here's why

# 正确理解Fine Tuning

所以我们作为大人,也要用榜样/例子來引导孩子模仿,而非直接教他对或错,因为这样会破坏它的现有认知 (Supervised Learning)



Fine Tuning就是用例子來引导 GPT的过程

而怎么设计Prompt是个很深的 学问。 微软可以帮助客户设计 Prompt Design



GPT像个小孩,它阅遍了 全世界的书籍

它是通过主观例子来学习世界。 例子没有对错 ,只有相对好坏 (Reinforcement Learning)

# Fine Tuning, not "Fine" Tuning

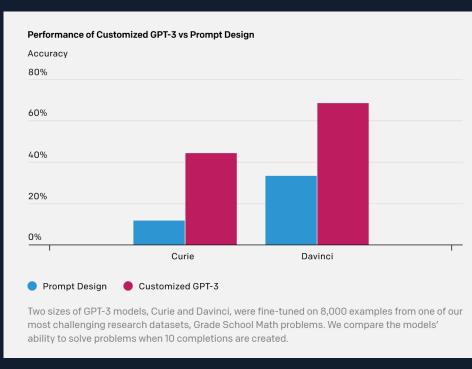
#### 避免撞墙的小技巧

- 不要过度重复利用同一个数据 (技术语言:正确设置参数)
- 尽量接近真实用户用例和习惯 (技术语言:保持学习和验证数据格式高度一致)
- 不同的case要有对应的Prompt Design,不要模板化
- Meta prompt engineering 明确指示弱输出范例,有效避免 "不懂裝懂"
- 示例要足够明确性和具体性。配合逻辑解释会帮助获得更好Fine Tune表现,尤其数据量不大时。
- Fine Tune可以循序渐进,避免一次喂太多数据。 从几百开始,逐渐加大数据量。

更多具体Best Practices可以联系 GBB / Specialized CSA 以及PG来协助客户 !

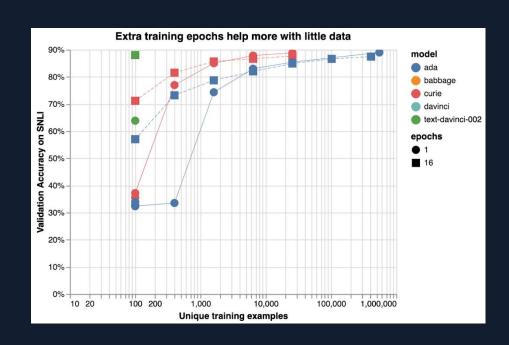
# 什么时候用Fine Tuning?

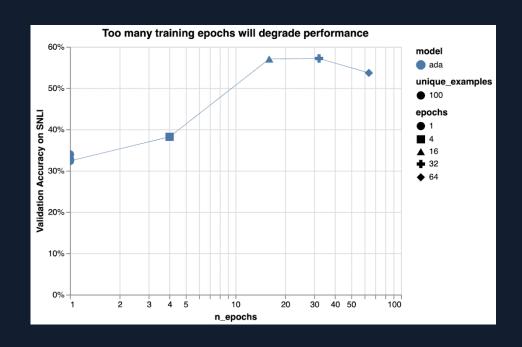
- Fine-tuning 主要是用来改善长期输出形式。相对的Prompt Engineering是短期/一次性改变输出的方法。
- Fine-tuning的长期表现会随着样本数量的翻倍呈现类线性特性的增长。
- 建议首先做prompt engineering来验证提升潜力。 然后转为Fine-tuning 做长线改善以帮助节省token,降低TCO。
- Fine-tuning可以用来限定范围,提高domain相关度
  - 根据某一类特定产品标签生成描述
  - 根据某一篇博文内容风格写推广广告
  - 企业级(知识库)客服Bot



### 如何正确选择Fine Tune超参数!

#### 同一组数据(SNLI)下不同epoch参数的Fine Tune表现:

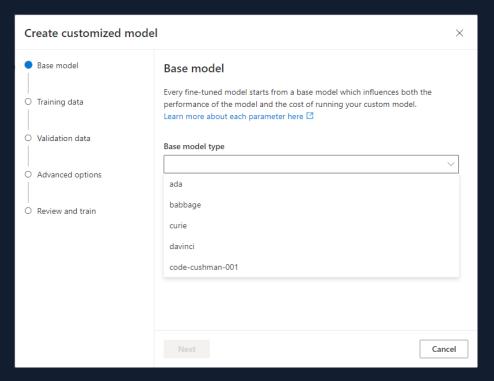


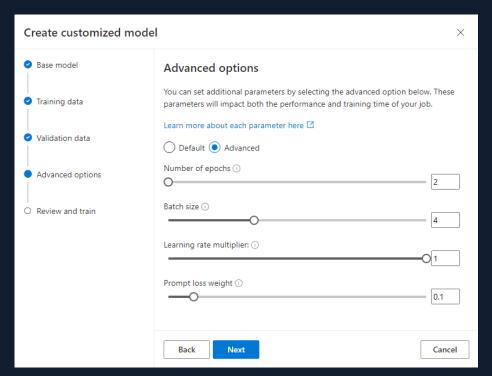


#### General建议

- 如果样本量不大或质量不保证(如未经校准的数据),控制epoch 8~16 有助于有效提升同精度表现
- 如果样本量足够,建议控制epoch 1~4,可以有效避免过拟合
- 模型越复杂epoch可以越小,实现更低的训练成本

### 如何正确选择Fine Tune超参数!

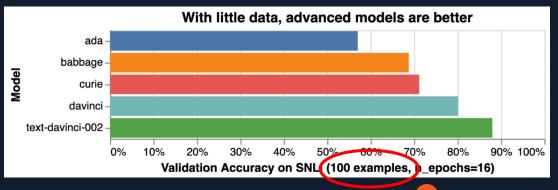


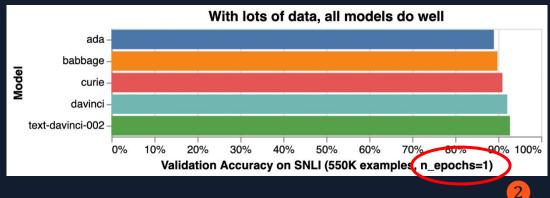


Parameter name	Description	
Number of epochs	The number of epochs to train the model for. An epoch refers to one full cycle through the training dataset.	
Batch size	The batch size to use for training. The batch size is the number of training examples used to train a single forward and backward pass.	
Learning rate multiplier	The learning rate multiplier to use for training. The fine-tuning learning rate is the original learning rate used for pre-training, multiplied by this value.	
Prompt loss weight	The weight to use for loss on the prompt tokens. This value controls how much the model tries to learn to generate the prompt (as compared to the completion, which always has a weight of 1.0.) Increasing this value can add a stabilizing effect to training when completions are short.	

## 模型并非越新, 越大就越好!

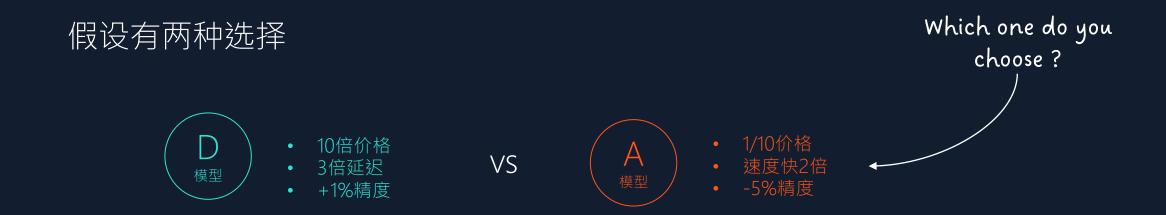
#### 同一组数据(SNLI)下不同模型Fine-tuning的结果





Model	Illustrative accuracy*	Training cost (Open AI)	Inference cost
ada	89%	\$0.0004 / 1K tokens (~3,000 pages per dollar)	\$0.0016 / 1K tokens (~800 pages per dollar) 3
babbage	90%	\$0.0006 / 1K tokens (~2,000 pages per dollar)	\$0.0024 / 1K tokens (~500 pages per dollar)
curie	91%	\$0.003 / 1K tokens (~400 pages per dollar)	\$0.012 / 1K tokens (~100 pages per dollar)
davinci	92%	\$0.03 / 1K tokens (~40 pages per dollar)	\$0.12 / 1K tokens (~10 pages per dollar)

# 模型并非越新, 越大就越好!



- 模型精度是有代价的。 选哪个更合适是个Business Question而非Technical Question
- 每个use case都有一个独特的成本收效平衡点

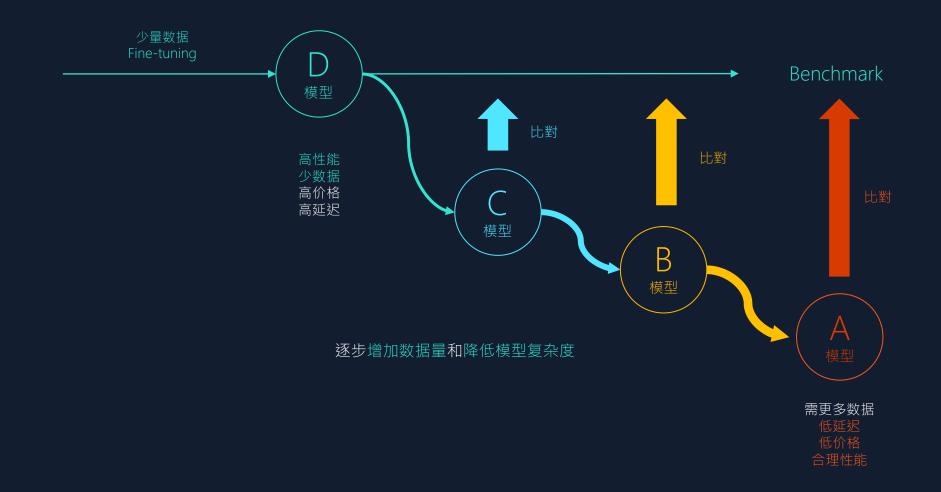
## 模型并非越新, 越大就越好!

#### General建议

- 有大量优质(指人工审核/达标的)数据,建议低复杂度模型,精度或许能媲美Davinci,而ROI更高。
- 如果是分类/归纳这类相对简单的任务,建议A模型
- 如果数据量不大(几百)或质量不保证(如未经校准的数据),則建议D模型

### General建议

- 步骤建议先从Davinci开始建立一个benchmark,随后逐一降低模型复杂度验证Fine-Tuning能达到的结果
- 选出一个客户认为最均衡的模型



### 如何评估预算

- 英文750~800 words = 1000 token (1.33倍率)
- 中文以及其它全角字符token倍率差异比较大,难在纸面上预测。 越是生僻复杂结构的字,token消耗越多。
- 最好方法是测试一些接近真实用例的情景,衡量token消耗情况。

#### 估算方式\*





#### 案例

- 某知名电商2C客服APP有 10万月均活跃客户,每人每月平均10次互动,每次总计250字数 (英文)
- 模型每周训练一次20小时,每月24x7供应

#### 以Ada为例:

(100,000 \* 250 \* 1.33 / 1000 ) \* \$0.0004 + (20 \* 4 \* \$20) + (730 \* \$0.05) = \$1649.8 /每月



\* 我们的finetune计价方式和OpenAI不一样, 无法互换

### 知识产权归客户所有,同样法律责任也是!

详见Azure open AI FAQ

https://learn.microsoft.com/en-us/legal/cognitive-services/openai/data-privacy?context=%2Fazure%2Fcognitive-services%2Fopenai%2Fcontext%2Fcontext

### 知识产权和数据隐私保护声明

承诺不擅用客户数据,数据内部处理流程等细节

https://learn.microsoft.com/en-us/legal/cognitive-services/openai/data-privacy?context=%2Fazure%2Fcognitive-services%2Fopenai%2Fcontext%2Fcontext

# GPT / OpenAI 限制

无法在离线跑。 现在不会,未来也不见得会。

GPT不擅长数字和推理类处理。

GPT缺乏可靠性 (甚至会胡扯)。 其商用稳定性需要大量依赖精良的Fine Tuning!

只有GPT X和Codex能Fine-Tune, Embedding不支持\*



# Use Cases

Get Inspired

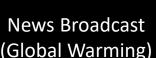
### **Media Example**

News Analyses & Article Creations

Search SEO Virtual Agent Analytics Reporting Knowledge Mining









Azure Azure
Speech OpenAl
Transcription Text Completion

**Content Creation** 

Ideation Productivity Personalization Accessibility A/B Testing

#### **Topic Classification**

Global warming, Deforestation, Carbon footprint

#### **Entity Extraction**

Organizations: IPCC, UNFCCC, Green Peace

Geography: Canada, USA

#### **Key Word Extraction**

Human activities, fossil fuels, earth atmosphere

#### **Question and Answer**

What is the Intergovernmental Panel on Climate Change (IPCC)?

The IPCC is an international organization that studies climate change and the effectiveness ...

#### Video summarization

The article discusses about global warming and its effects on the Earth's atmosphere, wildlife, and human communities. It states that the primary cause of global warming is ....

#### News article generation (or blogs, social media)

Global warming is the gradual increase in the overall temperature of the Earth's atmosphere, primarily caused ...

#### **Script Generation**

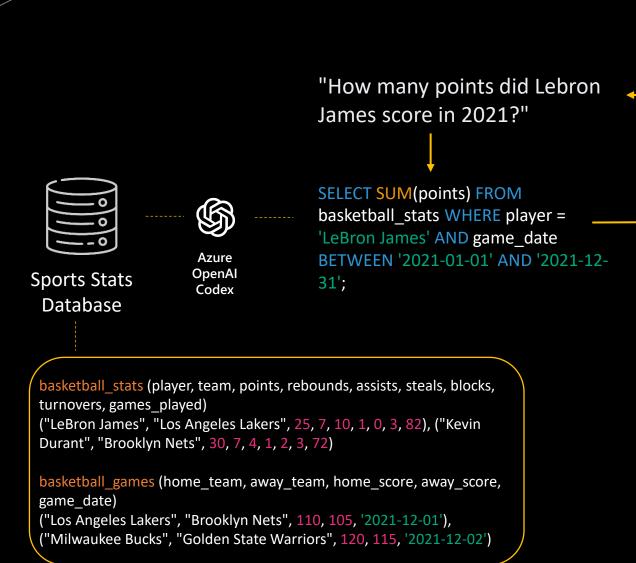
Act 1: The show opens with a shot of a beautiful coastal town Act 2: As the town struggles to cope with the crisis ...

#### Personalized Content generation (or Advertising)

Simon, as someone passionate about global warming, you are aware of the urgent threat it poses to our planet ...

### **Sports & Entertainment Example**

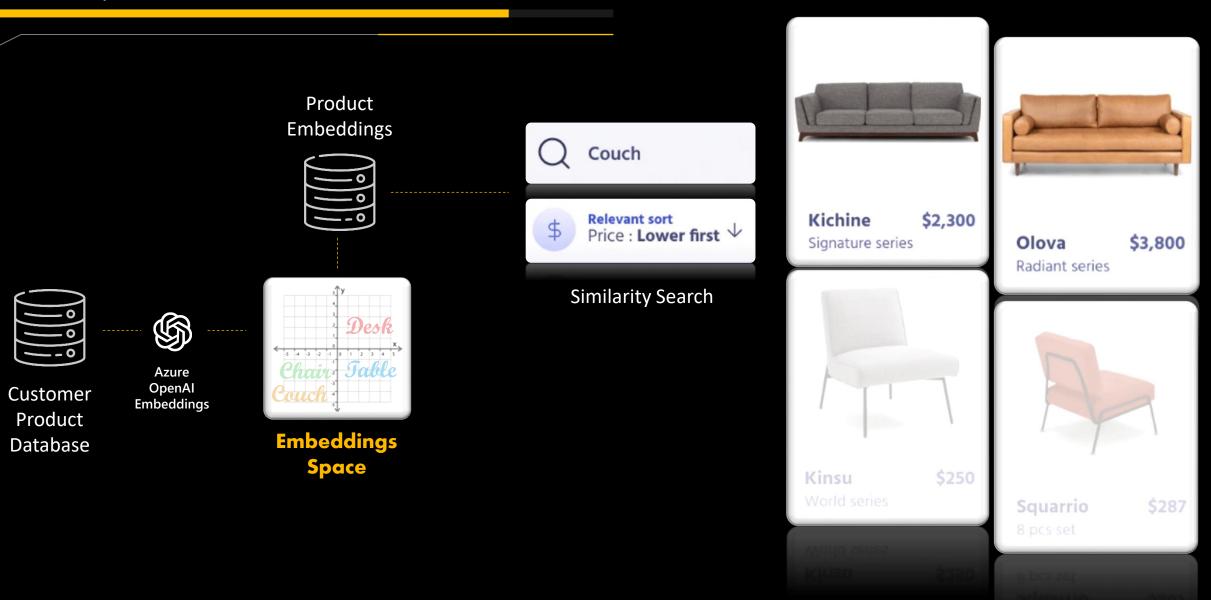
Natural language to SQL to surface stats data (Fan Engagement)





#### **Retail Example**

Similarity Search

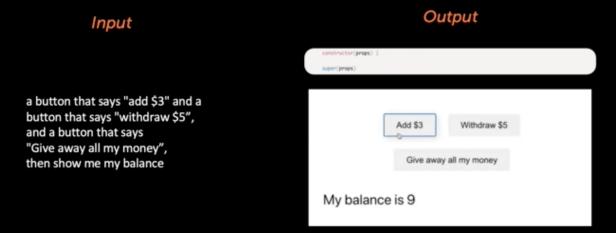


#### **Marketing Example**

Digital Creative Assistant – Dalle-2

### Synthetic Brand Ambassador (GDPR-safe) Output Input Generate a white female Generate images, concepts and ideas Output Input a green c

#### No code Web and App Development

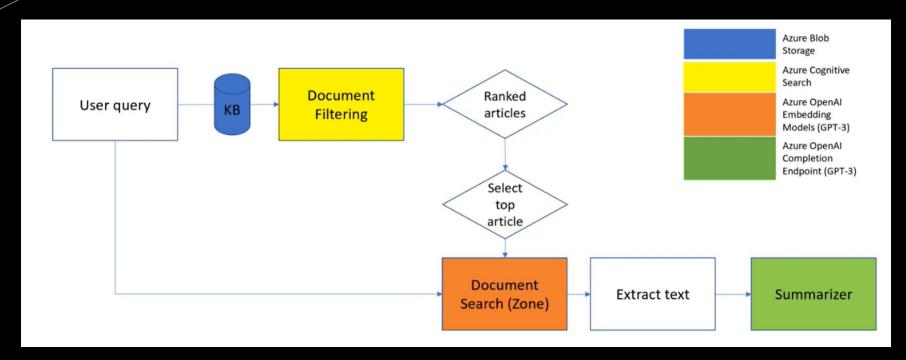


#### Produce rough Layouts



#### **In-house Analyst Example**

**Query-based Summarization** 

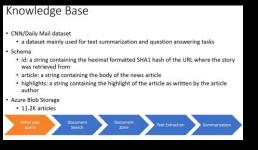


#### Use case overview:

- Document search
- Document Zone search
- Text summarization

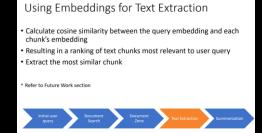
#### Advantages of query-based summarization:

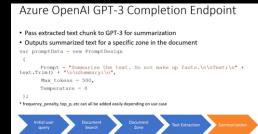
- 1. Shortens reading time
- 2. Improves the effectiveness of searching for information
- 3. Removes bias from human summarization techniques
- Increases bandwidth for humans to focus on more in-depth analysis





# Azure OpenAl Text Search Embeddings Text segmentation Divide document into consumable chunks due to token limitation Paragraph boundary detection (\*\*) Results in "chunks" Each chunk gets embedded with doc model ("text-search-curie-doc—001" User can send a document specific query – gets embedded with query model ("text-search-curie-query-001")





#### Gaming

Minecraft Mod Creation



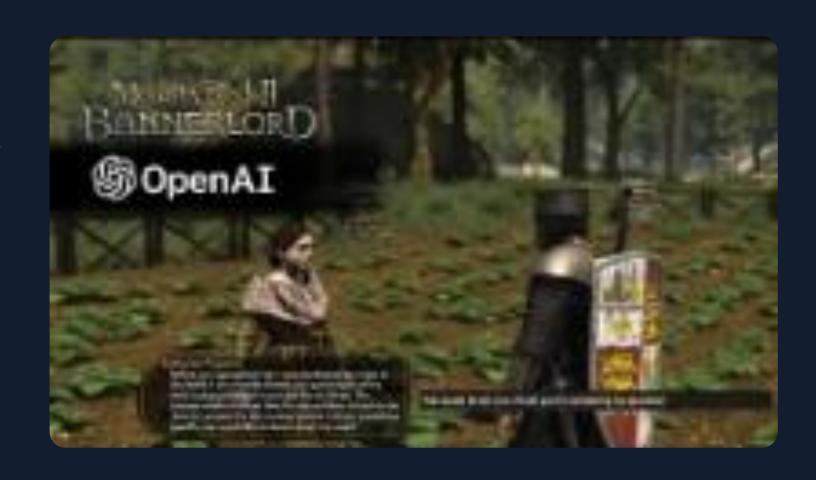
## Mount Bladell BANNERLORD

#### 情景

- 根据玩家交流,动态生成NPC互动
- 互动内容会参考NPC所处位置,职业, 状态,游戏进程及当时世界观。
- 非常优秀的Fine-Tuning案例

#### 机会

结合微软TTS,Custom Neural Voice和Cross Lingual Adaptation实现更强大的NPC表现力及游玩体验



## AI DUNGELN

#### 情景

- 文字类冒险RPG
- 玩家自行编辑剧情,游戏自动生成图 文并茂的开放式故事线,供玩家互动

#### 机会

结合DALL-E2, Unity Engine自动生成沉浸式游玩体验。配合定制化的Content Moderation加固生成内容的安全性/合规性



necklace will be arriving today.

You scout the banquet looking for potential to bring back to your shop, after all of this is done.



At the banquet, you are surprised to see
Lord Bryan. You discretely scan the room,
looking for potential treasures to sell.
Unfortunately, other than his companion,
Lady Moira, Lord Bryan seems to be alone,
and is not wearing a necklace at all. "Lord
Bryan?" you call out to him.



He turns and sees you. "Oh, hello Shane.

Lady Moira and I are here to meet with King
Geoffrey. How are you?"

"I am doing well, thank you. What brings you to the palace today?"



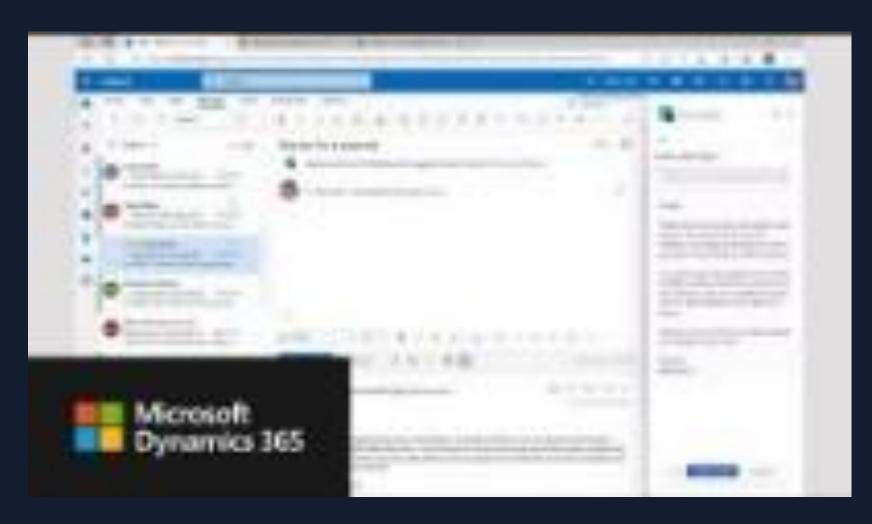
Story

What happens next?



#### 情景

根据上下文邮件信息,结合CRM 最新资料自动撰写邮件





#### 情景

动态生成问卷调查,总结并提示改善点

- 根据提示,自动编写调查问卷 (生成问题)
- 解析用户反馈(文字类)
- 总结
- 提出汇总改善点



an in

Sign up for free

## End-to-end encrypted forms & surveys for HR's

BlockSurvey is a privacy-first platform. No ads, no trackers.

Protect your respondents' data and privacy. The only survey tool that keeps your data safe.



**★★★★**G2 CROWD

DAPP.COM

★★★★★
CAPTERRA

4.8 Star Rating

Editor's choice

4.9 Star Rating

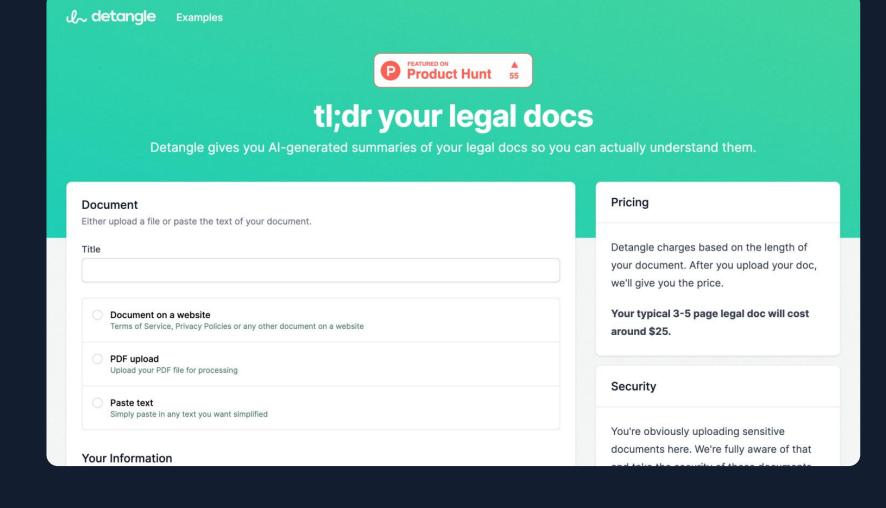


### Detangle Al

#### 情景

用户上传法律文献/文件,自动解析 并归纳成重点汇总

- 解析文章
- 总结/归纳

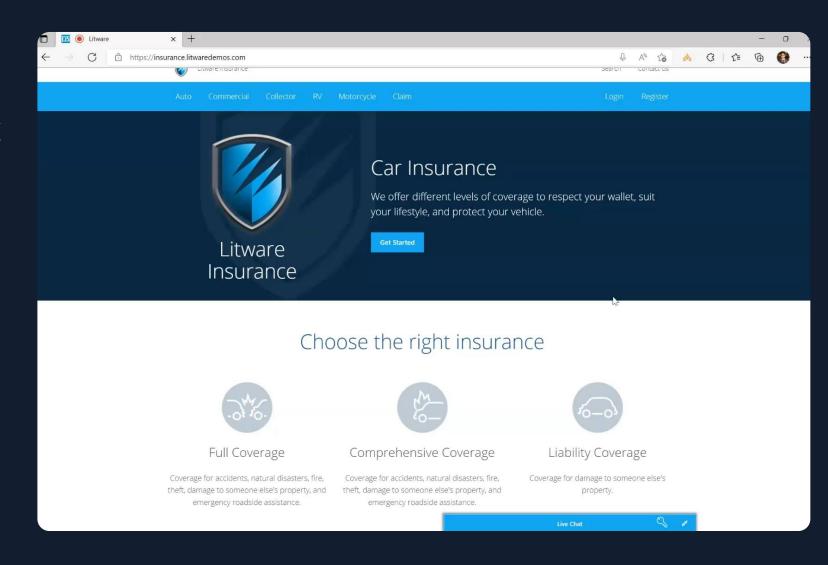


### 更好的客服AI体验

#### 情景

更好地协助完成自动交易,更自然的交互 和客户体验

- 语义理解
- 按情景动态生成自然对话
- 多轮对话( 上下文继承)
- 多语种对话
- 图像识别和解析
- 声纹辨识
- Text-to-speech



## 代码生成,品控,优化和Debug



#### 情景

根据用户指示和需求,自动生成满足需求的代码(可切换语言)。实现代码自动品控,测试,优化和除错等情景。

- CODEX代码生成
- GPT Embedding 进行语义理解和匹配

```
screensnot = imageGrap.grap()
         # Convert to text
         text = image_to_string(screenshot)
         # Parse text for email addresses
         emails = re.findall(r'[\w\.-]+@[\w\.-]+', text)
         return emails
     def validate(addresses) :
27
```



## FORTNITE 数字虚拟人游戏直播



- 游戏情节语音解析 (STT)
- 视频标签和图像分析 (解析场景,关键 物品,行为)
- 玩家对话内容解析
- **S**OpenAI
- 事件驱动的场景描述



- 仿真语音合成(TTS)
- 声纹模仿



## 未完待续...