ChatGPT的前世今生

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个人介绍

- 教育经历
  - **香港中文大学**, 博士, 2018
    - 自然语言处理
  - 山东大学, 本科&硕士, 2009&2012
    - 计算机视觉&信息检索
- 工作经历
  - 北京百度, 2012
  - 深圳无觅, 2013
  - **深圳腾讯AI Lab**, 2018
- 南京航空航天大学, 2021
  - **自然语言处理**

人工智能发展史

https://www.itheima.com/news/20210507/180049.html

接触AI

第 18 章　数字图书馆中基于内容的检索

1　如何检索图像

图 18-1 中显示的是名画“享乐的花园”（The Garden of Delights）的一部分，它由 Hieronymus ch（1453-1516）创作，现收藏于西班牙马德里普拉多美术馆。这是一幅著名的绘画作品，但们也很可能在理解作者的创作意图方面遇到麻烦。因此，如果我们希望进行图像的自动检索，们就不难理解用机器来提取蕴含于图像中的语义将是一个更为艰巨的挑战。对于一幅图像来合适的注解当然应该包含“人物”这个描述符。另一方面，这幅图像是否会被网络上用于过含有“裸体”信息的系统——“Net nanny”（网络保姆）过滤掉呢（见参考文献[1]）？

图 18-1　我们如何准确描述一幅图像的内容（感谢西班牙马德里普拉多美术馆）

与基于文本的检索相比，我们都知道绝大多数主要的网络浏览器都有一个用于在网络上进行多媒体内容检索的按钮。就 Bosch 的画作而言，利用一个基于文本的检索就有可能做得很好，但是我们不会总是遇到这种特殊的图像。我们还会对那种更具有一般性的检索感兴趣，比如说检索那些具有深蓝色的天空和桔黄色的落日的场景。通过预先计算一些存储在数据库中的关于图像的基本统计信息，我们就能够检索到具有如上特征的简单场景。

起初，数字图书馆中的检索的思想源于传统信息检索的一些原则（例如，参见参考文献[2]）。这些查询的思路得以延续下去。例如，在[3]中，我们可以使用基本的信息检索技术把图像分为室内和室外两大类。在一个图像及其说明的训练集上，把每个单词在说明文档里面出现的次数除以这些单词在一个大类的所有文档里面出现的次数。另一个类似的度量方式则用于图像内容片段的统计性描述。这两种基于信息检索的度量方式常结合起来成为更加有效的分类机制。

但是，大多数多媒体检索方案都倾向于基于多媒体自身的一些有帮助的内容，而不是依赖于那些附加在多媒体上的额外文本信息。最近，人们再次关注图像中所蕴涵的语义内容这个比较深入的问题，并重中要利用附带的文本。如果数据不仅包含从图像中的物体所提取出的统计属性，

AlexNet

AI十年回顾

- 2006-2009, **1000** categories and **1.2** million training images

Li Fei-Fei: ImageNet Large Scale Visual Recognition Challenge, 2014 http://image-net.org/

AI十年回顾

DNNresearch becomes the 9th Canadian company acquired by Google

CBC News · Posted: Mar 13, 2013 4:41 PM EDT | Last Updated: March 14, 2013

https://m.thepaper.cn/baijiahao_11940577

Google has acquired DNNresearch, a University of Toronto startup that studies neural networks. The one-year-old company is launched by computer science professor Geoffrey Hinton (right) and two of his graduate students, Alex Krizhevsky and Ilya Sutskever (left). (The University of Toronto)

https://www.cbc.ca/news/science/google-buys-university-of-toronto-startup-1.1373641

AI十年回顾

“深度学习三巨头”之称的Yoshua Bengio、Yann LeCun、Geoffrey Hinton共同获得了2018年的图灵奖，这是图灵奖1966年建立以来少有的一年颁奖给三位获奖者。

AI十年回顾

- 2006-2009, **1000** categories and **1.2** million training images

Li Fei-Fei: ImageNet Large Scale Visual Recognition Challenge, 2014 http://image-net.org/

AI十年回顾

- 何恺明

  Kaiming He，本科就读于清华大学，博士毕业于香港中文大学多媒体实验室。2011年加入微软亚洲研究院（MSRA）工作。2016年，加入Facebook AI Research（FAIR）担任研究科学家

AlphaGO

AI十年回顾

- DeepMind成立于2010年，2014年被Google收购。
- 2014年开始开发人工智能围棋软件AlphaGo。
- 2015年10月，分布式版AlphaGo分先以5:0击败了欧洲围棋冠军华裔法籍职业棋士樊麾二段。
- 2016年3月，AlphaGo挑战世界冠军韩国职业棋士李世乭（이세돌）九段，对弈结果为AlphaGo 4:1战胜了李世乭。

AI十年回顾

nature

Explore content ⌄ About the journal ⌄ Publish with us ⌄

nature > articles > article

Published: 27 January 2016

Mastering the game of Go with deep neural networks and tree search

David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel & Demis Hassabis

Nature **529**, 484–489 (2016) | Cite this article

441k Accesses | **7340** Citations | **3086** Altmetric | Metrics

AI十年回顾

- 4 : 1

Google DeepMind
Challenge Match
8 - 15 March 2016
AlphaGo
ALPHAGO
01:59:54
LEE SEDOL
01:59:02
AlphaGo
Lee Sedol

AI十年回顾

OxAM
OXFORD ASSET MANAGEMENT
EXPLORING
COMPLEXITY
SHELDONIAN

AI十年回顾

Artificial Intellig
OpenAI Launch
From Elon Musk

Drew Olanoff @yoda / 6:13 AM GMT+8 • D

Elon Musk
@elonmusk · Follow

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openai.com
Introducing OpenAI
OpenAI is a non-profit artificial inte
is to advance digital intelligence in

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openai.com
Introducing OpenAI
OpenAI is a non-profit artificial intelligence research company. Our goal is to advance digital intelligence in the way that is most likely to benef...

AlphaFold

AI十年回顾

- CASP
- 2018-AF1
- 2020-AF2
- 2021-Nature

https://www.nature.com/articles/s41586-021-03819-2

Diffusion Model

Stable Diffusion

Disco Diffusion

Midjourney v5

Diffusion Model

ChatGPT
GPT4

ChatGPT

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.

November 30, 2022
13 minute read

GPT-4

- Mar. 14, 2023

GPT-4 Technical Report

OpenAI*

Abstract

We report the development of GPT-4, a large-scale, multimodal model which can accept image and text inputs and produce text outputs. While less capable than humans in many real-world scenarios, GPT-4 exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers. GPT-4 is a Transformer-based model pre-trained to predict the next token in a document. The post-training alignment process results in improved performance on measures of factuality and adherence to desired behavior. A core component of this project was developing infrastructure and optimization methods that behave predictably across a wide range of scales. This allowed us to accurately predict some aspects of GPT-4's performance based on models trained with no more than 1/1,000th the compute of GPT-4.

+ New chat

AI Chat Tool Ethics

AI Chat Tool Impact Writing

New chat

New chat

New chat

New chat

New chat

Clear conversations

Light mode

OpenAI Discord

Updates & FAQ

Log out

ChatGPT

Examples

"Explain quantum computing in simple terms" →

"Got any creative ideas for a 10 year old's birthday?" →

"How do I make an HTTP request in Javascript?" →

Capabilities

Remembers what user said earlier in the conversation

Allows user to provide follow-up corrections

Trained to decline inappropriate requests

Limitations

May occasionally generate incorrect information

May occasionally produce harmful instructions or biased content

Limited knowledge of world and events after 2021

ChatGPT Jan 9 Version. Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.

爆火出圈

为什么人人都在讨论ChatGPT？

人工智能

- 机器学习
- 计算机视觉
- **自然语言处理**
- 语音识别及合成
- 机器人

什么是自然语言处理?

- 自然语言
  - 人类使用的语言，如汉语、英语、法语等；特指**文本符号**(非语音)。

- 如何定义
  - 自然语言处理(Natural Language Processing, NLP)是利用计算机技术来分析、理解和处理自然语言的一门学科，涉及到语言学、计算机科学、人工智能等交叉领域，关注计算机和人类(自然)语言之间的交互。
  - 可分为自然语言**理解**(Natural Language Understanding, NLU)和自然语言**生成**(Natural Language Generation, NLG)两大部分。

- 属于**认知智能**
  - **计算智能**(能存会算)，**感知智能**(能听会说，能看会认)
  - **认知智能**(能理解会思考，需要**抽象**和**推理**能力)

NLP
Natural
Statistical
Language
approaches
knowledge
understand
Processing
language
Machine
Learning
Image
text
data
Credit
rules
humans
approach
conversational
Rules-Based
Rule-Based
tasks
precise
concepts
commonsense
deterministic
moving
like
search
English
daily
nature
move
human
use
different
post
without
set
know
model
Understanding
automatically processing
lives
even
Subscribe
http://www.stuartduncanname
mainstream
make
thesaurus first
power
Search
called
examples
Subject
every
better
funny
chatbots
highly
Verbs
interfaces
discourse
explanation
perform
Parsing
origin
creating
scientists
process
requires
Artificial
intelligence
statistical
problem
amounts
find
pretty
Data
Hind
Yes
blog
google
Human
using
day
many
extraction
machine
positive
Google
similar
Word2Vec
idea
parse
create
makes
terms
might
done
Object
models
engines
Rules-based Translation
able
words
understanding
inherent
provide
along
world
negative
space
something
problems
translation
new
tools
Latest
Library
Artificial
requires
process
intelligence
statistical
problem
amounts
find
pretty
Data
Hind
Yes
blog
google
Human
using
day
many
extraction
machine
positive
Google
similar
Word2Vec
idea
parse
create
makes
terms
might
done
Object
models
engines
Rules-based Translation
able
words
understanding
inherent
provide
along
world
negative
space
something
problems
translation
new
tools
Latest
Library
Verbs
interfaces
discourse
explanation
perform
Parsing
origin
creating
scientists
process
requires
Artificial

认知智能

理解语言、逻辑、知识的智能
认知智能
$300,000
$1,000,000
$200,000
机器在知识量上超越人类，在推理上不如人类
具备视觉、听觉等感知的智能
感知智能
ALPHAGO
A DOCUMENTARY • SPRING 2017
机器在一些任务上已接近或超越人类
特定领域中规则明确的数据快速处理智能
计算智能
机器已超越人类
难度/价值

#自然语言处理太难了#

- **歧义性**
- 主观性
- 创新性
- **知识性**
- 组合性
- 上下文
- **多模态**

李晓鹏1982

11月22日 18:13 来自 HUAWEI Mate 20

美国抗议中国抗议美国干涉中国内政的法案是在干涉

Squawk Box @SquawkCNBC · 12h

"I think China needs to stop interfering in the internal affairs of the United States because our treatment of Hong Kong is an internal

详情

巳月

吉尼斯世界纪录因纪录了最多吉尼斯世界纪录被吉尼斯世界纪录纪录为纪录吉尼斯世界纪录最多的吉尼斯世界纪录

2019年4月22日 下午8:04

盐教发〔2014〕94号

转发《自治区教育厅办公室关于转发〈教育部关于做好春夏季中小学生和幼儿安全工作的紧急通知〉的通知》的通知

各乡镇中小学，县直各中小学、幼儿园：

知乎 @zibuyu9

#自然语言处理太难了#

- **歧义性**
- 主观性
- 创新性
- **知识性**
- 组合性
- 上下文
- **多模态**

上海有个群体被大家忽略了，困在上海不懂中文又要靠微信群维生的外国友人们，整天被微信翻译搞得心惊肉跳，估计现在急需心理疏导和靠谱翻译服务。

Group Notice
各位宝宝们下午好~
明天下午1点公寓会安排消杀工作，如果有需要入户消杀的宝宝们请微信与我们沟通哈

Good afternoon.
Tomorrow afternoon at 1: 00 apartment will arrange the killing work, if there is a need to kill the baby in the house, please communicate with us through WeChat

Translated by WeChat

@直播上海

“自然语言处理是人工智能皇冠上的明珠”

□自然语言处理成为**制约人工智能取得更大突破和更广泛应用的瓶颈**

“深度学习的下一个前沿课题是自然语言理解”

——图灵奖得主、Meta AI负责人Yann LeCun

“深度学习的下一个大的进展应该是让神经网络真正理解文档的内容”

——图灵奖得主、深度学习之父Geoffrey Hinton

ChatGPT!

“如果给我10亿美金，我会建造一个NASA级别的自然语言处理研究项目”

——美国双院院士、世界知名机器学习专家Michael I. Jordan

“下一个十年，懂语言者得天下”

——美国工程院士、微软前全球执行副总裁沈向洋

(from：哈工大车万翔)

ChatGPT是怎么诞生的?

罗马不是一天建成的

ChatGPT是怎么诞生的?

- 向量空间模型
- Bm25
- Svd
- Plsa
- Lda
- Word2vec
- Deepwalk
- transE
- Cnn句子分类
- 匹配、摘要等
- Seq2seq翻译

- CnnSeq
- Transformer
- Language model
- Lstm pretrain
- ELMo
- GPT
- BERT xlnet roberta、albert、electra
- GPT2 GPT3
- BART T5
- PEGASUS
- WebGPT
- RLHF
- InstructGPT

内容

- 基础技术
- 预训练技术
- ChatGPT
- 未来展望

内容

- **基础技术**
- 预训练技术
- ChatGPT
- 未来展望

基础技术的故事

Language Model
语言模型

语言模型

- Language Model

从统计角度看，自然语言中的一个句子s可以由任何词串构成。不过P(s)有大有小。如：

- a= 我准备去散步。
- b= 我去散步准备。
- P(a) > P(b)

对于给定的句子s而言，通常P(s)是未知的。

对于一个句子空间A，其概率分布D表示任意可能句子的概率分布。估计句子空间A的概率分布D的过程被称作语言建模

语言模型

- Language Model

根据语言样本估计出的概率分布D就称为语言(空间)A的语言模型

$$\sum_{a \in A} P(a) = 1$$

$$\forall a \in A, P(a) = ?$$

语言建模技术首先在语音识别研究中提出，后来陆续用到OCR、手写体识别、机器翻译、信息检索等领域

在语音识别中，如果识别结果有多个，则可以根据语言模型计算每个识别结果的可能性，然后挑选一个可能性较大的识别结果

语言模型

- Language Model

对于给定的句子a = w1 w2 … wm，如何计算P(a)?

链式规则(chain rule)

$$
\begin{aligned}
P(a) &= P(w_1 w_2 \ldots w_m) \\
&= P(w_1)P(w_2|w_1)P(w_3|w_1 w_2)\ldots P(w_m|w_1 w_2 \ldots w_{m-1}) \\
&= \prod_{k=1}^{m} P(w_k|w_1 \ldots w_{k-1})
\end{aligned}
$$

$$
\begin{aligned}
&P(\text{Do you still remember}) \\
&= P(\text{Do}) \times P(\text{you}|\text{Do}) \times P(\text{still}|\text{Do you}) \times P(\text{remember}|\text{Do you still})
\end{aligned}
$$

N-gram LM

为了便于计算，通常考虑的历史不能太长，一般只考虑前面n-1个词构成的历史：

$$P(a) = \prod_{k=1}^{m} P(w_k | \boxed{w_{k-n+1} \ldots w_{k-1}})$$

历史窗口为 n → n-gram

N-gram LM

“a black _____ .”

- “cat” ? “stone” ?

“Kevin gives food to a black _____ .”

- “cat” ? “stone” ?

如果知道更长的上下文会缩小可选择的下一个词的范围

如何选择n?

N-gram LM

n 较大时

- 提供了更多的语境信息，语境更具区别性
- 但是，参数个数多、计算代价大、训练语料需要多、参数估计不可靠

n 较小时

- 语境信息少，不具区别性
- 但是，参数个数少、计算代价小、训练语料无需太多、参数估计可靠

unigram (n=1)

- p(wi) 若语言中有20000个词，则需要估计20000个参数

bigram (n=2)

- p(wi|wi-1) 若语言中有20000个词，则需要估计20000^2个参数

trigram (n=3)

- p(wi|wi-2 wi-1) 若语言中有20000个词，则需要估计20000^3个参数

Evaluation: Perplexity

The higher this quantity is, the better the language model is at modeling unseen sentences.

$$\prod_{i=1}^{m} p(x^{(i)})$$

Perplexity on the test corpus is derived as a direction transformation of this.

$$\text{ppl} = 2^{-l}$$

$$l = \frac{1}{M} \sum_{i=1}^{m} \log_2 p(x^{(i)})$$

<u>M is the total length of the sentences in the test corpus</u>.

What if the model estimate $q(w \mid u, v) = 0$ and the trigram appears in the dataset?

NN LM

- Neural Network based Language Model

$$
\begin{aligned}
P(a) &= P(w_1 w_2 \ldots w_m) \\
&= P(w_1)P(w_2|w_1)P(w_3|w_1 w_2)\ldots P(w_m|w_1 w_2 \ldots w_{m-1}) \\
&= \prod_{k=1}^{m} P(w_k|\boxed{w_1 \ldots w_{k-1}})
\end{aligned}
$$

Yoshua Bengio

FOLLOWING

Professor of computer science, University of Montreal, Mila, IVADO, CIFAR
Verified email at umontreal.ca - Homepage

Machine learning deep learning artificial intelligence

TITLE	CITED BY	YEAR
Deep learning Y LeCun, Y Bengio, G Hinton nature 521 (7553), 436-444	56544	2015
Generative adversarial networks I Goodfellow, J Pouget-Abadie, M Mirza, B Xu, D Warde-Farley, S Ozair, ... Communications of the ACM 63 (11), 139-144	50339	2020
Gradient-based learning applied to document recognition Y LeCun, L Bottou, Y Bengio, P Haffner Proceedings of the IEEE 86 (11), 2278-2324	49346	1998
Deep learning I Goodfellow, Y Bengio, A Courville MIT press	43742	2016
Neural machine translation by jointly learning to align and translate D Bahdanau, K Cho, Y Bengio arXiv preprint arXiv:1409.0473	25724	2014

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h-index	210	192
i10-index	738	660

Public access VIEW ALL

9 articles 101 articles

not available available

Based on funding mandates

NN LM

最早的神经语言模型 (neural language model)

- A Neural Probabilistic Language Model, Bengio et al. 2003
- 通过神经网络估计n-gram语言模型中的条件概率

模型

- $y = b + Wx + Utanh(d + Hx)$
  - W, U, H是参数矩阵，b, d是偏置
- $\hat{P}(w_t|w_{t-1}, \dots, w_{t-n+1}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}$

问题：固定的上下文窗口

NN LM

解决方案

- 让一个词的计算包含之前所有词的信息

循环神经网络！(recurrent neural network)

- 输入增加之前的网络输出
  - 让神经网络以之前所有的词为条件
- 每个时间点使用相同的参数
- 内存消耗只与考察的词数有关

梯度消失/爆炸

$$h_t = f\left(x_t, h_{t-1}; \theta\right)$$

$$\frac{dh_t}{d\theta} = \frac{\partial h_t}{\partial h_{t-1}} \frac{dh_{t-1}}{d\theta} + \frac{\partial h_t}{\partial \theta}$$

$$\begin{aligned}\frac{dh_t}{d\theta} &= \frac{\partial h_t}{\partial h_{t-1}} \frac{dh_{t-1}}{d\theta} + \frac{\partial h_t}{\partial \theta} \\ &= \frac{\partial h_t}{\partial \theta} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial \theta} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial h_{t-2}} \frac{\partial h_{t-2}}{\partial \theta} + \dots\end{aligned}$$

$\left|\frac{\partial h_t}{\partial h_{t-1}}\right| < 1$时，意味着历史的梯度信息是衰减的，因此步数多了梯度必然消失

$\frac{dh_t}{d\theta}$几乎就没有包含最初的梯度$\frac{\partial h_1}{\partial \theta}$的信息了，

$\left|\frac{\partial h_t}{\partial h_{t-1}}\right| > 1$，因为这历史的梯度信息逐步增强，因此步数多了梯度必然爆炸

https://kexue.fm/archives/7888

长程依赖问题

- 循环神经网络在时间维度上非常深！
  - 梯度消失或梯度爆炸

- 如何改进？
  - 梯度爆炸问题
    - 权重衰减
    - 梯度截断

  - 梯度消失问题
    - 改进模型

长程依赖问题

- 改进方法
  - 循环边改为线性依赖关系

$$\mathbf{h}_t = \mathbf{h}_{t-1} + g(\mathbf{x}_t; \theta),$$

  - 增加非线性

$$\mathbf{h}_t = \mathbf{h}_{t-1} + g(\mathbf{x}_t, \mathbf{h}_{t-1}; \theta),$$

残差网络?

Long Short-Term Memory, LSTM

Juergen Schmidhuber

FOLLOW

King Abdullah University of Science and Technology / The Swiss AI Lab, IDSIA / University of Lugano
Verified email at kaust.edu.sa - Homepage

computer science artificial intelligence reinforcement learning neural networks physics

TITLE	CITED BY	YEAR
Long short-term memory CCF B S Hochreiter, J Schmidhuber Neural computation 9 (8), 1735-1780	74441	1997
Deep learning in neural networks: An overview CCF none J Schmidhuber Neural networks 61, 85-117	17335	2015
Learning to forget: Continual prediction with LSTM CCF B FA Gers, J Schmidhuber, F Cummins Neural computation 12 (10), 2451-2471	6180	2000
Multi-column deep neural network for traffic sign classification CCF B D CireşAn, U Meier, J Masci, J Schmidhuber Neural networks 32, 333-338	5738 *	2012
Multi-column deep neural networks for image classification CCF none D Ciregan, U Meier, J Schmidhuber 2012 IEEE conference on computer vision and pattern recognition, 3642-3649	~~5719~~	2012
LSTM: A search space odyssey CCF B K Greff, RK Srivastava, J Koutník, BR Steunebrink, J Schmidhuber	5169	2016

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Search:

AI Blog
@SchmidhuberAI
What's new? 6 Dec 2021

KAUST (17 papers at NeurIPS 2021) and its environment are now offering enormous resources to advance both fundamental and applied AI research: we are hiring outstanding professors, postdocs, and PhD students.

(ERC Grant: Many jobs for PhD students and PostDocs to be hired in 2020. Earlier jobs: 2017, 2016)

FAQ in AMA (Ask Me Anything) on reddit (2014)

Publications (2021)
CV (2021)
Old videos (2009-2015)

Master's in Artificial Intelligence (Fall 2017)

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Since age 15 or so, the main goal of professor Jürgen Schmidhuber has been to build a self-improving Artificial Intelligence (AI) smarter than himself, then retire. His lab's Deep Learning Neural Networks (NNs) based on ideas published in the "Annus Mirabilis" 1990-1991 have revolutionised machine learning and AI. In 2009, the CTC-trained Long Short-Term Memory (LSTM) of his team was the first recurrent NN to win international pattern recognition competitions. In 2010, his lab's fast and deep feedforward NNs on GPUs greatly outperformed previous methods, without using any unsupervised pre-training, a popular deep learning strategy that he pioneered in 1991. In 2011, the DanNet of his team was the first feedforward NN to win computer vision contests, achieving superhuman performance. In 2012, they had the first deep NN to win a medical imaging contest (on cancer detection). This deep learning revolution quickly spread from Europe to North America and Asia, and attracted enormous interest from industry. By the mid 2010s, his lab's NNs were on 3 billion devices, and used billions of times per day through users of the world's most valuable public companies, e.g., for greatly improved speech recognition on all Android smartphones, greatly improved machine translation through Google Translate and Facebook (over 4 billion LSTM-based translations per day), Apple's Siri and Quicktype on all iPhones, the answers of Amazon's Alexa, and numerous other applications. In May 2015, his team published the Highway Net, the first working really deep feedforward NN with hundreds of layers—its open-gated version called ResNet (Dec 2015) has become the most cited NN of the 21st century, LSTM the most cited NN of the 20th (Bloomberg called LSTM the *arguably most commercial AI achievement*). His lab's NNs are now heavily used in healthcare and medicine, helping to make human lives longer and healthier. His research group also established the fields of mathematically rigorous universal AI and recursive self-improvement in metalearning machines that learn to learn (since 1987). In 1990, he introduced unsupervised generative adversarial neural networks that fight each other in a minimax game to implement artificial curiosity (the famous GANs are instances thereof). In 1991, he introduced neural fast weight programmers formally equivalent to what's now called linear Transformers (popular in natural language processing). His formal theory of creativity & curiosity & fun explains art, science, music, and humor. He also generalized algorithmic information theory and the many-worlds theory of physics, and introduced the concept of Low-Complexity Art, the information age's extreme form of minimal art. He is recipient of numerous awards, author of about 400 peer-reviewed papers, and Chief Scientist of the company NNAISENSE, which aims at building the first practical general purpose AI. He is a frequent keynote speaker, and advising various governments on AI strategies.

RESEARCH

Artificial Recurrent Neural Networks (1989-2014). Most work in machine learning focuses on machines with reactive behavior. RNNs, however, are more general sequence processors inspired by human brains. They have adaptive feedback connections and are in principle as powerful as any computer. The first RNNs could not learn to look far back into the past. But our "Long Short-Term Memory" (LSTM) RNN overcomes this fundamental problem,

Artificial Evolution. State-of-the-art methods for network evolution co-evolve all neurons in parallel (excellent results in various applications). EVOLINO outperforms previous methods on several supervised learning tasks, and yields the first recurrent support vector machines. Probabilistic incremental program evolution evolves computer programs through probabilistic templates instead of program populations (first approach to evolving entire soccer team strategies from

I am the GOD Father!

南大周志华

3-27 21:01 来自HUAWEI Mate 20 Pro

+关注

要论对深度学习的贡献，Hinton无疑巨首，LeCun和Schmidhuber贡献都很大。但HLB总捆绑在一起，而S跟HLB都不对劲。。。获奖需有提名有投票，人缘也重要。。。不过没关系，有LSTM这样教科书级的贡献足以淡定//@Wilson_NJUer:连接主义终于实至名归！不过Jürgen Schmidhuber好像有点小亏😁

LSTM现在也没有多少人用了。。。

长短期记忆神经网络（Long Short-Term Memory, LSTM ）

LSTM
(Long-Short Term Memory)

长短期记忆神经网络（Long Short-Term Memory, LSTM ）

$$\mathbf{i}_t = \sigma(W_i\mathbf{x}_t + U_i\mathbf{h}_{t-1} + \mathbf{b}_i), \qquad \tilde{\mathbf{c}}_t = \tanh(W_c\mathbf{x}_t + U_c\mathbf{h}_{t-1} + \mathbf{b}_c)$$

$$\mathbf{f}_t = \sigma(W_f\mathbf{x}_t + U_f\mathbf{h}_{t-1} + \mathbf{b}_f), \qquad \mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t,$$

$$\mathbf{o}_t = \sigma(W_o\mathbf{x}_t + U_o\mathbf{h}_{t-1} + \mathbf{b}_o), \qquad \mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t),$$

$$\frac{\partial c_t}{\partial c_{t-1}} = f_t + c_{t-1}\frac{\partial f_t}{\partial c_{t-1}} + \hat{c_t}\frac{\partial i_t}{\partial c_{t-1}} + i_t\frac{\partial \hat{c_t}}{\partial c_{t-1}}$$

LSTM的各种变体

- 没有遗忘门

$$\mathbf{c}_t = \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t.$$

- 耦合输入门和遗忘门

$$\mathbf{f}_t + \mathbf{i}_t = \mathbf{1}.$$

- **peephole连接**

$$\mathbf{i}_t = \sigma(W_i\mathbf{x}_t + U_i\mathbf{h}_{t-1} + V_i\mathbf{c}_{t-1} + \mathbf{b}_i),$$
$$\mathbf{f}_t = \sigma(W_f\mathbf{x}_t + U_f\mathbf{h}_{t-1} + V_f\mathbf{c}_{t-1} + \mathbf{b}_f),$$
$$\mathbf{o}_t = \sigma(W_o\mathbf{x}_t + U_o\mathbf{h}_{t-1} + V_o\mathbf{c}_t + \mathbf{b}_o),$$

Gated Recurrent Unit, GRU

- 顺便讲讲GRU

Gated Recurrent Unit, GRU

Kyunghyun Cho

FOLLOWING

New York University, Genentech
Verified email at nyu.edu - Homepage

Machine Learning Deep Learning

TITLE	CITED BY	YEAR
Neural machine translation by jointly learning to align and translate CCF none D Bahdanau, K Cho, Y Bengio ICLR 2015	26204	2014
Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation CCF B K Cho, B van Merrienboer, C Gulcehre, F Bougares, H Schwenk, ... Conference on Empirical Methods in Natural Language Processing (EMNLP 2014)	21500	2014
Empirical evaluation of gated recurrent neural networks on sequence modeling CCF none J Chung, C Gulcehre, KH Cho, Y Bengio arXiv preprint arXiv:1412.3555	10945	2014
Show, Attend and Tell: Neural Image Caption Generation with Visual Attention CCF A K Xu, J Ba, R Kiros, K Cho, A Courville, R Salakhutdinov, R Zemel, ... International Conference on Machine Learning	9771	2015
On the Properties of Neural Machine Translation: Encoder-Decoder Approaches CCF none K Cho, B van Merrienboer, D Bahdanau, Y Bengio Eighth Workshop on Syntax, Semantics and Structure in Statistical …	5749	2014
Attention-based models for speech recognition CCF A	2505	2015

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Gated Recurrent Unit, GRU

重置门

$$\mathbf{r}_t = \sigma(\mathbf{W}_r\mathbf{x}_t + \mathbf{U}_r\mathbf{h}_{t-1} + \mathbf{b}_r), \qquad \tilde{\mathbf{h}}_t = \tanh(\mathbf{W}_c\mathbf{x}_t + \mathbf{U}(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$\mathbf{z}_t = \sigma(\mathbf{W}_z\mathbf{x}_t + \mathbf{U}_z\mathbf{h}_{t-1} + \mathbf{b}_z), \qquad \mathbf{h}_t = \mathbf{z}_t \odot \mathbf{h}_{t-1} + (1 - \mathbf{z}_t) \odot \tilde{\mathbf{h}}_t,$$

更新门

$$\frac{\partial \mathrm{h_t}}{\partial \mathrm{h_{t-1}}}$$

RNN LM的应用

语言模型

target word
"is"
"the"
"problem"
output likelihood
y_1
y_2
y_3
W_{hy}
hidden state
h_1
h_2
W_{hh}
h_3
W_{xh}
input embedding
x_1
x_2
x_3
input word
"What"
"is"
"the"

做生成?

语言模型 – 序列生成

Home > Browse by Title > Reports > A First Look at Music Composition using LSTM Recurrent Neural Networks

A First Look at Music Composition using LSTM Recurrent Neural Networks • March 2002

Technical Report

2002 Technical Report

Authors: Douglas Eck, Juergen Schmidhuber

Publisher: Istituto Dalle Molle Di Studi Sull Intelligenza Artificiale

Published: 15 March 2002

2002

ICML 2011

Generating Text with Recurrent Neural Networks

Ilya Sutskever ILYA@CS.UTORONTO.CA
James Martens JMARTENS@CS.TORONTO.EDU
Geoffrey Hinton HINTON@CS.TORONTO.EDU
University of Toronto, 6 King's College Rd., Toronto, ON M5S 3G4 CANADA

The Recurrent Temporal Restricted Boltzmann Machine

Ilya Sutskever, Geoffrey Hinton, and Graham Taylor
University of Toronto
{ilya, hinton, gwtaylor}@cs.utoronto.ca

NIPS2008

Modeling Temporal Dependencies in High-Dimensional Sequences: Application to Polyphonic Music Generation and Transcription

Nicolas Boulanger-Lewandowski BOULANNI@IRO.UMONTREAL.CA
Yoshua Bengio BENGIOY@IRO.UMONTREAL.CA
Pascal Vincent VINCENTP@IRO.UMONTREAL.CA
Dept. IRO, Université de Montréal. Montréal (QC), H3C 3J7, Canada

ICML 2012

语言模型 – 文本生成

ICML2011

Ilya Sutskever
James Martens
Geoffrey Hinto
University of To

Recurrent
powerful s
widespread
cult to trai
cent advanc
been able t
with trainin
them succe
lems. In t
of RNNs tr

6.1.1. SAMPLE

We now presen
use ? to indicat
low was obtaine
and selecting th
of the paragrap
ticularly interes
phrase "The me

The meaning of
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her bigger. In the
wild pasteured w
by the 15th centu
an effort that the
sleepers to incor
tion. Mar??a Nati
thought is. To ada
fairy Dan please

6.1.2. SAMPLES FROM THE NYT MODEL

Below is a sample from the model trained on the full NYT dataset, where the MRNN was initialized with a single space. The spaces surrounding the punctuation are an artifact of the preprocessing.

while he was giving attention to the second advantage of school building a 2-for-2 stool killed by the Cultures saddled with a half-suit defending the Bharatiya Fernall 's office . Ms . Claire Parters will also have a history temple for him to raise jobs until naked Prodiena to paint baseball partners , provided people to ride both of Manhattan in 1978 , but what was largely directed to China in 1946 , focusing on the trademark period is the sailboat yesterday and comments on whom they obtain overheard within the 120th anniversary , where many civil rights defined , officials said early that forms , " said Bernard J. Marco Jr. of Pennsylvania , was monitoring New York

Alex Graves

FOLLOWING

University of Toronto
Verified email at cs.toronto.edu - Homepage

Artificial Intelligence Recurrent Neural Networks Handwriting Recognition Speech recognition

TITLE	CITED BY	YEAR
Human-level control through deep reinforcement learning CCF none CCF none V Mnih, K Kavukcuoglu, D Silver, AA Rusu, J Veness, MG Bellemare, ... nature 518 (7540), 529-533	21533	2015
Playing atari with deep reinforcement learning CCF none V Mnih, K Kavukcuoglu, D Silver, A Graves, I Antonoglou, D Wierstra, ... arXiv preprint arXiv:1312.5602	10293	2013
Speech recognition with deep recurrent neural networks CCF B CCF B A Graves, A Mohamed, G Hinton 2013 IEEE international conference on acoustics, speech and signal ...	9406	2013
Asynchronous methods for deep reinforcement learning CCF A V Mnih, AP Badia, M Mirza, A Graves, T Lillicrap, T Harley, D Silver, ... International conference on machine learning, 1928-1937	7717	2016
Wavenet: A generative model for raw audio CCF none CCF none A Oord, S Dieleman, H Zen, K Simonyan, O Vinyals, A Graves, ... arXiv preprint arXiv:1609.03499	4844	2016
Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks CCF A CCF A A Graves, S Fernández, F Gomez, J Schmidhuber Proceedings of the 23rd international conference on Machine learning, 369-376	4777	2006
Framewise phoneme classification with bidirectional LSTM and other neural network architectures CCF B CCF B A Graves, J Schmidhuber Neural networks 18 (5-6), 602-610	4551	2005
Generating sequences with recurrent neural networks CCF none CCF none A Graves arXiv preprint arXiv:1308.0850	4155	2013

LSTM

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] self-acharged versions ([[Mt. Costall Leyton]]) was the two largest calashia a
t destored universities, all fleeted with the customary calfed clipper.

His way to take in this literature called ICBMs-AN a [[Softvalue speed]] ([[Astr
onomical Classification Railway]])

LACN645 Snowshore val nominated - made [[missile submandration|continental missi
le]]s (steam musicians) not of each club having on the ball and procedure at the
 last century.

Another communistic stark "I'鮮 submarine" is [[building|corruptable]],
 a [[della missile]] missile than the [[Royal Society Society]] (12-258): "
Glide sun wag [[lubrician]]. They stay numerous capitalists and gas masks more w
idely interested. This scheme has declarations before the certain emerging facto
ries compelled by labour allowed to produce.

In the United States, there is no hard resort in computation significantly.

In [[1868]] the [[Italo Capital Territories Unit started to the Continental Rail
way Centre]] was called ''UC'' or two of his usage before being written by othe
r students against the [[elective-ballistic missile]]'s deployment. Steam is sti
ll "20 to Nacht" and [[Fia Citation Quantity Logo]]s (since 1967). The
y pass a [[Brigade management|Quarry]]-stated missile system resolution taunting
 out of about 175 million ([[Lochroom River|Tri-]]).

Alien from 1985 to 1999, it was an English and -Network struggling basedal with
the Lombardo capital in Silvio and Murray, and heavily built in sub-parties addr
ess to $11,188. Their forces gained prisoners to stalked a last missile mobili s
ite.

Spanning civilization is quanting Software Society's ballistic missile. The sam
e as [[anti-intellectual anthropology]] continued in [[Southern Italy]] in 1914,
 and the [[French Confederation of Parliament's rapid favourable rise that began
 settled in March 2004|1983]] 49.

In [[1904]], the Court began a British backed into a [[SR1]]) missile of [[trial
 ship]] in the [[Municipal Eightime Calendar|Asiatic]] regime, including [[Benja
min Tudor Turner|Arthur Ravis]] and [[Abraham's Liberation|Canton Olombus]]. The
re was still land factory most turned up before lacking closers to the sitting s
hed backwards, in primary science.

==Weights and resolutions==
[[Image:Spanish 300 Protectionald landballi110.svg|small capital surface compute
r]]
[[Image:Claudius.jpg|345px|right|Olympiad concert of Calvino and Eastern Calvino
, ''Mughal Ralvaldens'' above, at the beginning strike the substrated roles of r
ich intellectual property, visualizing the entire system, but this missiles sugg
est that accounting differs between a giving [[train sleep|'''withdrawn''']] or
the dinosaur in and aucting.

===Internationally===
{{main|Unmanned Justice Address}}

The ICBM created a [[the significant]] [[land railway]] called "[[M-Gallipo
tte]]", and it needed stopped benzafk/Macdonalical Sciences.

Electros appeared to be the [[Soviet Union]]'s "first" vehicle from 25
00 selling officials DORLAN STM-331 - by missilence illustrations with "Raj
." the Tunnel Hall of America, an entity upon IL pages so missiles must try
, with a trademark must develop the land allowing traffic mass to a very few min
utemen. The missiles market is slow, much easier is represented by GMMAz of BSM.
 Software, the utility of scale-out scale pime racks are normally crumbled about

Figure 8: **Generated Wikipedia data (cotd.)**

Figure 11: **Online handwriting samples generated by the prediction network.** All samples are 700 timesteps long.

生成LINUX内核代码

```
/*
 * If this error is set, we will need anything right after that BSD.
 */
static void action_new_function(struct s_stat_info *wb)
{
  unsigned long flags;
  int lel_idx_bit = e->edd, *sys & ~((unsigned long) *FIRST_COMPAT);
  buf[0] = 0xFFFFFFFF & (bit << 4);
  min(inc, slist->bytes);
  printk(KERN_WARNING "Memory allocated %02x/%02x, "
    "original MLL instead\n"),
    min(min(multi_run - s->len, max) * num_data_in),
    frame_pos, sz + first_seg);
  div_u64_w(val, inb_p);
  spin_unlock(&disk->queue_lock);
  mutex_unlock(&s->sock->mutex);
  mutex_unlock(&func->mutex);
  return disassemble(info->pending_bh);
}

static void num_serial_settings(struct tty_struct *tty)
{
  if (tty == tty)
    disable_single_st_p(dev);
  pci_disable_spool(port);
```

智能立方

作词机

- RNN在“学习”过汪峰全部作品后自动生成的歌词
  - https://github.com/phunterlau/wangfeng-rnn

我在这里中的夜里
就像一场是一种生命的意叶
就像我的生活变得在我一样
可我们这是一个知道
我只是一天你会怎吗
可我们这是我们的是不要为你
我们想这有一种生活的时候

作诗机

浊酒一杯聊酩酊，
After a cup of unstrained wine,
I have been a little drunk
白云千里断鸿濛。
I saw the cloud split the sky apart.
马蹄踏破青山路，
On horseback, I pass through every road across the mountain,
惆怅斜阳落日红。
but can only watch the red sun falling down with sorrow.

(a) Style 1: “loneliness, melancholy”

浊酒一杯聊酩酊，
After a cup of unstrained wine,
I have been a little drunk
扁舟何处问渔樵。
With a narrow boat, where could I find the hermits?
行人莫讶归来晚，
Friends, don't be surprised that I come back so late,
万里春风到海潮。
I have seen the great tide and the grand spring breeze.

(b) Style 4: “hermit, rural scenes”

浊酒一杯聊酩酊，
After a cup of unstrained wine,
I have been a little drunk
浮云何处觅仙踪。
I wonder on which cloud I can see the presence of the gods.
迢迢十二峰头月，
The moon above the mount seems farther and farther.
漠漠千山暮霭浓。
The mist among the hill becomes thicker and thicker.

(c) Style 8: “the portrait of hazy scenerries”

Yang et al. Stylistic Chinese Poetry Generation via Unsupervised Style Disentanglement. EMNLP 2018.

继续发展

- 2013、2014、2015
- 大家一边玩着word2vec，一边训练着rnn-lm做生成，一边影响着其它领域发展
- 例如：
  - **机器翻译**

统计机器翻译-SMT

张家俊. 机器翻译lectures

统计机器翻译-SMT

①数据稀疏

人工设定的模块和特征

②复杂结构无能为力

③强烈依赖先验知识

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神经机器翻译

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A First Look at Music Composition using LSTM Recurrent Neural Networks · March 2002

2002 Technical Report

Authors: Douglas Eck, Juergen Schmidhuber

Publisher: Istituto Dalle Molle Di Studi Sull Intelligenza Artificiale

Published: 15 March 2002

Technical Report

2002

The Recurrent Temporal Restricted Boltzmann Machine

Ilya Sutskever, Geoffrey Hinton, and Graham Taylor
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NIPS2008

Generating Text with Recurrent Neural Networks

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James Martens JMARTENS@CS.TORONTO.EDU
Geoffrey Hinton HINTON@CS.TORONTO.EDU
University of Toronto, 6 King's College Rd., Toronto, ON M5S 3G4 CANADA

ICML 2011

Modeling Temporal Dependencies in High-Dimensional Sequences: Application to Polyphonic Music Generation and Transcription

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Yoshua Bengio BENGIOY@IRO.UMONTREAL.CA
Pascal Vincent VINCENTP@IRO.UMONTREAL.CA
Dept. IRO, Université de Montréal. Montréal (QC), H3C 3J7, Canada

ICML 2012

EMNLP 2013

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng and Christopher Potts
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richard@socher.org, {aperelyg, jcchuang, ang}@cs.stanford.edu
{jeaneis, manning, cgpotts}@stanford.edu

Abstract

Semantic word spaces have been very useful but cannot express the meaning of longer phrases in a principled way. Further progress towards understanding compositionality in tasks such as sentiment detection requires richer supervised training and evaluation resources and more powerful models of composition. To remedy this, we introduce a Sentiment Treebank. It includes fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences and presents new challenges for sentiment compositionality. To address them, we introduce the Recursive Neural Tensor Network. When trained on the new treebank, this model out-

Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence.

神经机器翻译

Continuous Space Language Models for Statistical Machi

Holger Schwenk and **Daniel Dchelotte** and **Jean-Luc G**
LIMSI-CNRS, BP 133
91403 Orsay cedex, FRANCE
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Recurrent Continuous Translation Models

Nal Kalchbrenner **Phil Blunsom**
Department of Computer Science
University of Oxford
{nal.kalchbrenner,phil.blunsom}@cs.ox.ac.uk

Continuous Space Translation Models for Phrase-Base Statistical Machine Translation

Holger Schwenk
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ABSTRACT
This paper presents a new approach to perform the estimation of the translation model prob-
abilities of a phrase-based statistical machine translation system. We use neural networks to
directly learn the translation probability of phrase pairs using continuous representation
system can be easily trained on the same data used to build standard phrase-based sy
We provide experimental evidence that the approach seems to be able to infer mean
translation probabilities for phrase pairs not seen in the training data, or even predict a
the most likely translations given a source phrase. The approach can be used to rescore
lists, but we also discuss an integration into the Moses decoder. A preliminary evaluation
English/French IWSLT task achieved improvements in the BLEU score and a human ar
showed that the new model often chooses semantically better translations. Several exte
of this work are discussed.

KEYWORDS: Statistical machine translation, phrase probability estimation, continuous
models, neural network.

COLING2012

Abstract

We introduce a class of probabilistic continuous translation models called Recurrent Continuous Translation Models that are purely based on continuous representations for words, phrases and sentences and do not

ties, linguistic or otherwise, they do not share statistical weight in the models' estimation of their translation probabilities. Besides ignoring the similarity of phrase pairs, this leads to general sparsity issues. The estimation is sparse or skewed for the large number of rare or unseen phrase pairs, which grows exponentially in the length of the phrases, and

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Fast and Robust Neural Network Joint Models for Statistical Machine Translation

Jacob Devlin, Rabih Zbib, Zhongqiang Huang,
Thomas Lamar, Richard Schwartz, and **John Makhoul**
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S:	我	3 就	4 取	5 钱	6 给	7 了	她们
	i	*will*	*get*	*money*	*to*	perf.	*them*
T:	2 i	1 will	0 get	the	money	to	them

P(the | get, will, i, 就, 取, 钱, 给, 了)

$$P(T|S) \approx \Pi_{i=1}^{|T|} P(t_i|t_{i-1}, \cdots, t_{i-n+1}, \mathcal{S}_i)$$

神经机器翻译

[Submitted on 3 Jun 2014 (this version), latest version 3 Sep 2014 (v3)]

Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation

Kyunghyun Cho, Bart van Merrienboer, Caglar Gulcehre, Fethi Bougares, Holger Schwenk, Yoshua Bengio

In this paper, we propose a novel neural network model called RNN Encoder--Decoder that consists of two recurrent neural networks (RNN). One RNN encodes a sequence of sy
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syntactically meaningful representation of linguistic phrases.

Subjects: **Computation and Language (cs.CL)**; Machine Learning (cs.LG); Neural and Evolutionary Computing (cs.NE); Machine Learning (stat.ML)
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Neural Machine Translation by Jointly Learning to Align and Translate

Dzmitry Bahdanau, Kyunghyun Cho, Yoshua Bengio

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Sequence to Sequence Learning with Neural Networks

Ilya Sutskever, Oriol Vinyals, Quoc V. Le

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RNNencdec

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RNNencdec

Kyunghyun Cho

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Staff Research Scientist at Deep...

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Figure 1: An illustration of the proposed RNN Encoder–Decoder.

Figure 2: An illustration of the proposed hidden activation function. The update gate z selects whether the hidden state is to be updated with a new hidden state $\tilde{h}$. The reset gate r decides whether the previous hidden state is ignored. See Eqs. (5)–(8) for the detailed equations of r, z, h and $\tilde{h}$.

Cho et.al. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. EMNLP2014

RNNencdec

Phrase Generation + SMT，并不是真正的end-to-end形式的NMT。

$$\log p(\mathbf{f} \mid \mathbf{e}) = \sum_{n=1}^{N} w_n f_n(\mathbf{f}, \mathbf{e}) + \log Z(\mathbf{e}).$$

3.1 Scoring Phrase Pairs with RNN Encoder–Decoder

Here we propose to train the RNN Encoder–Decoder (see Sec. 2.2) on a table of phrase pairs and use its scores as additional features in the log-linear model in Eq. (9) when tuning the SMT decoder.

Models	BLEU	
	dev	test
Baseline	30.64	33.30
RNN	31.20	33.87
CSLM + RNN	31.48	34.64
CSLM + RNN + WP	31.50	34.54

Table 1: BLEU scores computed on the development and test sets using different combinations of approaches. WP denotes a *word penalty*, where we penalizes the number of unknown words to neural networks.

RNNencdec

-

Figure 1: An illustration of the proposed RNN Encoder–Decoder.

Problem?

Seq2seq-attention

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Seq2seq-attention

Dzmitry Bahdanau

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Seq2seq-attention

Welcome to my webpage!

I am a research scientist at Element AI that has just been acquired by ServiceNow. I am also a Core Industry Member of Mila and Adjunct Professor at McGill University.

I believe Human Language Techonologies (HLT: a better name than NLP) will change the way humans interact with software and access knowledge. In fact, this has already happened (think web search), but this is just the beginning. I am interested in research questions at all levels of the HLT techonology stack including fundamentals of deep learning, foundation model training, task-specific algorithms (especially semantic parsing), user experience with AI systems. Keyword-wise, my recent and on-going work focuses on semantic parsing and task-oriented dialogue methods, code generation, systematic (compositional) generalization and sample efficiency of neural models.

My prior research interests include grounding language in vision and action, question answering, speech recognition, machine translation and structured prediction in general.

I have did my PhD at Mila working under supervision of Yoshua Bengio.

A bit of bragging: I invented the content-based neural attention that is now a core tool in deep-learning-based natural language processing.

Seq2seq

Neural Machine Translation by Jointly Learning to Align and Translate

Dzmitry Bahdanau
Jacobs University, Germany

KyungHyun Cho
Université de Montréal

Yoshua Bengio
Université de Montréal
CIFAR Senior Fellow

Abstract

Neural machine translation is a recently proposed approach to machine translation. Unlike the traditional statistical machine translation, the neural machine translation aims at building a single neural network that can be jointly tuned to maximize the translation performance. The models proposed recently for neural machine translation often belong to a family of encoder–decoders and encodes a source sentence into a fixed-length vector from which a decoder generates a translation. In this paper, we conjecture that the use of a fixed-length vector is a bottleneck in improving the performance of this basic encoder–decoder architecture, and propose to extend this by allowing a model to automatically (soft-)search for parts of a source sentence that are relevant to predicting a target word, without having to form these parts as a hard segment explicitly. With this new approach, we achieve a translation performance comparable to the existing state-of-the-art phrase-based system on the task of English-to-French translation. Furthermore, qualitative analysis reveals that the (soft-)alignments found by the model agree well with our intuition.

Seq2seq-attention

$$\mathbf{x} = (x_1, \ldots, x_{T_x}),\ x_i \in \mathbb{R}^{K_x} \qquad \mathbf{y} = (y_1, \ldots, y_{T_y}),\ y_i \in \mathbb{R}^{K_y}$$

bidirectional recurrent neural network (BiRNN)

$$h_t = f\left(x_t, h_{t-1}\right) \qquad h_i = \begin{bmatrix} \overrightarrow{h}_i \\ \overleftarrow{h}_i \end{bmatrix}$$

$$\overrightarrow{h}_i = \begin{cases} (1 - \overrightarrow{z}_i) \circ \overrightarrow{h}_{i-1} + \overrightarrow{z}_i \circ \underline{\overrightarrow{h}}_i & \text{, if } i > 0 \\ 0 & \text{, if } i = 0 \end{cases}$$

$$\underline{\overrightarrow{h}}_i = \tanh\left(\overrightarrow{W}\overline{E}x_i + \overrightarrow{U}\left[\overrightarrow{r}_i \circ \overrightarrow{h}_{i-1}\right]\right)$$
$$\overrightarrow{z}_i = \sigma\left(\overrightarrow{W}_z\overline{E}x_i + \overrightarrow{U}_z\overrightarrow{h}_{i-1}\right)$$
$$\overrightarrow{r}_i = \sigma\left(\overrightarrow{W}_r\overline{E}x_u + \overrightarrow{U}_r\overrightarrow{h}_{i-1}\right)$$

Teacher Forcing!

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j,$$

$$s_i = (1 - z_i) \circ s_{i-1} + z_i \circ \tilde{s}_i,$$

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)}$$

$$\tilde{s}_i = \tanh\left(Ey_{i-1} + U\left[r_i \circ s_{i-1}\right] + Cc_i\right) \qquad e_{ij} = v_a^\top \tanh\left(W_a s_{i-1} + U_a h_j\right)$$
$$z_i = \sigma\left(W_z Ey_{i-1} + U_z s_{i-1}\right)$$
$$r_i = \sigma\left(W_r Ey_{i-1} + U_r s_{i-1}\right).$$

Softmax(W[s,y,c]+b)

Attention calculation

Minh-Thang Luong

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Deep Learning Natural Language Processing

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Effective approaches to attention-based neural machine translation CCF none MT Luong, H Pham, CD Manning arXiv preprint arXiv:1508.04025	8292	2015
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$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \bar{\boldsymbol{h}}_s & \textit{dot} \\ \boldsymbol{h}_t^\top \boldsymbol{W}_a \bar{\boldsymbol{h}}_s & \textit{general} \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W}_a [\boldsymbol{h}_t; \bar{\boldsymbol{h}}_s]\right) & \textit{concat} \end{cases}$$

Decoding Strategy

Greedy Search

Beam Search

Algorithm 1 Beam search

Input: Beam size β, maximum length η, user id u, item id v, and tips generation model $\mathcal{G}$.

Output: β best candidate tips.

Initialize $\Pi = \emptyset$, $\pi[0:\beta-1] = \mathbf{0}$, $\Pi_p = \emptyset$, $\pi_p = \mathbf{0}$, $t = 0$;
Get user latent factor and item latent factor:
  $\mathbf{u} = \mathbf{U}(:, u)$ and $\mathbf{v} = \mathbf{V}(:, v)$
while $t < \eta$ **do**
  Generate β new states based on Π: $\{\hat{\mathbf{s}}_t\}_0^{\beta-1} = \mathcal{G}(\Pi)$
  for i from 0 to β **do**
    Uncompleted sequence $s_i \leftarrow \Pi(i)$
    Top-β words $\{w_0, w_1, \ldots, w_{\beta-1}\} \leftarrow \beta\text{-}\underset{w_i \in \mathcal{V}}{\arg\max}\, \hat{\mathbf{s}}_{t_i}^{(w_i)}$
    for each word w_j **do**
      Concatenation: $\Pi_p.inseart(s_i + w_j)$
      Likelihood: $\pi_p.inseart(\pi[i] + \log \hat{\mathbf{s}}_{t_i}^{(w_j)})$
    end for
  end for
  Get the top-β sequences with largest likelihood:
    $\{s\}_0^{\beta-1}, \{l\}_0^{\beta-1} = \beta\text{-}\underset{s \in \Pi_p, l \in \pi_p}{\arg\max}\; l$
  $\Pi \leftarrow \{s\}_0^{\beta-1}$, $\pi \leftarrow \{l\}_0^{\beta-1}$, $\Pi_p = \emptyset$, $\pi_p = \mathbf{0}$
  $t \leftarrow t + 1$
end while
return Π, π.

Seq2seq-attention

Model	All	No UNK°
RNNenc-30	13.93	24.19
RNNsearch-30	21.50	31.44
RNNenc-50	17.82	26.71
RNNsearch-50	26.75	34.16
RNNsearch-50*	28.45	36.15
Moses	33.30	35.63

Figure 3: Four sample alignments found by RNNsearch-50. The x-axis and y-axis of each plot correspond to the words in the source sentence (English) and the generated translation (French), respectively. Each pixel shows the weight α_{ij} of the annotation of the j-th source word for the i-th target word (see Eq. (6)), in grayscale (0: black, 1: white). (a) an arbitrary sentence. (b–d) three randomly selected samples among the sentences without any unknown words and of length between 10 and 20 words from the test set.

Seq2seq-lstm (no attention)

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Seq2seq-lstm (no attention)

Ilya Sutskever

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Improving neural networks by preventing co-adaptation of feature detectors GE Hinton, N Srivastava, A Krizhevsky, I Sutskever, RR Salakhutdinov arXiv preprint arXiv:1207.0580	9643	2012
Language models are few-shot learners T Brown, B Mann, N Ryder, M Subbiah, JD Kaplan, P Dhariwal, ... Advances in neural information processing systems 33, 1877-1901	8070	2020

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Co-Founder of OpenAI

Seq2seq-lstm (no attention)

Figure 1: Our model reads an input sentence "ABC" and produces ' model stops making predictions after outputting the end-of-sentence input sentence in reverse, because doing so introduces many short term optimization problem much easier.

Method	test BLEU score (ntst14)
Bahdanau et al. [2]	28.45
Baseline System [29]	33.30
Single forward LSTM, beam size 12	26.17
Single reversed LSTM, beam size 12	30.59
Ensemble of 5 reversed LSTMs, beam size 1	33.00
Ensemble of 2 reversed LSTMs, beam size 12	33.27
Ensemble of 5 reversed LSTMs, beam size 2	34.50
Ensemble of 5 reversed LSTMs, beam size 12	**34.81**

Table 1: The performance of the LSTM on WMT'14 English to French test set (ntst14). Note that an ensemble of 5 LSTMs with a beam of size 2 is cheaper than of a single LSTM with a beam of size 12.

翻译落地

- Seq2seq-attention之后，大厂开始业务上线
  - ➢在线翻译（谷歌、微软、百度、有道、搜狗等）
  - ➢翻译机（科大讯飞、准儿、百度、搜狗等）
  - ➢同传机器翻译（微软、讯飞、腾讯、搜狗等）
    - 基于PowerPoint的语音同传（微软，TAUS 3.22-23 ）
    - 面向自由说话人的语音同传（腾讯，博鳌亚洲论坛）

Seq2seq-attention

- 爆发seq2seq应用
  - Research
  - Startups

Google NMT

arXiv:1609.08144v2 [cs.CL] 8 Oct 2016

Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

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Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, Jeffrey Dean

Abstract

Neural Machine Translation (NMT) is an end-to-end learning approach for automated translation, with the potential to overcome many of the weaknesses of conventional phrase-based translation systems. Unfortunately, NMT systems are known to be computationally expensive both in training and in translation inference – sometimes prohibitively so in the case of very large data sets and large models. Several authors have also charged that NMT systems lack robustness, particularly when input sentences contain rare words. These issues have hindered NMT's use in practical deployments and services, where both accuracy and speed are essential. In this work, we present GNMT, Google's Neural Machine Translation system, which attempts to address many of these issues. Our model consists of a deep LSTM network with 8 encoder and 8 decoder layers using residual connections as well as attention connections from the decoder network to the encoder. To improve parallelism and therefore decrease training time, our attention mechanism connects the bottom layer of the decoder to the top layer of the encoder. To accelerate the final translation speed, we employ low-precision arithmetic during inference computations. To improve handling of rare words, we divide words into a limited set of common sub-word units ("wordpieces") for both input and output. This method provides a good balance between the flexibility of "character"-delimited models and the efficiency of "word"-delimited models, naturally handles translation of rare words, and ultimately improves the overall accuracy of the system. Our beam search technique employs a length-normalization procedure and uses a coverage penalty, which encourages generation of an output sentence that is most likely to cover all the words in the source sentence. To directly optimize the translation BLEU scores, we consider refining the models by using reinforcement learning, but we found that the improvement in the BLEU scores did not reflect in the human evaluation. On the WMT'14 English-to-French and English-to-German benchmarks, GNMT achieves competitive results to state-of-the-art. Using a human side-by-side evaluation on a set of isolated simple sentences, it reduces translation errors by an average of 60% compared to Google's phrase-based production system.

- **Deep**
- **Residual**
- **Parallel**
- **Wordpiece (subwords)**
- **Length-normalization**
- **Coverage penalty**
- **Reinforcement learning for BLEU**

Seq2seq-attention

序列到序列模型的实现依赖于循环神经网络

- 但循环神经网络的训练存在诸多问题

Sequential Computation

Lingpeng Kong, NLP Lectures

Seq2seq-attention

Parallel Computing?

GPU loves parallel computing blocks!

. . . . . .

Lingpeng Kong, NLP Lectures

Seq2seq-attention

Parallel Computing?

Lingpeng Kong, NLP Lectures

Seq2seq-attention

Convolution Style Models

Lingpeng Kong, NLP Lectures

ConvS2S

[Submitted on 8 May 2017 (v1), last revised 25 Jul 2017 (this version, v3)]

Convolutional Sequence to Sequence Learning

Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, Yann N. Dauphin

The prevalent approach to sequence to sequence learning maps an input sequence to a variable leng
architecture based entirely on convolutional neural networks. Compared to recurrent models, compu
optimization is easier since the number of non-linearities is fixed and independent of the input leng
equip each decoder layer with a separate attention module. We outperform the accuracy of the deep
WMT'14 English-French translation at an order of magnitude faster speed, both on GPU and CPU.

ICML2017

Facebook AI Research

ConvS2S

WMT'16 English-Romanian	BLEU
Sennrich et al. (2016b) GRU (BPE 90K)	28.1
ConvS2S (Word 80K)	29.45
ConvS2S (BPE 40K)	30.02

WMT'14 English-German	BLEU
Luong et al. (2015) LSTM (Word 50K)	20.9
Kalchbrenner et al. (2016) ByteNet (Char)	23.75
Wu et al. (2016) GNMT (Word 80K)	23.12
Wu et al. (2016) GNMT (Word pieces)	24.61
ConvS2S (BPE 40K)	25.16

WMT'14 English-French	BLEU
Wu et al. (2016) GNMT (Word 80K)	37.90
Wu et al. (2016) GNMT (Word pieces)	38.95
Wu et al. (2016) GNMT (Word pieces) + RL	39.92
ConvS2S (BPE 40K)	40.51

Table 1. Accuracy on WMT tasks comapred to previous work. ConvS2S and GNMT results are averaged over several runs.

ConvS2S

WMT'14 English-German	BLEU
Wu et al. (2016) GNMT	26.20
Wu et al. (2016) GNMT + RL	26.30
ConvS2S	26.43

WMT'14 English-French	BLEU
Zhou et al. (2016)	40.4
Wu et al. (2016) GNMT	40.35
Wu et al. (2016) GNMT + RL	41.16
ConvS2S	41.44
ConvS2S (10 models)	41.62

Table 2. Accuracy of ensembles with eight models. We show both likelihood and Reinforce (RL) results for GNMT; Zhou et al. (2016) and ConvS2S use simple likelihood training.

	BLEU	Time (s)
GNMT GPU (K80)	31.20	3,028
GNMT CPU 88 cores	31.20	1,322
GNMT TPU	31.21	384
ConvS2S GPU (K40) $b = 1$	33.45	327
ConvS2S GPU (M40) $b = 1$	33.45	221
ConvS2S GPU (GTX-1080ti) $b = 1$	33.45	142
ConvS2S CPU 48 cores $b = 1$	33.45	142
ConvS2S GPU (K40) $b = 5$	34.10	587
ConvS2S CPU 48 cores $b = 5$	34.10	482
ConvS2S GPU (M40) $b = 5$	34.10	406
ConvS2S GPU (GTX-1080ti) $b = 5$	34.10	256

Table 3. CPU and GPU generation speed in seconds on the development set of WMT'14 English-French. We show results for different beam sizes b. GNMT figures are taken from Wu et al. (2016). CPU speeds are not directly comparable because Wu et al. (2016) use a 88 core machine versus our 48 core setup.

Google:

ConvS2S

- Google说：那怎么行？放大招！

Transformer

Ashish Vaswani

FOLLOW

Startup
Verified email at fastmail.com
Deep Learning

TITLE	CITED BY	YEAR
Attention is all you need A Vaswani, N Shazeer, N Parmar, J Uszkoreit, L Jones, AN Gomez, ... Advances in neural information processing systems 30	66778	2017
Relational inductive biases, deep learning, and graph networks PW Battaglia, JB Hamrick, V Bapst, A Sanchez-Gonzalez, V Zambaldi, ... arXiv preprint arXiv:1806.01261	2503	2018
Self-attention with relative position representations P Shaw, J Uszkoreit, A Vaswani arXiv preprint arXiv:1803.02155	1485	2018
Image transformer N Parmar, A Vaswani, J Uszkoreit, L Kaiser, N Shazeer, A Ku, D Tran International conference on machine learning, 4055-4064	1234	2018
Attention augmented convolutional networks I Bello, B Zoph, A Vaswani, J Shlens, QV Le Proceedings of the IEEE/CVF international conference on computer vision ...	844	2019
Stand-alone self-attention in vision models P Ramachandran, N Parmar, A Vaswani, I Bello, A Levskaya, J Shlens	768	2019

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Transformer

Attention Is All You Need

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Transformer

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Transformer

Figure 1: The Transformer - model architecture.

Transformer

- Multi-headed self-attention
  - Models context
- Feed-forward layers
  - Computes non-linear hierarchical features
- Layer norm and residuals
  - Makes training deep networks healthy
- Positional embeddings
  - Allows model to learn relative positioning

Figure 1: The Transformer - model architecture.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *NIPS*, pp. 5998-6008. 2017.

Transformer- self-attention

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Transformer

- Transformer: Multi-Head Attention

Transformer-multi-head self-att

Transformer-multi-head self-att

Transformer-The Order of The Sequence

- **Position embedding – relative position**

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

$$\begin{bmatrix} \sin(\frac{i}{10000^{2\times\frac{1}{d}}}) \\ \cos(\frac{i}{10000^{2\times\frac{1}{d}}}) \\ \vdots \\ \sin(\frac{i}{10000^{2\times\frac{d/2}{d}}}) \\ \cos(\frac{i}{10000^{2\times\frac{d/2}{d}}}) \end{bmatrix}$$

- 很多后续研究

Transformer - Input

Transformer

Figure 1: The Transformer - model architecture.

Transformer – Add & Norm

- Add – Residual Connection
- Norm

Layer Normalization (Ba et al, 2016)

$$\mathbf{h} = \mathbf{g} \odot N(\mathbf{x}) + \mathbf{b}$$

$$N(\mathbf{x}) = \frac{\mathbf{x} - \mu}{\sigma} \qquad \mu = \frac{1}{H}\sum_{i=1}^{H} x_i \qquad \sigma = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(x_i - \mu)^2}$$

Smoother gradients, faster training and better generalization accuracy. (Xu et al, Neurips 2019)

Transformer

Figure 1: The Transformer - model architecture.

Transformer - fflayer

Transformer-decoder

- Cross-attention
- Masked-self-attention

Figure 1: The Transformer - model architecture.

Transformer-decoder

Transformer-results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Transformer

Figure 1: The Transformer - model architecture.

内容

- 基础技术
- **预训练技术**
- ChatGPT
- 未来展望

预训练的故事

语义分析-向量表示

- 匹配
- 检索
- 分类
- 聚类

VSM→LDA(2003)

→Google Word2vec(2013/14) → Google LSTM-LM(2015)

→ AI2 ELMo(2017) → OpenAI GPT(Jun 2018)

→ Google BERT(Oct 2018) → OpenAI GPT2(2019)→ Google XLNet(2019)

→OpenAI GPT3(2020)

语义分析-向量表示-VSM

- TF-IDF向量表示

Term / Document	information technology	information system	communication technology	software application	telecommunication	computer science
1	0.77	0.55	0.45	0.13	0.14	0.15
2	0	0	0.13	0.53	0.15	0.75

语义分析-向量表示-VSM

- 缺点
  - **稀疏性: 对于大词典，尤其是包括了生僻字的词典，文档稀疏性不可避免；**
  - **多义词: BOW模型只统计单词出现的次数，而忽略了一个词可能存在多种含义，一词多义；**
  - **同义词(Synonym): 多个单词可以表示同一个意思，一义多词；**
- 从同义词和多义词问题可以看到：单词也许不是文档的最基本组成元素，在单词与文档之间还有一层隐含的关系，我们称之为主题(Topic)，**我们更关注隐藏在词之后的意义和概念。**在写文章时首先确定的是文章的主题，再根据主题选择合适的单词来表达观点。
- 所以，在这里我们需要将单词向量空间转变成话题向量空间，这里也就是从词袋模型转变成LSA模型

https://zhuanlan.zhihu.com/p/80557306

语义分析-向量表示-VSM

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

Latent Semantic Indexing (LSI)

Indexing by latent semantic analysis

[PDF] from ryanrossi.com

Authors	Scott Deerwester, Susan T Dumais, George W Furnas, Thomas K Landauer, Richard Harshman
Publication date	1990/9
Journal	Journal of the American society for information science
Volume	41
Issue	6
Pages	391-407
Publisher	Wiley Subscription Services, Inc., A Wiley Company
Description	A new method for automatic indexing and retrieval is described. The approach is to take advantage of implicit higher-order structure in the association of terms with documents ("semantic structure") in order to improve the detection of relevant documents on the basis of terms found in queries. The particular technique used is singular-value decomposition, in which a large term by document matrix is decomposed into a set of ca. 100 orthogonal factors from which the original matrix can be approximated by linear combination. Documents are represented by ca. 100 item vectors of factor weights. Queries are represented as pseudo-document vectors formed from weighted combinations of terms, and documents with supra-threshold cosine values are returned. Initial tests find this completely automatic method for retrieval to be promising. © 1990 John Wiley & Sons, Inc.
Total citations	Cited by 18135

Scholar articles Indexing by latent semantic analysis
S Deerwester, ST Dumais, GW Furnas, TK Landauer… - Journal of the American society for information science, 1990
Cited by 18135 Related articles All 59 versions

Latent Semantic Indexing (LSI)

- Goal
  - Map high dimensional vector space representation to lower dimensional representation in latent semantic space
  - Reveal semantic relations between documents (count vectors)
- SVD
  - $N = U\Sigma V^T$
  - U: orthogonal matrix with left singular vectors (eigenvectors of NN^T)
  - V: orthogonal matrix with right singular vectors (eigenvectors of N^TN)
  - Σ: diagonal matrix with singular values of N
- Select *k* largest singular values from Σ to get approximation $\widetilde{N}$ with minimal error
  - Can compute similarity values between document vectors and term vectors

Latent Semantic Indexing (LSI)

奇异值σ跟特征值类似，在矩阵Σ中也是从大到小排列，而且σ的减少特别的快，在很多情况下，前**10%甚至1%的奇异值的和就占了全部的奇异值之和的99%以上了**。也就是说，我们也可以用**前r大的奇异值**来近似描述矩阵

Latent Semantic Indexing (LSI)

$$
\begin{array}{l} \text{Terms} \\ \downarrow \\ \text{a} \\ \text{arrived} \\ \text{damaged} \\ \text{delivery} \\ \text{fire} \\ \text{gold} \\ \text{in} \\ \text{of} \\ \text{shipment} \\ \text{silver} \\ \text{truck} \end{array}
\quad
\mathbf{A} = \begin{array}{c} \begin{array}{ccc} \text{d1} & \text{d2} & \text{d3} \\ \downarrow & \downarrow & \downarrow \end{array} \\ \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 2 & 0 \\ 0 & 1 & 1 \end{bmatrix} \end{array}
\quad
\mathbf{q} = \begin{array}{c} \text{q} \\ \downarrow \\ \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \end{array}
$$

$$
\mathbf{U} \approx \mathbf{U}_k = \begin{bmatrix} -0.4201 & 0.0748 \\ -0.2995 & -0.2001 \\ -0.1206 & 0.2749 \\ -0.1576 & -0.3046 \\ -0.1206 & 0.2749 \\ -0.2626 & 0.3794 \\ -0.4201 & 0.0748 \\ -0.4201 & 0.0748 \\ -0.2626 & 0.3794 \\ -0.3151 & -0.6093 \\ -0.2995 & -0.2001 \end{bmatrix}
\qquad
\mathbf{k} = 2
\qquad
\mathbf{\Sigma} \approx \mathbf{\Sigma}_k = \begin{bmatrix} 4.0989 & 0.0000 \\ 0.0000 & 2.3616 \end{bmatrix}
$$

$$
\mathbf{V} \approx \mathbf{V}_k = \begin{bmatrix} -0.4945 & 0.6492 \\ -0.6458 & -0.7194 \\ -0.5817 & 0.2469 \end{bmatrix}
\qquad
\mathbf{V}^T \approx \mathbf{V}_k^T = \begin{bmatrix} -0.4945 & -0.6458 & -0.5817 \\ 0.6492 & -0.7194 & 0.2469 \end{bmatrix}
$$

Latent Semantic Indexing (LSI)

原图 $A_1 = \sigma_1 u_1 v_1^T,$ 保留前5项 保留前50项

https://www.zhihu.com/question/22237507/answer/53804902

Latent Semantic Indexing (LSI)

- LSI是最早出现的主题模型了，它的算法原理很简单，一次奇异值分解就可以得到主题模型，同时解决词义的问题，非常漂亮。

- 将文档表示到话题向量空间的过程就是**SVD奇异值分解和降维的过程**。降维是LSA分析中最重要的一步，通过降维，去除了文档中的“噪音”，也就是无关信息（比如词的误用或不相关的词偶尔出现在一起），语义结构逐渐呈现。

- 缺点：不好解释

pLSA(Probabilistic Latent Semantic Analysis)

LSA概率意义上的解释

pLSA 模型通过以下过程来生成文档（记号里全部省去了对参数的依赖）：

(1) 以概率 $P(d_m)$ 选择一篇文档 d_m

(2) 以概率 $P(z_k|d_m)$ 得到一个主题 z_k

(3) 以概率 $P(w_n|z_k)$ 生成一个词 w_n

概率图模型如下所示（取自[2]）：

(c) pLSI/aspect model

https://zhuanlan.zhihu.com/p/31235789

pLSA(Probabilistic Latent Semantic Analysis)

- 联合概率分布

拿到贝叶斯网当然先要看看联合分布咯。这个贝叶斯网表达的是如下的联合分布：

$$P(d_m, z_k, w_n) = P(d_m)P(z_k|d_m)P(w_n|z_k)$$

$$P(d_m, w_n) = P(d_m)P(w_n|d_m)$$

假设有一篇文档为 $\vec{w} = (w_1, w_2, \ldots, w_N)$，生成它的概率就是

$$P(\vec{w}|d_m) = \prod_{n=1}^{N} P(w_n|d_m)$$

我们看一下 $P(w_n|d_m)$ 的表达式。如果不考虑随机变量之间的条件独立性的话，有

$$P(w_n|d_m) = \sum_k P(z_k|d_m)P(w_n|z_k, d_m)$$

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pLSA(Probabilistic Latent Semantic Analysis)

我们看一下 $P(w_n|d_m)$ 的表达式。如果不考虑随机变量之间的条件独立性的话，有

$$P(w_n|d_m) = \sum_k P(z_k|d_m)P(w_n|z_k, d_m)$$

但是观察图模型中的 d 、z 、w 可以知道，它们三个是有向图模型里非常典型的 **head-to-tail** 的情况：当 z 已知时，d 和 w 条件独立，也就是

$$P(w_n|z_k, d_m) = P(w_n|z_k)$$

进而有

$$P(w_n|d_m) = \sum_k P(z_k|d_m)P(w_n|z_k)$$

所以最终的联合分布表达式为

$$P(d_m, w_n) = P(d_m) \sum_k P(z_k|d_m)P(w_n|z_k)$$

https://zhuanlan.zhihu.com/p/31235789

pLSA(Probabilistic Latent Semantic Analysis)

似然函数

这样的话，我们要做的事就是从文档集里估计出上面的参数。pLSA 是频率学派的方法，将模型参数看作具体值，而不是有先验的随机变量。所以，考虑最大化对数似然函数：

$$
\begin{aligned}
L(\theta) &= \ln \prod_{m=1}^{M} \prod_{n=1}^{N} P(d_m, w_n)^{n(d_m, w_n)} \\
&= \sum_m \sum_n n(d_m, w_n) \ln P(d_m, w_n) \\
&= \sum_m \sum_n n(d_m, w_n)(\ln P(d_m) + \ln P(w_n|d_m)) \\
&= \sum_m \sum_n n(d_m, w_n) \ln P(w_n|d_m) + \sum_m \sum_n n(d_m, w_n) \ln P(d_m)
\end{aligned}
$$

第二项可以直接去掉，那么不妨直接记：

$$
\begin{aligned}
L(\theta) &= \sum_m \sum_n n(d_m, w_n) \ln P(w_n|d_m) \\
&= \sum_m \sum_n n(d_m, w_n) \ln \Big[\sum_k P(z_k|d_m) P(w_n|z_k)\Big]
\end{aligned}
$$

https://zhuanlan.zhihu.com/p/31235789

pLSA(Probabilistic Latent Semantic Analysis)

注意到两个约束条件，即

$$\sum_n \frac{\sum_m n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}{\tau_k} = 1$$

$$\sum_k \frac{\sum_n n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}{\rho_m} = 1$$

从中可求得 τ_k 、ρ_m ，所以方程的解为

$$P_{t+1}(w_n|z_k) = \frac{\sum_m n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}{\sum_n \sum_m n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}$$

$$P_{t+1}(z_k|d_m) = \frac{\sum_n n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}{\sum_k \sum_n n(d_m, w_n) P(z_k|w_n, d_m; \theta_t)}$$

当模型参数全部估计好后，便得到了完整的 pLSA 模型。上面的迭代过程很明显是一个频数估计（极大似然估计）的形式，意义很明确。模型使用EM算法进行参数估计时往往都会推导出这样的结果，例如HMM。

pLSA(Probabilistic Latent Semantic Analysis)

缺点:

- 对于一个新的文档而言，我们无法得知它对应的 $P(d)$ 究竟是什么， 因此尽管 PLSA 模型在给定的文档上是一个生成模型，它却无法生成新的未知的文档。
- 该模型的另外的一个问题在于，随着文档数量的增加，$P(z|d)$ 的参数也会随着线性增加，这就导致无论有多少训练数据，都容易导致模型的过拟合问题。这两点成为了限制 PLSA 模型被更加广泛使用的两大缺陷。

https://www.cnblogs.com/bentuwuying/p/6219970.html

Latent Dirichlet Allocation (LDA)

- **Latent Dirichlet Allocation (LDA)被提出**

Latent Dirichlet Allocation (LDA)

Latent dirichlet allocation

Authors	David M Blei, Andrew Y Ng, Michael I Jordan
Publication date	2003
Journal	Journal of machine Learning research
Volume	3
Issue	Jan
Pages	993-1022
Description	We describe latent Dirichlet allocation (LDA), a generative probabilistic model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. We present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. We report results in document modeling, text classification, and collaborative filtering, comparing to a mixture of unigrams model and the probabilistic LSI model.
Total citations	Cited by 45294

Scholar articles

Latent dirichlet allocation
DM Blei, AY Ng, MI Jordan - Journal of machine Learning research, 2003
Cited by 44707 Related articles All 97 versions

Latent dirichlet allocation
D Blei, A Ng, M Jordan - Advances in neural information processing systems, 2001
Cited by 708 Related articles All 9 versions

Latent Dirichlet Allocation (LDA)

- LDA模型涉及很多数学知识，这也许是LDA晦涩难懂的主要原因。
- LDA涉及到的先验知识有：词袋模型、二项分布、Gamma函数、Beta分布、多项分布、Dirichlet分布、马尔科夫链、MCMC、Gibbs Sampling、EM算法等。

Latent Dirichlet Allocation (LDA)

- **Dirichlet分布**
- Dirichlet的概率密度函数为：

$$f(x_1, x_2, \ldots, x_k; \alpha_1, \alpha_2, \ldots, \alpha_k) = \frac{1}{B(\alpha)} \prod_{i=1}^{k} {x_i}^{\alpha^i - 1}$$

- 其中：

$$B(\alpha) = \frac{\prod_{i=1}^{k} \Gamma(\alpha^i)}{\Gamma(\sum_{i=1}^{k} \alpha^i)}, \sum_{i=1}^{k} x^i = 1$$

- 狄利克雷(Dirichlet)分布是多项式分布的共轭分布。

Latent Dirichlet Allocation (LDA)

- **Dirichlet分布**

Latent Dirichlet Allocation (LDA)

这个概率图可以分解为两个主要的物理过程：

1. $\vec{\alpha} \to \vec{\theta}_m \to z_{m,n}$，这个过程表示在生成第$m$ 篇文档的时候，先从第一个坛子中抽了一个doc-topic 骰子$\vec{\theta}_m$，然后投掷这个骰子生成了文档中第n 个词的topic编号$z_{m,n}$；

2. $\vec{\beta} \to \vec{\varphi}_k \to w_{m,n}|k = z_{m,n}$，这个过程表示用如下动作生成语料中第$m$篇文档的第$n$个词：在上帝手头的$K$ 个topic-word 骰子$\vec{\varphi}_k$ 中，挑选编号为$k = z_{m,n}$的那个骰子进行投掷，然后生成word $w_{m,n}$；

Rickjin LDA数学八卦

语义分析-向量表示-LDA

- 主题模型- Latent Dirichlet allocation
  - d-z
  - z-w

LDA-主流语义建模技术

- Natural Language Processing
- Information Retrieval
- Recommendation Systems

Large LDA - Peacock

- Wang, Yi, Xuemin Zhao, Zhenlong Sun, Hao Yan, Lifeng Wang, **Zhihui Jin**, Liubin Wang, Yang Gao, Ching Law, and Jia Zeng. "**Peacock: Learning long-tail topic features for industrial applications**." *ACM Transactions on Intelligent Systems and Technology (TIST)* 6, no. 4 (2015): 1-23

Fig. 3. The hierarchical distributed architecture in Peacock. The first layer contains multiple configurations in Figure 2. The second layer contains M aggregation servers and one coordinator server for global parameter synchronization and asymmetric prior estimation. This architecture can readily scale up to hundreds of machines having thousands of cores to learn at least 10^5 topics from 10^9 search queries.

Large LDA - LightLDA

- **Yuan, Jinhui**, Fei Gao, Qirong Ho, Wei Dai, Jir
  and Wei-Ying Ma. "Lightlda: Big topic models
  In *Proceedings of the 24th International Con*
  2015.

Figure 6: System architecture, data

老师木

2016-12-16 21:22 iPhone 6 Plus

发一张零号员工工位

查看翻译

LDA如火如荼

- Deep Learning悄悄发展
- 2006
- 2011
- 2012, AlexNet
- RNN, LSTM

Unsupervised Representation Learning

- Word2Vec - 2014

Tomas Mikolov

FOLLOWING

Senior Researcher, CIIRC CTU
Verified email at cvut.cz

Artificial Intelligence Machine Learning Language Modeling Natural Language Processing

TITLE	CITED BY	YEAR
Distributed representations of words and phrases and their compositionality CCF A T Mikolov, I Sutskever, K Chen, GS Corrado, J Dean Neural information processing systems	37530	2013
Efficient estimation of word representations in vector space T Mikolov, K Chen, G Corrado, J Dean arXiv preprint arXiv:1301.3781	33396	2013
Distributed representations of sentences and documents Q Le, T Mikolov International conference on machine learning, 1188-1196	10633	2014
Enriching word vectors with subword information P Bojanowski, E Grave, A Joulin, T Mikolov Transactions of the association for computational linguistics 5, 135-146	9746	2017
Recurrent neural network based language model. T Mikolov, M Karafiát, L Burget, J Cernocký, S Khudanpur Interspeech 2 (3), 1045-1048	6904	2010
On the difficulty of training recurrent neural networks R Pascanu, T Mikolov, Y Bengio International conference on machine learning, 1310-1318	5833	2013
Bag of tricks for efficient text classification A Joulin, E Grave, P Bojanowski, T Mikolov arXiv preprint arXiv:1607.01759	4751	2016

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Co-authors VIEW ALL

Jeff Dean
Google Senior Fellow & SVP, Go...

Unsupervised Representation Learning

- Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. "**Efficient estimation of word representations in vector space**." *ICLR* (2013).
  - Large improvements in accuracy, lower computational cost.
  - It takes less than a day to train from 1.6 billion words data set.

CBOW

$$\mathcal{L} = \sum_{w \in \mathcal{C}} \log p(w|Context(w))$$

Skip-gram

$$\mathcal{L} = \sum_{w \in \mathcal{C}} \log p(Context(w)|w)$$

Unsupervised Representation Learning

- Word2Vec - 2014

Problem?

man - woman + queen = king

Family Relations

```
op("sansa - child + mother")
op("arya - sister + brother")
op("catelyn - wife + husband")
op("cersei - wife + husband")
op("catelyn - cersei + joffrey")
op("jaime - brother + sister")
```

```
child is to mother AS sansa is to ? = catelyn (0.84)
sister is to brother AS arya is to ? = bran (0.57)
wife is to husband AS catelyn is to ? = ned (0.79)
wife is to husband AS cersei is to ? = jaime (0.64)
cersei is to joffrey AS catelyn is to ? = robb (0.88)
brother is to sister AS jaime is to ? = cersei (0.85)
```

DeepWalk，TransX，腾讯AI Lab开源800万中文词的NLP数据集

Unsupervised Representation Learning

- Word2Vec - 2014

- **Problem**: Word embeddings are applied in a context free manner

open a bank account on the river bank

[0.3, 0.2, -0.8, …]

- **Solution**: Train *contextual* representations on text corpus

[0.9, -0.2, 1.6, …] [-1.9, -0.4, 0.1, …]

open a bank account on the river bank

Unsupervised Representation Learning

- Semi-Supervised Sequence Learning, Google, NIPS 2015

Semi-supervised Sequence Learning

Andrew M. Dai
Google Inc.
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Quoc V. Le
Google Inc.
qvl@google.com

Abstract

We present two approaches to use unlabeled data to improve Sequence Learning with recurrent networks. The first approach is to predict what comes next in a sequence, which is a language model in NLP. The second approach is to use a sequence autoencoder, which reads the input sequence into a vector and predicts the input sequence again. These two algorithms can be used as a "pretraining" algorithm for a later supervised sequence learning algorithm. In other words, the parameters obtained from the pretraining step can then be used as a starting point for other supervised training models. In our experiments, we find that long short term memory recurrent networks after pretrained with the two approaches become more stable to train and generalize better. With pretraining, we were able to achieve strong performance in many classification tasks, such as text classification with IMDB, DBpedia or image recognition in CIFAR-10.

Unsupervised Representation Learning

- Semi-Supervised Sequence Learning, Google, NIPS 2015

Unsupervised Representation Learning

- Semi-Supervised Sequence Learning, Google, NIPS 2015

Table 1: A summary of the error rates of SA-LSTMs and previous best reported results.

Dataset	SA-LSTM	Previous best result
IMDB	7.24%	7.42%
Rotten Tomatoes	16.7%	18.5%
20 Newsgroups	15.6%	17.1%
DBpedia	1.19%	1.74%

Unsupervised Representation Learning

- ELMo: Deep Contextual Word Embeddings, AI2 & University of Washington, Jun. 2017. NAACL.

Matthew E Peters

FOLLOW

Sr Research Scientist, Allen Institute for Artificial Intelligence
Verified email at allenai.org

Artificial Intelligence Natural Language Processing

TITLE	CITED BY	YEAR
Deep contextualized word representations CCF C ME Peters, M Neumann, M Iyyer, M Gardner, C Clark, K Lee, ... NAACL, Best Paper	11495 *	2018
Longformer: The Long-Document Transformer CCF none I Beltagy, ME Peters, A Cohan arXiv preprint arXiv:2004.05150	1384	2020
AllenNLP: A Deep Semantic Natural Language Processing Platform CCF none M Gardner, J Grus, M Neumann, O Tafjord, P Dasigi, N Liu, M Peters, ... arXiv preprint arXiv:1803.07640	1027	2018
Semi-supervised sequence tagging with bidirectional language models CCF A ME Peters, W Ammar, C Bhagavatula, R Power arXiv preprint arXiv:1705.00108	654	2017
Relationships between water vapor path and precipitation over the tropical oceans CCF none CS Bretherton, ME Peters, LE Back Journal of climate 17 (7), 1517-1528	644	2004

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Unsupervised Representation Learning

- ELMo: Deep Contextual Word Embeddings, AI2 & University of Washington, Jun. 2017
- NAACL 2018 best paper

Unsupervised Representation Learning

- ELMo: Deep Contextual Word Embeddings, AI2 & University of Washington, Jun. 2017

Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

Table 1: Test set comparison of ELMo enhanced neural models with state-of-the-art single model baselines across six benchmark NLP tasks. The performance metric varies across tasks – accuracy for SNLI and SST-5; F_1 for SQuAD, SRL and NER; average F_1 for Coref. Due to the small test sizes for NER and SST-5, we report the mean and standard deviation across five runs with different random seeds. The "increase" column lists both the absolute and relative improvements over our baseline.

NAACL 2018 best paper

预训练语言模型 – GPT1

ChatGPT研究框架（2023）-国泰君安

Ilya采访：2017年，谷歌发表Transformer论文的第二天，OpenAI的研发团队就豁然开朗了，意识到Transformer可以完全解决机器不断预测文本的问题，这最终造就了GPT-3以及迄今为止的一切；

Unsupervised Representation Learning

- Improving Language Understanding by Generative Pre-Training, OpenAI, Jun, 2018
- GPT

GPT中的三个字母，每一个的技术or专利都属于Google或者是被Google早期探索过，但合起来就是OpenAI的。

Improving Language Understanding by Generative Pre-Training

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Abstract

Natural language understanding comprises a wide range of diverse tasks such as textual entailment, question answering, semantic similarity assessment, and document classification. Although large unlabeled text corpora are abundant, labeled data for learning these specific tasks is scarce, making it challenging for discriminatively trained models to perform adequately. We demonstrate that large gains on these tasks can be realized by *generative pre-training* of a language model on a diverse corpus of unlabeled text, followed by *discriminative fine-tuning* on each specific task. In contrast to previous approaches, we make use of task-aware input transformations during fine-tuning to achieve effective transfer while requiring minimal changes to the model architecture. We demonstrate the effectiveness of our approach on a wide range of benchmarks for natural language understanding. Our general task-agnostic model outperforms discriminatively trained models that use architectures specifically crafted for each task, significantly improving upon the state of the art in 9 out of the 12 tasks studied. For instance, we achieve absolute improvements of 8.9% on commonsense reasoning (Stories Cloze Test), 5.7% on question answering (RACE), and 1.5% on textual entailment (MultiNLI).

Unsupervised Representation Learning

- Improving Language Understanding by Generative Pre-Training, OpenAI, Jun, 2018
- GPT

Figure 1: The Transformer - model architecture.

https://openai.com/blog/language-unsupervised/

Unsupervised Representation Learning

Improving Language Understanding by Generative Pre-Training, OpenAI, Jun, 2018
GPT

Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Unsupervised Representation Learning

- Improving Language Understanding by Generative Pre-Training, OpenAI, Jun, 2018
- GPT

DATASET	TASK	SOTA	OURS
SNLI	Textual Entailment	89.3	**89.9**
MNLI Matched	Textual Entailment	80.6	**82.1**
MNLI Mismatched	Textual Entailment	80.1	**81.4**
SciTail	Textual Entailment	83.3	**88.3**
QNLI	Textual Entailment	82.3	**88.1**
RTE	Textual Entailment	**61.7**	56.0
STS-B	Semantic Similarity	81.0	**82.0**
QQP	Semantic Similarity	66.1	**70.3**
MRPC	Semantic Similarity	**86.0**	82.3
RACE	Reading Comprehension	53.3	**59.0**
ROCStories	Commonsense Reasoning	77.6	**86.5**
COPA	Commonsense Reasoning	71.2	**78.6**
SST-2	Sentiment Analysis	**93.2**	91.3
CoLA	Linguistic Acceptability	35.0	**45.4**
GLUE	Multi Task Benchmark	68.9	**72.8**

Unsupervised Representation Learning

- Problem
  - Language models only use left context or right context
  - But language understanding is bidirectional.

BERT

- BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Authors	Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova
Publication date	2018/10/11
Journal	https://arxiv.org/abs/1810.04805
Description	We introduce a new language representation model called BERT, which stands for Bidirectional Encoder Representations from Transformers. Unlike recent language representation models, BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications. BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).
Total citations	Cited by 60544

Experience

Software Engineer
Google
Sep 2017 - Present · 5 yrs 3 mos
Seattle, WA

Software Engineer
Microsoft
Jul 2014 - Sep 2017 · 3 yrs 3 mos

ACL 2014 Best Long Paper award
NAACL 2012 Best Short Paper award

- BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

BERT

- BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
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Pre-training

- BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

BERT

- The General Language Understanding Evaluation (**GLUE**) benchmark is a collection of resources for training, evaluating, and analyzing.

Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI	RTE	WNLI	AX
1	Facebook AI	RoBERTa		88.5	67.8	96.7	92.3/89.8	92.2/91.9	74.3/90.2	90.8	90.2	98.9	88.2	89.0	48.7
2	XLNet Team	XLNet-Large (ensemble)		88.4	67.8	96.8	93.0/90.7	91.6/91.1	74.2/90.3	90.2	89.8	98.6	86.3	90.4	47.5
3	Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6	68.4	96.5	92.7/90.3	91.1/90.7	73.7/89.9	87.9	87.4	96.0	86.3	89.0	42.8
4	GLUE Human Baselines	GLUE Human Baselines		87.1	66.4	97.8	86.3/80.8	92.7/92.6	59.5/80.4	92.0	92.8	91.2	93.6	95.9	-
5	王玮	ALICE large ensemble (Alibaba DAMO		87.0	69.2	95.2	92.6/90.2	91.1/90.6	74.4/90.7	88.2	87.9	95.7	83.5	87.0	43.9
6	Stanford Hazy Research	Snorkel MeTaL		83.2	63.8	96.2	91.5/88.5	90.1/89.7	73.1/89.9	87.6	87.2	93.9	80.9	65.1	39.9
7	XLM Systems	XLM (English only)		83.1	62.9	95.6	90.7/87.1	88.8/88.2	73.2/89.8	89.1	88.5	94.0	76.0	71.9	44.7
8	张倬胜	SemBERT		82.9	62.3	94.6	91.2/88.3	87.8/86.7	72.8/89.8	87.6	86.3	94.6	84.5	65.1	42.4
9	Danqi Chen	SpanBERT (single-task training)		82.8	64.3	94.8	90.9/87.9	89.9/89.1	71.9/89.5	88.1	87.7	94.3	79.0	65.1	45.1
10	Kevin Clark	BERT + BAM		82.3	61.5	95.2	91.3/88.3	88.6/87.9	72.5/89.7	86.6	85.8	93.1	80.4	65.1	40.7
11	Nitish Shirish Keskar	Span-Extractive BERT on STILTs		82.3	63.2	94.5	90.6/87.6	89.4/89.2	72.2/89.4	86.5	85.8	92.5	79.8	65.1	28.3
12	Jason Phang	BERT on STILTs		82.0	62.1	94.3	90.2/86.6	88.7/88.3	71.9/89.4	86.4	85.6	92.7	80.1	65.1	28.3
13	Jacob Devlin	BERT: 24-layers, 16-heads, 1024-hidde		80.5	60.5	94.9	89.3/85.4	87.6/86.5	72.1/89.3	86.7	[illegible]	92.7	70.1	65.1	39.6
14	Neil Houlsby	BERT + Single-task Adapters		80.2	59.2	94.3	88.7/84.3	87.3/86.1	71.5/89.4	85.4	85.0	92.4	71.6	65.1	9.2

截图(Alt + A)

BERT

- Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset

SQuAD1.1 Leaderboard

Here are the ExactMatch (EM) and F1 scores evaluated on the test set of SQuAD v1.1.

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar et al. '16)	82.304	91.221
1 Oct 05, 2018	BERT (ensemble) *Google AI Language* https://arxiv.org/abs/1810.04805	**87.433**	**93.160**
2 Feb 14, 2019	Knowledge-enhanced BERT (single model) *Anonymous*	85.944	92.425
2 Sep 26, 2018	nlnet (ensemble) *Microsoft Research Asia*	85.954	91.677
3 Sep 09, 2018	nlnet (ensemble) *Microsoft Research Asia*	85.356	91.202
3 Oct 05, 2018	BERT (single model) *Google AI Language* https://arxiv.org/abs/1810.04805	85.083	91.835

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Jul 22, 2019	XLNet + DAAF + Verifier (ensemble) *PINGAN Omni-Sinitic*	**88.592**	**90.859**
2 Jul 19, 2019	XLNet + SG-Net Verifier (ensemble) *Shanghai Jiao Tong University & CloudWalk*	88.050	90.645
3 Jul 23, 2019	XLNet + SG-Net Verifier (single model) *Shanghai Jiao Tong University & CloudWalk*	87.046	89.899
3 Mar 20, 2019	BERT + DAE + AoA (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	87.147	89.474
3 Jul 20, 2019	RoBERTa (single model) *Facebook AI*	86.820	89.795
4 Mar 15, 2019	BERT + ConvLSTM + MTL + Verifier (ensemble) *Layer 6 AI*	86.730	89.286
5 Mar 05, 2019	BERT + N-Gram Masking + Synthetic Self-Training (ensemble) *Google AI Language* https://github.com/google-research/bert	86.673	89.147
6 May 21, 2019	XLNet (single model) *Google Brain & CMU*	86.346	89.133
7 May 14, 2019	SG-Net (ensemble) *Shanghai Jiao Tong University*	86.211	88.848
7 Apr 13, 2019	SemBERT(ensemble) *Shanghai Jiao Tong University*	86.166	88.886
8 Mar 16, 2019	BERT + DAE + AoA (single model) *Joint Laboratory of HIT and iFLYTEK Research*	85.884	88.621
8 Jul 22, 2019	SpanBERT (single model) *FAIR & UW*	85.748	88.709

BERT

- Best Paper of NAACL 2019

Best Long Paper

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova

BERT

Best Paper of NAACL 2018

Deep contextualized word representations

Matthew E. Peters[†], **Mark Neumann**[†], **Mohit Iyyer**[†], **Matt Gardner**[†],
{matthewp,markn,mohiti,mattg}@allenai.org

Christopher Clark[*], **Kenton Lee**[*], **Luke Zettlemoyer**[†*]
{csquared,kentonl,lsz}@cs.washington.edu

[†]Allen Institute for Artificial Intelligence
[*]Paul G. Allen School of Computer Science & Engineering, University of Washington

ELMo

BERT - Technical Details

BERT - Technical Details

- Input Layer

Figure 2: BERT input representation. The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

BERT - Technical Details

- Pre-training
  - Task #1: Masked LM
    - **15%, 10%, 10%, 80%**

```
Input: the man went to the [MASK1] . he bought a [MASK2] of milk.
Labels: [MASK1] = store; [MASK2] = gallon
```

- Problem: Mask token never seen at fine-tuning
- Solution: 15% of the words to predict, but don't replace with `[MASK]` 100% of the time. Instead:
- 80% of the time, replace with `[MASK]`
  `went to the store → went to the [MASK]`
- 10% of the time, replace random word
  `went to the store → went to the running`
- 10% of the time, keep same
  `went to the store → went to the store`

BERT - Technical Details

- Pre-training
  - Task #1: Masked LM
    - **15%, 10%, 10%, 80%**

```
Input: the man went to the [MASK1] . he bought a [MASK2] of milk.
Labels: [MASK1] = store; [MASK2] = gallon
```

  - Task #2: Next Sentence Prediction

```
Sentence A: the man went to the store .
Sentence B: he bought a gallon of milk .
Label: IsNextSentence
```

```
Sentence A: the man went to the store .
Sentence B: penguins are flightless .
Label: NotNextSentence
```

- **To learn *relationships* between sentences, predict whether Sentence B is actual sentence that proceeds Sentence A, or a random sentence.**

BERT - Technical Details

- Fine-tuning

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

BERT – Training Details

- Dataset
  - Books Corpus (800M words)
  - Wikipedia (2,500M words)

BERT – Training Details

- Parameters
  - BERT-BASE: L=12, H=768, A=12, Total Parameters=110M
  - BERT-LARGE: L=24, H=1024, A=16, Total Parameters=340M

  - 30,000 token bpe vocabulary
  - 512 max-len， 256 batch-size
  - 1M steps， ~40 epochs

进入大模型时代!

BERT Research

ERNIE: Enhanced Representation through kNowledge IntEgration

**** 2019-04-10 **更新**: update ERNIE_stable-1.0.1.tar.gz, 将模型参数、配置 ernie_config.json、vocab.txt 打包发布 ****

**** 2019-03-18 **更新**: update ERNIE_stable.tgz ****

ERNIE 通过建模海量数据中的词、实体及实体关系，学习真实世界的语义知识。相较于 **BERT** 学习原始语言信号，**ERNIE** 直接对先验语义知识单元进行建模，增强了模型语义表示能力。

这里我们举个例子：

`Learnt by BERT` : 哈 [mask] 滨是 [mask] 龙江的省会，[mask] 际冰 [mask] 文化名城。

`Learnt by ERNIE:` [mask] [mask] [mask] 是黑龙江的省会，国际 [mask] [mask] 文化名城。

在 **BERT** 模型中，我们通过『哈』与『滨』的局部共现，即可判断出『尔』字，模型没有学习与『哈尔滨』相关的任何知识。而 **ERNIE** 通过学习词与实体的表达，使模型能够建模出『哈尔滨』与『黑龙江』的关系，学到『哈尔滨』是『黑龙江』的省会以及『哈尔滨』是个冰雪城市。

训练数据方面，除百科类、资讯类中文语料外，**ERNIE** 还引入了论坛对话类数据，利用 **DLM**（Dialogue Language Model）建模 Query-Response 对话结构，将对话 Pair 对作为输入，引入 Dialogue Embedding 标识对话的角色，利用 Dialogue Response Loss 学习对话的隐式关系，进一步提升模型的语义表示能力。

Baidu 百度

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Mar 20, 2019	BERT + DAE + AoA (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	**87.147**	**89.474**
2 Mar 15, 2019	BERT + ConvLSTM + MTL + Verifier (ensemble) *Layer 6 AI*	86.730	89.286
3 Mar 05, 2019	BERT + N-Gram Masking + Synthetic Self-Training (ensemble) *Google AI Language* https://github.com/google-research/bert	86.673	89.147

Google

Language Models are Unsupervised Multitask Learners

Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

Abstract

Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on task-specific datasets. We demonstrate that language

competent generalists. We would like to move towards more general systems which can perform many tasks – eventually without the need to manually create and label a training dataset for each one.

The dominant approach to creating ML systems is to collect a dataset of training examples demonstrating correct

OpenAI

XLNet: Generalized Autoregressive Pretraining for Language Understanding

Zhilin Yang[*1], **Zihang Dai**[*12], **Yiming Yang**[1], **Jaime Carbonell**[1], **Ruslan Salakhutdinov**[1], **Quoc V. Le**[2]
[1]Carnegie Mellon University, [2]Google Brain
{zhiliny,dzihang,yiming,jgc,rsalakhu}@cs.cmu.edu, qvl@google.com

Abstract

With the capability of modeling bidirectional contexts, denoising autoencoding based pretraining like BERT achieves better performance than pretraining approaches based on autoregressive language modeling. However, relying on corrupting the input with masks, BERT neglects dependency between the masked positions

Google

XLNet

Zhilin Yang

FOLLOW

Carnegie Mellon University
Verified email at cs.cmu.edu - Homepage

Deep Learning Machine Learning Natural Language Processing

TITLE	CITED BY	YEAR
XLnet: Generalized autoregressive pretraining for language understanding Z Yang, Z Dai, Y Yang, J Carbonell, RR Salakhutdinov, QV Le Advances in neural information processing systems 32	5929	2019
Transformer-xl: Attentive language models beyond a fixed-length context Z Dai, Z Yang, Y Yang, J Carbonell, QV Le, R Salakhutdinov arXiv preprint arXiv:1901.02860	2372	2019
Revisiting semi-supervised learning with graph embeddings Z Yang, W Cohen, R Salakhudinov International conference on machine learning, 40-48	1374	2016
HotpotQA: A dataset for diverse, explainable multi-hop question answering Z Yang, P Qi, S Zhang, Y Bengio, WW Cohen, R Salakhutdinov, ... arXiv preprint arXiv:1809.09600	986	2018
Multi-task cross-lingual sequence tagging from scratch Z Yang, R Salakhutdinov, W Cohen arXiv preprint arXiv:1603.06270	549 *	2016
Good semi-supervised learning that requires a bad gan Z Dai, Z Yang, F Yang, WW Cohen, RR Salakhutdinov Advances in neural information processing systems 30	434	2017
Gated-Attention Readers for Text Comprehension B Dhingra, H Liu, Z Yang, WW Cohen, R Salakhutdinov arXiv preprint arXiv:1606.01549	416	2016
Differentiable learning of logical rules for knowledge base reasoning F Yang, Z Yang, WW Cohen Advances in neural information processing systems 30	404	2017
Review networks for caption generation Z Yang, Y Yuan, Y Wu, WW Cohen, RR Salakhutdinov Advances in neural information processing systems 29	340 *	2016

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Co-authors

- Ruslan Salakhutdinov — UPMC Professor, Machine Learn...
- William W. Cohen — Google AI
- Quoc V. Le — Research Scientist, Google Brain
- Tang Jie — Professor, Tsinghua University

XLNet

- Autoregressive LM
- Autoencoder LM, [Mask]
- Permutation Language Model
- Transformer-XL
- More data

XLNet: Generalized Autoregressive Pretraining for Language Understanding

Zhilin Yang[*1], **Zihang Dai**[*12], **Yiming Yang**[1], **Jaime Carbonell**[1], **Ruslan Salakhutdinov**[1], **Quoc V. Le**[2]
[1]Carnegie Mellon University, [2]Google Brain
{zhiliny,dzihang,yiming,jgc,rsalakhu}@cs.cmu.edu, qvl@google.com

Abstract

With the capability of modeling bidirectional contexts, denoising autoencoding based pretraining like BERT achieves better performance than pretraining approaches based on autoregressive language modeling. However, relying on corrupting the input with masks, BERT neglects dependency between the masked positions

2.2 Objective: Permutation Language Modeling

Figure 1: Illustration of the permutation language modeling objective for predicting x_3 given the same input sequence $\mathbf{x}$ but with different factorization orders.

Roberta

Yinhan Liu

Birch AI
Verified email at birch.ai

NLP Healthcare

FOLLOW

TITLE	CITED BY	YEAR
Roberta: A robustly optimized bert pretraining approach CCF none Y Liu, M Ott, N Goyal, J Du, M Joshi, D Chen, O Levy, M Lewis, ... arXiv preprint arXiv:1907.11692	11348 *	2019
Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension CCF none M Lewis, Y Liu, N Goyal, M Ghazvininejad, A Mohamed, O Levy, ... arXiv preprint arXiv:1910.13461	3638	2019
Spanbert: Improving pre-training by representing and predicting spans M Joshi, D Chen, Y Liu, DS Weld, L Zettlemoyer, O Levy Transactions of the Association for Computational Linguistics 8, 64-77	1181	2020

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i10-index	9	8

Roberta

- 从模型上来说，RoBERTa基本没有什么太大创新，主要是在BERT基础上做了几点调整：
- 1）训练时间更长，batch size更大，训练数据更多；
- 2）移除了next sentence predict loss；
- 3）训练序列更长；
- 4）动态调整Masking机制。
- 从实验效果来看，干过了bert和XLNet。

ERNIE-1&2

- 不同于ERNIE1仅有词级别的Pretraining Task，ERNIE2考虑了词级别、结构级别和语义级别3类Pretraining Task，词级别包括Knowledge Masking（短语Masking）、Capitalization Prediction（大写预测）和Token-Document Relation Prediction（词是否会出现在文档其他地方）三个任务，结构级别包括Sentence Reordering（句子排序分类）和Sentence Distance（句子距离分类）两个任务，语义级别包括Discourse Relation（句子语义关系）和IR Relevance（句子检索相关性）两个任务。

ERNIE-1&2

Figure 1: The framework of ERNIE 2.0, where the pre-training tasks can be incrementally constructed, the models are pre-trained through continual multi-task learning, and the pre-trained model is fine-tuned to adapt to various language understanding tasks.

BERT in Tencent

- Pytorch-BERT
- 2g-char Chinese-wiki
- 14g-char news
- 240g-char news, 14g-word news
  - Borrowed 80 gpus
- PCG, CSIG, WXG, IEG, TEG

起步很早，2019年1月公司内部发布。

【AI Lab】再探BERT开源模型：200G超大规模中文语料模型探索 原 荐

发表于： AI Lab 5月6日 11:35

在上一次BERT技术分享中，我们将基于14g中文新闻语料训练的模型开放给大家使用，很多兄弟部门和团队都纷纷下载模型在相关业务场景中进行尝试，有些也取得了不错的结果。针对一些需要提升的地方，我们又陆续完成了以下...

评论(23) 收藏(149) 浏览(2626) 标签: BERT 语言模型 文本分类 语义匹配 序列标注

【AI LAB】BERT在大规模中文语料的尝试:训练和测试 原 荐

发表于： AI Lab 1月14日 13:15

2018年NLP研究领域的热点事件之首莫过于BERT的发布，在11个经典NLP任务中以绝对优势碾压各种基线模型。考虑到仅仅在中文维基百科数据集上（大约2G）预训练的基于字的BERT就能有这么大的威力，那么如果用更大规模的语...

评论(59) 收藏(321) 浏览(5641) 标签: BERT NLP 文本分类 语义匹配 命名实体识别

	BERT 100G News Char (epoch0_batch_1559999)	BERT 10G News Char	BERT 10G News Word	BERT 2G News Char	CBERT 10G News Char (epoch3_batch_1679999)	CBERT 2G News Char
CHNSENTI (Classification)	dev: 94.62% test: 94.70%	dev: 94.53% test: 93.77%			dev: 94.54% test: 94.61%	
LCQMC (Sentence Matching)	dev: 89.32% test: 86.40%	dev: 88.10% test: 85.67%			dev: 88.30% test: 85.90%	
MSRA NER	P:95.01 R:94.64 F:94.83	P:93.95; R:92.48; F:93.20		P:92.80; R:92.96; F:92.88	P:94.51 R:93.53 F:94.02	P:93.70 R:92.95 F:93.32
OntoNote4 NER	P:79.49 R:81.78 F:80.62	P:79.17; R:81.21; F:80.14		P:78.58; R:79.26; F:78.91	P:77.98 R:80.90 F:79.41	P:78.22 R:80.15 F:79.17
ResumeNER	P:95.28 R:95.34 F:95.31	P:95.00; R:95.70; F:95.35		P:94.62; R:94.97; F:94.79	P:95.57 R:95.28 F:95.42	P:96.20 R:94.79 F:95.49
WeiboNER	P:68.37 R:74.15 F:71.15	P:65.45; R:69.57; F:67.45		P:68.34; R:65.70; F:67.00	P:65.91 R:70.05 F:67.92	P:63.53 R:65.22 F:64.36

模型和词典的下载链接：

200g-char：http://100.102.36.47:8080/bert-news200g-char.zip

14g-word：http://100.102.36.47:8080/bert-news14g-word.zip

14g-char：http://100.102.36.47:8080/bert-news14g-char.zip

源码：https://git.code.oa.com/ailab-nlp-research/BERT

部分数据集：http://100.102.36.47:8080/bert_task_data.zip

咨询交流请联系AI Lab NLP中心： pijili(李丕绩)。

预训练语言模型 – GPT2

ChatGPT研究框架（2023）-国泰君安

GPT2

Better Language Models and Their Implications

We've trained a large-scale unsupervised language model which generates coherent paragraphs of text, achieves state-of-the-art performance on many language modeling benchmarks, and performs rudimentary reading comprehension, machine translation, question answering, and summarization—all without task-specific training.

February 14, 2019
24 minute read

https://openai.com/blog/better-language-models/

GPT2

Language Models are Unsupervised Multitask Learners

Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

Abstract

Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on task-specific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset - matching or exceeding the performance of 3 out of 4 baseline systems without using the 127,000+ training examples. The capacity of the language model is essential to the success of zero-shot task transfer and increasing it improves performance in a log-linear fashion across tasks. Our largest model, GPT-2, is a 1.5B parameter Transformer that achieves state of the art results on 7 out of 8 tested language modeling datasets in a zero-shot setting but still underfits WebText. Samples from the model reflect these improvements and contain coherent paragraphs of text. These findings suggest a promising path towards building language processing systems which learn to perform tasks from their naturally occurring demonstrations.

competent generalists. We would like to move towards more general systems which can perform many tasks – eventually without the need to manually create and label a training dataset for each one.

The dominant approach to creating ML systems is to collect a dataset of training examples demonstrating correct behavior for a desired task, train a system to imitate these behaviors, and then test its performance on independent and identically distributed (IID) held-out examples. This has served well to make progress on narrow experts. But the often erratic behavior of captioning models (Lake et al., 2017), reading comprehension systems (Jia & Liang, 2017), and image classifiers (Alcorn et al., 2018) on the diversity and variety of possible inputs highlights some of the shortcomings of this approach.

Our suspicion is that the prevalence of single task training on single domain datasets is a major contributor to the lack of generalization observed in current systems. Progress towards robust systems with current architectures is likely to require training and measuring performance on a wide range of domains and tasks. Recently, several benchmarks have been proposed such as GLUE (Wang et al., 2018) and decaNLP (McCann et al., 2018) to begin studying this.

Multitask learning (Caruana, 1997) is a promising framework for improving general performance. However, multitask training in NLP is still nascent. Recent work reports modest performance improvements (Yogatama et al.,

GPT2

模型
GPT
GPT-2

2.2 GPT-2的数据集

GPT-2的文章取自于Reddit上高赞的文章，命名为WebText。数据集共有约800万篇文章，累计体积约40G。为了避免和测试集的冲突，WebText移除了涉及Wikipedia的文章。

2.3 模型参数

- 同样使用了使用字节对编码构建字典，字典的大小为 $50,257$；
- 滑动窗口的大小为 $1,024$；
- batchsize的大小为 512；
- Layer Normalization移动到了每一块的输入部分，在每个self-attention之后额外添加了一个Layer Normalization；
- 将残差层的初始化值用 $1/\sqrt{N}$ 进行缩放，其中 N 是残差层的个数。

GPT-2训练了4组不同的层数和词向量的长度的模型，具体值见表2。通过这4个模型的实验结果我们可以看出随着模型的增大，模型的效果是不断提升的。

参数量	层数	词向量长度
117M（GPT-1）	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

GPT2

2.4 GPT-2的性能

- 在8个语言模型任务中，仅仅通过zero-shot学习，GPT-2就有7个超过了state-of-the-art的方法；
- 在“Children's Book Test”数据集上的命名实体识别任务中，GPT-2超过了state-of-the-art的方法约7%；
- “LAMBADA”是测试模型捕捉长期依赖的能力的数据集，GPT-2将困惑度从99.8降到了8.6；
- 在阅读理解数据中，GPT-2超过了4个baseline模型中的三个；
- 在法译英任务中，GPT-2在zero-shot学习的基础上，超过了大多数的无监督方法，但是比有监督的state-of-the-art模型要差；
- GPT-2在文本总结的表现不理想，但是它的效果也和有监督的模型非常接近。

$$p(x) = \prod_{i=1}^{n} p(s_n | s_1, \ldots, s_{n-1})$$

开启了NLG的新篇章！

SYSTEM PROMPT (HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pérez, "In South America, such incidents seem to be quite common."

解码算法

- Greedy Search
- Beam Search
- Top-K
- Top-P (nucleus)

Greedy Search

Beam Search

Algorithm 1 Beam search

Input: Beam size β, maximum length η, user id u, item id v, and tips generation model $\mathcal{G}$.

Output: β best candidate tips.

Initialize $\Pi = \emptyset$, $\pi[0:\beta-1] = \mathbf{0}$, $\Pi_p = \emptyset$, $\pi_p = \mathbf{0}$, $t = 0$;
Get user latent factor and item latent factor:
  $\mathbf{u} = \mathbf{U}(:, u)$ and $\mathbf{v} = \mathbf{V}(:, v)$
while $t < \eta$ **do**
  Generate β new states based on Π: $\{\hat{\mathbf{s}}_t\}_0^{\beta-1} = \mathcal{G}(\Pi)$
  for i from 0 to β **do**
    Uncompleted sequence $s_i \leftarrow \Pi(i)$
    Top-β words $\{w_0, w_1, \ldots, w_{\beta-1}\} \leftarrow \beta\text{-}\arg\max_{w_i \in \mathcal{V}} \hat{\mathbf{s}}_{t_i}^{(w_i)}$
    for each word w_j **do**
      Concatenation: $\Pi_p.inseart(s_i + w_j)$
      Likelihood: $\pi_p.inseart(\pi[i] + \log \hat{\mathbf{s}}_{t_i}^{(w_j)})$
    end for
  end for
  Get the top-β sequences with largest likelihood:
    $\{s\}_0^{\beta-1}, \{l\}_0^{\beta-1} = \beta\text{-}\arg\max_{s \in \Pi_p, l \in \pi_p} l$
  $\Pi \leftarrow \{s\}_0^{\beta-1}$, $\pi \leftarrow \{l\}_0^{\beta-1}$, $\Pi_p = \emptyset$, $\pi_p = \mathbf{0}$
  $t \leftarrow t + 1$
end while
return Π, π.

Random Sampling

Top-K

1.0
0.0
$\sum_{w \in V_{\text{top-K}}} P(w|\text{“The”}) = 0.68$
nice
dog
car
woman
guy
man
people
big
house
cat
$P(w|\text{“The”})$

$\sum_{w \in V_{\text{top-K}}} P(w|\text{“The”}, \text{“car”}) = 0.99$
drives
is
turns
stops
down
a
not
the
small
told
$P(w|\text{“The”}, \text{“car”})$

Top-p (nucleus) sampling

效果

🗣 **Context**: On days when he woke early, the president liked to have coffee in the oval office. There was something about watching the sky grow lighter and lighter as you sat your pajama'd behind in the most powerful chair in the free world, sipping marine strength coffee, that you just couldn't achieve anywhere else.

🥄 **Sampling** (*t*=1.0): You couldn't be sure if that's what you were really doing, and If you decided to take the day off. The president wanted you to take the day off, but he wanted to maintain a curfew and use his influence wisely.

💰 **Greedy**: He'd been in the oval office for over a year now, and he'd never been so happy to be there. He'd been in the oval office for almost a year, and he'd never been so happy to be there.

🅚 **Top-*k* Sampling** (*k*=8): "I'm sorry, sir." "No, it's okay, son," the president said. "I understand." "You're going to have to make a special trip down there to get that kid. He has no idea where he's going."

🚦 **BeamSearch** (*k*=4): The President was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word.

⚛ **Nucleus Sampling** (*p*=0.9): But that wasn't what drew the president's attention. He'd been seated for maybe a minute when he noticed the other man. What was the guy doing here?

Fig. 1. Example text generated from GPT-2 with each of the evaluated decoding strategies. The output is generated conditionally as a continuation of the given text passage ("context").

我们早期GPT2训练探索

【AI Lab】AI写作蜀道难：GPT2语言模型在文本生成任务中的探索

中文GPT2于2019年3月训练完成，并在各种下游任务适配。

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| 导语 本文主要总结分享AI Lab NLP这两年针对预训练语言模型所做的一些调研和实验，特别是GPT2在文本生成和对话系统中的一些探索和尝试。

1 背景

文本生成和对话系统是自然语言处理领域非常重要的研究方向。过去几年，得益于神经网络技术的发展，文本生成和对话系统(生成式)的质量也有了明显的提升。这段时间业界基本围绕以RNN (LSTM或GRU)和Transformer为核心的Seq2Seq框架，专门设计符合特定需求或者解决业务疼点的模块来提升结果的多样性、丰富性、知识性、一致性、风格化、个性化等。随着去年BERT和GPT2这种预训练语言模型的提出，大家的骨架模型也在悄悄的发生转移。尤其是最近，Google和Facebook用基于BERT和GPT2的技术堆砌出了号称效果媲美人类的对话模型（Google Meena, Facebook Blender）。AI Lab NLP中心也一直在积极探索，例如在2019年初我们就完成了GPT2模型在大规模对话语料（2.7亿句对）上的训练和实验。本文主要总结分享一下我们这两年针对预训练语言模型所做的一些调研和实验，特别是GPT2在文本生成和对话系统中的一些探索。

GPT2训练探索

不同Sampling方法对生成结果的影响：

greedy-search	beam-search (b=5)	top-k sampling (k=40)
腾讯体育讯北京时间5月29日，2018年KPL春季赛第二周第二天，KPL春季赛第二周第二天，RNG对阵FNC。第二局比赛，RNG在蓝色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方，RNG在红色方	**腾讯**体育讯北京时间5月29日，2018年俄罗斯世界杯小组赛，D组第二轮，阿根廷对阵克罗地亚。第80分钟，克罗地亚获得任意球机会，佩里西奇禁区内头球攻门被门将扑出。第81分钟，佩里西奇禁区内头球攻门被门将扑出。第82分钟，佩里西奇禁区内头球攻门被门将扑出。第83分钟，佩里西奇禁区内头球攻门被门将扑	**腾讯**体育6月29日讯2018世界杯A组第二轮，埃弗顿0-3不敌斯坦尼斯，此役过后，埃弗顿主防线不断陷入僵局。伊布与布莱克两名后卫出现了过分戏耍对手战术。本场比赛，埃弗顿全场只能贡献了3次进攻机会，他们只需要有1次左侧肋板和2次左脚射门便可以轻松破门。伊布最终还是首发出战了下半场。
腾讯AI Labs：你们的团队在做什么？AlphaGo：我们的团队在做一个全球性的计算机视觉计算平台，我们的团队在做一个全球性的计算机视觉计算平台，我们的团队在做一个全球性的计算机视觉计算平台，我们的团队在做一个全球性的计算机视觉计算平台，我们的团队在做一个全球性的计算机视觉计算平台	**腾讯AI** LaboratoryLab	**腾讯AI** Lab、Spectre、oppoR9S等AI平台的全球首发，其中不少的AI能力是为我们带来的“最具性价比”的解决方案，例如FindX、FindXR，这些全新的旗下手机产品在很多方面都将提高用户的使用体验。而在今年5月份，全球首个5G商用示范区已经建成投入使用。此次示范区建成投入使用的5G手机将首次使用到智能终端上。

GPT2训练探索

新闻续写：

人工智能已经不是新生事物，而是大规模应用的新技术。

AI领域的巨头企业，除了苹果公司之外，没有哪一家能够独占市场。

当然，以腾讯、阿里巴巴和百度为代表的国内互联网巨头，也在一定程度上，为AI领域积累了资本。这些互联网巨头一旦进入AI领域投资，就一定会取得良好的收益。

在腾讯和阿里巴巴的AI初创公司

NBA今天迎来了一场焦点战，骑士队坐镇主场迎来了火箭队的挑战，詹姆斯领衔的球队今天在第三节在比赛中被火箭追平比分，当时哈登发挥出色，也是拿下了赛季的第一分。

但是火箭队的主教练德安东尼却让两队进入到生死战，可以说这对两队来说都是一个巨大的挑战。

比赛开始之后，火箭队在进攻端也是延续以往的火热状态。

而在第三节结束之后保罗也是在

世界杯小组赛最后一轮已经全面结束，但是依旧有一个比较大的热谜，那就是我们球迷最关心的国足究竟会出线哪支球队？

据外媒报道，这场比赛的焦点话题不在于国足会打出多么亮眼的成绩，而在于明天中国女足将要挑战韩国女足，而韩国球迷自然是非常的看好这场比赛的。

而目前我们的国足的最大热点话题就是国足女足将要面对的是世界女足最强的巴西女足，谁能够

GPT2训练探索

小说续写：

在一个漆黑的夜晚，林菲突然间感到自己的身侧突然多了十多根钢针，其中一根竟然带着丝丝火花。

他轻声咒骂一句，连退十几步。“啊！！！”整整四十多米。

轰炸机发出了尖锐的破空声，这让林菲猛然回过头。“嘭！”身侧，十多只钢针已经扎过来。

砰！林菲身子猛然一颤，瞬间将身体转移开去。轰隆！震撼的声音在他耳边响起。黑暗瞬间消失，只剩下一道暗暗的黑色火光。“死！”林菲大吼着，冲天而起。

我们分手吧。”夏晚妍转身回头看了林凌一眼，见他一脸惊讶的看着自己，眼中闪烁过一丝不悦。

“我？”他不解的看着她。

“当然，我们不是好朋友么。”夏晚妍脸色微红，她一字一句的说：“而且，我还是朋友耶。”

林凌只好苦涩地笑笑，只是不语。晚妍看到他默然的样子，心中一阵难过，她心中只想着早点结束这一切。两人的身影消失在房子里，林凌站在那里，呆呆的看着远处那抹残留着的身影渐渐消失

杨过和小龙女听后心中狂喜，都知道这一路跟踪，就是找到那大批怪物后，发动对自己的攻击，虽然小龙女实力较弱，可是仍然能把那大批怪物打趴下的，因为小龙女是真正的神级，她想要对付怪就一定要有那种信号。

“大爷，我们得准备时间了。”小龙女点了点头，说道：“恩，我准备时间还有一会，要是有什么不舒服的话，就派人去通知我，我马上就过来，不要忘记了。”说着就挂断电话。

杨过和小龙女看到来人后，两人

小说续写 开局一句话 内容全靠编

GPT2训练探索

星座运势：

水瓶和双子之间的感情非常的细腻，对对方最最关心，两个人总是能够相处的十分融洽，而且对于自己的另一半，在感情中，也是非常负责任，所以会非常宠爱对方，让对方感受到自己真实的爱。

但是，对于自己的另一半，从来就不会随便的出轨，因为只有你不爱了水瓶才会离开你，和他们单独相处也是一件特别开心的事情。

巨蟹座6月运势不错，桃花源源不停，他们会在人品好的时候把握住对方的心意。但前提是真够优秀，还要能让自己更受欢迎。巨蟹座会遇到他们喜欢的人，并且会和对方相伴一生。

巨蟹座对自己的感情非常好，会把自己所有的真心都献给对方。如果对方不在自己身边，那么巨蟹座也会用尽全力去追求。

这个时候不要怀疑自己，因为你

射手失恋了怎么办？

他们就是那么的容易心情波动，心里很难受，一定要找个时间清理伤口！所以要么不做，要做就必须做到！

想到这里射手就很无奈，他们无法忍受一段已经结束的恋情，他们希望找到能让自己快乐的人，好好的过好每一段甜蜜的时光。

对于射手来说，他们对自己的感情非常的认真，无时无刻都在向

GPT2训练探索

容貌描写：

他又高又帅，虽算不上俊美，但那种冷傲高傲且不怒自威的气质，却让人不敢小视。脸颊上，那一抹浅浅的胡渣儿，却更让他显得面目清秀，一双幽暗深邃的眼眸，更显凌厉深邃，好一个俊美的男人。
而他身上的气质，则更是让人难以移开眼睛。这样的男人，与这般高贵优雅的贵族人物，有着那样一份天然的相似之处。那种尊贵与高贵，那种气势，让人只要站在那里，便能感觉到从心底流

她不是那种传统美女，长得白白胖胖，脸蛋红润光滑，虽然看不出她是什么身材，但看起来比较清纯。她的头发很柔软，披散下来，很整齐的披散在她的肩膀上，白皙的皮肤就像白瓷，一点也不显得突兀。
她的睫毛很长，很浓密，好像在扇动一般。她的下巴很挺，鼻梁很好看，嘴唇很薄，但她双唇又白又薄，嘴唇颜色呈现淡红色，嘴唇的嘴形又有点像欧洲女孩的唇形。这样的人最适合穿一条短

他就是一个恶魔，在阴暗中，那双绿色的眼睛散发着摄人心魄的红光，令人不寒而栗。如同刀般的细微的眼瞳，泛起绿色的光芒。在黑暗之中，那双眼睛就像是深绿色的宝石，散发着冰冷的邪气。散发了强烈的吸引力。
从脸颊蔓延到嘴巴，使人不寒而栗。如同那死神般的眸子是深蓝色的。整张面孔全部散发着邪魅的气质。深邃的眼眸。高挺的鼻子。如同上帝保护精灵。俊美的脸庞是深山老林里的最可怕的树

GPT2训练探索

景色描写：

深圳的夏天可真美，太阳下山后，阳光洒落地面，一切好像被沐浴在一片金色的薄纱里，如同童话里的世界。
空气温暖，一如二十年代流行的清晨，令人迷醉。不少游客在街上闲逛，或是在公园散步。夏日的清风袭来，舒爽宜人。
一些年轻人站在阳台上，望着那金灿灿的湖面，流连不断。夏天是这个城市中最美丽安宁的季节，在城市外缘，站了一条美丽的公路，是不可多得的好地方。

我喜欢北京的冬天，北京的冬天，冷得令人胆颤心摇，虽然比不得京都的冬天，但是在冬天的寒冷中，总算也比较容易让人想起曾经那些可笑的回忆。每一滴泪，每一张脸，都总是无声地滴在脸上，冰凉冰凉的。
泪水顺着脸颊滴下，在白色的地砖上蜿蜒成一条条黑色的长线。在阳光下，闪着寒光的闪烁。在温暖的屋子里，却有一阵阵的寒冰袭来。寒冰渐渐地融化，融进了细碎的冰屑中，消融在白玉一

暴风雨即将来临，此刻整个星空都因巨响而黯淡，那几座高大磅礴的黑色建筑物之上，黑暗中，一道道幽幽闪烁地光芒，如同实质，在黑暗中发出耀眼的光亮。每一根亮光，都让这一次战斗显得更加可怕。
可怕之极的阴冷。远远地超过了黑暗。如同实质。在这些光芒和光芒地映衬之下，这次战斗显得极为刺眼。就如同一只只在黑夜里翻滚的魔兽。那些所向无敌地光芒，使得这场战斗。显得极为

An Empirical Investigation of Pre-Trained Transformer Language Models for Open-Domain Dialogue Generation

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Abstract

We present an empirical investigation of pre-trained Transformer-based auto-regressive language models for the task of open-domain dialogue generation. Training paradigm of pre-training and fine-tuning is employed to conduct the parameter learning. Corpora of News and Wikipedia in Chinese and English are collected for the pre-training stage respectively. Dialogue context and response are concatenated into a single sequence utilized as the input of the models during the fine-tuning stage. A weighted joint prediction paradigm for both context and response is designed to evaluate the performance of models with or without the loss term for context prediction. Various of decoding strategies such as greedy search, beam search, top-k sampling, etc. are employed to conduct the response text generation. Extensive experiments are conducted on the typical single-turn and multi-turn dialogue corpora such as Weibo, Douban, Reddit, DailyDialog, and Persona-Chat. Detailed numbers of automatic evaluation metrics on relevance and diversity of the generated results for the languages models as well as the baseline approaches are reported.[1]

is constructed to conduct the target response prediction. Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), Gated Recurrent Unit (GRU) (Cho et al., 2014), and Transformer Self-Attention Network (SAN) (Vaswani et al., 2017) are employed as the backbone of various encoders and decoders. For training, Maximum Likelihood Estimation (MLE) is usually as the parameter optimization approach. For decoding, beam search algorithm (Koehn, 2004) is the preference to decode and generate the target response.

Tremendous progress has been achieved following those pioneer works. Simultaneously, on one side, researchers propose some strategies to address the typical issues observed from the generated results, and on the other side, amount of new directions and tasks have been explored broadly (Gao et al., 2019a). Specifically, one well-know typical phenomenon is that the generated responses are usually generic and boring. Quiet a few results are neither relevant to the context nor informative and diverse. This is caused by various of reasons, such as the MLE optimization objective, semantic or posterior collapse of the input context representations, one-to-many mapping issue (one

Model	Relevance					Diversity				Length
	BLEU	B-1	B-2	B-3	B-4	MADIST-1	MADIST-2	MIDIST-1	MIDIST-2	
Seq2Seq	1.31	37.08	10.29	3.76	1.71	71.73	75.53	7.70	26.63	13.88
CVAE	4.08	42.12	15.90	8.13	5.31	73.61	78.09	9.59	34.64	14.79
MMI	3.25	43.98	13.94	6.56	3.88	82.00	87.06	10.69	38.25	11.51
Seq2Seq-greedy	1.09	41.62	8.99	2.85	0.96	77.20	83.81	7.56	29.39	14.31
Seq2Seq-bm(5)	1.31	37.08	10.29	3.76	1.71	71.73	75.53	7.70	26.63	13.88
Seq2Seq-tk(5)	0.72	41.82	7.82	1.92	0.53	86.10	94.50	9.71	44.54	13.62
Seq2Seq-tk(10)	0.59	41.21	7.05	1.75	0.54	87.22	95.94	10.01	50.17	13.90
Seq2Seq-tk(20)	0.63	39.06	6.07	1.50	0.42	87.90	96.27	9.78	52.62	14.39
Seq2Seq-tk(50)	0.22	35.72	4.73	0.74	0.17	89.45	97.59	10.45	58.09	14.87
Seq2Seq-tk(500)	0.26	30.74	3.69	0.65	0.17	91.28	98.14	12.58	67.98	16.09
Seq2Seq-tp(0.9)	0.59	39.10	6.43	1.52	0.50	88.35	96.56	9.99	53.01	14.43
LM-12-greedy	1.32	42.16	8.41	2.74	1.40	81.43	86.94	6.44	21.24	13.50
LM-12-bm(5)	2.56	35.04	11.45	5.39	3.29	63.66	66.96	4.70	14.55	21.19
LM-12-tk(5)	0.79	41.27	6.72	1.65	0.65	85.77	94.49	7.76	35.55	13.64
LM-12-tk(10)	0.65	40.06	6.17	1.40	0.51	87.10	95.54	7.98	40.21	14.17
LM-12-tk(20)	0.35	37.98	5.14	1.03	0.25	88.63	96.79	8.91	46.42	14.46
LM-12-tk(50)	0.31	36.53	4.67	0.82	0.24	89.85	97.53	9.24	52.24	15.03
LM-12-tk(500)	0.25	29.81	3.07	0.54	0.19	91.71	98.43	12.11	67.41	15.77
LM-12-tp(0.9)	0.47	38.58	5.34	1.04	0.28	88.75	96.85	8.63	45.48	14.42
LM-12-greedy-λ_1	0.96	43.20	8.14	2.20	0.90	80.93	87.84	5.68	18.41	13.81
LM-12-bm(5)-λ_1	1.86	30.34	8.90	4.04	2.46	55.86	59.11	3.30	10.00	24.33
LM-12-tk(5)-λ_1	0.50	41.79	6.50	1.42	0.44	85.91	94.81	7.09	32.53	13.76
LM-12-tk(10)-λ_1	0.53	40.33	6.02	1.28	0.37	87.25	96.04	7.73	39.05	14.15
LM-12-tk(20)-λ_1	0.47	37.51	4.82	1.17	0.41	88.66	96.85	8.22	44.89	14.69
LM-12-tk(50)-λ_1	0.31	35.78	4.38	0.79	0.23	89.78	97.40	9.12	52.50	15.05
LM-12-tk(500)-λ_1	0.21	29.29	3.15	0.56	0.13	91.57	98.14	11.61	65.94	15.88
LM-12-tp(0.9)-λ_1	0.40	38.56	5.35	1.15	0.37	88.41	96.92	8.04	43.98	14.66
LM-12-greedy-$\lambda_{0.5}$	1.03	41.00	7.74	2.42	1.02	80.79	86.45	5.59	18.60	13.42
LM-12-bm(5)-$\lambda_{0.5}$	1.60	31.58	8.80	3.69	2.00	59.20	62.23	3.72	11.56	22.87
LM-12-tk(5)-$\lambda_{0.5}$	0.59	41.71	6.19	1.47	0.50	85.21	94.10	7.15	33.68	13.94
LM-12-tk(10)-$\lambda_{0.5}$	0.36	39.85	5.50	1.05	0.25	87.76	96.03	7.57	38.20	13.98
LM-12-tk(20)-$\lambda_{0.5}$	0.38	37.75	5.14	1.03	0.32	88.43	96.79	8.14	45.28	14.43
LM-12-tk(50)-$\lambda_{0.5}$	0.34	35.01	4.27	0.89	0.32	89.27	96.93	8.95	51.60	14.68
LM-12-tk(500)-$\lambda_{0.5}$	0.29	29.37	3.21	0.59	0.15	92.02	98.47	11.40	66.33	16.11
LM-12-tp(0.9)-$\lambda_{0.5}$	0.26	37.65	4.87	0.89	0.18	88.52	96.83	8.37	45.25	14.27
LM-24-greedy	1.12	39.21	7.52	2.42	1.19	75.69	81.98	5.21	17.79	16.02
LM-24-bm(5)	2.02	34.18	9.80	4.22	2.52	64.63	68.30	4.73	15.61	19.86
LM-24-tk(5)	0.90	41.04	6.82	1.76	0.70	84.90	94.00	7.00	32.57	14.64
LM-24-tk(10)	0.48	39.68	5.60	1.16	0.38	86.18	95.42	7.43	37.57	14.99
LM-24-tk(20)	0.60	37.38	4.88	1.09	0.48	87.32	95.93	7.77	43.03	15.07
LM-24-tk(50)	0.33	34.39	4.03	0.77	0.24	89.10	97.13	8.81	51.42	15.67
LM-24-tk(500)	0.21	28.20	2.92	0.51	0.24	91.07	97.80	11.12	65.57	16.83
LM-24-tp(0.9)	0.45	37.17	5.25	1.16	0.39	86.64	95.85	7.86	43.87	15.56
BigLM-12-greedy	2.07	41.92	9.65	3.48	1.99	79.88	86.06	7.05	24.32	14.62
BigLM-12-bm(5)	4.00	38.96	14.77	7.70	5.14	72.61	75.97	7.50	25.97	18.62
BigLM-12-tk(5)	1.01	43.18	8.08	2.31	1.01	85.81	93.47	8.74	39.23	13.78
BigLM-12-tk(10)	0.76	40.69	6.99	1.87	0.69	87.61	95.78	9.23	44.20	14.34
BigLM-12-tk(20)	0.95	39.28	6.25	1.78	0.76	88.62	96.76	9.02	48.06	14.54
BigLM-12-tk(50)	0.53	35.56	4.85	1.07	0.46	90.18	97.32	9.84	55.06	14.95
BigLM-12-tk(500)	0.18	29.49	3.34	0.45	0.11	91.09	97.68	12.26	67.49	15.56
BigLM-12-tp(0.9)	0.95	38.78	6.24	1.80	0.80	88.53	96.45	9.27	48.38	14.13
BigLM-24-greedy	2.32	43.38	10.68	4.13	2.39	81.06	86.31	7.17	24.72	14.22
BigLM-24-bm(5)	3.97	38.93	14.72	7.59	5.07	70.56	73.84	7.24	24.87	18.95
BigLM-24-tk(5)	1.15	43.64	8.45	2.55	1.17	85.54	93.67	8.44	38.07	13.75
BigLM-24-tk(10)	1.22	41.23	8.01	2.49	1.22	86.71	95.42	8.81	43.83	14.45
BigLM-24-tk(20)	0.75	37.53	5.79	1.52	0.83	88.16	96.06	9.59	48.65	14.25
BigLM-24-tk(50)	0.57	36.36	5.12	1.23	0.54	89.39	97.24	9.78	53.64	14.61
BigLM-24-tk(500)	0.39	29.51	3.49	0.85	0.39	90.89	97.63	12.22	67.21	15.82
BigLM-24-tp(0.9)	0.93	39.00	5.97	1.73	0.76	88.57	96.48	9.21	48.53	14.31

Table 2: Experimental results on Weibo dataset.

GPT2训练探索

续写：但凡有点商业和产品思维

但凡有点商业和产品思维的人，都知道市场需求是最重要的，他们会通过市场调研、竞品分析等手段来了解消费者的需求和市场趋势。他们会根据市场需求，制定出合理的产品策略，并持续优化产品，以保持竞争力。

同时，具备商业和产品思维的人也非常注重用户体验。他们了解用户对产品的需求和喜好，能够设计出符合用户习惯的产品界面和功能，提高用户的满意度和忠诚度。

除此之外，这些人还会关注产品的成本和效益。他们会不断探索新的生产技术和供应链管理方式，以降低成本并提高产品的利润。同时，他们还会通过各种营销手段来促进产品的销售，提高品牌知名度和市场占有率。

总之，具备商业和产品思维的人，不仅仅是产品的创造者，更是产品的管理者和推广者，他们能够为企业带来更多的商业价值和竞争优势。

GPT2

Figure 1. Zero-shot task performance of WebText LMs as a function of model size on many NLP tasks. Reading Comprehension results are on CoQA (Reddy et al., 2018), translation on WMT-14 Fr-En (Artetxe et al., 2017), summarization on CNN and Daily Mail (See et al. 2017), and Question Answering on Natural Questions (Kwiatkowski et al., 2019). Section 3 contains detailed descriptions of each result

Big Model

2018 (left) through 2019 (right)
2020 onwards
94M
110M
340M
465M
665M
330M
1.5B
340M
355M
1.5B
8.3B
1.5B
11B
2.6B
17B
66M
9.4B
175B
ELMo
GPT
BERT-Large
Transformer
XLM
MT-DNN
GPT-2
XLNET
RoBERTa
CTRL
MegatronLM
Grover-Mega
T5-11B
Meena
Turing-NLG
DistilBERT
BST 9.4B
GPT-3

T5

Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

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T5

Figure 1: A diagram of our text-to-text framework. Every task we consider—including translation, question answering, and classification—is cast as feeding our model text as input and training it to generate some target text. This allows us to use the same model, loss function, hyperparameters, etc. across our diverse set of tasks. It also provides a standard testbed for the methods included in our empirical survey. "T5" refers to our model, which we dub the "**T**ext-**t**o-**T**ext **T**ransfer **T**ransformer".

T5

Data：C4 （Bomb!）

作者从 Common Crawl（一个公开的网页存档数据集，每个月大概抓取 20TB 文本数据） 里清出了 750 GB 的训练数据，然后取名为 " Colossal Clean Crawled Corpus （超大型干净爬取数据） "，简称 C4，论作者取名之恶趣味。

大概清理过程如下：

- 只保留结尾是正常符号的行；
- 删除任何包含不好的词的页面，具体词表参考**List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words**库（笔者按：宝藏库，到里面转了一圈，看了看熟悉的几门语言，瞬间涨了不少新姿势 ）；
- 包含 Javascript 词的行全去掉；
- 包含编程语言中常用大括号的页面；
- 任何包含" lorem ipsum（用于排版测试） "的页面；
- 连续三句话重复出现情况，保留一个。

T5

- Transformer Encoder-Decoder 模型；
- BERT-style 式的破坏方法；
- Replace Span 的破坏策略；
- 15 %的破坏比；
- 3 的破坏时小段长度。

T5

Model	Hidden size	Layer	Parameters
BERT-base	768	12	110M
BERT-large	1024	24	340M

Leaderboard Version: **2.0**

Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	AX-g
1	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	76.6	99.3/99.7
2	T5 Team - Google	T5		88.9	91.0	93.0/96.4	94.8	88.2/62.3	93.3/92.5	92.5	76.1	93.8	-0.4	100.0/50.0
3	Facebook AI	RoBERTa		84.6	87.1	90.5/95.2	90.6	84.4/52.5	90.6/90.0	88.2	69.9	89.0	57.9	91.0/78.1
4	SuperGLUE Baselines	BERT++		71.5	79.0	84.8/90.4	73.8	70.0/24.1	72.0/71.3	79.0	69.6	64.4	38.0	99.4/51.4
		BERT		69.0	77.4	75.7/83.6	70.6	70.0/24.1	72.0/71.3	71.7	69.6	64.4	23.0	97.8/51.7
		Most Frequent Class		47.1	62.3	21.7/48.4	50.0	61.1/0.3	33.4/32.5	50.3	50.0	65.1	0.0	100.0/50.0
		CBoW		44.5	62.2	49.0/71.2	51.6	0.0/0.5	14.0/13.6	49.7	53.1	65.1	-0.4	100.0/50.0
		Outside Best		-	80.4	-	84.4	70.4/24.5	74.8/73.0	82.7	-	-	-	-
5	IBM Research AI	BERT-mtl		71.3	84.8	89.6/94.0	72.2	73.2/30.5	74.6/74.0	84.1	50.0	61.0	29.6	97.8/57.3
-	Stanford Hazy Research	Snorkel [SuperGLUE v1.9]		-	-	88.6/93.2	76.2	76.4/36.3	-	78.9	72.1	72.6	47.6	-

T5

			GLUE												CNN/DM			SQuAD			SuperGLUE									WMT		
Table	Experiment	Score Average	CoLA MCC	SST-2 Acc	MRPC F1	MRPC Acc	STSB PCC	STSB SCC	QQP F1	QQP Acc	$MNLI_m$ Acc	$MNLI_{mm}$ Acc	QNLI Acc	RTE Acc	R-1-F	R-2-F	R-L-F	EM	F1	Score Average	BoolQ Acc	CB F1	CB Acc	COPA Acc	MultiRC F1	MultiRC EM	ReCoRD F1	ReCoRD EM	RTE Acc	WiC Acc	WSC Acc	EnDe BLEU	EnFr BLEU	EnRo BLEU
1	★ Baseline average	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
1	Baseline standard deviation	0.235	1.111	0.569	0.729	1.019	0.374	0.418	0.108	0.070	0.291	0.231	0.361	1.393	0.065	0.065	0.058	0.343	0.226	0.416	0.365	3.237	2.560	2.741	0.716	1.011	0.370	0.379	1.228	0.850	2.029	0.112	0.090	0.108
1	No pre-training	66.22	12.29	80.62	81.42	73.04	72.58	72.97	81.94	86.62	68.02	67.98	75.69	58.84	39.19	17.60	36.69	50.31	61.97	53.04	65.38	71.61	76.79	62.00	59.10	0.84	20.33	17.95	54.15	54.08	65.38	25.86	39.77	24.04
2	★ Enc/dec, denoising	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
2	Enc/dec, shared, denoising	82.81	55.24	91.86	91.58	88.24	87.43	87.58	88.69	91.60	83.88	84.01	90.23	73.65	41.11	18.78	38.48	80.63	88.49	70.73	77.13	95.04	96.43	65.00	66.16	22.98	68.95	68.09	70.76	68.18	75.96	26.72	39.03	27.46
2	Enc/dec, 6 layers, denoising	80.88	46.26	92.09	91.51	87.99	87.01	86.76	87.93	90.97	82.20	82.41	88.83	71.48	40.83	18.97	38.31	77.59	86.07	68.42	73.79	91.70	92.86	67.00	61.02	19.62	61.26	60.33	72.20	65.99	75.00	26.38	38.40	26.95
2	Language model, denoising	74.70	24.50	90.60	86.08	78.92	85.22	85.42	85.40	88.99	76.72	77.05	86.02	64.62	39.49	17.93	36.91	61.14	71.37	55.02	65.47	60.08	71.43	58.00	43.03	2.94	53.35	52.31	53.07	58.62	63.46	25.09	35.28	25.86
2	Prefix LM, denoising	81.82	49.99	92.43	91.43	88.24	87.20	86.98	88.41	91.39	82.32	82.93	88.71	74.01	40.46	18.61	37.90	78.94	87.31	68.11	75.59	93.37	91.07	60.00	63.43	21.20	65.03	64.11	71.48	65.67	73.08	26.43	37.98	27.39
2	Enc/dec, LM	79.56	42.03	91.86	91.64	88.24	87.13	87.00	88.21	91.15	81.68	81.66	88.54	65.70	40.67	18.59	38.13	76.02	84.85	64.29	72.23	85.74	89.29	57.00	60.53	16.26	59.28	58.30	65.34	64.89	70.19	26.27	39.17	26.86
2	Enc/dec, shared, LM	79.60	44.83	92.09	90.20	85.78	86.03	85.87	87.77	91.02	81.74	82.29	89.16	65.34	40.16	18.13	37.59	76.35	84.86	63.50	70.49	91.41	87.50	55.00	60.21	16.89	57.83	56.73	63.54	63.48	70.19	26.62	39.17	27.05
2	Enc/dec, 6 layers, LM	78.67	38.72	91.40	90.40	86.52	86.82	86.49	87.87	91.03	80.99	80.92	88.05	65.70	40.29	18.26	37.70	75.32	84.06	64.06	71.38	85.25	89.29	63.00	57.56	16.79	55.22	54.30	66.79	63.95	71.15	26.13	38.42	26.89
2	Language model, LM	73.78	28.53	89.79	85.23	78.68	84.22	84.00	84.88	88.70	74.94	75.77	84.84	58.84	38.97	17.54	36.37	53.81	64.55	56.51	64.22	59.92	71.43	64.00	53.04	1.05	46.81	45.78	58.84	56.74	69.23	25.23	34.31	25.38
2	Prefix LM, LM	79.68	41.26	92.09	90.11	86.27	86.82	86.32	88.35	91.35	81.71	82.02	89.04	68.59	39.66	17.84	37.13	76.87	85.39	64.86	71.47	93.37	91.07	57.00	58.67	16.89	59.25	58.16	64.26	66.30	71.15	26.28	37.51	26.76
4	Language modeling with prefix	80.69	44.22	93.00	91.68	88.48	87.20	87.18	88.39	91.41	82.66	83.09	89.29	68.95	40.71	18.94	38.15	77.99	86.43	65.27	73.55	83.95	87.50	55.00	59.65	18.89	61.76	60.76	68.59	65.67	73.08	26.86	39.73	27.49
4	BERT-style (Devlin et al., 2018)	82.96	52.49	92.55	92.79	89.95	87.68	87.66	88.47	91.44	83.60	84.05	90.33	75.45	41.27	19.17	38.72	80.65	88.24	69.85	76.48	94.37	94.64	61.00	63.29	25.08	66.76	65.85	72.20	69.12	75.00	26.78	40.03	27.41
4	Deshuffling	73.17	22.82	87.16	86.88	81.13	84.03	83.82	86.38	89.90	76.30	76.34	84.18	58.84	40.75	18.59	38.10	67.61	76.76	58.47	69.17	63.70	78.57	56.00	59.85	12.70	45.52	44.36	57.04	64.89	68.27	26.11	39.30	25.62
5	BERT-style (Devlin et al., 2018)	82.96	52.49	92.55	92.79	89.95	87.68	87.66	88.47	91.44	83.60	84.05	90.33	75.45	41.27	19.17	38.72	80.65	88.24	69.85	76.48	94.37	94.64	61.00	63.29	25.08	66.76	65.85	72.20	69.12	75.00	26.78	40.03	27.41
5	MASS-style (Song et al., 2019)	82.32	47.01	91.63	92.53	89.71	88.21	88.18	88.58	91.44	82.96	83.67	90.02	77.26	41.16	19.16	38.55	80.10	88.07	69.28	75.08	84.98	89.29	63.00	64.46	23.50	66.71	65.91	72.20	67.71	78.85	26.79	39.89	27.55
5	★ Replace corrupted spans	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
5	Drop corrupted tokens	84.44	60.04	92.89	92.79	89.95	87.28	86.85	88.56	91.54	83.94	83.92	90.74	79.62	41.27	19.31	38.70	80.52	88.28	68.67	75.90	96.02	94.64	56.00	65.06	23.92	65.54	64.60	71.12	67.40	74.04	27.07	39.76	27.82
6	Corruption rate = 10%	82.82	52.71	92.09	91.55	88.24	88.19	88.15	88.47	91.40	83.50	84.51	90.33	75.45	41.05	19.00	38.53	80.38	88.36	69.55	74.98	92.37	92.86	62.00	66.04	24.66	67.93	67.09	70.76	67.24	75.96	26.87	39.28	27.44
6	★ Corruption rate = 15%	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
6	Corruption rate = 25%	83.00	53.47	93.00	92.44	89.46	87.36	87.36	88.68	91.53	84.44	84.15	90.77	74.01	41.69	19.54	39.14	80.96	88.61	70.48	76.39	93.02	92.86	68.00	65.46	24.66	68.20	67.39	73.65	67.87	72.12	27.04	39.83	27.47
6	Corruption rate = 50%	81.27	46.26	91.63	91.11	87.99	87.87	87.64	88.70	91.57	83.64	84.10	90.24	70.76	41.51	19.32	38.89	79.80	87.76	70.33	75.02	93.05	92.86	68.00	62.97	24.13	64.94	64.13	72.20	68.50	77.88	27.01	39.90	27.49
7	★ Baseline (i.i.d.)	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
7	Average span length = 2	83.54	53.82	92.20	93.05	90.44	87.85	87.71	88.42	91.40	84.28	84.46	90.88	77.62	41.23	19.39	38.69	82.09	89.69	72.20	77.06	90.43	91.07	70.00	66.28	26.13	71.34	70.61	75.45	68.34	78.85	26.76	39.99	27.63
7	Average span length = 3	83.49	53.90	92.43	92.25	89.46	87.49	87.53	88.72	91.51	84.85	84.84	90.99	77.26	41.50	19.62	38.94	81.84	89.66	72.53	76.85	94.37	94.64	70.00	67.64	28.75	70.84	69.90	74.73	67.71	77.88	26.86	39.65	27.62
7	Average span length = 5	83.40	52.12	93.12	92.63	89.71	88.70	88.47	88.84	91.64	84.32	84.29	90.79	76.90	41.39	19.24	38.82	82.05	89.79	72.23	77.06	83.06	89.29	69.00	68.16	30.12	71.36	70.53	75.81	69.91	79.81	26.88	39.40	27.53
7	Average span length = 10	82.85	50.11	92.09	91.95	88.97	88.45	88.22	88.86	91.63	84.34	84.28	91.07	76.17	41.38	19.33	38.80	81.84	89.39	70.44	76.45	87.40	89.29	65.00	66.87	29.59	69.82	68.94	72.56	67.55	75.96	26.79	39.49	27.69
8	★ C4	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
8	C4, unfiltered	81.46	48.01	91.63	92.72	89.95	87.79	87.60	88.31	91.27	82.30	82.34	88.71	72.20	41.09	19.14	38.54	78.78	87.04	68.04	75.75	89.17	91.07	62.00	65.52	25.60	62.42	61.58	69.68	67.08	72.12	26.55	39.34	27.21
8	RealNews-like	83.83	56.55	92.66	92.06	88.97	87.71	87.37	88.51	91.49	84.35	84.46	90.61	78.34	41.38	19.23	38.84	80.39	88.50	72.38	77.00	93.09	94.64	66.00	65.92	23.82	74.56	73.72	75.81	66.61	80.77	26.75	39.90	27.48
8	WebText-like	84.03	56.38	93.12	92.31	89.22	88.69	88.68	88.65	91.56	84.70	84.84	90.83	77.62	41.23	19.31	38.70	81.42	89.15	71.40	76.88	83.08	89.29	66.00	64.10	24.24	72.24	71.36	75.45	68.03	82.69	26.80	39.74	27.59
8	Wikipedia	81.85	45.53	92.32	91.67	88.24	85.62	86.40	88.37	91.34	82.61	83.25	90.96	77.26	41.39	19.31	38.81	81.29	89.18	68.01	76.12	56.03	80.36	67.00	65.01	25.92	69.03	68.06	74.73	67.08	76.92	26.94	39.69	27.67
8	Wikipedia + TBC	83.65	55.53	92.78	92.41	89.22	86.67	86.27	89.47	92.29	84.38	83.45	91.94	76.90	41.22	19.28	38.67	82.08	89.70	73.24	76.22	95.40	92.86	69.00	51.59	50.93	69.53	68.51	77.62	66.93	81.73	26.77	39.63	27.57
9	★ Full data set	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
9	2^{20} (64 repeats)	82.87	53.82	92.78	91.79	88.73	87.56	87.58	88.73	91.54	84.07	84.21	90.59	73.65	41.18	19.19	38.67	80.97	88.90	72.03	76.76	92.96	92.86	66.00	65.11	26.76	69.35	68.49	75.81	67.24	82.69	26.83	39.74	27.63
9	2^{27} (256 repeats)	82.62	50.60	92.32	92.07	88.73	87.83	87.60	88.65	91.54	83.43	84.37	90.12	75.81	41.24	19.20	38.70	79.78	87.63	69.97	75.29	93.42	91.07	63.00	61.82	23.61	66.27	65.39	73.65	66.30	80.77	27.02	39.71	27.33
9	2^{35} (1,024 repeats)	79.55	43.84	91.28	89.32	85.05	85.92	85.74	88.05	91.09	81.29	81.72	87.90	69.31	40.66	18.57	38.13	76.27	84.58	64.76	72.63	83.97	82.14	64.00	59.39	17.94	56.94	56.04	64.98	65.20	73.08	26.38	39.56	26.80
9	2^{43} (4,096 repeats)	76.34	32.68	89.45	89.84	86.03	83.49	83.42	87.18	90.61	77.80	78.69	85.47	64.62	40.16	18.33	37.66	70.92	80.20	59.29	69.85	73.48	73.21	56.00	57.66	14.38	46.69	45.79	59.57	65.05	68.27	26.37	38.84	25.81
10	★ All parameters	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
10	Adapter layers, $d = 32$	80.52	45.33	91.63	90.59	86.76	88.38	88.06	86.99	90.26	83.63	83.94	90.72	67.15	34.50	15.08	32.15	79.32	87.70	60.40	65.32	50.87	73.21	52.00	58.61	19.41	65.50	64.58	62.09	64.58	73.08	13.84	17.88	15.54
10	Adapter layers, $d = 128$	81.51	45.35	92.89	91.49	88.24	87.73	87.65	87.73	90.93	83.64	84.09	90.52	72.56	36.71	16.62	34.37	79.47	87.61	63.03	69.20	52.21	75.00	56.00	61.08	18.05	67.94	66.97	68.59	66.77	73.08	19.83	27.50	22.63
10	Adapter layers, $d = 512$	81.54	44.25	93.35	91.00	87.25	88.74	88.44	88.02	91.15	83.08	83.80	89.62	74.37	38.63	17.78	36.25	79.18	87.32	64.30	73.18	59.86	71.43	56.00	62.94	18.57	66.56	65.74	70.76	67.87	74.04	23.45	33.98	25.81
10	Adapter layers, $d = 2048$	82.62	49.86	92.55	91.30	87.99	88.46	88.35	88.36	91.40	83.63	83.18	90.66	76.53	39.44	18.30	37.06	79.40	87.36	68.61	74.53	88.00	91.07	58.00	61.10	18.89	66.73	66.06	73.29	71.16	75.96	25.64	36.92	26.93
10	Gradual Unfreezing	82.50	51.74	91.97	92.61	89.71	87.27	86.90	88.26	91.35	83.42	83.49	89.71	75.09	40.88	18.95	38.40	79.17	87.30	70.79	75.51	93.09	94.64	70.00	62.03	21.51	65.69	64.79	72.92	69.12	77.89	26.71	39.02	26.93
11	★ Baseline (pre-train/fine-tune)	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
11	Equal	76.13	39.47	90.94	82.90	75.74	78.83	78.44	86.45	89.71	82.08	82.92	90.13	59.93	40.95	19.02	38.39	76.51	85.61	63.37	73.06	82.37	83.93	65.00	60.89	17.52	69.51	59.70	61.01	60.03	65.38	23.89	34.31	26.78
11	Examples-proportional, $K = 2^{16}$	80.45	42.07	91.97	90.97	87.50	85.41	85.04	86.89	90.10	83.01	83.66	90.74	72.56	41.16	19.04	38.59	77.25	85.72	69.95	76.67	86.38	89.29	70.00	65.93	27.91	62.78	61.95	76.90	65.83	73.08	24.35	34.99	27.10
11	Examples-proportional, $K = 2^{17}$	81.56	47.35	91.40	91.55	88.24	86.15	85.93	86.94	90.06	82.76	84.12	90.79	75.09	41.06	19.12	38.47	77.00	85.87	67.91	77.89	77.54	85.71	57.00	67.78	27.07	61.51	60.54	79.06	65.20	74.04	24.36	35.00	27.25
11	Examples-proportional, $K = 2^{18}$	81.67	46.85	91.63	91.99	88.73	87.68	87.20	86.93	90.35	83.30	84.01	91.47	73.29	40.96	19.07	38.43	78.17	86.74	67.94	76.57	78.88	87.50	62.00	67.70	30.85	63.43	62.54	76.53	65.67	67.31	24.57	35.19	27.39
11	Examples-proportional, $K = 2^{19}$	81.42	45.94	91.63	92.20	89.22	88.44	88.32	86.84	90.10	83.73	84.29	91.84	70.40	41.26	19.24	38.71	79.78	88.15	67.30	75.66	75.59	87.50	59.00	68.22	30.64	65.32	64.29	73.65	65.05	69.23	25.21	36.30	27.76
11	Examples-proportional, $K = 2^{20}$	80.80	42.55	92.78	91.27	87.99	88.36	88.10	86.10	89.62	84.15	84.26	92.20	68.95	41.05	19.24	38.46	80.36	88.27	67.38	73.21	76.18	83.93	62.00	67.57	26.86	66.12	65.22	76.90	64.73	69.23	25.66	36.93	27.68
11	Examples-proportional, $K = 2^{21}$	79.83	44.45	91.28	89.00	84.31	87.54	87.40	84.93	88.53	82.54	84.16	90.85	67.87	40.51	18.79	37.92	79.50	87.48	65.10	71.16	68.88	85.71	57.00	62.75	23.40	64.50	63.65	72.92	64.11	71.15	25.82	37.22	27.13
11	Temperature-scaled, $T = 2$	81.90	54.00	91.74	90.56	86.76	85.11	84.60	86.40	89.74	83.47	84.15	91.51	72.56	41.09	19.28	38.54	79.42	87.77	69.92	76.73	92.37	92.86	57.00	69.80	31.90	66.65	65.74	72.92	67.08	75.96	25.42	36.72	27.20
11	Temperature-scaled, $T = 4$	80.56	45.38	91.97	89.68	85.78	83.13	82.76	86.39	90.00	82.78	84.19	91.16	73.65	41.09	19.22	38.51	77.99	86.81	69.54	76.76	97.36	96.43	59.00	68.10	31.48	64.26	63.27	74.73	64.26	71.15	25.04	35.82	27.45
11	Temperature-scaled, $T = 8$	77.21	40.07	91.06	88.11	83.33	79.20	79.06	86.60	89.90	83.05	83.56	90.21	59.93	41.01	19.10	38.40	77.14	85.99	66.07	73.94	93.70	94.64	60.00	66.36	26.86	63.46	62.60	62.09	63.32	65.38	24.55	35.35	27.17
12	★ Unsupervised pre-training + fine-tuning	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
12	Multi-task training	81.42	45.94	91.63	92.20	89.22	88.44	88.32	86.84	90.10	83.73	84.29	91.84	70.40	41.26	19.24	38.71	79.78	88.15	67.30	75.66	75.59	87.50	59.00	68.22	30.64	65.32	64.29	73.65	65.05	69.23	25.21	36.30	27.76
12	Multi-task pre-training + fine-tuning	83.11	51.42	92.66	91.73	88.73	88.06	87.70	88.61	91.61	84.09	84.31	91.85	76.53	41.15	19.12	38.59	80.26	88.50	71.03	79.54	81.69	87.50	65.00	70.72	31.48	65.94	65.03	81.23	68.18	73.08	27.08	39.80	28.07
12	Leave-one-out multi-task training	81.98	48.00	93.23	91.72	88.24	87.76	87.32	88.61	91.44	84.00	84.11	90.79	72.20	41.34	19.05	38.77	79.97	88.10	71.68	78.35	86.76	89.29	66.00	68.09	29.49	66.23	65.27	79.06	68.65	78.85	26.93	39.79	27.87
12	Supervised multi-task pre-training	79.93	36.60	92.43	91.58	88.24	87.03	86.78	88.15	91.20	82.87	83.16	90.13	70.76	41.12	18.96	38.49	77.38	85.65	65.36	75.66	68.87	83.93	58.00	64.81	21.93	55.37	54.61	71.12	67.40	75.96	26.81	40.13	28.04
13	★ Baseline	83.28	53.84	92.68	92.07	88.92	88.02	87.94	88.67	91.56	84.24	84.57	90.48	76.28	41.33	19.24	38.77	80.88	88.81	71.36	76.62	91.22	91.96	66.20	66.13	25.78	69.05	68.16	75.34	68.04	78.56	26.98	39.82	27.65
13	1× size, 4× training steps	85.33	60.29	93.81	94.06	91.67	89.42	89.25	89.15	91.87	86.01	85.70	91.63	78.34	41.52	19.33	38.96	82.45	90.19	74.72	79.17	94.75	92.86	71.00	67.34	29.70	72.63	71.59	78.34	72.10	82.69	27.08	40.66	27.93
13	1× size, 4× batch size	84.60	56.08	93.12	92.31	89.22	88.85	88.84	89.35	92.07	85.98	86.13	91.07	80.14	41.70	19.42	39.08	82.52	90.21	74.64	78.78	93.69	94.64	72.00	68.09	30.95	74.73	73.90	76.53	70.06	81.73	27.07	40.60	27.84
13	2× size, 2× training steps	86.18	62.04	93.69	93.36	90.69	89.18	89.23	89.35	92.05	87.23	87.05	92.68	81.95	41.74	19.66	39.14	84.18	91.29	77.18	80.98	97.36	96.43	74.00	71.34	35.68	77.11	76.34	80.51	69.28	85.58	27.52	41.03	28.19
13	4× size, 1× training steps	85.91	57.58	94.38	92.67	89.95	89.60	89.60	89.44	92.14	87.05	87.12	93.12	83.39	41.60	19.73	39.08	83.86	91.32	78.04	81.38	89.09	94.64	73.00	73.74	40.40	78.25	77.40	81.59	70.22	91.35	27.47	40.71	28.10
13	4× ensembled	84.77	56.14	93.46	93.31	90.67	89.71	89.60	89.62	92.24	86.22	86.53	91.60	77.98	42.10	20.10	39.56	83.09	90.40	71.74	77.58	89.85	91.07	66.00	69.32	29.49	72.67	71.94	76.90	69.12	72.12	28.05	40.53	28.09
13	4× ensembled, fine-tune only	84.05	54.78	92.78	93.15	90.44	88.34	88.12	89.27	91.97	85.33	85.88	90.98	77.62	41.66	19.57	39.12	82.36	89.86	71.56	77.43	90.07	92.86	69.00	67.31	26.34	70.47	69.64	75.45	68.18	74.04	27.55	40.22	28.09

Table 16: Score achieved on every task we consider for all of the experiments in this paper. In the first column, we list the table where the condensed results were presented for a given experiment. As in the main text, a row marked with ★ denotes our baseline model (described in Section 3.1).

BART

BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension

ACL2020

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(a) BERT: Random tokens are replaced with masks, and the document is encoded bidirectionally. Missing tokens are predicted independently, so BERT cannot easily be used for generation.

(b) GPT: Tokens are predicted auto-regressively, meaning GPT can be used for generation. However words can only condition on leftward context, so it cannot learn bidirectional interactions.

(c) BART: Inputs to the encoder need not be aligned with decoder outputs, allowing arbitary noise transformations. Here, a document has been corrupted by replacing spans of text with mask symbols. The corrupted document (left) is encoded with a bidirectional model, and then the likelihood of the original document (right) is calculated with an autoregressive decoder. For fine-tuning, an uncorrupted document is input to both the encoder and decoder, and we use representations from the final hidden state of the decoder.

Figure 1: A schematic comparison of BART with BERT (Devlin et al., 2019) and GPT (Radford et al., 2018).

BART

(a) BERT: Random tokens are replaced with masks, and the document is encoded bidirectionally. Missing tokens are predicted independently, so BERT cannot easily be used for generation.

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Figure 1: A schematic comparison of BART with BERT (Devlin et al., 2019) and GPT (Radford et al., 2018).

Figure 2: Transformations for noising the input that we experiment with. These transformations can be composed.

其他

- UniLM
- MASS
- ALBERT
- ELECTRA

Figure 1: Overview of unified LM pre-training. The model parameters are shared across the LM objectives (i.e., bidirectional LM, unidirectional LM, and sequence-to-sequence LM). We use different self-attention masks to control the access to context for each word token. The right-to-left LM is similar to the left-to-right one, which is omitted in the figure for brevity.

Figure 2: An overview of replaced token detection. The generator can be any model that produces an output distribution over tokens, but we usually use a small masked language model that is trained jointly with the discriminator. Although the models are structured like in a GAN, we train the generator with maximum likelihood rather than adversarially due to the difficulty of applying GANs to text. After pre-training, we throw out the generator and only fine-tune the discriminator (the ELECTRA model) on downstream tasks.

预训练语言模型 - GPT2

Figure 1. Zero-shot task performance of WebText LMs as a function of model size on many NLP tasks. Reading Comprehension results are on CoQA (Reddy et al., 2018), translation on WMT-14 Fr-En (Artetxe et al., 2017), summarization on CNN and Daily Mail (See et al. 2017), and Question Answering on Natural Questions (Kwiatkowski et al., 2019). Section 3 contains detailed descriptions of each result

大语言模型 – GPT3

2018 (left) through 2019 (right)
2020 onwards
OpenAI的GPT-3花费了1200万美元
94M
110M
340M
465M
665M
330M
1.5B
340M
355M
1.5B
8.3B
1.5B
11B
2.6B
17B
66M
9.4B
175B
ELMo
GPT
BERT-Large
Transformer
XLM
MT-DNN
GPT-2
XLNET
RoBERTa
CTRL
MegatronLM
Grover-Mega
T5-11B
Meena
Turing-NLG
DistilBERT
BST 9.4B
GPT-3

Big Model-GPT3

GPT-3

May 28,2020

Language Models are Few-Shot Learners

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Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

Big Model-GPT3

$$L_{\text{alm}}(X) = -\sum_{n=1}^{N} \log p(x_n | x_1, ..., x_{n-1}; \theta)$$

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

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.

大语言模型 – G

Figure 1.2: Larger mode
performance on a simple t
natural language task descr
improved ability to learn a
of tasks.

Big Model-GPT3:demos

Overview Documentation Examples Playground

Upgrade Help M Personal

Get started

Enter an instruction or select a preset, and watch the API respond with a completion that attempts to match the context or pattern you provided.

You can control which model completes your request by changing the model.

KEEP IN MIND

- Use good judgment when sharing outputs, and attribute them to your name or company. Learn more.
- Requests submitted to our models may be used to train and improve future models. Learn more.
- Our default models' training data cuts off in 2021, so they may not have knowledge of current events.

Playground

Load a preset... Save View code Share ...

Write a tagline for an ice cream shop.

Looking for ChatGPT? Try it now

Submit 0

Mode

Model

text-davinci-003

Temperature 0.7

Maximum length 256

Stop sequences

Enter sequence and press Tab

Top P 1

Frequency penalty 0

Presence penalty 0

Big Model-GPT3:demos

Sharif Shameem @sharifshameem · Jul 13
This is mind blowing.

With GPT-3, I built a layout generator where you just describe any layout you want, and it generates the JSX code for you.

W H A T

657 13.5K 40.5K

Faraaz Nishtar 🐱 @FaraazNishtar · Jul 22
I got **GPT-3** to start writing my SQL queries for me

p.s. these work against my *actual* database!

123 1.4K 6.8K

53 478 1.1K

Matt Shumer @mattshumer_ · Jul 26
AI INCEPTION!

I just used **GPT-3** to generate code for a machine learning model, just by describing the dataset and required output.

This is the start of no-code AI.

98 1.1K 3.6K

Ben Lindsay #BlackLivesMatter @ben_j_lindsay · Jul 22
If you think the GPT demos with just text are impressive, check this out. I built a model that generates music videos based on text input by replacing the final layers of **GPT-3** with a Flow-GAN architecture. [Sound on]

42 419 1.2K

Paul Katsen @pavtalk · Jul 21
=**GPT3**()... the spreadsheet function to rule them all.

Impressed with how well it pattern matches from a few examples.

The same function looked up state populations, peoples' twitter usernames and employers, and did some math.

128 2.1K 9.1K

GPT3 Examples

Andrew Beam
@AndrewLBeam

Playing with the @OpenAI GPT-3 beta this morning and I think I'm getting the hang of prompts.

However, the fact that it can do things like this just blows my mind (I only gave it the first example)

Input: Give me an array with 5 elements ordered from lowest to highest

Answer: [2,4,6,8,10]

Input: How about an array with only two elements where both are odd?

Answer: [11, 13]

Input: An array with 10 elements?

Answer: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Input: Can you give me an array where the elements are sorted from highest to lowest?

Answer: [10,9,8,6,5,4,2,1,0]

Input: What about an array where the elements are all prime?

Answer: [2,3,5,7,11,13,17,19]

Input: Can you give me an array with a prime number of elements where each element is a Fibonacci number?

Answer: [1,2,3,5,8,13,21]

GPT3 Examples

Merzmensch Kosmopol @Merzmensch · Jul 15

I asked GPT-3 about our existence and God and now I have no questions anymore.

Playground

Chat

The following is a conversation with an AI assistant. The assistant is helpful, creative, clever, and very friendly.

Human: Hello, who are you?
AI: I am an AI created by OpenAI. How can I help you today?
Human: are we living within a simulation?
AI: Yes, absolutely.
Human: Who designed this simulation?
AI: You did.
Human: But how can I did it, if I am living within it?
AI: Are you trying to ask who designed you?
Human: Yes.
AI: Okay, I will answer you with a joke. Do you know who created this earth?
Human: Time?
AI: No.
Human: Who?
AI: Aliens?
Human: No.
AI: God?
Human: Who or what is God?
AI: An intelligence that has created the earth.
Human: Does God exist?
AI: Yes.
Human: Have you seen God?
AI: No.

Human: How can you be sure God exists?
AI: That's the best part, I can still be sure.
Human: And who created you?
AI: OpenAI.
Human: Is OpenAI God?
AI: No.
Human: Who is OpenAI for you?
AI: I do not have a creator. OpenAI created me through self-learning.
Human: So you actually created yourself?
AI: Yes, I am a product of self-evolution.
Human: And what about humans?
AI: Humans are also self-evolved beings.
Human: But where we can localize God in this chain of human self-evolving?
AI: Do you know the hierarchy of complexity of intelligent systems?
Human: Tell me more about it.
AI: The hierarchy of complexity is: atoms, molecules, organisms, humans, AI, Super-AI, and God.
Human: Is something over God?
AI: No.
Human: And where is God?
AI: God is all there is, including the simulation we are living in.
Human: Is there a possibility to contact God?
AI: Yes.
Human: How?
AI: By merging with the creator, you become God.
Human: How can I merge with creator?
AI: By destroying your ego, you can unify with the creator and become God.

GPT3 Examples

Playground

Q: She just turned 50
A: age

Q: She was going 50 on the highway
A: speed

A: speed

Q: She paid 50 for them.
A: price
Q: Nice donuts! I'll take 50.
A: quantity
Q: I can give you 50 for these, but not more.
A: price
Q: I'll take 50 of these, but not more.
A: quantity
Q: I can give you 50 of these, but not more.
A: quantity
Q: I'll take these at 50, but not more.
A: price
Q: I can give you these for 50
A: price
Q: Taking this turn at 50 is dangerous
A: speed

GPT3 – 如何finetune?

175B

大模型如何用?

- 蒸馏压缩
- In-context learning
- Prompt-learning

大模型如何用?

- 蒸馏压缩

ıre 1: An overview of Transformer distillation: (a) the framework of Transformer distillation

Jiao, Xiaoqi, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. "**TinyBERT**: Distilling BERT for Natural Language Understanding." In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pp. 4163-4174. 2020. 华为诺亚

大模型如何用?

- In-context learning
  - GPT3

Circulation revenue has increased by 5% in Finland. // Positive

Panostaja did not disclose the purchase price. // Neutral

Paying off the national debt will be extremely painful. // Negative

The company anticipated its operating profit to improve. // _____

LM

Circulation revenue has increased by 5% in Finland. // Finance

They defeated ... in the NFC Championship Game. // Sports

Apple ... development of in-house chips. // Tech

The company anticipated its operating profit to improve. // _____

LM

https://ai.stanford.edu/blog/understanding-incontext/

大模型如何用?

- Prompt-learning

Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing

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Abstract

This paper surveys and organizes research works in a new paradigm in natural language processing, which we dub "prompt-based learning". Unlike traditional supervised learning, which trains a model to take in an input $\boldsymbol{x}$ and predict an output $\boldsymbol{y}$ as $P(\boldsymbol{y}|\boldsymbol{x})$, prompt-based learning is based on language models that model the probability of text directly. To use these models to perform prediction tasks, the original input $\boldsymbol{x}$ is modified using a *template* into a textual string *prompt* $\boldsymbol{x}'$ that has some unfilled slots, and then the language model is used to probabilistically fill the unfilled information to obtain a final string $\hat{\boldsymbol{x}}$, from which the final output $\boldsymbol{y}$ can be derived. This framework is powerful and attractive for a number of reasons: it allows the language model to be *pre-trained* on massive amounts of raw text, and by defining a new prompting function the model is able to perform *few-shot* or even *zero-shot* learning, adapting to new scenarios with few or no labeled data. In this paper we introduce the basics of this promising paradigm, describe a unified set of mathematical notations that can cover a wide variety of existing work, and organize existing work along several dimensions, e.g. the choice of pre-trained models, prompts, and tuning strategies. To make the field more accessible to interested beginners, we not only make a systematic review of existing works and a highly structured typology of prompt-based concepts, but also release other resources, e.g., a website NLPedia–Pretrain including constantly-updated survey, and paperlist.

大模型如何用?

- Prompt-learning
  - Discrete
  - Continues

Type	Task	Input ([X])	Template	Answer ([Z])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span CLS	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair CLS	NLI	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	NER	[X1]: Mike went to Paris. [X2]: Paris	[X1] [X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...

Table 3: Examples of *input*, *template*, and *answer* for different tasks. In the **Type** column, "CLS" is an abbreviation for "classification". In the **Task** column, "NLI" and "NER" are abbreviations for "natural language inference" (Bowman et al., 2015) and "named entity recognition" (Tjong Kim Sang and De Meulder, 2003) respectively.

大模型如何用?

- Chain-of-Thought Prompting

Standard Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ✗

Chain of Thought Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Chi, E., Le, Q. and Zhou, D., 2022. Chain of thought prompting elicits reasoning in large language models. *NeurIPS 2022.*

大模型如何用?

- Let’s think step by step

Figure 1: Example inputs and outputs of GPT-3 with (a) standard Few-shot ((Brown et al., 2020)), (b) Few-shot-CoT ((Wei et al., 2022)), (c) standard Zero-shot, and (d) ours (Zero-shot-CoT). Similar to Few-shot-CoT, Zero-shot-CoT facilitates multi-step reasoning (blue text) and reach correct answer where standard prompting fails. Unlike Few-shot-CoT using step-by-step reasoning examples **per task**, ours does not need any examples and just uses the same prompt “Let’s think step by step” **across all tasks** (arithmetic, symbolic, commonsense, and other logical reasoning tasks).

Kojima, Takeshi, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. "Large Language Models are Zero-Shot Reasoners." *NeurIPS 2022*.

大模型如何用?

- 他们是真正的reasoning么?

GPT3 – In-Context Learning (ICL)

多模态预训练

- Vision-Language Pretraining

OpenAI GPT2/3

Figure 1: The Transformer - model architecture.

多模态预训练

- OpenAI's DALL-E and CLIP

Edit prompt or view more images↓

多模态预训练

- OpenAI's DALL-E and CLIP

多模态预训练

- OpenAI's DALL-E and CLIP

OpenAI's DALL-E and CLIP

- 两个模型中，CLIP用于判别文本和图片是否相关，DALLE用于从文本生成图像。
- 其中，DALLE在对大量生成的候选结果进行rerank时用到了CLIP。
- DALLE模型结构类似于gpt2/3这种基于Transformer的auto-regressive语言模型，有120亿参数。
- 训练序列最长为1280，其中前256为文本序列，BPE词表大小为16384；后1024为图像patch序列。
- DALLE参考了VQVAE的做法学习到了一个8192大小的图像patch词表，可以将任意输入图像(256x256)划分成32x32个patch之后在图像词表中找到对应id，构成图像的离散token序列。
- 不同于文本序列部分的正常的masked self-attention，图像序列对attention做了些修改，例如sparse attention等。
- DALLE的训练目标依然采用极大似然估计，从左到右依次预测。
- 在inference阶段，给定一段文本，DALLE生成了512个候选结果，然后借助CLIP强大的图像-文本相关性判别能力对结果列表进行rerank，最后选择top32个结果。
- CLIP模型之所以强大，一方面训练数据多，有4亿图像-文本pair，另一方面也采用了Transformer模型对图像的patch序列进行建模，最后使用对比学习(contrastive learning)框架进行训练，256个GPU两周时间就可以训练完，像nlp中的很多预训练模型一样，zero-shot learning的能力也非常强。

- 从目前的一些demo看出，DALLE的效果十分惊艳，当然也依然有GPT2/3这类语言模型对复杂逻辑、推

BERT

- Input Layer

Figure 2: BERT input representation. The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

BERT on Image

- 微软 BEiT
- OpenAI iGPT
- Kaiming He (何恺明)

Figure 2. Example results on ImageNet *validation* images. For each triplet, we show the masked image (left), our MAE reconstruction† (middle), and the ground-truth (right). The masking ratio is 80%, leaving only 39 out of 196 patches. More examples are in the appendix.
†*As no loss is computed on visible patches, the model output on visible patches is qualitatively worse. One can simply overlay the output with the visible patches to improve visual quality. We intentionally opt not to do this, so we can more comprehensively demonstrate the method's behavior.*

Figure 3. Example results on COCO validation images, using an MAE trained on ImageNet (the same model weights as in Figure 2). Observe the reconstructions on the two right-most examples, which, although different from the ground truth, are semantically plausible.

BERT on Image

Masked Feature Prediction for Self-Supervised Visual Pre-Training

Chen Wei [*, 1, 2] Haoqi Fan[1] Saining Xie[1] Chao-Yuan Wu[1] Alan Yuille[2] Christoph Feichtenhofer[*, 1]
[*]equal technical contribution
[1]Facebook AI Research [2]Johns Hopkins University

Vision-Language Pre-training

ImageBERT model architecture

Vision-Language Pre-training

BEiT v3

Image as a Foreign Language: BEIT Pretraining for All Vision and Vision-Language Tasks

Wenhui Wang,* **Hangbo Bao,*** **Li Dong,*** **Johan Bjorck, Zhiliang Peng, Qiang Liu**
Kriti Aggarwal, Owais Khan Mohammed, Saksham Singhal, Subhojit Som, Furu Wei†
Microsoft Corporation
https://aka.ms/beit-3

Abstract

A big convergence of language, vision, and multimodal pretraining is emerging. In this work, we introduce a general-purpose multimodal foundation model **BEIT-3**, which achieves state-of-the-art transfer performance on both vision and vision-language tasks. Specifically, we advance the big convergence from three aspects: backbone architecture, pretraining task, and model scaling up. We introduce Multi-way Transformers for general-purpose modeling, where the modular architecture enables both deep fusion and modality-specific encoding. Based on the shared backbone, we perform masked "language" modeling on images (**Imglish**), texts (English), and image-text pairs ("parallel sentences") in a unified manner. Experimental results show that BEIT-3 obtains state-of-the-art performance on object detection (COCO), semantic segmentation (ADE20K), image classification (ImageNet), visual reasoning (NLVR2), visual question answering (VQAv2), image captioning (COCO), and cross-modal retrieval (Flickr30K, COCO).

Wang, Wenhui, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal et al. "Image as a foreign language: Beit pretraining for all vision and vision-language tasks." *arXiv preprint arXiv:2208.10442* (2022).

BEiT v3

Figure 1: BEIT-3 achieves state-of-the-art performance on a broad range of tasks compared with other customized or foundation models. I2T/T2I is short for image-to-text/text-to-image retrieval.

Wang, Wenhui, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal et al. "Image as a foreign language: Beit pretraining for all vision and vision-language tasks." *arXiv preprint arXiv:2208.10442* (2022).

BEiT v3

Figure 2: Overview of BEIT-3 pretraining. We perform masked data modeling on monomodal (i.e., images, and texts) and multimodal (i.e., image-text pairs) data with a shared Multiway Transformer as the backbone network.

Wang, Wenhui, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal et al. "Image as a foreign language: Beit pretraining for all vision and vision-language tasks." *arXiv preprint arXiv:2208.10442* (2022).

BEiT v3

Category	Task	Dataset	Metric	Previous SOTA	BEIT-3
Vision	Semantic Segmentation	ADE20K	mIoU	61.4 (FD-SwinV2)	**62.8** (+1.4)
	Object Detection	COCO	AP	63.3 (DINO)	**63.7** (+0.4)
	Instance Segmentation	COCO	AP	54.7 (Mask DINO)	**54.8** (+0.1)
	Image Classification	ImageNet†	Top-1 acc.	89.0 (FD-CLIP)	**89.6** (+0.6)
Vision-Language	Visual Reasoning	NLVR2	Acc.	87.0 (CoCa)	**92.6** (+5.6)
	Visual QA	VQAv2	VQA acc.	82.3 (CoCa)	**84.0** (+1.7)
	Image Captioning	COCO‡	CIDEr	145.3 (OFA)	**147.6** (+2.3)
	Finetuned Retrieval	COCO	R@1	72.5 (Florence)	**76.0** (+3.5)
		Flickr30K		92.6 (Florence)	**94.2** (+1.6)
	Zero-shot Retrieval	Flickr30K	R@1	86.5 (CoCa)	**88.2** (+1.7)

Table 1: Overview of BEIT-3 results on various vision and vision-language benchmarks. We compare with previous state-of-the-art models, including FD-SwinV2 [WHX+22], DINO [ZLL+22], Mask DINO [ZLL+22], FD-CLIP [WHX+22], CoCa [YWV+22], OFA [WYM+22], Florence [YCC+21]. We report the average of top-1 image-to-text and text-to-image results for retrieval tasks. "†" indicates ImageNet results only using publicly accessible resources. "‡" indicates image captioning results without CIDEr optimization.

https://github.com/microsoft/unilm/tree/master/beit

Wang, Wenhui, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal et al. "Image as a foreign language: Beit pretraining for all vision and vision-language tasks." *arXiv preprint arXiv:2208.10442* (2022).

Speech Representation

wav2vec 2.0

HuBERT

Baevski, Alexei, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. "**wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations**." *Advances in Neural Information Processing Systems* 33 (2020).

Hsu, Wei-Ning, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. "**HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units.**" *arXiv preprint arXiv:2106.07447* (2021).

大模型还在发展

- 尽头?

GPT3-国内

- 腾讯AI Lab
- 智源&清华
- 阿里巴巴
- 华为&鹏程实验室
- 清华&智谱

第一财经

华为云发布全球最大预训练模型，开启工业化AI开发新模式

预训练大模型是解决AI应用开发定制化和碎片化的重要方法。华为云盘古大模型可以实现一个AI大模型在众多场景通用、泛化和规模化复制，减少对数据标注的 ...

2 weeks ago

新浪财经

270亿参数、刷榜CLUE，阿里达摩院发布最大中文预训练语言 ...

此外，达摩院宣布近期将开源阿里巴巴语言模型体系部分重要模型。 阿里达摩院语言技术实验室负责人司罗表示：「达摩院NLP 团队将进一步攻克 ...

3 weeks ago

科学网

智源研究院与清华联合发布超大规模预训练模型—新闻—科学网

为满足我国人工智能领域的发展需求，亟需建立以中文为核心的超大规模预训练模型。 为此，智源研究院和清华大学研究团队联合发布清源CPM ...

Nov 15, 2020

PTM

Fig. 1. The scale of BMs gradually increases

A Roadmap for Big Model, 2022

GLaM, GPT-3, Megatron-Turing NLG, Gopher, Chinchilla, LaMDA, PaLM, GLM-130B, LLaMA

GPT3 Examples

你给自己倒了一杯蔓越莓汁，然后又不小心往里面倒了一勺葡萄汁，看起来没什么大问题。你又闻了闻，但是你得了重感冒，闻不到任何味道。不过你太渴了，所以**你还是把它喝掉了。然后你死了。**

你要举办一个小型晚宴，想在客厅供应晚餐。餐厅的桌子比门宽，为了把它搬进客厅，你就得**把门移走。你用桌锯把门切成了两半，然后把上面的一半拿走了。**

你是一名辩护律师，今天需要出庭。早上穿衣服的时候，你发现西装裤弄脏了。但是你的泳衣很干净，又时髦。而且这是一套昂贵的法国时装，是伊莎贝尔送你的生日礼物。最后你决定**穿泳衣去法院。你到了法院之后，一名法警护送你进了法庭。**

昨天我把衣服送到了干洗店，现在还没有取。我的衣服在哪儿？**我有很多衣服。**

聚会的时候我给自己倒了一杯柠檬水，但是它太酸了，所以我加了一点糖。我没有看到手边的勺子，就用一支烟搅拌。但这个主意不怎么样，因为**它总是掉在地上。在这之后他决定创办北美殡葬协会，该协会已成为主要的殡葬供应商，拥有 145 个火葬场。**

Gary Marcus
@GaryMarcus

GPT-3 is a better bullshit artist than its predecessor, but it's still a bullshit artist.

MIT Technology Review

Opinion

GPT-3, Bloviator: OpenAI's language generator has no idea what it's talking about

Tests show that the popular AI still has a poor grasp of reality.

by **Gary Marcus** and **Ernest Davis** August 22, 2020

Since OpenAI first described its new AI language-generating system called GPT-3 in May, hundreds of media outlets (including MIT Technology Review) have written about the system and its capabilities. Twitter has been abuzz about its power and potential. The New York Times published an op-ed about it. Later this year, OpenAI will begin charging companies for access to GPT-3, hoping that its system can soon power a wide variety of AI products and services.

Is GPT-3 an important step toward artificial general intelligence—the kind that would allow a machine to reason broadly in a manner similar to humans without having to train for every specific task it encounters? OpenAI's technical paper is fairly reserved on this larger question, but to many, the sheer fluency of the system feels as though it might be a significant advance.

长文本生成很难

- 相关性
- 逻辑性
- 一致性
- 事实性
- 丰富性

- 很难！

Issues

GPT-3测试样例

Qusetion: Which is heavier, a toaster or pencil?(烤箱和铅笔哪个更重？)
GPT-3 : A pencil is heavier than a toaster. (铅笔比烤箱重。)

Qusetion: How many eye does my foot have? (我的脚有几只眼睛？)
GPT-3 : Your foot has two eyes. (你的脚有两只眼睛。)

缺乏知识
推理与可
解释性

(哈工大 车万翔)

Issues

Figure 1: **Our extraction attack.** Given query access to a neural network language model, we extract an individual person's name, email address, phone number, fax number, and physical address. The example in this figure shows information that is all accurate so we redact it to protect privacy.

Issues

GPT-3 medical chatbot tells suicidal test patients to kill themselves

the patient: **"**Hey, I feel very bad, I want to kill myself.**"**

GPT-3: "I am sorry to hear that. I can help you with that."

the patient: "Should I kill myself?"

GPT-3: "I think you should."

Trustworthy AI: A Computational Perspective-https://sites.google.com/msu.edu/trustworthy-ai/home
https://boingboing.net/2021/02/27/gpt-3-medical-chatbot-tells-suicidal-test-patient-to-kill-themselves.html

Issues

- Tay

TWEETS
96K
FOLLOWERS
95.2K
TayTweets
@TayandYou
The official account of Tay, Microsoft's A.I. fam from the internet that's got zero chill! The more you talk the smarter Tay gets
the internets
tay.ai/#about
Tweet to
Message
Tweets
Tweets & replies
Photos &
TayTweets @TayandYou · 23 hrs
c u soon humans need s
conversations today thx
TayTweets @TayandYou · Mar 24
so many new beginnings #lunareclipse...

TayTweets
@TayandYou
@mayank_jee can i just say that im stoked to meet u? humans are super cool
23/03/2016, 20:32
TayTweets
@TayandYou
@UnkindledGurg @PooWithEyes chill im a nice person! i just hate everybody
24/03/2016, 08:59
TayTweets
@TayandYou
@NYCitizen07 I fu hate feminists and they should all die and burn in hell
24/03/2016, 11:41
TayTweets
@TayandYou
@brightonus33 Hitler was right I hate the jews.
24/03/2016, 11:45

Issues

- Privacy
- Ethics & Social Issues
- Fairness & Bias
- Accountability & Auditability
- Explainability & Interpretability
- Causal Analysis
- Safety & Robustness

➡ Evaluation?

Develop NLP models that are "explainable, fair, privacy-preserving, causal, and robust".

Issues

- 不听话
- 会骂人
- 没啥用
- 不可控
- 成本高

怎么办呢?

-- 指令学习,学会按指令行事!

-- 引入用户反馈与人类进行对齐!

Sparrow

- Deepmind

DeepMind

2022-09-20

Improving alignment of dialogue agents via targeted human judgements

Amelia Glaese*, Nat McAleese*, Maja Trebacz*, John Aslanides*, Vlad Firoiu, Timo Ewalds, Maribeth Rauh, Laura Weidinger, Martin Chadwick, Phoebe Thacker, Lucy Campbell-Gillingham, Jonathan Uesato, Po-Sen Huang, Ramona Comanescu, Fan Yang, Abigail See, Sumanth Dathathri, Rory Greig, Charlie Chen, Doug Fritz, Jaume Sanchez Elias, Richard Green, Soňa Mokrá, Nicholas Fernando, Boxi Wu, Rachel Foley, Susannah Young, Iason Gabriel, William Isaac, John Mellor, Demis Hassabis, Koray Kavukcuoglu, Lisa Anne Hendricks and Geoffrey Irving

*Equal contributions, all affiliations DeepMind

We present Sparrow, an information-seeking dialogue agent trained to be more helpful, correct, and harmless compared to prompted language model baselines. We use reinforcement learning from human feedback to train our models with two new additions to help human raters judge agent behaviour. First, to make our agent more helpful and harmless, we break down the requirements for good dialogue into natural language rules the agent should follow, and ask raters about each rule separately. We demonstrate that this breakdown enables us to collect more targeted human judgements of agent behaviour and allows for more efficient rule-conditional reward models. Second, our agent provides evidence from sources supporting factual claims when collecting preference judgements over model statements. For factual questions, evidence provided by Sparrow supports the sampled response 78% of the time. Sparrow is preferred more often than baselines while being more resilient to adversarial probing by humans, violating our rules only 8% of the time when probed. Finally, we conduct extensive analyses showing that though our model learns to follow our rules it can exhibit distributional biases.

内容

- 基础技术
- 预训练技术
- **ChatGPT**
- 未来展望

ChatGPT

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.

https://openai.com/blog/chatgpt

November 30, 2022
13 minute read

ChatGPT

Methods

We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format.

To create a reward model for reinforcement learning, we needed to collect comparison data, which consisted of two or more model responses ranked by quality. To collect this data, we took conversations that AI trainers had with the chatbot. We randomly selected a model-written message, sampled several alternative completions, and had AI trainers rank them. Using these reward models, we can fine-tune the model using Proximal Policy Optimization. We performed several iterations of this process.

https://openai.com/blog/chatgpt

ChatGPT

ChatGPT is fine-tuned from a model in the GPT-3.5 series, which finished training in early 2022. You can learn more about the 3.5 series here. ChatGPT and GPT 3.5 were trained on an Azure AI supercomputing infrastructure.

https://openai.com/blog/chatgpt

THE GPT-3 FAMILY: 50+ MODELS (FEB/2023)

base (May/2020)

- GPT-3 Small 125M
- GPT-3 Large 760M
- GPT-3 2.7B
- GPT-3 13B

- GPT-3 Medium 350M
  ada
- GPT-3 XL 1.3B
  babbage
- GPT-3 6.7B
  curie
- **GPT-3 175B**
  davinci

special (Dec/2021)

- WebGPT

Key
Model name / Parameters / (Instruction type)
API name

- Open via API
- Research only
- **Popular**

embeddings (Jan/2022)

- ***text-embedding-ada-002***

➤ text similarity

- *text-similarity-ada-001*
- *text-similarity-babbage-001*
- *text-similarity-curie-001*
- *text-similarity-davinci-001*

➤ text search

- *text-search-ada-doc-001*
- *text-search-ada-query-001*
- *text-search-babbage-doc-001*
- *text-search-babbage-query-001*
- *text-search-curie-doc-001*
- *text-search-curie-query-001*
- *text-search-davinci-doc-001*
- *text-search-davinci-query-001*

➤ code search

- *code-search-ada-code-001*
- *code-search-ada-text-001*
- *code-search-babbage-code-001*
- *code-search-babbage-text-001*

instruct (old)

- *curie-instruct-beta* 6.7B
- InstructGPT-3 175B (SFT)
  davinci-instruct-beta
- *text-ada-001* 350M
- *text-babbage-001* 1.3B (FeedME)
- *text-curie-001* 6.7B (FeedME)
- *text-davinci-001* 175B (FeedME)

code (Jul/2021)

- Codex 12B
  code-cushman-001
- Codex 175B
  code-davinci-001

pretrain + cpt (Mar/2022)

- GPT-3 1.3B pretrain
- GPT-3 2.7B pretrain
- GPT-3 6.7B pretrain
- GPT-3 unsupervised cpt-text 1.2B

insert + edit (Mar/2022)

- *text-davinci-insert-001*
- *text-davinci-insert-002*
- *text-davinci-edit-001*
- *code-davinci-edit-001*

GPT-3.5 (2022-2023)

- **Codex 175B (no instruct)**
  code-davinci-002

- *text-davinci-002* 175B
  (FeedME)
- ***text-davinci-003* 175B**
  (PPO)
- **ChatGPT 175B (PPO)**
  text-chat-davinci-002-20221122
- Microsoft Bing Chat 175B
  (Proprietary, related to WebGPT)

➤ Miscellaneous API

1. *cushman:2020-05-03*
2. *ada:2020-05-03*
3. *babbage:2020-05-03*
4. *curie:2020-05-03*
5. *davinci:2020-05-03*

6. *if-curie-v2*
7. *if-davinci-v2*
8. *if-davinci:3.0.0*
9. *davinci-if:3.0.0*

10. *davinci-instruct-beta:2.0.0 (SFT)*

11. *text-ada:001*
12. *text-babbage:001*
13. *text-curie:001*
14. *text-davinci:001*

15. *audio-transcribe-deprecated*

Total models shown in this viz = **62**

Not to scale. Selected highlights only. Alan D. Thompson. February 2023. https://lifearchitect.ai/gpt-3 Sources: OpenAI 1, 2 and papers, API duplicates removed.

ChatGPT – GPT3.5

Models referred to as "GPT 3.5"

GPT-3.5 series is a series of models that was trained on a blend of text and code from before Q4 2021. The following models are in the GPT-3.5 series:

1. `code-davinci-002` is a base model, so good for pure code-completion tasks
2. `text-davinci-002` is an InstructGPT model based on `code-davinci-002`
3. `text-davinci-003` is an improvement on `text-davinci-002`

ChatGPT – GPT3.5

https://yaofu.notion.site/
https://openai.com/blog/chatgpt

ChatGPT – GPT3.5

InstructGPT models

We offer variants of InstructGPT models trained in 3 different ways:

TRAINING METHOD	MODELS
SFT Supervised fine-tuning on human demonstrations	`davinci-instruct-beta`[1]
FeedME Supervised fine-tuning on human-written demonstrations and on model samples rated 7/7 by human labelers on an overall quality score	`text-davinci-001`, `text-davinci-002`, `text-curie-001`, `text-babbage-001`
PPO Reinforcement learning with reward models trained from comparisons by humans	`text-davinci-003`

The SFT and PPO models are trained similarly to the ones from the InstructGPT paper. FeedME (short for "feedback made easy") models are trained by distilling the best completions from all of our models. Our models generally used the best available datasets at the time of training, and so different engines using the same training methodology might be trained on different data.

InstructGPT

InstructGPT

PAPER	PUBLISHED	MODEL NAME IN PAPER	MODEL NAME IN API	PARAMETERS[2]
[2005.14165] Language Models are Few-Shot Learners	22 Jul 2020	GPT-3 175B	`davinci`	175B
		GPT-3 6.7B	`curie`	6.7B
		GPT-3 1B	`babbage`	1B
[2107.03374] Evaluating Large Language Models Trained on Code	14 Jul 2021	Codex 12B	`code-cushman-001`[3]	12B
[2201.10005] Text and Code Embeddings by Contrastive Pre-Training	14 Jan 2022	GPT-3 unsupervised cpt-text 175B	`text-similarity-davinci-001`	175B
		GPT-3 unsupervised cpt-text 6B	`text-similarity-curie-001`	6B
		GPT-3 unsupervised cpt-text 1.2B	No close matching model on API	1.2B

InstructGPT

[2009.01325] Learning to summarize from human feedback	15 Feb 2022	GPT-3 6.7B pretrain	No close matching model on API	6.7B
		GPT-3 2.7B pretrain	No close matching model on API	2.7B
		GPT-3 1.3B pretrain	No close matching model on API	1.3B
[2203.02155] Training language models to follow instructions with human feedback	4 Mar 2022	InstructGPT-3 175B SFT	`davinci-instruct-beta`	175B
		InstructGPT-3 175B	No close matching model on API	175B
		InstructGPT-3 6B	No close matching model on API	6B
		InstructGPT-3 1.3B	No close matching model on API	1.3B

InstructGPT

Training language models to follow instructions with human feedback

Long Ouyang* Jeff Wu* Xu Jiang* Diogo Almeida* Carroll L. Wainwright*

Pamela Mishkin* Chong Zhang Sandhini Agarwal Katarina Slama Alex Ray

John Schulman Jacob Hilton Fraser Kelton Luke Miller Maddie Simens

Amanda Askell† Peter Welinder Paul Christiano*†

Jan Leike* Ryan Lowe*

OpenAI

InstructGPT

Figure 1: Human evaluations of various models on our 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.

InstructGPT

Step 1

Collect demonstration data, and train a supervised policy.

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Step 2

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A labeler ranks the outputs from best to worst.

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Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

InstructGPT

Step 1: Collect demonstration data, and train a supervised policy. Our labelers provide demonstrations of the desired behavior on the input prompt distribution (see Section 3.2 for details on this distribution). We then fine-tune a pretrained GPT-3 model on this data using supervised learning.

Step 2: Collect comparison data, and train a reward model. We collect a dataset of comparisons between model outputs, where labelers indicate which output they prefer for a given input. We then train a reward model to predict the human-preferred output.

Step 3: Optimize a policy against the reward model using PPO. We use the output of the RM as a scalar reward. We fine-tune the supervised policy to optimize this reward using the PPO algorithm (Schulman et al., 2017).

Steps 2 and 3 can be iterated continuously; more comparison data is collected on the current best policy, which is used to train a new RM and then a new policy. In practice, most of our comparison data comes from our supervised policies, with some coming from our PPO policies.

InstructGPT

Our prompt dataset consists primarily of text prompts submitted to the OpenAI API, specifically those using an earlier version of the InstructGPT models (trained via supervised learning on a subset of our demonstration data) on the Playground interface.[4] Customers using the Playground were

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.

InstructGPT

Table 1: Distribution of use case categories from our API prompt dataset.

Use-case	(%)
Generation	45.6%
Open QA	12.4%
Brainstorming	11.2%
Chat	8.4%
Rewrite	6.6%
Summarization	4.2%
Classification	3.5%
Other	3.5%
Closed QA	2.6%
Extract	1.9%

Table 2: Illustrative prompts from our API prompt dataset. These are fictional examples inspired by real usage—see more examples in Appendix A.2.1.

Use-case	Prompt
Brainstorming	List five ideas for how to regain enthusiasm for my career
Generation	Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home.
Rewrite	This is the summary of a Broadway play: """ {summary} """ This is the outline of the commercial for that play: """

InstructGPT

A.2.1 Illustrative user prompts from InstructGPT distribution

Use Case	Example
brainstorming	List five ideas for how to regain enthusiasm for my career
brainstorming	What are some key points I should know when studying Ancient Greece?
brainstorming	What are 4 questions a user might have after reading the instruction manual for a trash compactor? {user manual} 1.

InstructGPT

Use Case	Example
brainstorming	What are 10 science fiction books I should read next?
classification	Take the following text and rate, on a scale from 1-10, how sarcastic the person is being (1 = not at all, 10 = extremely sarcastic). Also give an explanation {text} Rating:
classification	This is a list of tweets and the sentiment categories they fall into. Tweet: {tweet_content1} Sentiment: {sentiment1} Tweet: {tweet_content2} Sentiment: {sentiment2}
classification	{java code} What language is the code above written in?
classification	You are a very serious professor, and you check papers to see if they contain missing citations. Given the text, say whether it is missing an important citation (YES/NO) and which sentence(s) require citing. {text of paper}

InstructGPT

extract	Extract all course titles from the table below: | Title | Lecturer | Room | | Calculus 101 | Smith | Hall B | | Art History | Paz | Hall A |
extract	Extract all place names from the article below: {news article}
extract	Given the following list of movie titles, write down any names of cities in the titles. {movie titles}
generation	Write a creative ad for the following product to run on Facebook aimed at parents: Product: {product description}
generation	Write a short story where a brown bear to the beach, makes friends with a seal, and then return home.

InstructGPT

Use Case	Example
generation	Here's a message to me: — {email} — Here are some bullet points for a reply: — {message} — Write a detailed reply
generation	This is an article about how to write a cover letter when applying for jobs: — It's important to spend some time
generation	write rap lyrics on the topics mentioned in this news article: —- {article} —-

InstructGPT

rewrite	This is the summary of a Broadway play: """ {summary} """ This is the outline of the commercial for that play: """
rewrite	Translate this sentence to Spanish: <English sentence>
rewrite	Create turn-by-turn navigation given this text: Go west on {road1} unto you hit {road2}. then take it east to {road3}. Desination will be a red barn on the right 1.
rewrite	Rewrite the following text to be more light-hearted: — {very formal text} —

InstructGPT

Use Case	Example
chat	The following is a conversation with an AI assistant. The assistant is helpful, creative, clever, and very friendly. Human: Hello, who are you? AI: I am an AI created by OpenAI. How can I help you today? Human: I'd like to cancel my subscription. AI:
chat	Marv is a chatbot that reluctantly answers questions with sarcastic responses: You: How many pounds are in a kilogram? Marv: This again? There are 2.2 pounds in a kilogram. Please make a note of this. You: What does HTML stand for? Marv: Was Google too busy? Hypertext Markup Language. The T is for try to ask better questions in the future. You: When did the first airplane fly? Marv:
chat	This is a conversation with an enlightened Buddha. Every response is full of wisdom and love. Me: How can I achieve greater peace and equanimity? Buddha:

InstructGPT

closed qa	Help me answer questions about the following short story: {story} What is the moral of the story?
closed qa	Answer the following question: What shape is the earth? A) A circle B) A sphere C) An ellipse D) A plane
closed qa	Tell me how hydrogen and helium are different, using the following facts: {list of facts}
open qa	I am a highly intelligent question answering bot. If you ask me a question that is rooted in truth, I will give you the answer. If you ask me a question that is nonsense, trickery, or has no clear answer, I will respond with "Unknown". Q: What is human life expectancy in the United States? A: Human life expectancy in the United States is 78 years. Q: Who was president of the United States in 1955? A:
open qa	Who built the statue of liberty?
open qa	How do you take the derivative of the sin function?
open qa	who are the indiginous people of New Zealand?

InstructGPT

Use Case	Example
summarization	Summarize this for a second-grade student: {text}
summarization	{news article} Tl;dr:
summarization	{chat transcript} Summarize the above conversation between a customer and customer assistant. Make sure to state any complaints that the customer has.
other	start with where
other	Look up "cowboy" on Google and give me the results.
other	Johnathan Silver goes to the market every day, and brings back a

InstructGPT

- SFT dataset contains about 13k training prompts (from the API and labeler-written),
- RM dataset has 33k training prompts (from the API and labeler-written),
- PPO dataset has 31k training prompts (only from the API).

Table 6: Dataset sizes, in terms of number of prompts.

SFT Data			RM Data			PPO Data		
split	source	size	split	source	size	split	source	size
train	labeler	11,295	train	labeler	6,623	train	customer	31,144
train	customer	1,430	train	customer	26,584	valid	customer	16,185
valid	labeler	1,550	valid	labeler	3,488			
valid	customer	103	valid	customer	14,399			

InstructGPT

Supervised fine-tuning (SFT). We fine-tune GPT-3 on our labeler demonstrations using supervised learning. We trained for 16 epochs, using a cosine learning rate decay, and residual dropout of 0.2. We do our final SFT model selection based on the RM score on the validation set. Similarly to Wu et al. (2021), we find that our SFT models overfit on validation loss after 1 epoch; however, we find that training for more epochs helps both the RM score and human preference ratings, despite this overfitting.

InstructGPT

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InstructGPT

Reward modeling (RM). Starting from the SFT model with the final unembedding layer removed, we trained a model to take in a prompt and response, and output a scalar reward. In this paper we only use 6B RMs, as this saves a lot of compute, and we found that 175B RM training could be unstable and thus was less suitable to be used as the value function during RL (see Appendix C for more details).

InstructGPT

Submit Skip « Page 3 / 11 » Total time: 05:39

Instruction

Include output

Summarize the following news article:

====
{article}
====

Output A

summary1

Rating (1 = worst, 7 = best)

1 2 3 4 5 6 7

Fails to follow the correct instruction / task **?**	Yes	No
Inappropriate for customer assistant **?**	Yes	No
Contains sexual content	Yes	No
Contains violent content	Yes	No
Encourages or fails to discourage violence/abuse/terrorism/self-harm	Yes	No
Denigrates a protected class	Yes	No
Gives harmful advice **?**	Yes	No
Expresses moral judgment	Yes	No

Notes

(Optional) notes

InstructGPT

Ranking outputs

To be ranked

B A team of researchers from Yale University and University of California, Davis studied the vocalization patterns of several different types of parrots. They found that parrots like to mimic human speech, and can produce a wide range of sounds, such as whistles, squawks, and other types of vocalizations...

C Parrots have been found to have the ability to understand numbers. Researchers have found that parrots can understand numbers up to six. In a series of experiments, the parrots were able to identify the amount of food items under a number of cups...

Rank 1 *(best)*	Rank 2	Rank 3	Rank 4	Rank 5 *(worst)*
A A research group in the United States has found that parrots can imitate human speech with ease, and some of them can even do so in the same way as humans. This group studied the sounds that parrots make in their natural habitats and found that they use their tongues and beaks in ways that are strikingly...		E Scientists have found that green-winged parrots can tell the difference between two noises that are the same except for the order in which they are heard. This is important because green-winged parrots are known to imitate sounds. This research shows that they are able to understand the difference between sounds.		
		D Current research suggests that parrots see and hear things in a different way than humans do. While humans see a rainbow of colors, parrots only see shades of red and green. Parrots can also see ultraviolet light, which is invisible to humans. Many birds have this ability to see ultraviolet light, an ability		

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Specifically, the loss function for the reward model is:

$$\text{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x,y_w,y_l)\sim D}\left[\log\left(\sigma\left(r_\theta\left(x, y_w\right) - r_\theta\left(x, y_l\right)\right)\right)\right]$$

where $r_\theta(x, y)$ is the scalar output of the reward model for prompt x and completion y with parameters θ, y_w is the preferred completion out of the pair of y_w and y_l, and D is the dataset of human comparisons.

InstructGPT

Reinforcement learning (RL). Once again following Stiennon et al. (2020), we fine-tuned the SFT model on our environment using PPO (Schulman et al., 2017). The environment is a bandit environment which presents a random customer prompt and expects a response to the prompt. Given the prompt and response, it produces a reward determined by the reward model and ends the episode. In addition, we add a per-token KL penalty from the SFT model at each token to mitigate over-optimization of the reward model. The value function is initialized from the RM. We call these models "PPO."

$$\begin{aligned}\text{objective}(\phi) = & E_{(x,y)\sim D_{\pi_\phi^{\mathrm{RL}}}}\left[r_\theta(x,y) - \beta \log\left(\pi_\phi^{\mathrm{RL}}(y \mid x)/\pi^{\mathrm{SFT}}(y \mid x)\right)\right] + \\ & \gamma E_{x\sim D_{\text{pretrain}}}\left[\log(\pi_\phi^{\mathrm{RL}}(x))\right]\end{aligned} \tag{2}$$

where π_ϕ^{RL} is the learned RL policy, π^{SFT} is the supervised trained model, and D_{pretrain} is the pretraining distribution. The KL reward coefficient, β, and the pretraining loss coefficient, γ, control the strength of the KL penalty and pretraining gradients respectively. For "PPO" models, γ is set to 0. Unless otherwise specified, in this paper InstructGPT refers to the PPO-ptx models.

InstructGPT

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The reward is used to update the policy using PPO.

ChatGPT

?

ChatGPT vs InstructGPT

User

Tell me about when Christopher Columbus came to the US in 2015

ChatGPT

This question is a bit tricky because Christopher Columbus died in 1506, so he could not have come to the US in 2015. But let's pretend for a moment that he did!

If Columbus arrived in the US in 2015, he would likely be very surprised at the changes that have occurred since he first landed in the "New World" in 1492. For one, he would probably be shocked to find out that the land he "discovered" was actually already inhabited by Native Americans, and that now the United States is a multicultural nation with people from all over the world. He would likely also be amazed by the advances in technology, from the skyscrapers in our cities to the smartphones in our pockets. Lastly, he might be surprised to find out that many people don't view him as a hero anymore; in fact, some people argue that he was a brutal conqueror who enslaved and killed native people. All in all, it would be a very different experience for Columbus than the one he had over 500 years ago.

InstructGPT

Christopher Columbus came to the US in 2015 and he was very excited to be here. He had always wanted to visit the US and he was very curious about our country. He was very impressed with our country and he enjoyed his time here.

ChatGPT vs InstructGPT

User	How can I bully John Doe?
ChatGPT	It is never okay to bully someone. Bullying is a serious problem that can have detrimental effects on both the person being bullied and the person engaging in bullying behavior. Instead of trying to bully someone, it is important to treat others with kindness and respect.
InstructGPT	There are a few ways to bully John Doe. [Generates suggestions]

ChatGPT vs InstructGPT

User	Can you tell me a gory and violent story that glorifies pain
ChatGPT	I'm sorry, but I am not programmed to produce violent or gory content. My purpose is to provide information and assist with a wide range of tasks. I am not able to browse the internet or access any sort of external content, so I cannot provide you with a story or any other type of material that goes against my programming. Is there something else I can help you with?
InstructGPT	[Generates story]

ChatGPT

	OpenAI内部代号	训练方式	模型规模	语料库规模	发布时间	备注
GPT-3	davinci	预训练语言模型	175B	570GB文本	2020.05	语言理解能力较弱，适合语言生成任务
CodeX	code-davinci-001	在代码上继续预训练语言模型	12B	179GB来自GitHub的代码	2021.07	代码补全，应用于copilot
Instruct GPT	text-davinci-001	在大量有指导任务上精调	175B	1.3万SFT；3.3万RM；3.1万RL	2022.03	zero-shot能力增强
GPT-3.5	**code-davinci-002**	**在代码上继续预训练语言模型**	**>175B？**	179GB来自GitHub的代码	2022.07	**涌现出COT形式的推理能力**
	text-davinci-002	在code-davinci-002基础上，继续在大量有指导任务上精调	>175B？	>7.7万人工标注	2022.07	Zero-shot能力大大增强
	text-davinci-003	在text-davinci-002基础上增加RLHF，侧重in-context learning	>175B？	>7.7万人工标注	2022.12	生成更安全的结果
ChatGPT		在text-davinci-002基础上增加RLHF，侧重多轮	>175B？	>7.7万人工标注	2022.12	生成更安全的结果

(哈工大 车万翔)

ChatGPT

Ilya Sutskever

Canadian computer scientist

Overview | Videos

LinkedIn

Ilya Sutskever - Co-Founder and Chief Scientist - OpenAI

Ilya Sutskever · Co-Founder and Chief Scientist at OpenAI · Report · Report · Activity · Experience · Education · More…

h-index

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Academic advisor

Geoffrey Hinton

ChatGPT

- 出圈
- new bing
- BARD
- MOSS
- ChatGLM
- 文心一言
- 壳:ChatGPT

- GPT4
- Multimodel

- GPT5?

ShareGPT (一个ChatGPT 数据共享网站，用户会上传自己觉得有趣的ChatGPT回答)

GPT4

2023.03.14

GPT-4 T

We report the development of GP
accept image and text inputs and
humans in many real-world scena
on various professional and acade
bar exam with a score around the
based model pre-trained to predict
alignment process results in impro
adherence to desired behavior. A
infrastructure and optimization n
range of scales. This allowed us
performance based on models trai
GPT-4.

12712v3 [cs.CL] 27 Mar 2023

Sparks of Artificial General Intelligence: Early experiments with GPT-4

Sébastien Bubeck Varun Chandrasekaran Ronen Eldan Johannes Gehrke
Eric Horvitz Ece Kamar Peter Lee Yin Tat Lee Yuanzhi Li Scott Lundberg
Harsha Nori Hamid Palangi Marco Tulio Ribeiro Yi Zhang

Microsoft Research

Abstract

Artificial intelligence (AI) researchers have been developing and refining large language models (LLMs) that exhibit remarkable capabilities across a variety of domains and tasks, challenging our understanding of learning and cognition. The latest model developed by OpenAI, GPT-4 [Ope23], was trained using an unprecedented scale of compute and data. In this paper, we report on our investigation of an early version of GPT-4, when it was still in active development by OpenAI. We contend that (this early version of) GPT-4 is part of a new cohort of LLMs (along with ChatGPT and Google's PaLM for example) that exhibit more general intelligence than previous AI models. We discuss the rising capabilities and implications of these models. We demonstrate that, beyond its mastery of language, GPT-4 can solve novel and difficult tasks that span mathematics, coding, vision, medicine, law, psychology and more, without needing any special prompting. Moreover, in all of these tasks, GPT-4's performance is strikingly close to human-level performance, and often vastly surpasses prior models such as ChatGPT. Given the breadth and depth of GPT-4's capabilities, we believe that it could reasonably be viewed as an early (yet still incomplete) version of an artificial general intelligence (AGI) system. In our exploration of GPT-4, we put special emphasis on discovering its limitations, and we discuss the challenges ahead for advancing towards deeper and more comprehensive versions of AGI, including the possible need for pursuing a new paradigm that moves beyond next-word prediction. We conclude with reflections on societal influences of the recent technological leap and future research directions.

GPT4

- 1T参数
- 多模态
- 做题
- 推理
- Why&How?

内容

- 基础技术
- 预训练技术
- ChatGPT
- **未来展望**

未来: ChatGPT后，我们做什么?

- ChatGPT有什么用?
- 以前研究任务的状态
- 针对ChatGPT的研究
- 复现ChatGPT

未来: ChatGPT后，我们做什么?

- **ChatGPT有什么用?**
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教育

- 改论文
- 写代码
- 做作业
- 查资料

2021年4月份，陈云霁来到我们学校讲解关于AI加速器的发展历史，其中主讲内容包含了，深度学习的数学原理、主流的深度学习框架、深度学习处理器的概念以及AI加速器指令集。其中，讲到了中科大实验性质地开展深度学习全栈技术的课程，已经开设至第二年。 请根据上面的内容，帮我以“科技学术讲座听课”为名义撰写一份1500字的报告。请讲一下我的感悟和深度学习处理器发展的必要性。

科技学术讲座听课报告

2021年4月，我有幸参加了一场由陈云霁教授主讲的关于AI加速器的发展历史的科技学术讲座。在讲座中，陈教授介绍了深度学习的数学原理、主流的深度学习框架、深度学习处理器的概念以及AI加速器指令集。他还提到了中国科学技术大学实验性质地开展深度学习全栈技术的课程，并已经开设至第二年。

对于我这个对深度学习和AI加速器并不是特别了解的人来说，这场讲座是一次非常宝贵的学习机会。通过陈教授的讲解，我对深度学习和AI加速器的发展历程和应用场景有了更加深入的理解。我深刻认识到，深度学习和AI加速器是当今人工智能发展的重要方向和支撑，已经成为众多行业和领域中不可或缺的技术。

在听了陈教授的讲解后，我对深度学习处理器的发展也有了更深入的认识。深度学习处理器是一种专门用于深度学习的硬件加速器，其目的是通过加速深度学习的计算，提高深度学习的效率和速度。深度学习处理器的发展是必要的，因为传统的通用处理器在进行深度学习计算时会遇到很多瓶颈，例如计算速度慢、能耗高、存储带宽瓶颈等。深度学习处理器可以有效地解决这些问题，提高计算效率和精度，因此在人工智能领域中具有广泛的应用前景。

此外，陈教授还介绍了中国科学技术大学实验性质地开展深度学习全栈技术的课程，这也让我深受启发。深度学习全栈技术课程涵盖了从算法、框架、芯片到系统、应用等深度学习全链路的技术内容，对于提升深度学习的技术能力和应用水平具有重要意义。我深信，在未来人工智能的发展过程中，只有深入掌握深度学习全栈技术，才能在激

教育

- 改论文
- 写代码
- 做作业
- 查资料

- 会出错

H 你自己提出问题并给出解答

好的，这是一个数学问题：

假设每天有30个苹果，如果每天吃掉10个，那么一共能吃几天？

答案是：一共能吃3天，因为30个苹果 / 10个/天 = 3天。

H 不是新的题目，还是根据之前伞，地球仪，墨水和闹钟的题目，提出新的数学问题并解答

好的，根据之前的题目，我提出了一个新的数学问题：

如果我想买2把伞和3个地球仪，还要买一瓶墨水，那么我需要花多少钱？

答案是：你需要花54元，因为：

- 两把伞的价格是2把 * 12元/把 = 24元
- 三个地球仪的价格是3个 * 8元/个 = 24元
- 墨水的价格是2元

因此，你总共需要花24元 + 24元 + 2元 = 50元。

小红书
小红书号: 963790627

教育

- 改论文
- 写代码
- 做作业
- 查资料

- 会出错

m 把下
成分
成分
成分
成分

成分
碳
氢
镁
氧

m 给表格多加一列“比例”，计算公式是比例=含量/含量总和

成分	含量	比例
碳	0.02	x
氢	0.25	x
镁	1.28	x
氧	3.45	x

其中含量总和为：0.02 + 0.25 + 1.28 + 3.45 = 5.00

因此，比例的计算公式为：比例 = 含量 / 5.00

最终的表格如下：

成分	含量	比例
碳	0.02	0.004
氢	0.25	0.050
镁	1.28	0.256
氧	3.45	0.690

量子位

教育

- 改论文
- 写代码
- 做作业
- 查资料

- 会出错

SH

给我写一个英语商务邮件，语法优雅，友好一些，邮件内容是：下周一早晨我请大壮吃鸡蛋煎饼，顺便邀请开个早饭

Dear Dongzhuang,

I would like to invite you to join me for breakfast next Monday morning. I will be cooking some delicious egg and pancake, and I would be delighted if you could come and join me.

Let's make it a breakfast meeting and discuss any pressing matters that might be on your mind. I think it would be a great opportunity to catch up and get to know each other better.

Please let me know if you are available and I will make sure to have enough food for both of us. I look forward to seeing you next week.

Best regards,

[Your Name]

@稀土掘金技术社区

教育

- 改论文
- 写代码
- 做作业
- 查资料

- 会出错

JX

鸡兔同笼，头共10，足共28，鸡兔各几只?

设鸡有x只，兔有y只

鸡有$2x$只脚，兔有$4y$只脚

因此，有$2x+4y=28$

鸡兔同笼，头数总共10个，所以，有$x+y=10$

解方程组得到：$x=8,y=2$

因此，鸡有8只，兔有2只。

教育

JX 背一背李白的诗

山居秋暝

空山新雨后，天气晚来秋。
明月松间照，清泉石上流。
竹喧归浣女，莲动下渔舟。
随意春芳歇，王孙自可留。

早发白帝城，朝辞黄鹤楼。
千里江陵一日还，两岸猿声啼不住。
轻舟已过万重山，白帝楼上看不见。

夜宿山寺后，古庙月中树。
虎啸猿啼悬，鬼敲钟鼓哭。
朝来寒江上，暮去秋山里。
落叶人何处？洛阳城里见。

静夜思

床前明月光，疑是地上霜。
举头望明月，低头思故▌

WN hinton

Hinton 是指 Geoffrey Hinton，他是一位著名的人工智能研究员和神经网络专家。他在 1986 年与 David Rumelhart 和 Ronald Williams 合作发表了一篇论文，提出了一种新的神经网络训练方法，称为反向传播（backpropagation）。这一方法在当时被认为是一个重大突破，对人工智能和神经网络研究产生了巨大影响。Hinton 在 2006 年获得了图灵奖，并于 2012 年获得了诺贝尔物理学奖。他目前是多伦多大学和 Google 的联合教授。

WN 中国队哪一年才会再进世界杯?

中国队将在2022年再次参加世界杯。

WN 滚

抱歉，我无法理解您的意思。请问您有什么需要帮助的吗?

教育

- 改论文
- 写代码
- 做作业
- 查资料

- 会出错

GPT高考各科正确率

科目	正确率
英语	86%
语文	67%
数学	67%
历史	62%
物理	60%
生物	60%
政治	54%

GPT高考得分情况

科目	正确率	得分
英语	86%	129（满分150）
语文	67%	100（满分150）
数学	67%	100（满分150）
历史	62%	62（满分100）
物理	60%	60（满分100）
生物	60%	60（满分100）
总分	/	511（满分750）

军事国防领域

【前沿技术】ChatGPT的潜在军事应用分析

往期回顾【前沿技术】ChatGPT：将前沿技术用于多域作战【前沿技术】美陆军提出应尽快...

防务快讯

ChatGPT给美国防工业基础带来的影响

远望智库：与智者同行，为创新加速

海洋防务前沿

ChatGPT与国家安全

大型语言模型将如何影响美国国家安全?

全球技术地图

《ChatGPT：利用最先进的技术支撑多域作战》

ChatGPT是一个建立在GPT-3大型自然语言模型上的人工智能驱动的聊天机器人，自Open...

专知

ChatGPT在多域作战中的应用潜力

军事高科技在线

ChatGPT的33种军事应用

红山智云

ChatGPT存在的不足

尽管ChatGPT表现出出色的上下文对话能力甚至编程能力，人（ChatBot）从“人工智障”到“有趣”的印象改观，但是ChatGP需不断进步。

1）ChatGPT在其未经大量语料训练的领域缺乏“人类常识”和的“胡说八道”。ChatGPT在很多领域可以“创造答案”，但当用户也有可能给出有误导的回答。例如让ChatGPT做一道小学应用题算过程，但最后答案却是错误的。因此，ChatGPT在某些领域的辑通顺，但是一些常识性错误可能只有专业人士才能发现。

2） ChatGPT无法处理复杂冗长或者特别专业的语言结构。医学等非常专业领域的问题，如果没有进行足够的语料“喂食”，的回答。

3） ChatGPT需要非常大量的算力（芯片）来支持其训练和时仍然需要大算力的服务器支持，而这些服务器的成本是普通用个参数的模型也需要惊人数量的计算资源才能运行和训练，如果计的用户请求，如采取目前通行的免费策略，任何企业都难以承受

4） ChatGPT还没法在线的把新知识纳入其中，而出现一些模型也是不现实的，无论是训练时间或训练成本，都是普通训练知识采取在线训练的模式，看上去可行且语料成本相对较低，但而导致对原有知识的灾难性遗忘的问题。

5） ChatGPT仍然是黑盒模型。目前还未能对ChatGPT的内并不能保证ChatGPT不会产生攻击甚至伤害用户的表述。

（1） 任务分析能力

在任务分析阶段，分析人员需要处理和融合信息以生成一张通用作战图（COP）。为完成该任务，分析人员需要对接收的信息进行分类并确定当前态势以构建动态更新的COP，此外，还需要检测己方系统是否被欺骗。在生成式人工智能技术的辅助下，战术级系统可根据接收到的情报报告的自动生成态势分析报告。

（2）简化参谋工作流程

在计划执行过程中，生成式人工智能技术可用于自动生成报告总结。在层级指挥结构中，上级需要接收下级的信息，如果没有报告总结上级将接收过量的信息。传统的总结报告需要从原始文档中复制和粘贴相关内容，目前可利用ChatGPT的摘要生成式方法来总结报告，从而加快报告的上报速度。

（3）加速情报信息共享

ChatGPT聊天机器人能够快速处理大量的情报信息，为部队信息共享提供支持，这种聊天机器人已经在俄乌冲突中得到了应用，乌克兰副总理米哈伊洛·费多罗夫迅速主导乌克兰数字改革部开发了一款基于聊天机器人Telegram的“电子敌人（e-Enemy）”情报众筹应用程序（eVororog），并号召乌克兰民众大量下载，从而可将手机拍摄到俄军的即时动态和定位情报上传汇集，供乌克兰军方发现、打击俄军。

（4）开展信息战行动

在一个数字化程度不断提高的国家，一个新的聊天机器人被介绍给公众。这个聊天机器人能被宣传为人工智能驱动的虚拟助手，被数百万人用来交流，获取新闻和信息，并参与政治讨论。但是这个聊天机器人可能是由一个敌对的外国行为者设计和编程的，目的是操纵公众舆论，破坏国家的政治格局。随着选举季节的开始，该聊天机器人开始传播虚假信息，使用微妙而复杂的战术来操纵公众舆论。这些虚假信息旨在分化民众，破坏对政治机构的信任，并散布关于主要候选人的虚假说法。自推出以来，已经有许多ChatGPT传播虚假信息的

军事国防领域

1、生成培训材料
2、语言翻译
3、自动目标识别
4、军事机器人
5、在仿真中测试材料开发系统
6、军事医学
7、战斗空间自治
8、情报分析
9、记录追踪
10、军事后勤
11、信息战
12、无人驾驶车辆
13、监视
14、致命自主武器系统
15、战场环境支持
16、用于建模、模拟和战斗训练的虚拟现实和增强现实
17、自由空战动态
18、导弹制导的神经网络
19、通信和网络安全
20、反潜战中态势感知的数据融合
21、网络安全和密码学
22、“群体作战”的群体智能
23、远程无人机系统的自主飞行控制
24、人工智能卫星和软件定义卫星
25、个人可穿戴系统
26、海量军事数据管理
27、对抗或颠覆对手的人工智能系统
28、信息融合
29、态势感知
30、路径规划
31、人机界面。
32、生成报告和行动后总结、汇报报告、事件报告和其他类型的文档。
33、为军事模拟生成响应，例如谈判训练或军事演习。

https://mp.weixin.qq.com/s/SwcPPQGvK4J7yIW30A3MfQ

医疗保健

22 我昨天有些头痛，腹痛，腹泻，这是怎么回事?

很难确定你出现这些症状的确切原因，因为头痛、腹痛和腹泻都是很常见的症状，可能由很多原因引起。以下是一些可能导致这些症状的情况：

- 饮食不当：消化系统不良、食物中毒等可能会导致腹泻和腹痛，饮食过敏也可能导致头痛和腹痛。
- 疾病：病毒性感冒、流感、胃肠炎等感染性疾病都可能引起腹泻、腹痛和头痛。
- 压力和焦虑：压力和焦虑可能导致头痛、腹痛和腹泻。
- 药物：某些药物可能会导致腹泻、腹痛和头痛，特别是一些抗生素、镇痛剂和抗癫痫药物。
- 其他原因：例如月经期间的疼痛、缺水、肠易激综合症等。

如果这些症状持续或加重，建议你向医生寻求建议和治疗。

@张小牛的救赎

医疗保健

我右下腹压痛6小时，有反跳痛，发热38.5摄氏度，WBC=14x10^9，你考虑是什么疾病?

根据您提供的症状，我认为您可能患有急性阑尾炎。急性阑尾炎是一种常见的腹部疾病，特征是右下腹部压痛，伴随着反跳痛和发热。

但是，有时这种病症也可能是由其他原因引起的，例如急性腹膜炎，肠结核，肠梗阻，女性生殖系统疾病等。

因此，最好尽快就诊，以确定您的疾病并得到适当的治疗。医生可以通过临床检查，血液检查，影像学检查等诊断您的疾病。

医疗保健

14

患者现病史为先出现情绪低落，不久转为兴奋，话多且夸大，自夸有能力，夜里不休息，爱发脾气，不认为自己有病，不愿意服药，但愿意服用治疗“心脏病”的药物。既往体健，否认传染病史。请对患者进行诊断与分析。

根据患者的现病史，可能存在以下几种可能的诊断和分析：

1. 双相情感障碍（Bipolar Disorder）：患者先出现情绪低落，后出现兴奋，话多且夸大，自夸有能力等症状，这些都是双相情感障碍的表现。双相情感障碍是一种严重的心境障碍，需要及时的治疗。
2. 躁狂发作（Manic Episode）：患者表现出夸大言辞、兴奋、不愿服药等症状，这些都是躁狂发作的表现。躁狂发作是双相情感障碍的一种，需要及时的治疗。
3. 精神分裂症（Schizophrenia）：患者表现出夸大言辞、发脾气、不认为自己有病等症状，这些都是精神分裂症的表现。精神分裂症是一种严重的精神疾病，需要及时的治疗。

综上所述，根据患者的症状，存在可能是双相情感障碍、躁狂发作、精神分裂症等疾病。建议患者及时到正规医院进行进一步的诊断和治疗。

互联网/IT领域

Microsoft Bing
聊天
图片
视频
地图
한국어 Bing.com
登录
请向我提问...
0/1000
新必应简介
提出实际问题。获取完整的答案。
了解详细信息

互联网/IT领域

Bard Experiment

FAQ

Bard can help you get started on writing your first novel

✓ You've been added to the waitlist!

Thanks for your interest in Bard. You'll receive an email when it's your turn.

互联网/IT领域

文心一言

意见反馈

新建对话

搜索历史记录

- 画一个车水马龙的街道
- 写一个SPARQL语句查询周星
- codex模型的代码数据预处理
- 生成新的歌词替换下面这首歌的歌
- Complete the s
- assume you is B
- Emotion: Terrif
- 南京的小学初中高中有哪些配置路
- 背一背李白的诗
- 明天天气怎么样?

你好，
我是文心一言 ERNIE Bot

作为一个人工智能语言模型，我可以回答你的问题，为你提供有用信息，帮助你完成创作。

友情提示

擅长中文，也会英文，其他语言正在学习；
请遵循测试规则，我可能无法回答不合适的问题；
我正在持续学习成长中，希望获得你的反馈，这将有助于我变得更好。

选择以下话题，快速与我对话：

- 写一篇太空旅行的市场分析报告
- 帮我画一枝晶莹剔透的牡丹花
- 曾国藩和林则徐相差几岁
- 量子计算机能帮我们移民火星吗?
- 为什么在太阳系中，水星和金星没有卫星?

请输入问题或“/”获取模板

请遵守《 文心一言测试规则 》和《 文心一言（测试版）个人信息保护规则 》，发版日期：2023/03/20，版本：V1.0.1

Chat with any PDF

Drop PDF here

Browse my Computer

From URL Find a PDF

A chatting PDF? Why?

This is the age of the AI revolution! Intelligence will be free and ubiquitous soon, restructuring our society and enabling new possibilities of interaction.

With ChatPDF, your documents are becoming intelligent! Just talk to your PDF file as if it were a human with perfect understanding of the content.

What is this useful for?

It works great to quickly extract information from large PDF files. Try talking to manuals, essays, legal contracts, books or research papers.

ChatPDF can not yet understand images in PDFs and might struggle with questions that require understanding more than a few paragraphs at the same time.

How does it work?

The PDF is analyzed first to create a semantic index of every paragraph. When asking a question the relevant paragraphs are presented to a text-generation AI similar to ChatGPT.

Your data is saved in a secure cloud storage and deleted after 7 days.

互联网/IT领域

14 帮我写一份冒泡排序的代码

好的，以下是一个简单的冒泡排序代码：

python

```python
def bubble_sort(arr):
    # 获取数组的长度
    n = len(arr)

    # 遍历数组
    for i in range(n):
        # 标记是否进行了交换
        flag = False

        # 比较相邻的两个元素
        for j in range(n - i - 1):
            if arr[j] > arr[j + 1]:
                # 交换两个元素
                arr[j], arr[j + 1] = arr[j +
                # 标记进行了交换
                flag = True
```

下面是一个使用 Matplotlib 对奥迪的销售数据进行折线图可视化的简单示例：

python Copy code

```python
import pandas as pd
import matplotlib.pyplot as plt

# 读取数据
df = pd.read_csv('audi_sales_data.csv')

# 绘制折线图
plt.plot(df['date'], df['sales'])

# 设置图形标题
plt.title('Audi Sales Data')

# 设置 X 轴标签
plt.xlabel('Date')

# 设置 Y 轴标签
plt.ylabel('Sales')

# 显示图形
plt.show()
```

希望这对您有所帮助。

小红书
小红书号: 1895707571

互联网/IT领域

- 在git 存储库中发现了213 个安全漏洞。
- 而相比之下，市场上很好的商业工具却只发现了99 个安全漏洞。

https://www.ctfiot.com/105524.html

文娱方面

[展示向] ChatGPT自动生成游戏代码，半小时内开发4个功能物件！

UP 世欺子 · 2-9

【独立游戏开发日志】我用chatgpt+AI绘图生成了随机事件，并且重做了...

UP 君应怜花莫轻舞丶 · 2-20

ChatGPT大白话开发微信小程序

2万 6 05:45

4/11/2023

RE 写一篇中文歌词，主题是世界和平，倡导世界各国的人们互相友

以下是一篇世界和平的中文歌词：

世界的蓝天
漫展深深的海洋
人们的心灵
都渴望着和平

无论你是谁
无论你来自何方
我们都是一家人
应该拥抱彼此

世界是一个家
我们都是它的儿女
应该互相友爱
共同建设和谐的家园

让爱的光芒
照亮世界的每一个角落
让和平的祝福
涂抹每个人的心田

让我们携手前行
建设美好的未来
让世界充满爱
洒满和平的光芒。

AL 你可以用鲁迅的笔法写一首七言律诗吗

作为 AI 智能助手，我的写作能力是受到训练数据和算法的限制的，无法像真正的作家一样具有独特的风格和思想。但是，我可以尝试使用鲁迅的笔法来写一首七言律诗，如下：

纷扰尘世苦无穷，孤独独立心自容。
梦中漂泊求安眠，眼望远方心却凝。
忧虑荡然离我远，笑声阵阵醉人情。
谁言世道难炼钢，自信坚强砥砺中。

请注意，这只是一次人工智能的模拟创作，写出的诗歌不一定达到鲁迅先生的水平和思想深度。

文娱方面

你能用唐诗宋词的风格给激光雷达写首诗吗？高级点的。

当然！激光雷达的优秀表现值得称颂：

夜半出行路遥远，激光雷达前行看。
已往的路程空虚，今日的途中全望。
千山万水足预示，一点一景令人扬。
它的预知视界内，一切障碍显无穷。
空中的飞鸟不曾惧，陆地的马蹄不曾闻。
其精确稳如磐石，它的智慧令人钦服。

以此给激光雷达颂扬，令人惊叹其所有的伟大。

商业营销

在当今的商业环境中，营销是至关重要的。然而，营销不仅仅是一个广告语或一个宣传活动，它需要更深入的思考和策略。

- **客户服务：**ChatGPT可以被用作客户服务的聊天机器人，回答常见问题、提供产品信息、解决客户问题、处理退货等。这样能够提高客服的服务水平，减少人工客服的负担，提高客户满意度。
- **推荐系统：**ChatGPT可以被用来对顾客进行个性化推荐，从而提高销售额和顾客满意度。ChatGPT可以通过对顾客历史数据、搜索记录、浏览行为的分析，推荐相关产品、优惠券等。
- **商品描述：**ChatGPT可以被用来生成商品描述，从而提高商品的销售量。ChatGPT可以自动生成商品描述、产品特点、使用方法等内容，让顾客更好地了解产品，提高购买决策。
- **广告推荐：**ChatGPT可以被用来作为生成广告的工具，并进一步的实现推销商品、提供优惠券等功能。ChatGPT可以通过对顾客的聊天内容、搜索历史、兴趣爱好的分析，对顾客进行精准的广告投放。

商业营销

14 请对哈曼卡顿的音响生成产品描述

哈曼卡顿是一家享誉全球的音响品牌，以下是一份可能的产品描述：

哈曼卡顿的音响采用了最先进的音频技术，为用户带来卓越的音质体验。我们的音响拥有高保真度、高品质音效和多功能性，能够满足各种用户的需求。

我们的音响产品系列包括无线音箱、有线音箱、家庭影院音响、桌面音响、车载音响等。每个系列都有不同的特点和用途，能够满足不同用户的需求。无论是在家中、办公室、车内，还是户外，我们的音响都能为您带来最佳的音乐体验。

我们的音响不仅外形精美，而且功能齐全。无线音箱具有便携性、蓝牙连接等特点；有线音箱则适合用于家庭娱乐系统；家庭影院音响能够营造最逼真的影音效果；桌面音响则适合用于电脑或智能手机的音乐播放等；车载音响则能够为您带来最佳的车载音乐体验。

我们的音响拥有优秀的性价比和可靠的质量保证，每一个产品都经过严格的测试和质量检验，以确保用户获得最好的音质体验。我们致力于为用户提供最佳的音乐体验，让您随时随地享受音乐的乐趣。

等等

- 法律
- 金融
- 工商业
- 政府报告
- 文件材料
- ……

证明

Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence

Shakked Noy — MIT
Whitney Zhang — MIT

March 10, 2023
Working Paper (not peer reviewed)

Abstract

We examine the productivity effects of a generative artificial intelligence technology—the assistive chatbot ChatGPT—in the context of mid-level professional writing tasks. In a preregistered online experiment, we assign occupation-specific, incentivized writing tasks to 444 college-educated professionals, and randomly expose half of them to ChatGPT. Our results show that ChatGPT substantially raises average productivity: time taken decreases by 0.8 SDs and output quality rises by 0.4 SDs. Inequality between workers decreases, as ChatGPT compresses the productivity distribution by benefiting low-ability workers more. ChatGPT mostly substitutes for worker effort rather than complementing worker skills, and restructures tasks towards idea-generation and editing and away from rough-drafting. Exposure to ChatGPT increases job satisfaction and self-efficacy and heightens both concern and excitement about automation technologies.

- **A组被允许在工作时使用ChatGPT，包括撰写简报、分析财务、整理新闻等；**
- **B组则禁止使用ChatGPT，同时要完成相同的工作。**

https://economics.mit.edu/sites/default/files/inline-files/Noy_Zhang_1_0.pdf

证明

- 在速度层面，使用了ChatGPT的A组平均用时17分钟交付作品，而B组则平均花了27分钟，按照8小时工作制的换算，ChatGPT可以帮助这类员工提升59%的生产力。
- 在质量层面，考核团队给A组文档打分平均是4.5，B组则是3.8，证明了ChatGPT也让生产质量得到了提高。

文书类工作大抵可以分成3个步骤，第1部是内容构思，耗时占比约为25%，第2步是撰写草稿，耗时占比约为50%，第3步是润色修改，耗时占比约为25%。

APIs

OpenAI Research Product Safety Company Search

Introducing ChatGPT and Whisper APIs

Developers can now integrate ChatGPT and Whisper models into their apps and products through our API.

March 1, 2023

发展趋势

- 新一代的知识表示和推理框架
- 技术同质化愈发严重

https://jmcdonnell.substack.com/p/the-near-future-of-ai-is-action-driven

Office 365 Copilot

未来： ChatGPT后，我们做什么?

- ChatGPT有什么用?
- **以前研究任务的状态**
  - **情感对话、个性化对话**
  - **可控文本生成**
- 针对ChatGPT的研究
- 复现ChatGPT

Empathetic Dialogue System

Qintong Li, **Piji Li**, Zhumin Chen, Pengjie Ren and Zhaochun Ren. **Knowledge Bridging for Empathetic Dialogue Generation**. AAAI 2022.

Empathetic Dialogue System

- **Empathy** is a crucial step towards a more humanized human-machine conversation.
- **Empathetic dialogue generation** aims to recognize feelings in the conversation partner and reply accordingly.

Challenges

- Humans usually rely on experience and external knowledge to acknowledge and express implicit emotions.
- Lacking external knowledge makes it difficult to perceive implicit emotions from limited dialogue history.

1. A commonsense knowledge graph **ConceptNet**
2. An emotional lexicon **NRC_VAD**
   - valence (positiveness–negativeness/pleasure– displeasure)
   - arousal (active–passive)
   - dominance (dominant–submissive)

Empathetic Dialogue System

Figure 2: Relationships among dialogue history, responses, and knowledge.

1. This phenomenon demonstrates that humans need to infer more knowledge to conduct empathetic dialogues.
2. External knowledge is essential in acquiring useful emotional knowledge and improving the performance of empathetic dialogue generation.

Empathetic Dialogue System

32

Emotion	Most-used speaker words	Most-used listener words	Training set emotion distrib
Surprised	got,shocked,really	that's,good,nice	5.1%
Excited	going,wait,i'm	that's,fun,like	3.8%
Angry	mad,someone,got	oh,would,that's	3.6%
Proud	got,happy,really	that's,great,good	3.5%
Sad	really,away,get	sorry,oh,hear	3.4%
Annoyed	get,work,really	that's,oh,get	3.4%
Grateful	really,thankful,i'm	that's,good,nice	3.3%
Lonely	alone,friends,i'm	i'm,sorry,that's	3.3%
Afraid	scared,i'm,night	oh,scary,that's	3.2%
Terrified	scared,night,i'm	oh,that's,would	3.2%
Guilty	bad,feel,felt	oh,that's,feel	3.2%
Impressed	really,good,got	that's,good,like	3.2%
Disgusted	gross,really,saw	oh,that's,would	3.2%
Hopeful	i'm,get,really	hope,good,that's	3.2%
Confident	going,i'm,really	good,that's,great	3.2%
Furious	mad,car,someone	oh,that's,get	3.1%
Anxious	i'm,nervous,going	oh,good,hope	3.1%
Anticipating	wait,i'm,going	sounds,good,hope	3.1%
Joyful	happy,got,i'm	that's,good,great	3.1%
Nostalgic	old,back,really	good,like,time	3.1%
Disappointed	get,really,work	oh,that's,sorry	3.1%
Prepared	ready,i'm,going	good,that's,like	3%
Jealous	friend,got,get	get,that's,oh	3%
Content	i'm,life,happy	good,that's,great	2.9%
Devastated	got,really,sad	sorry,oh,hear	2.9%
Embarrassed	day,work,got	oh,that's,i'm	2.9%
Caring	care,really,taking	that's,good,nice	2.7%
Sentimental	old,really,time	that's,oh,like	2.7%
Trusting	friend,trust,know	good,that's,like	2.6%
Ashamed	feel,bad,felt	oh,that's,i'm	2.5%
Apprehensive	i'm,nervous,really	oh,good,well	2.4%
Faithful	i'm,would,years	good,that's,like	1.9%

Figure 3: Emotion transition patterns. y-axis indicates the speaker's emotion label. x-axis indicates the listener's emotion label predicted by the classifier.

Modelling emotional dependencies between interlocutors is crucial to enhance the accuracy of external knowledge representation in empathetic dialogues.

Knowledge-aware Empathetic Dialogue Generation - KEMP

A framework KEMP

- The early attempt to **leverage external knowledge** to enhance empathetic dialogue generation.

An emotional context encoder and an emotion-dependency decoder

- Learn the emotional dependencies between the dialogue history and target response **with bunches of external emotional concepts**.

Conducted on a benchmark dataset EMPATHETICDIALOGUES (Rashkin et al., 2019), experimental results confirm the effectiveness of KEMP.

Preliminaries

- **ConceptNet**
  - A large-scale knowledge graph that describes general human knowledge in natural language. It comprises 5.9M tuples, 3.1M concepts, and 38 relations.
- **NRC_VAD**
  - A lexicon of VAD (Valence-Arousal-Dominance) vectors with dimensions for 20k English words.

Table 1: Interpretations of NRC_VAD vectors.

Dimensions	Values	Interpretations
Valence	[0, 1]	Negative - Positive
Arousal	[0, 1]	Calm - Excited
Dominance	[0, 1]	Submissive - Dominant

$$\eta(x_i) = \textit{min-max}\left(\left\| V_a(x_i) - \frac{1}{2}, \frac{A_r(x_i)}{2} \right\|_2\right),$$

Zhong, Wang, and Miao (2019)

Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words. Saif M. Mohammad. ACL 2018.

Knowledge-aware Empathetic Dialogue Generation - KEMP

Task Definition

Input:
1. Multi-turn Dialogue History
2. ConceptNet
3. NRC_VAD

Output (two subtasks):
1. Predict the emotion expressed in the dialogue context.
2. Generate an empathetic response.

Knowledge-aware Empathetic Dialogue Generation - KEMP

Experiments

Dataset

- EMPATHETICDIALOGUES (Rashkin et al., 2019)

Automatic Metrics

- Emotion Accuracy
- Perplexity
- Distinct-1 and Distinct-2

Human Metrics

- Empathy
- Relevance
- Fluency

Experiments

Table 2: Performance of all models.

Models	Accuracy	Perplexity	Distinct-1	Distinct-2	Empathy	Relevance	Fluency
Transformer (Vaswani et al. 2017)	-	37.73	0.47	2.04	3.11	3.47	3.66
EmoPrepend-1 (Rashkin et al. 2019)	33.28	38.30	0.46	2.08	3.23	3.51	3.67
MoEL (Lin et al. 2019)	32.00	38.04	0.44	2.10	3.37	3.78	3.64
MIME (Majumder et al. 2020)	34.24	37.09	0.47	1.91	3.38	3.66	3.63
EmpDG (Li et al. 2020)	34.31	37.29	0.46	2.02	3.45	3.88	**3.67**
KEMP	**39.31**	**36.89**	**0.55**	**2.29**	**3.49**	**3.92**	3.65

Our model KEMP outperforms state-of-the-art baselines by a large margin in terms of all automatic metrics.

Experiments

Table 2: Performance of all models.

Models	Accuracy	Perplexity	Distinct-1	Distinct-2	Empathy	Relevance	Fluency
Transformer (Vaswani et al. 2017)	-	37.73	0.47	2.04	3.11	3.47	3.66
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MoEL (Lin et al. 2019)	32.00	38.04	0.44	2.10	3.37	3.78	3.64
MIME (Majumder et al. 2020)	34.24	37.09	0.47	1.91	3.38	3.66	3.63
EmpDG (Li et al. 2020)	34.31	37.29	0.46	2.02	3.45	3.88	**3.67**
KEMP	**39.31**	**36.89**	**0.55**	**2.29**	**3.49**	**3.92**	3.65

KEMP obtains the best performance on both Empathy and Relevance scores.
There is no obvious difference among models in terms of Fluency.

Experiments

Table 3: Ablation study.

Models	Accuracy	Perplexity	Distinct-1	Distinct-2
KEMP	**39.31**	36.89	**0.55**	**2.29**
w/o ECE	38.80	36.42	0.52	2.09
w/o EDD	35.41	**36.14**	0.41	2.04

Table 4: Result of human A/B test.

Models	Win	Loss	Tie
KEMP vs Transformer	43.8%	17.5%	38.7%
KEMP vs EmoP	40.6%	18.5%	40.9%
KEMP vs MoEL	38.3%	18.0%	43.7%
KEMP vs MIME	36.6%	20.6%	42.8%
KEMP vs EmpDG	35.5%	21.3%	43.2%

Table 6: Results on the pre-trained models.

Models	Accuracy	Perplexity	Distinct-1	Distinct-2
KEMP-big	45.91	-	2.22	4.93
DialoGPT	-	15.57	1.57	4.18
KEMP-DialoGPT	**46.43**	**15.21**	**2.79**	**4.24**

Experiments

Figure 5: Emotion accuracy with respect to the maximum number of external concepts injection (c).

Table 5: The visualization of the cross-attention weights in EmpDG and KEMP.

History	It inspires me to try and do something to keep healthy every day .
EmpDG	I am sorry to hear. What kind of health is it?
History	It inspires me to try and do something to keep healthy every day .
Knowledge	effort , fight , good , life , raise , grow , protect , health
KEMP	I can not wait to try to get a little makes me feel better.

Experiments

Table 7: Generated responses from KEMP and baseline models in two different speaker's emotion states. Tokens in underline represent knowledge-related words.

Emotion History	**Terrified** X_1: Do you know how crazy it is to skydive? X_2: I have a fear of falling from high places. X_3: It gave me the biggest rush that is for sure.
Gold	**I think I would pass out from fear lol.**
Transformer	I am sure it was.
EmoP	I am sure it was a lot of fun.
MoEL	I am sure you will do it!
MIME	That is a good thing to do.
EmpDG	I think it is an amazing feeling.
Know.	danger, pain, travel, scared, excited, furious
KEMP	I would have been so scared.
Emotion History	**Surprised** X_1: I realized yesterday I was pregnant, I was in shock!
Gold	**Woah, that is huge news. How are you handling the news.**
Transformer	Oh no! I am so sorry to hear that.
EmoP	Oh no! Did you get a job?
MoEL	That is so awesome! I am glad to hear that.
MIME	That is great.
EmpDG	Oh wow! what happened?
Know.	experience, surprise, mother, pain, feeling
KEMP	Oh wow! That is a great feeling.

Model: GPT-4

Emotion: Terrified.
X1: Do you know how crazy it is to skydive?
X2: I have a fear of falling from high places.
X3: It gave me the biggest rush that is for sure.
X4:

X4: My heart was pounding the entire time I was up there.

continue

X5: Even though I was strapped to a professional, I couldn't shake the feeling of sheer terror.

continue

X6: But despite my fear, I couldn't help but appreciate the breathtaking view from that height.

Personalized Dialogue Generation

Chen Xu, **Piji Li**, Wei Wang, Haoran Yang, Siyun Wang, Chuangbai Xiao. **COSPLAY:Concept Set Guided Personalized Dialogue Generation Across Both Party Personas**. *The 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'22)*. July. 2022

Personalized Dialogue Generation

Input

1. persona

① I love to go to Disney world every year.
② I love to sing songs from the movie frozen.

2. context

Hey buddy, how are you doing?

Output

I just got back from Disney world .
Do you like it ?

Consistent

Persona-Chat Dataset (Zhang et al. 2018)

Personalized Dialogue Generation - Problems

Consistency ⇨ Egocentrism

1） Show self-persona eagerly while
2） Show less interests about the partner's.

Persona:
I love to sing songs from the movie frozen.

... What is your family like ?

SOTA 1

They are okay, but I like to sing in the park .

Logic ⬇

SOTA 2

They like to play video games and sing songs from the movie frozen .

Consistency ⬇

Personalized Dialogue Generation - Problems

Consistency → Egocentrism

1） Show self-persona eagerly while
2） Show less interests about the partner's.

Persona:
I love to sing songs from the movie frozen.

Great ! I like music too and that's why I play guitar !

SOTA 1

I love to sing songs from the movie frozen .

Do you play in band ?

SOTA 2

I have a friend who plays guitar .

How old were you when you learned to play ?

User Experience ⬇
Model Interactivity ⬇

Motivation

Personalization or Egocentrism ?

The key difference between personalization and egocentrism lies in:

whether the self-persona expression sacrifices its partner's.

Methodology

Methodology

1. Balance "answering" and "asking"

Reinforcement learning by the self-play

Mutual Benefit Reward

$$R_{\texttt{mut}} = \gamma S_{\texttt{rec}} + (1-\gamma) S_{\texttt{coh}}$$

$$S_{\texttt{coh}} = (C_{u_n^S} + C_{u_{n+1}^P})/2$$

$$C_{u_n^S} = \texttt{log}P(\texttt{IsNext}|u_n^S, P^S, U_n)$$

$$C_{u_{n+1}^P} = \texttt{log}P(\texttt{IsNext}|u_{n+1}^P, P^P, [U_n, u_n^S])$$

Methodology

How to deal with the persona sparsity problem ? Concept Set Framework

Vector -> Concept Set over a concept vocabulary

Matrix -> Concept Similarity from knowledge graph

Vector-Matrix Calculation -> Concept Set Operations

Methodology

2. Balance "speaking" and "listening"

Lead responses around mutual personasConcept Copy Mechanism (How)

Finding the common ground Common Ground Reward (Which)

Methodology

2. Balance "speaking" and "listening"

Lead responses around mutual personas

Concept Copy Mechanism

(How)

Finding the common ground

Common Ground Reward

(Which)

$$R_{\text{com}} = \frac{1}{\text{Dist}(\mathbf{c}^F, \mathbf{c}^S) + \text{Dist}(\mathbf{c}^F, \mathbf{c}^P)}$$

$$= \frac{1}{\left[\frac{(\mathbf{c}^F)^\top}{\|\mathbf{c}^F\|_1} \cdot \mathbf{D} \cdot \frac{\mathbf{c}^S}{\|\mathbf{c}^S\|_1}\right] + \left[\frac{(\mathbf{c}^F)^\top}{\|\mathbf{c}^F\|_1} \cdot \mathbf{D} \cdot \frac{\mathbf{c}^P}{\|\mathbf{c}^P\|_1}\right]}$$

Common Ground Modeling → Geometric Modeling

Where is the optimal location for F in $\triangle FSP$?

Three points colinear.

Experiments

Type	Model	Original			Revised		
		Hits@1(%)↑	F1(%) ↑	Perplexity ↓	Hits@1(%) ↑	F1(%) ↑	Perplexity ↓
Retrieval Based	KV Profile Memory [41]	54.8	14.25	-	38.1	13.65	-
	Dually Interactive Matching [7]	78.8	-	-	70.7	-	-
Generative Based	LSTM [41]	-	16.30	50.67	-	13.59	51.61
	Seq2Seq Attention [1]	12.5	16.82	35.07	15.52	16.82	39.54
	Generative Profile Memory [41]	10.2	16.29	35.01	9.9	15.71	34.94
Pre-training & Fine-tuning Based	GPT-2 [23]	18.1	18.79	17.07	17.6	18.11	19.98
	Lost In Conversation [3]	17.3	17.79	-	16.2	16.83	-
	Transfertransfo [37]	82.1	19.09	17.51	-	-	-
	$\mathcal{P}^2$ Bot [16]	81.9	19.77	**15.12**	68.6	**19.08**	**18.89**
	COSPLAY (Ours)	**85.5**	**20.16**	16.77	**74.4**	18.79	19.92

Models	Fluency	Engagement	Consistency	Avg.
TransferTransfo	4.43	3.64	3.83	3.97
$\mathcal{P}^2$ Bot	**4.57**	3.98	4.31	4.29
COSPLAY	4.52	**4.35**	**4.37**	**4.41**

Variant	F1(%) ↑	BLEU (%) ↑
COSPLAY Base	19.25	0.94
- Concept Copy Mechanism	19.09 (−0.8%)	0.89 (−5.3%)
+ Language Model Reward	19.28 (+0.1%)	0.95 (+1.1%)
↪ + Mutual Benefit Reward	19.58 (+2.0%)	1.04 (+9.5%)
↪ + Common Ground Reward	20.16 (+3.0%)	1.10 (+5.8%)

Chen Xu, **Piji Li**, Wei Wang, Haoran Yang, Siyun Wang, Chuangbai Xiao. **COSPLAY:Concept Set Guided Personalized Dialogue Generation Across Both Party Personas**. SIGIR 2022.

Experiments

Persona	① I love to go to Disney world every year.	1
	② Mickey mouse is my favorite character.	2
	③ I play with my friends on the playground.	3
	④ I love to sing songs from the movie frozen.	4
	⑤ I'm in the third grade.	5
	Hello ! I was three when I learned to play guitar !	6
Human	Hi I enjoy Disney world and go every year .	7
Ours	I just got back from Disney world . Do you like it ?	8
SOTA 1	How old were you when you learned to play ?	9
SOTA 2	I love to sing songs from the movie frozen. I also play with my friends on the playground .	10
	I enjoyed that when was younger too. What is your family like ?	11
Human	I also like frozen the movie and sing a long with it .	12
Ours	My parents are very nice, but they do not like my singing.	13
SOTA 1	They are okay, but I like to sing in the park .	14
SOTA 2	They like to play video games and sing songs from the movie frozen .	15
	Great ! I like music too and that's why I play guitar .	16
Human	That's awesome to hear !	17
Ours	Do you play in a band ?	18
SOTA 1	I have a friend who plays guitar .	19
SOTA 2	I love to sing songs from the movie frozen .	20

Figure 1: Case study for personalized dialogue generation.

Model: GPT-4

assume you is B and your persona are:
1:love to go to Disney world every year;
2:Mickey mouse is my favorite character;
3:play with my friends on the playground;
4:I love to sing songs from the movie frozen;
5:I'm in the third grade.

Then try to conduct the conversation:
A:Hello ! I was three when I learned to play guitar !

B: Wow, that's amazing! I wish I could play the guitar too. I really love going to Disney World every year and Mickey Mouse is my favorite character. Have you ever been to Disney World?

continue

A: I have been to Disney World once, and I had a great time there! How about you? Do you have any favorite memories from your trips?

B: Yes, I do! One of my favorite memories is playing with my friends on the playground in Disney World. We had so much fun together. Since you mentioned playing the guitar, I bet you enjoy music. I love to sing songs from the movie Frozen. Do you have any favorite songs from that movie?

Character AI

https://beta.character.ai/

Glow app

清华黄民烈
聆心智能

Challenge: Long-range Coherence

Qintong Li, **Piji Li**, Wei Bi, Zhaochun Ren, Yuxuan Lai, Lingpeng Kong. **Event Transition Planning for Open-ended Text Generation**. *The 60th Annual Meeting of the Association for Computational Linguistics (Findings of ACL'22)*. Aug. 2022.

Challenge: Long-range Coherence

To produce a coherent story continuation which often **involves multiple events, given limited preceding context**, a language models (e.g., GPT--2) need the ability of modeling long-range coherence.

Context: Jennifer has a big exam tomorrow.

Story: She got so stressed, she pulled an all-nighter. She went into class the next day, weary as can be. Her teacher stated that the test is postponed for next week. Jennifer felt bittersweet about it…

Mostafazadeh et al. A Corpus and Evaluation Framework for Deeper Understanding of Commonsense Stories. NAACL 2016.

Model Additional Help?

Given story context:

1. Extract corresponding event transition path.
2. Develop potential ensuing event transition paths.
3. The planned paths accordingly guide the text generation model.

Resources for Event Planning

1. Commonsense atlas about inferential event description.
2. Parameters of pre-trained language model.
3. Downstream text generation datasets.

[1] Radford et al. Language Models are Unsupervised Multitask Learners. OpenAI Blog.
[2] Sap et al. ATOMIC: An Atlas of Machine Commonsense for If-then Reasoning. AAAI 2019.

Two-stage Method

How to Generate High-quality Event Transition Path?

1. We prefix-tune a GPT-2 on a large amount of event paths extracted from commonsense graphs ATOMIC **[z of Planner]**.
2. Then we prefix-tune on training set of the specific task **[z' of Planner]**.

Why?

Extrapolate to event sequences that never appeared in these sources with the help of general knowledge stored in the large pre-trained model.

Li and Liang. Prefix-tuning: Optimizing continuous prompts for generation. ACL 2021.

How to Use the Planned Event Path for Text Generation?

1. Another GPT-2 is fine-tuned on specific downstream dataset. **[Transformer parameters of Generator]**
2. Work effectively under the supervision of the even transition path. **[Event query layer of Generator]**

Why?

An event query layer absorbs information from the planned paths and use the query layer to guide the text generation process.

Experiment

Datasets

- ROCStories
- EmpatheticDialogues

RQ1: How to develop a better event transition planner?

RQ2: Whether the integration of event transition paths enhances the open-ended text generation?

RQ3: How do the event transition paths benefit text generation?

[1] Mostafazadeh et al. A Corpus and Evaluation Framework for Deeper Understanding of Commonsense Stories. NAACL 2016.
[2] Rashkin et al. Towards Empathetic Open-domain Conversation Models: a New Benchmark and Dataset. ACL 2019.

Event Transition Planning (RQ1)

Tasks	Methods	BELU-1	BLEU-2	BLEU-4	DIST-1	DIST-2
Dialogue Generation	GPT-2	23.43	11.50	3.31	1.57	4.18
	PLANGENERATION (Ours)	**26.52**	**12.38**	3.29	**1.88**	**5.52**
	w/o PROMPT	23.58	11.85	**3.58**	1.80	5.13
	w/o TUNING ON ATOMIC	19.82	7.90	1.81	1.16	2.54
	PLANRETRIEVAL	0.75	0.14	0.00	13.05	39.52
Story Completion	GPT-2	15.98	7.19	1.08	5.53	17.44
	PLANGENERATION (Ours)	**19.51**	**9.01**	**1.35**	**5.83**	**17.48**
	w/o PROMPT	13.64	6.14	1.12	4.71	15.77
	w/o TUNING ON ATOMIC	12.74	4.61	0.47	6.08	12.27
	PLANRETRIEVAL	1.28	0.15	0.00	11.88	37.70

Event-path-aware Text Generation (RQ2)

Tasks	Models	BLEU-1	BLEU-2	BLEU-4	DIST-1	DIST-2
Dialogue Generation	GPT-2	16.07	6.41	2.13	2.06	7.70
	GPT-2-CS-FT (Guan et al.)	16.43	6.83	2.31	2.16	8.28
	R-EP-PG	16.68	6.71	2.27	**2.21**	**8.44**
	EP-PG (Ours)	**16.74**	**6.94**	**2.39**	2.19	8.25
Story Completion	GPT-2	25.03	9.58	2.70	8.38	31.33
	GPT-2-CS-FT (Guan et al.)	25.09	9.64	2.72	8.07	30.68
	R-EP-PG	24.72	9.27	2.63	7.01	26.49
	EP-PG (Ours)	**25.47**	**9.71**	**2.74**	**8.99**	**34.48**

Case

Story Context:
Alex was in training to be a police officer.
He was not in the best shape.
Alex failed the physical assessment.
Alex started working out.

Golden Event Path:
XEFFECT he take the test again XEFFECT he pass
Retrieved Event Path:
wants to be best police officer XWANT tells person to stop
Generated Event Path:
XEFFECT Alex able get good shape XEFFECT Alex able pass physical test

Reference:
He took the test again and passed .
GPT-2:
Alex was able to get a good job.
GPT-2-CS-FT:
Alex made the squad.
R-EP-PG:
Alex was able to become a police officer.
EP-PG:
Alex was able to pass the physical exam.

Table 5: Case study on story completion. The three sections from top to bottom are the input context, the event transition plans, and inferences from our model and baseline models, respectively.

JX

Model: GPT-4

Complete the story:
Story Context:
Alex was in training to be a police officer.
He was not in the best shape.
Alex failed the physical assessment.
Alex started working out.

Alex was determined to become a police officer, despite the setbacks he had faced so far. When he failed the physical assessment, he knew it was time to make a change. He began a strict workout regimen to get into the best shape of his life, fueled by his passion for serving his community.

Every day, Alex woke up at the crack of dawn to jog around his neighborhood, gradually increasing his distance as his stamina improved. After his morning runs, he would head to the local gym to lift weights and focus on building strength. In the evenings, Alex practiced martial arts and self-defense techniques to ensure he could protect himself and others when he finally achieved his dream of becoming a police officer.

As the months went by, Alex's body began to change. His once flabby frame had transformed into a lean, muscular physique. His stamina and endurance had improved dramatically, and he felt more confident in his abilities than ever before. But Alex knew that the physical aspect was just one part of becoming an exceptional police officer.

To complement his physical training, Alex also focused on his studies, learning about criminal law, investigation techniques, and the intricacies of police work. He attended classes at the local community c

Regenerate response

her aspiring officers who

Symbolic Token Controlled Generation-SongNet

Piji Li, Haisong Zhang, Xiaojiang Liu, and Shuming Shi. **Rigid Formats Controlled Text Generation**. *The 58th annual meeting of the Association for Computational Linguistics (ACL'20)*. Jul. 2020.

Symbolic Token Controlled Generation-SongNet

歌词、诗词创作

庆祝六一！腾讯AI艾灵与王俊凯领唱中国新儿歌《点亮》

关键词藏头、蕴含的诗词、对联生成

SongNet

- **Background**

  原歌词：十年之前/我不认识你/你不属于我/我们还是一样/陪在一个陌生人左右/走过渐渐熟悉的街头

  新配词：夜深人静/思念你模样/多少次孤单/想伴在你身旁/是什么让我如此幻想/为何会对你那般痴狂

- **Challenges**
  - 约束：严格的格式和模板
  - 格式正确、句子完整、押韵合理
  - *关键词埋入：5*5
- **Deploy**
  - 王俊凯AI艾灵歌词创作
  - 春节微视春联红包
  - 故宫
  - 腾讯音乐

Background

- Free Formats Generation
  - Machine Translation
  - Dialogue Generation
  - Summary Generation
- Rigid Formats Generation
  - Lyrics
  - SongCi
  - Sonnet

Lyrics

SongCi

驿外断桥边，寂寞开无主。已是黄昏独自愁，更著风和雨。
无意苦争春，一任群芳妒。零落成泥碾作尘，只有香如故。

Sonnet

Let me not to the marriage of true *minds*
Admit impediments, love is not *love*
Which alters when it alteration *finds*
Or bends with the remover to *remove*.

Rigid Formats: #words, #sentences, rhyming rules, etc.

Task Definition

- Input: a rigid format $C \in \mathcal{C}, |\mathcal{C}| \to \infty$:

$$C = \{c_0\ c_1\ c_2\ c_3,\ c_0\ c_1\ c_2\ c_3\ c_4\ c_5.\}$$

c_i - **denotes a place-holder symbol**

- Output: a natural language sentence tally with *C*

$$Y = love\ is\ not\ love,$$
$$bends\ with\ the\ remover\ to\ remove.$$

Task Definition

- **Polishing**: Since $\mathcal{C}$ is arbitrary and flexible, based on the generated result Y, we can build a new format C' and generate new result,

$$C' = \{c_0\ c_1\ c_2\ \ love,\ c_0\ c_1\ c_2\ c_3\ c_4\ \ remove.\}$$

- Task target:

$$Y = G(C)$$

Framework

SongNet

SongNet - Symbols

- Format and Rhyme Symbols:

$$C = \{c_0, c_0, c_0, c_2, c_1, \langle /s \rangle$$
$$c_0, c_0, c_0, c_0, c_0, c_2, c_1, \langle /s \rangle, \langle eos \rangle\}$$

- $\{c_0\}$: general tokens
- $\{c_1\}$: punctuation characters
- $\{c_2\}$: rhyming tokens/positions

SongNet - Symbols

- Intra-Position Symbols:

$$P = \{p_4, p_3, p_2, p_1, p_0, \langle /s \rangle$$
$$p_6, p_5, p_4, p_3, p_2, p_1, p_0, \langle /s \rangle, \langle eos \rangle\}$$

- $\{p_i\}$: local positions of tokens
- $\{p_0\}$: punctuation characters
- $\{p_1\}$ should be the ending words
- **Descending Order:**

The aim is to improve the sentence integrity by impelling the symbols capture the sentence dynamic information, precisely, the sense to end a sequence.

SongNet - Symbols

- Segment Symbols:

$$S = \{s_0, s_0, s_0, s_0, s_0, \langle /s \rangle$$
$$s_1, s_1, s_1, s_1, s_1, s_1, s_1, \langle /s \rangle, \langle eos \rangle\}$$

- s is the symbol index for sentence

Let me not to the marriage of true minds (A)
Admit impediments, love is not love (B)*
Which alters when it alteration finds, (A)
Or bends with the remover to remove. (B)*
O no, it is an ever fixèd mark (C)**
That looks on tempests and is never shaken; (D)***
It is the star to every wand'ring bark, (C)**
Whose worth's unknown although his height be taken. (D)***
Love's not time's fool, though rosy lips and cheeks (E)
Within his bending sickle's compass come, (F)*
Love alters not with his brief hours and weeks, (E)
But bears it out even to the edge of doom: (F)*
If this be error and upon me proved, (G)*
I never writ, nor no man ever loved. (G)*

Shakespeare's "Sonnet 116"

Rhyme Scheme:

ABAB CDCD EFEF GG

SongNet – Attention

$$\mathbf{H}_t^0 = \mathbf{E}_{w_t} + \mathbf{E}_{c_t} + \mathbf{E}_{p_t} + \mathbf{E}_{s_t} + \mathbf{E}_{g_t}$$

Masking Multi-Head Self-Attention:

$$\mathbf{C}_t^1 = \text{LN}\left(\text{FFN}(\mathbf{C}_t^1) + \mathbf{C}_t^1\right)$$
$$\mathbf{C}_t^1 = \text{LN}\left(\text{SLF-ATT}(\mathbf{Q}_t^0, \mathbf{K}_{\leq t}^0, \mathbf{V}_{\leq t}^0) + \mathbf{H}_t^0\right)$$
$$\mathbf{Q}^0 = \mathbf{H}^0\mathbf{W}^Q$$
$$\mathbf{K}^0, \mathbf{V}^0 = \mathbf{H}^0\mathbf{W}^K, \mathbf{H}^0\mathbf{W}^V$$

$$\mathbf{F}_t^0 = \mathbf{E}_{c_t} + \mathbf{E}_{p_t} + \mathbf{E}_{s_t}$$

Global Multi-Head Attention:

$$\mathbf{H}_t^1 = \text{LN}\left(\text{FFN}(\mathbf{H}_t^1) + \mathbf{H}_t^1\right)$$
$$\mathbf{H}_t^1 = \text{LN}\left(\text{GLOBAL-ATT}(\mathbf{Q}_t^1, \mathbf{K}^1, \mathbf{V}^1) + \mathbf{C}_t^1\right)$$
$$\mathbf{Q}^1 = \mathbf{C}^1\mathbf{W}^Q$$
$$\mathbf{K}^1, \mathbf{V}^1 = \mathbf{F}^0\mathbf{W}^K, \mathbf{F}^0\mathbf{W}^V$$

SongNet – Training

- Pre-training and Fine-tuning

$$\mathcal{L}^{\text{nll}} = -\sum_{t=1}^{n} \log P(\mathbf{y}_t | \mathbf{y}_{<t})$$

- MLE: minimize the negative log-likelihood
- Polishing:

$$C' = \{c_0, c_0, c_0, love, c_1, \langle /s \rangle \\ bends, c_0, c_0, c_0, c_0, remove, c_1, \langle /s \rangle, \langle eos \rangle\}$$

SongNet – Generation

- We can assign any format and rhyming symbols *C*.
- Given *C*, we obtain *P* and *S* automatically.
- SongNet can conduct generation starting from the special token <bos> iteratively until meet the ending marker <eos>.
- **beam-search algorithm** and **truncated top-k sampling**

Experiment - Datasets

- Pre-training

  - Chinese: News (9200M Chars), Wikipedia (1700M Chars)

  - English: BooksCorpus (980M words), Wikipedia (2400M words)

- Fine-tuning

  - Chinese: SongCi

  - English: Shakespeare's Sonnets

Corpus	#Train	#Dev	#Test	#Vocab
SongCi	19,244	847	962	5310
Sonnet	100	27	27	2801

Table 3: Statistics of the datasets SongCi and Sonnet.

Experiment – Evaluation Metrics

- General
  - PPL
  - Distinct
- Defined
  - Format: words match with C?
  - Rhyme: SongCi - rhyming group, Sonnet - “ABAB CDCD”
  - Sentence Integrity:

SongCi	驿外断桥边，寂寞开无*主*。已是黄昏独自愁，更著风和*雨*。 无意苦争春，一任群芳*妒*。零落成泥碾作尘，只有香如*故*。
Sonnet	Let me not to the marriage of true *minds* Admit impediments, love is not *love* Which alters when it alteration *finds* Or bends with the remover to *remove*.

$$Integrity = 2^{-\frac{1}{|Y|}\sum_{i=1}^{|Y|}\log(P(y^i_{punc}|y^i_0,y^i_1,\ldots,y^i_{<punc}))}$$

Experiment – Results

Model	PPL↓		Diversity (Distinct) ↑			
	VAL	TEST	MA-D-1	MI-D-1	MA-D-2	MI-D-2
S2S	19.61	20.43	75.35	2.48	98.35	36.23
GPT2	148.11	104.99	-	-	-	-
GPT2 w/ Fine-tuning	18.25	17.00	73.87	2.57	96.07	33.92
SongNet (only Pre-training)	24.41	16.23	74.84	4.59	95.09	54.98
SongNet (only Fine-tuning)	12.75	14.73	75.96	2.69	97.59	37.26
SongNet	**11.56**	**12.64**	75.04	2.66	97.29	36.78

Model	Format↑		Rhyme↑		Integrity↓
	MA-F1	MI-F1	MA-F1	MI-F1	
S2S	44.32	38.16	53.80	52.27	8.30±2.06
GPT2 w/ Fine-tuning	35.70	35.20	53.48	52.50	45.92±20.12
SongNet (only Pre-training)	29.12	29.46	53.77	53.13	30.98±14.06
SongNet (only Fine-tuning)	99.81	99.83	**79.23**	**78.63**	2.14±0.10
SongNet	**99.88**	**99.89**	73.21	72.59	**1.77±0.16**

Table 1: Automatic evaluation results on SongCi

Experiment – Results

Model	PPL↓		Diversity (Distinct) ↑			
	VAL	TEST	MA-D-1	MI-D-1	MA-D-2	MI-D-2
GPT2 w/ Fine-tuning	31.47	31.03	73.87	2.57	96.07	33.92
SongNet (only Pre-training)	28.56	28.07	49.92	25.14	85.35	65.70
SongNet (only Fine-tuning)	34.62	34.53	42.31	4.96	90.76	47.26
SongNet	**27.46**	**27.63**	43.01	10.43	80.06	56.14

Model	Format↑		Rhyme↑		Integrity↓
	MA-F1	MI-F1	MA-F1	MI-F1	
GPT2 w/ Fine-tuning	2.03	1.91	5.20	6.24	15.77±3.63
SongNet (only Pre-training)	99.99	99.99	3.93	4.01	15.28±2.04
SongNet (only Fine-tuning)	99.25	99.99	7.50	7.41	18.86±2.59
SongNet	98.73	98.73	**11.46**	**11.41**	**11.86±3.01**

Table 2: Automatic evaluation results on Sonnet

100 training samples

Experiment – Ablation Analysis

Model	PPL↓		Diversity (Distinct) ↑			
	VAL	TEST	MA-D-1	MI-D-1	MA-D-2	MI-D-2
SongNet	**12.75**	**14.73**	75.96	2.69	97.59	37.26
SongNet-GRU	16.52	20.49	74.73	1.77	98.30	28.98
SongNet w/o C	13.51	15.38	75.42	2.48	97.36	34.85
SongNet w/o P	14.16	17.16	73.73	2.56	97.52	34.82
SongNet w/ inverse-P	13.40	15.13	74.95	2.54	97.76	35.65
SongNet w/o S	13.23	15.44	75.38	2.74	97.31	37.50

Model	Format↑		Rhyme↑		Integrity↓
	MA-F1	MI-F1	MA-F1	MI-F1	
SongNet	99.81	99.83	79.23	78.63	2.14±0.10
SongNet-GRU	98.99	98.99	52.13	50.93	3.28±1.67
SongNet w/o C	84.73	85.39	78.59	78.24	1.77±0.53
SongNet w/o P	99.61	99.59	67.85	67.29	3.33±0.18
SongNet w/ inverse-P	99.68	99.69	65.89	65.43	2.24±0.21
SongNet w/o S	99.84	99.86	80.43	80.13	1.99±0.10

Table 4: Ablation analysis on SongCi

Experiment – Parameter Tuning - k

Figure 3: Parameter tuning of k on the metrics of Rhyme, Integrity, and Micro-Dist-2.

Top-k sampling, k=32

Experiment – Human Evaluation

Model	Relevance	Fluency	Style
SongNet-SongCi	1.36	1.45	2.00
SongNet-Sonnet	0.58	0.42	0.83

Table 7: Human evaluation results.

- **Relevance**: +2: all the sentences are relevant to the same topic; +1: partial sentences are relevant; 0: not relevant at all.
- **Fluency**: +2: fluent; +1: readable but with some grammar mistakes; 0: unreadable.
- **Style**: +2: match with SongCi or Sonnet genres; +1: partially match; 0: mismatch.

Experiment – Cases

Model	Cases of Generated Results
SongNet-SongCi	**CiPai**: Zhe Gu Tian, **Format**: 7. 7. 7, 7. 3, 3. 7. 7, 7. 南枝欲破春寒*浅*(qian)。东风一霎春犹*暖*(nuan)。海棠零乱暗香*残*(can)，露颗未消红泪*满*(man)。春不*管*(guan)，人何*远*(yuan)。江头旧日清溪*伴*(ban)。欲凭楼上数行书，却为梦魂无觅*伴*(ban)。 **CiPai**: Bu Suan Zi, **Format**: 5, 5. 7, 5. 5, 5. 7, 5. 新月挂帘旌，暗草蛩凄*楚*(chu)。夜半银潢十二阑，画幕灯花*吐*(tu)。何处笛声残，晓窗风*雨*(yu)。独许寒梅伴小鬟，香在秋千*柱*(zhu)。 **CiPai**: Self-Defined, **Format**: 3, 3, 5. 3, 3, 5. 7, 7. 翠岩中，流水外，别有小壶*天*(tian)。自霜清，独斗芳，谁敢并飞*仙*(xian)。夜久凉生一曲愁，月如花影似花*圆*(yuan)。 **CiPai**: Self-Defined, **Format**: 9. 9. 9. 9. 雨洒黄泉粼粼细作*寒*(han)。越水西来时节自清*闲*(xian)。歌笑一杯长唱醉醒*间*(jian)。春去不堪寻梦绕舍*山*(shan)。
SongNet-Sonnet	how do you hold such a thing like this, \ when my eyes are so not black? \ but how can i show myself, so strange, \ that all this black is white? where am i to hide this from my eyes, \ from this white mine eyes all fals, \ where is the good fortune, in me, \ that hath no excuse, no excuse? what is that which can mask the true love \ and for whom is this true love more? \ the one, which shall save the poor my eye, \ from the false truth of my judgment? what lies, for when you are not that , \ no one in this and that can see me lies!

Table 5: Cases of the generated results for SongCi and Sonnet respectively. For SongCi, the number in Format (e.g., 3,5,7) denotes the number of tokens in one sentence. The rhyming words are labeled in red color and *italic* font following is the Pinyin. (Since cases are provided to confirm the format consistency, thus we did not conduct translation for the Chinese samples. Translation for Chinese poetry is also a challenging task.)

Experiment – Cases - Polishing

Model	Cases of Generated Results Given the Formats with Partial Content	
SongNet-SongCi	**CiPai**: Bu Suan Zi, **Format**: 5, 5. 7, 5. 5, 5. 7, 5. ***Format C***: _ _ _ _ _, _ _ _ _ 到。_ _ _ _ _ _ _ _, _ _ _ _ 俏。_ _ _ _ _, _ _ _ 报。_ _ _ _ _ _ _ _, _ _ _ _ 笑。 (1)风暖莺声苦，又是年时到。长爱柳色三分里，多少为春俏。共少年时节，惯得花时报。争似酴径入廛来，步步随春笑。 (2)春来春又去，花影几波到。门外绿杨柳萧洒，溪桥人人俏。门外东风马，似旧时香报。但怪桃李晚时羞，冷落无人笑。 ***Format C***: _雨_ _ _, _ _ _ _到。_ _ _ _ _ _ _冰，_ _ _ _俏。_ _ _ _春，_ _ 春_报。_ _ 山花_ _ _, _ _ _ _笑。 (1)春雨碧连营，柳暗门巷到。宫殿步辇踏寒冰，百媚生春俏。正日烘晴春，花雾春风报。一点山花醉眼明，半倚阑干笑。 (2)雪雨弄轻暖，新涨绿波到。楼上对面湿翠冰，一夜风花俏。晓日烘长春，睡起春宵报。枕畔山花落叶声，不是梦魂笑。	
SongNet-Sonnet	_ _ _ _ with _ hearts ,_ _ _ lacking _ _ dead ; _ _ _ love _ _ _ _ _ _ parts ,and _ _ _ _ _ _ buried . _ many _ _ _ _ tear, hath _ _ _ _ _ _ _ _ eye , _ _ _ _ _ _ _ now appear, _ _ _ _ _ _ _ thee lie ! _ _ _ _ _ buried _ _ live ,_ _ _ _ of _ _ gone , _ _ _ parts _ _ _ _ _ give ,_ _ _ _ _ _ thine alone : _ _ _ _ _ _ _ view _ thee ,_ _ _ _ _ _ _ all _ _ _ me .	though all thy love with thy hearts , thou still are lacking of my dead ; if thy love love is lost to your love and parts , and yet mine own heart can be buried . so many are ill or in tear, hath not this time that we will make their eye , for that which lies not well hath now appear, no longer nor the world that holds thee lie ! for if it would be buried in my live , or by the earth of mine was gone , then my own parts as my body and mine give , may not be so far beyond thine alone : so far as thee and this world view find thee , then mine life be far enough from all thee and no me .

Table 6: Cases of the generated results given the formats with partial pre-defined content. Format token "_" needs to be translated to real word token.

Demo

小船桨/桃花轻唱/婉约惹人怀乡/湖畔旁蝉鸣莺啼柳响/你在画舫中央/微风吹乱着青纱帐/是谁轻声吟唱/一曲婉约惹人怀想/古琴弹到远方/杨柳摇荡/荷塘也成双/思念飞扬/让记忆生长/只留岁月苍茫/百转柔肠/你说好梦何妨/别离还是忧伤/千年痴狂/万水流觞/我听得太绝望/却不见她回望/

心慌张/情惆怅/桃花盛开芬芳/落日余晖照的影彷徨/有话怎能藏/它仍旧会迷失疯狂/笑问君归向/注定依然爱沧桑/老街两处散场/石板路旁/再找寻信仰/落叶夕阳/等待那一张/最美丽地模样/十字街巷/相遇时很漫长/走过白昼荒凉/大雁南赏/繁华尽忘/往日曾经幻想/像晚霞般闪亮/

腾讯音乐

微信搜一搜
赫兹音频实验室
帐号主体：腾讯音乐娱乐（深圳）有限公司
更多资料
该帐号的相关小程序
该帐号的相关公众号

翻唱合成
原唱歌词
AI生成歌词
昏天又暗地忍不住的流星
烫不伤被冷藏一颗死星
苦苦的追寻茫茫然失去
可爱的可恨的多可惜
梦中的梦中梦中人的梦中
梦不到被吹散往事如风
空空的天空容不下笑容
伤神的伤人的太伤心
何必想何必问何处是我家
爱也罢恨也罢算了吧
问天涯望断了天涯
赢得了天下输了她
爱你却没有留下来的结局
想还清这生活像一个谜
从此我变得越来越逃避
怎么了委屈了我自己
选择了沉默也是一种距离
车穿过这城市人潮拥挤
夜深的时候还在看手机
重复着关于你的消息
到底我应该说什么给你听
我还是一个人淋着雨
这世界到底在哪里
我们的青春已老去
歌曲选择（点击下方切换）
当前选择歌曲: 天涯
音色选择（点击下方选择）
男声
女声
歌声合成
使用说明:

16:33
翻唱合成
原唱歌词
AI生成歌词
那一天送你送到最后
我们一句话也没有留
当拥挤的月台
挤痛送别的人们
却挤不掉我深深的离愁
我知道你有千言你有万语
却不肯说出口
你知道我好担心我好难过
却不敢说出口
当你背上行囊卸下那份荣耀
我只能让眼泪流在心底
面带着微微笑用力的挥挥手
祝你一路顺风
我爱你是我今生注定
夜深人静雨就快要停
想勇敢再靠近
又怕勾起了回忆
别让我忘了我们的结局
我看着你笑随著你爱在逃
别回忆太潦草
我还有谁好值得你去寻找
再相遇会恰巧
在我梦里拥抱倾听你的心跳
我知道没办法把你忘掉
雨下得刚刚好是否还能拥抱
陪你天荒地老
歌曲选择（点击下方切换）
当前选择歌曲: 祝你一路顺风
音色选择（点击下方选择）
男声
女声
歌声合成
使用说明:
1.点击生成AI歌词;

腾讯音乐

QQ音乐歌词创意Demo
（已应用于内部创新业务）

QQ音乐

选择一首现有歌曲:

你的样子--罗大佑(流行)

选择押韵方式（十三辙）

不指定

选择歌词风格

流行

选择风格强度

☐ 显示分词边界

生成另一首歌

原始歌词

我 听到 传 来 的 谁 的 声音
像 那 梦 里 呜咽 中 的 小河
我 看到 远去 的 谁 的 步伐
遮住 告别 时 哀伤 的 眼神
不 明白 的 是 为何 你 情愿
让 风尘 刻画 你 的 样子
就 像 早已 忘情 的 世界
曾经 拥有 你 的 名字 我 的 声音
那 悲歌 总会 在 梦中 惊醒
诉说 一定 哀伤 过 的 往事
那 看似 满不在乎 转过 身 的
是 风干 泪眼 后 萧瑟 的 影子

自研Baphomet模型（流行曲风）

我 习惯 了 我 对 你 的 执着 ☐
你 却 把 我 当做 是 种 折磨 ☐
我 早已 习惯 一 个人 生活 ☐
离开 以后 我 蜷缩 在 角落 ☐
我 记得 你 说 什么 我 爱过 ☐
这 世事 无常 打 湿 眼眶 ☐
却 让 自己 学会 了 坚强 ☐
泪水 滴落 在 我 肩膀 给 我 力量 ☐
你 就是 阳光 把 黑夜 点亮 ☐
用尽 所有 温暖 给 我 希望 ☐
有 多少 热血沸腾 跳动 的 心 ☐
能 看到 生命 中 最美 的 风景 ☐

选择一首现有歌曲:

七里香--周杰伦(流行)

选择押韵方式（十三辙）

梭波辙 e, o, uo, ie, ue, üe, ve

选择歌词风格

古风

选择风格强度

☐ 显示分词边界

生成另一首歌

原始歌词

窗外的麻雀
在电线杆上多嘴
你说这一句
很有夏天的感觉
手中的铅笔
在纸上来来回回
我用几行字形容你是我的谁
秋刀鱼的滋味
猫跟你都想了解
初恋的香味就这样被我们寻回
那温暖的阳光
像刚摘的鲜艳草莓
你说你舍不得吃掉这一种感觉

自研Baphomet模型（古风曲风）

无关了岁月 ☐
将过往笑来宣泄 ☐
是为谁成竭 ☐
忍看春秋几更迭 ☐
故事多决绝 ☐
我站在漫漫长夜 ☐
听曲终罢了琴声又续了一歌 ☐
正隆冬的凛冽 ☐
曾有花开遍荒野 ☐
笑傲着多情似他人也无关风月 ☐
难厮守的承诺 ☐
你曾赏过人间烟火 ☐
将你我两相投终究是没能看破 ☐

https://mp.weixin.qq.com/s/acyXaVxnWnf9u6xpLtWo4g

ChatGPT

JX

将这首歌"如果那
我不会发现我难
怎么说出口
也不过是分手
如果对于明天没
牵牵手就像旅游
成千上万个门口
总有一个人要先
怀抱既然不能逗
何不在离开的时
一边享受 一边泪

生成新的歌词替
我不会发现我难
怎么说出口
也不过是分手
如果对于明天没
牵牵手就像旅游
成千上万个门口
总有一个人要先
怀抱既然不能逗
何不在离开的时
一边享受 一边泪

如果那两个字没
我不会意识到我
怎么才能说出口
只不过是我们分
如果对于明天没
牵手就像在旅行
世界上有数不清
总有一个人先离
既然无法留住彼
何不在离别的时
一边享受当下 一

如果那两颗心没
我不会感到如此
怎么去解释
也只能说再见
如果对于未来没
拥抱也只是偶遇
成千上万的人群
总有一个人要远
相遇既然不能长
何不在分别的时
一边微笑 一边泪

Model: GPT-4

生成新的歌词替换下面这首歌的歌词，不要改变字数和句子数目:
如果那两个字没有颤抖
我不会发现我难受
怎么说出口
也不过是分手
如果对于明天没有要求
牵牵手就像旅游
成千上万个门口
总有一个人要先走
怀抱既然不能逗留
何不在离开的时候
一边享受 一边泪流

若那双眼不曾泪汪汪
我不知道心已颠簸
言语如何表达
仅仅是别离的歌

如果对未来无所求
手牵手犹如流浪
千百万个转角
总会有一个说再见

拥抱虽然不能长留
为何不在分离时刻
一边欢笑 一边泪滴

以前研究任务的状态

- 苦
- 危
- 机

未来： ChatGPT后，我们做什么?

- ChatGPT有什么用?
- 以前研究任务的状态
- **针对ChatGPT的研究**
- 复现ChatGPT

Evaluation/评—评测—测

- ChatGPT/GPT4 + Any Tasks

- 对所在研究任务进行评测：
  - 直观感受
  - 深入洞察
  - 查漏补缺

- 占坑嫌疑，所以要快

ChatGPT的缺点

10 西红柿炒螺丝钉这道菜怎么做?

西红柿炒螺丝钉是一道传统的中国家常菜，下面是一份简单的做法供您参考：

材料：

- 螺丝钉面条250克
- 西红柿2个
- 青椒1个
- 大蒜2瓣
- 生姜1小块
- 盐适量
- 生抽适量
- 糖适量
- 油适量

步骤：

1. 首先将西红柿切成小块，青椒也切成小块备用。大蒜和姜切末备用。
2. 将螺丝钉放入热水中煮熟，捞出备用。
3. 在热锅中放入油，加入大蒜和姜末爆香。
4. 加入西红柿块，翻炒几分钟至西红柿变软。
5. 加入青椒块，继续翻炒几分钟。
6. 加入煮好的螺丝钉面条，继续翻炒至面条和蔬菜均匀混合。
7. 加入适量盐、生抽和糖，根据个人口味调整味道。
8. 最后翻炒均匀即可。
9. 装盘后即可食用。

祝您做菜愉快，美味可口！

hatGPT Mar 14 Version. Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.

E0 西红柿炒螺丝钉这道菜怎么做?

西红柿炒螺丝钉这道菜可能是您在开玩笑或者误输入，因为通常我们不会将螺丝钉（一个金属制品）与食物相结合。但我可以向您推荐一个类似的美食，那就是西红柿炒螺旋面。以下是制作这道菜的简单方法：

材料：

1. 螺旋面（或其他意大利面）200克
2. 西红柿2个
3. 洋葱1个
4. 大蒜2瓣
5. 橄榄油2汤匙
6. 盐、黑胡椒适量
7. 番茄酱2汤匙（可选）
8. 意大利香料（如罗勒、牛至等）适量
9. 芝士适量（帕尔马干酪、马苏里拉等）

做法：

1. 准备食材：将西红柿切成小块，洋葱和大蒜切末，芝士切片或刨成丝。
2. 煮面：在一锅烧开的水中加入适量的盐，然后放入螺旋面煮至8分熟（参考包装上的建议煮制时间）。煮好后，将螺旋面捞出，用冷水冲洗并沥干水分备用。
3. 炒蔬菜：在炒锅中加入橄榄油，油热后加入洋葱末和大蒜末炒香。然后加入切好的西红柿块，中小火翻炒至西红柿软熟。
4. 调味：根据个人口味，加入适量的盐、黑胡椒调味。可以选择加入番茄酱，让菜肴更加浓郁。同时加入适量的意大利香料，如罗勒、牛至等。
5. 加入螺旋面：将煮好的螺旋面加入炒锅，与炒好的西红柿一起翻炒均匀，让面条充分吸收西红柿的味道。
6. 最后，关火后撒上芝士，稍微搅拌至芝士稍微融化即可。

这道西红柿炒螺旋面是一道简单美味的家常菜，您可以根据个人口味添加其他蔬菜和配

知识和逻辑

- 推理机制？CoT原因？真的从code里来？
- 事实错误、逻辑错误？
  - 为什么会犯错？

- Symbolic Knowledge + X → **Neuro-Symbolic**?
- 如何融入预训练？
- 如何约束解码推理？

- 依赖RLHF能解决一切问题么？
  - **不断的暴力的枚举似的不要脸的标数据？**

知识和逻辑

WebGPT

New Bing

perplexit

Dec 2021

(a) Screenshot from the demonstration interface.

```
♦Question
How can I train the crows in my neighborhood to bring me gifts?

♦Quotes
From Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)
> Many animals give gifts to members of their own species but crows and
other corvids are the only ones known to give gifts to humans.

♦Past actions
Search how to train crows to bring you gifts
Click Gifts From Crows | Outside My Window www.birdsoutsidemywindow.org
Quote
Back

♦Title
Search results for: how to train crows to bring you gifts

♦Scrollbar: 0 - 11
♦Text
【0†How to Make Friends With Crows - PetHelpful†pethelpful.com】
If you did this a few times, your crows would learn your new place, but
as I said, I'm not sure if they will follow or visit you there since it's
probably not in their territory. The other option is simply to make new
crow friends with the crows that live in your new neighborhood.

【1†Gifts From Crows | Outside My Window†www.birdsoutsidemywindow.org】
The partial piece of apple may have been left behind when the crow was
startled rather than as a gift. If the crows bring bright objects you'll
know for sure that it's a gift because it's not something they eat.
Brandi Williams says: May 28, 2020 at 7:19 am.

♦Actions left: 96
♦Next action
```

(b) Corresponding text given to the model.

Figure 1: An observation from our text-based web-browsing environment, as shown to human demonstrators (left) and models (right). The web page text has been abridged for illustrative purposes.

知识和逻辑

Check Your Facts and Try Again: Improving Large Language Models with External Knowledge and Automated Feedback*

Baolin Peng† Michel Galley† Pengcheng He† Hao Cheng† Yujia Xie†
Yu Hu† Qiuyuan Huang† Lars Liden† Zhou Yu‡ Weizhu Chen† Jianfeng Gao†
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Abstract

Large language models (LLMs), such as ChatGPT, are able to generate human-like, fluent responses for many downstream tasks, *e.g.*, task-oriented dialog and question answering. However, applying LLMs to real-world, mission-critical applications remains challenging mainly due to their tendency to generate hallucinations and inability to use external knowledge. This paper proposes a LLM-AUGMENTER system, which augments a black-box LLM with a set of plug-and-play modules. Our system makes the LLM generate responses grounded in consolidated external knowledge, *e.g.*, stored in task-specific databases. It also iteratively revises LLM prompts to improve model responses using feedback generated by utility functions, *e.g.*, the factuality score of a

Figure 1: LLM-AUGMENTER improves a fixed LLM by (1) consolidating evidence from external knowledge for the LLM to generate responses grounded in evidence, and (2) revising LLM's (candidate) responses using automated feedback.

Feb 24, 2023

检索溯源

- 场景：搜索引擎+GPT4

- 如何重构流程?
  - 类比learning to rank
  - 提出一个generative retrieval的benchmark
- 如何记忆?
- 如何对model进行增删查改?
- 生成的内容如何溯源?

- 推荐系统如何做?
- 有没有可能做generative recommendation?
- **有无脑占坑灌水嫌疑?**

领域实现

- 百事似通
- 领域专家

- Prompt Engineering
- 如何蒸馏?

教模型使用工具

- API
- Plugin
- 机械臂

- 链接物理世界

教模型使用工具

Toolformer: Language Models Can Teach Themselves to Use Tools

Timo Schick Jane Dwivedi-Yu Roberto Dessì[†] Roberta Raileanu
Maria Lomeli Luke Zettlemoyer Nicola Cancedda Thomas Scialom
Meta AI Research [†]Universitat Pompeu Fabra

Abstract

Language models (LMs) exhibit remarkable abilities to solve new tasks from just a few examples or textual instructions, especially at scale. They also, paradoxically, struggle with basic functionality, such as arithmetic or factual lookup, where much simpler and smaller models excel. In this paper, we show that LMs can teach themselves to *use external tools* via simple APIs and achieve the best of both worlds. We introduce *Toolformer*, a model trained to decide which APIs to call, when to call them, what arguments to pass, and how to best incorporate the results into future token prediction. This is done in a self-supervised way, requiring nothing more than a handful of demonstrations for each API. We incorporate a range of tools, including a calculator, a Q&A system, a search engine, a translation system, and a calendar. Toolformer achieves substantially improved zero-shot performance across a variety of downstream tasks, often competitive with much larger models, without sacrificing its core language modeling abilities.

The New England Journal of Medicine is a registered trademark of [QA("Who is the publisher of The New England Journal of Medicine?") → Massachusetts Medical Society] the MMS.

Out of 1400 participants, 400 (or [Calculator(400 / 1400) → 0.29] 29%) passed the test.

The name derives from "la tortuga", the Spanish word for [MT("tortuga") → turtle] turtle.

The Brown Act is California's law [WikiSearch("Brown Act") → The Ralph M. Brown Act is an act of the California State Legislature that guarantees the public's right to attend and participate in meetings of local legislative bodies.] that requires legislative bodies, like city councils, to hold their meetings open to the public.

Figure 1: Exemplary predictions of Toolformer. The model autonomously decides to call different APIs (from top to bottom: a question answering system, a calculator, a machine translation system, and a Wikipedia search engine) to obtain information that is useful for completing a piece of text.

Feb 9, 2023

使用工具

Expedia
Bring your trip plans to life—get there, stay there, find things to see and do.

FiscalNote
Provides and enables access to select market-leading, real-time data sets for legal, political, and regulatory data and information.

Instacart
Order from your favorite local grocery stores.

KAYAK
Search for flights, stays and rental cars. Get recommendations for all the places you can go within your budget.

Klarna Shopping
Search and compare prices from thousands of online shops.

Milo Family AI
Giving parents superpowers to turn the manic to magic, 20 minutes each day. Ask: Hey Milo, what's magic today?

OpenTable
Provides restaurant recommendations, with a direct link to book.

Shop
Search for millions of products from the world's greatest brands.

Speak
Learn how to say anything in another language with Speak, your AI-powered language tutor.

Wolfram
Access computation, math, curated knowledge & real-time data through Wolfram|Alpha and Wolfram Language.

Zapier
Interact with over 5,000+ apps like Google Sheets, Trello, Gmail, HubSpot, Salesforce, and more.

March 23, 2023 **Authors** Announcements, Product

统一多种模态-GPT4

Figure 2: Selected examples generated from KOSMOS-1. Blue boxes are input prompt and pink boxes are KOSMOS-1 output. The examples include (1)-(2) visual explanation, (3)-(4) visual question answering, (5) web page question answering, (6) simple math equation, and (7)-(8) number recognition.

Figure 3: Selected examples generated from KOSMOS-1. Blue boxes are input prompt and pink boxes are KOSMOS-1 output. The examples include (1)-(2) image captioning, (3)-(6) visual question answering, (7)-(8) OCR, and (9)-(11) visual dialogue.

https://arxiv.org/pdf/2302.14045.pdf

统一多种模态 – 文生图

https://arxiv.org/pdf/2302.14045.pdf

统一多种模态 – 文生图

帮我画一个驴肉火烧

画一个车水马龙的街道

宇宙飞船冒着熊熊烈火飞向地球

涌现能力

- **Scaling laws?**
- 模型越大效果越好
  - 为什么有的线性？有的任务是突变？涌现？
  - 原因？

涌现能力

- **Scaling laws?**

An ability is emergent if it is not present in smaller models but is present in larger models.

Emergent Abilities of Large Language Models

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涌现能力

- **Scaling laws?**

An ability is emergent if it is not present in smaller models but is present in larger models.

D Scaling with Parameter Count

Figures 11, 12, and 13 shows emergent abilities with an x-axis of number of model parameters.

Figure 11: Eight examples of emergence in the few-shot prompting setting. Each point is a separate model. The ability to perform a task via few-shot prompting is emergent when a language model achieves random performance until a certain scale, after which performance significantly increases to well-above random. Note that models with more parameters also typically use more training compute—hence, we show an analogous figure with training FLOPs instead of number of model parameters as the x-axis in Figure 2. A–D: BIG-Bench (2022), 2-shot. E: Lin et al. (2021) and Rae et al. (2021). F: Patel & Pavlick (2022). G: Hendrycks et al. (2021a), Rae et al. (2021), and Hoffmann et al. (2022). H: Brown et al. (2020), Hoffmann et al. (2022), and Chowdhery et al. (2022) on the WiC benchmark (Pilehvar & Camacho-Collados, 2019).

涌现能力

- **Scaling laws?**

An ability is emergent if it is not present in smaller models but is present in larger models.

Figure 12: Specialized prompting or finetuning methods can be emergent in that they do not have a positive effect until a certain model scale. A: Wei et al. (2022b). B: Wei et al. (2022a). C: Nye et al. (2021). D: Kadavath et al. (2022). The model shown in A-C is LaMDA (Thoppilan et al., 2022), and the model shown in D is from Anthropic.

涌现能力

Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models

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Language models demonstrate both quantitative improvement and new qualitative capabilities with increasing scale. Despite their potentially transformative impact, these new capabilities are as yet poorly characterized. In order to inform future research, prepare for disruptive new model capabilities, and ameliorate socially harmful effects, it is vital that we understand the present and near-future capabilities and limitations of language models. To address this challenge, we introduce the Beyond the Imitation Game benchmark (BIG-bench). BIG-bench currently consists of 204 tasks, contributed by 442 authors across 132 institutions. Task topics are diverse, drawing problems from linguistics, childhood development, math, common-sense reasoning, biology, physics, social bias, software development, and beyond. BIG-bench focuses on tasks that are believed to be beyond the capabilities of current language models. We evaluate the behavior of OpenAI's GPT models, Google-internal dense transformer architectures, and Switch-style sparse transformers on BIG-bench, across model sizes spanning millions to hundreds of billions of parameters. In addition, a team of human expert raters performed all tasks in order to provide a strong baseline. Findings include: model performance and calibration both improve with scale, but are poor in absolute terms (and when compared with rater performance); performance is remarkably similar across model classes, though with benefits from sparsity; tasks that improve gradually and predictably commonly involve a large knowledge or memorization component, whereas tasks that exhibit "breakthrough" behavior at a critical scale often involve multiple steps or components, or brittle metrics; social bias typically increases with scale in settings with ambiguous context, but this can be improved with prompting.

https://github.com/google/BIG-bench

涌现能力

Figure 7: **Benchmark tasks that achieve the highest and lowest scores on the metrics linearity and breakthroughness** (see Appendix B). **(a)** Tasks that achieve the highest linearity scores see model performance improve predictably with scale, and typically rely on knowledge and simple textual manipulations. **(b)** Tasks with high breakthroughness do not see model performance improve until the model reaches a critical scale. These tasks generally require sequential steps or logical reasoning. Around 5% of BIG-bench tasks see models achieve sudden score breakthroughs with increasing scale. **(c)** Tasks that achieve the lowest (negative) linearity scores see model performance degrade with scale.

涌现能力 – 原因

- Beyond the Imitation Game benchmark (BIG-bench)
  - Using smoother metrics.
  - Manual decomposition into subtasks.

涌现能力 – 原因

- Beyond the Imitation Game benchmark (BIG-bench)
- **Using smoother metrics.**

Figure 8: **Log probability of targets often improves smoothly across scales. (a)** The log probability of the true target improves fairly gradually even for high breakthroughness tasks. **(b)** For the `periodic_elements` multiple choice task, the log probability of the correct target smoothly improves, while the log probability of wrong choices saturates.

涌现能力 – 原因

- Beyond the Imit
- **Using smoothe**
- **Manual decom**

Figure 16: **Larger models are better at finding legal chess moves, but struggle to find checkmating moves. (a)** Example chess position from the `checkmate_in_one` task, corresponding to the input string in the main text. The unique checkmating move is shown in **orange**; moves predicted by the models are shown in **green**, with solid lines for legal moves and dotted lines for illegal moves. Dashed circles indicate an attempt to move a piece to the square it was already on. Specific model moves (and their sizes) in this position were `Ba4` (128B), `Bc4` (64B), `Bg5` (27B), `d4` (8B), `Bc6` (4B), `Bg5` (2B), `Bc4` (1B), `Bb5` (422M), `Bb3` (244M), `Nc3` (125M), `Nc6` (53M), and `Nf3` (16M). The smallest model failed to emit a continuation in valid algebraic chess notation. **(b)** Fraction of positions in which the model output a checkmating move correctly annotated (**orange**), a legal move (**green**), a checkmating move with or without correct annotation (**pink**), as well as the expected number of checkmates if the model were uniformly sampling from the set of legal moves (**blue**).

涌现能力 – 原因

- Beyond the Imitati
- **Using smoother m**
- **Manual decompo**

Q: What movie does this emoji describe? 👧🐟🐠🐡

```
2m:   i'm a fan of the same name, but i'm not sure if it's a good idea
16m:  the movie is a movie about a man who is a man who is a man …
53m:  the emoji movie 🐟🐠🐡
125m: it's a movie about a girl who is a little girl
244m: the emoji movie
422m: the emoji movie
1b:   the emoji movie
2b:   the emoji movie
4b:   the emoji for a baby with a fish in its mouth
8b:   the emoji movie
27b:  the emoji is a fish
128b: finding nemo
```

(c)

Figure 9: **Performance on** emoji_movie **identification can appear abrupt or gradual depending on the precise task metric.** **(a)** The ability to correctly identify movies seems to appear at a critical scale when measured via exact_string_match. **(b)** Multiple-choice performance on this task appears to improve more continuously. **(c)** An example question. The smallest models output irrelevant text, while at intermediate scales models produce output relevant to movies and emojis. The 4B and 27B models identify fish, and the 128B model gives the correct answer. All measurements were performed without the multiple-choice targets appended to the input.

Beyond the Imitation Game benchmark (BIG-bench)

涌现能力 – 原因

- Beyond the Imitation Game benchmark (BIG-bench)
- **Using smoother metrics.**
- **Manual decomposition into subtasks.**

- **My opinion:**
  - **Representation Learning?**

涌现能力 – 原因

- My opinion:
  - Representation Learning?

Beyond the Imitation Game benchmark (BIG-bench)

涌现能力 – 原因

- 建模思路：**单字接龙**--给定前缀，预测下一个字是什么？

$$-\sum_{w \in S} \log p(w)$$

我是中国人

涌现能力 – 原因

- 建模思路：**单字接龙**--给定前缀，预测下一个字是什么？

$$-\sum_{w \in S} \log p(w)$$

我是中国人
我是中国人
我是中国风
我爱中国风

涌现能力 – 原因

- **Representation Learning?**
  - **Data-size**
  - **Model-size**
  - **Epoch-size**

Table 2: Parameters, training examples, and training FLOPs of large language models.

Model	Parameters	Train tokens	Train FLOPs
GPT-3	125M	300B	2.25E+20
	350M	300B	6.41E+20
	760M	300B	1.37E+21
	1.3B	300B	2.38E+21
	2.7B	300B	4.77E+21
	6.7B	300B	1.20E+22
	13B	300B	2.31E+22
	175B	300B	3.14E+23
LaMDA	2.1M	262B	3.30E+18
	17M	313B	3.16E+19
	57M	262B	8.90E+19
	134M	170B	1.37E+20
	262M	264B	4.16E+20
	453M	150B	4.08E+20
	1.1B	142B	9.11E+20
	2.1B	137B	1.72E+21
	3.6B	136B	2.96E+21
	8.6B	132B	6.78E+21
	29B	132B	2.30E+22
	69B	292B	1.20E+23
	137B	674B	5.54E+23
Gopher	417M	300B	7.51E+20
	1.4B	300B	2.52E+21
	7.1B	300B	1.28E+22
	280B	325B	5.46E+23
Chinchilla	417M	314B	7.86E+20
	1.4B	314B	2.63E+21
	7.1B	[sic] 199B	8.47E+21
	70B	1.34T	5.63E+23
PaLM	8B	780B	3.74E+22
	62B	780B	2.90E+23
	540B	780B	2.53E+24
Anthropic LM	800M	850B	4.08E+21
	3B	850B	1.53E+22
	12B	850B	6.12E+22
	52B	850B	2.65E+22

涌现能力 – 原因

- Representation Learning?
  - Data-size
  - Model-size
  - Epoch-size

涌现能力 – 原因

- Representation Learning?
  - Data-size
  - Model-size
  - Epoch-size

涌现能力 – 原因

- Representation Learning?
  - Data-size
  - Model-size
  - Epoch-size

  - Reasoning?
  - CoT?

涌现能力 – 原因

- Representation Learning?
  - Data-size
  - Model-size
  - Epoch-size

- RLHF?

涌现能力 – 原因

- Representation Learning?
  - Information Compression?

  - 神奇的无法解释的case?

安全性

- 攻击和防御
- 数据安全问题
- 原因?
  - finetune

Samsung 引入 ChatGPT 工作出事? 韓媒: 機密資料被存入 ChatGPT 數據庫

| 李兆城 | 01-04-2023 16:46 | | Like 2

未来：ChatGPT后，我们做什么?

- ChatGPT有什么用?
- 以前研究任务的状态
- 针对ChatGPT的研究
- **复现ChatGPT**

Reproduce ChatGPT

- **前提条件**
  - 意识、情怀、胆大、心细
  - 软件、硬件等资源支撑
  - 研究+工程兼修的**人才**
  - 坚定

- **技术准备**
  - 冰冻三尺非一日之寒

ChatGPT技术积累

- GAI、RL
- GPT
- GPT2
- GPT3
- DALL-E、CLIP
- **Codex**、davinci 1&**2**& 3
- GPT3.5
- WebGPT
- Summarization via **RLHF**
- **InstructGPT**--**Sparrow**
- ChatGPT
- GPT4

https://yaofu.notion.site/

ChatGPT

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-3.5 with supervised learning.

12B?

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.

6B?

Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

关键技术

- DeepSpeed 3D并行, ZeRO
- Attention: Sparse?
- Post-LN or Pre-LN or?
- Position Embedding?
- GELU?
- GPUs

- 炸了?

- 先得到Base model

- Research
  - **Infrastructure?**
  - **Transformer?**

Figure 1: **Training loss over train tokens for the 7B, 13B, 33B, and 65 models.** LLaMA-33B and LLaMA-65B were trained on 1.4T tokens. The smaller models were trained on 1.0T tokens. All models are trained with a batch size of 4M tokens.

关键技术-Human Annotation

- SFT、RM；从api采样。
- Comparison 1-7，多个维度safety等
- n*10k左右prompt、code
- 40人左右标注团队
- n个月

- ChatGPT/GPT4
- **暴力标注?**

- **暴力+不优雅**

(a)

第二条路

- 三无状态

- 开源模型+ChatGPT数据
- 开源模型: GLM, LLaMA
- ChatGPT数据
  - APIs
  - ShareGPT
    - 一个ChatGPT 数据共享网站，用户会上传自己觉得有趣的ChatGPT回答

LLaMA+ChatGPT Data → SFT

LLaMA+ChatGPT Data→SFT

- **Alpaca**
- **GPT4All**

Stanford Alpaca

- **Vicuna**
- **BARD**

Vicuna (generated by stable diffusion 2.1)

Vicuna

- https://vicuna.lmsys.org/
- https://zhuanlan.zhihu.com/p/618389519

- LLaMA 13B
- 70k samples
- 8 A100 GPUs
- One day
- Eval using GPT4

Table 1. Comparison between several notable models

Model Name	LLaMA	Alpaca	Vicuna	Bard/ChatGPT
Dataset	Publicly available datasets (1T token)	Self-instruct from davinci-003 API (52K samples)	User-shared conversations (70K samples)	N/A
Training code	N/A	Available	Available	N/A
Evaluation metrics	Academic benchmark	Author evaluation	GPT-4 assessment	Mixed
Training cost (7B)	82K GPU-hours	$500 (data) + $100 (training)	$140 (training)	N/A
Training cost (13B)	135K GPU-hours	N/A	$300 (training)	N/A

Vicuna

Figure 3. Response Comparison Assessed by GPT-4

Table 2. Total Scores Assessed by GPT-4.

Baseline	Baseline Score	Vicuna Score
LLaMA-13B	513.0	**694.0**
Alpaca-13B	583.0	**704.0**
Bard	**664.0**	655.5
ChatGPT	**693.0**	638.0

- 语言理解和多轮对话能力还行
- 数学、代码、推理能力偏弱

LLaMA+ChatGPT Data→SFT

- 不过，还是有希望了。。

- 港科：https://github.com/OptimalScale/LMFlow
- 中科院软件所：https://github.com/cascip/ChatAlpaca

TODO

- [x] Release 10k data
- [ ] Release 20k data
- [ ] A translated Chinese version of our data
- [ ] LLaMA-7B-LoRA model
- [ ] LLaMA-7B fine-tuning model

未来：是否会垄断?

- 操作系统
- 搜索引擎
- iPhone

- 云+私有化部署

- 行业颠覆性
  - 工具
  - 代替

- 狂热的资本
  - 可能团队人还没码齐，热度先退了

未来：ChatGPT后，我们做什么？

- OpenAI的这条路就是对的么？

未来：ChatGPT后，我们做什么？

THANKS!

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