ChatGLM: An Alternative to ChatGPT

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Slides available at: http://keg.cs.tsinghua.edu.cn/jietang/ or Google Jie Tang
What is ChatGLM

• ChatGPT and GPT4 has gained enormous popularity
  – However, techniques behind GPT become a secret to all
• ChatGLM, an open-source ChatGPT alternative, toward unclosing the secret
  – GLM-130B: an open-source LLM base model
  – ChatGLM-6B: a lightweight open-source ChatGPT alternative
  – ChatGLM-130B: not open-sourced, but available through API

https://github.com/THUDM/GLM-130B

https://github.com/THUDM/ChatGLM3
ChatGLM-6B: An Open-Source Alternative

• ChatGLM-6B: 6.2B parameters, INT4 quantization (only need 6G memory)
• >50,000 stars on github
• >10,000,000 downloads on Huggingface
• No. 1 on Github Trending (2 week)
• No. 1 on Huggingface Trending (2 weeks)

https://github.com/THUDM/GLM-130B

>600 Open-Sourced Apps developed based on ChatGLM

https://github.com/THUDM/ChatGLM3
ChatGPT vs. ChatGLM

- ChatGPT
- DALL.E
- Codex
- WebGPT
- GPT-4V

VS

GPT

GLM

- ChatGLM
- CogView
- CodeGeeX
- WebGLM
- GLM-4V on the way (CogVLM, Agent...)

4
I am an AI assistant named ChatGLM, which is developed based on the language model jointly trained by Tsinghua University KEG Lab and Zhipu AI Company in 2023. My job is to provide appropriate answers and support to users’ questions and requests.

Sure, here’s a blog outline that introduces ChatGLM:

I. Introduction
   A. Brief overview of ChatGLM
   B. Importance of AI assistants in today’s world

II. How ChatGLM works
   A. Basics of AI language models
Story generation

tell a 100 words story about athens in english, chinese, and greek

English: Athens, Greece's stunning capital, is a city of ancient ruins, modern architecture, and vibrant culture. Celebrated for its role in democracy, philosophy, and the Olympic Games, Athens offers visitors a unique blend of the past and present. Explore the Acropolis, Plaka, and Syntagma Square, or relax at one of the many beautiful parks and beaches. Enjoy mouthwatering Greek cuisine, from gyros to spanakopita, and immerse yourself in the city's lively arts and music scene. Athens is a destination where history comes alive and memories are made to last a lifetime.

中文：雅典，希腊美丽的首都，是一座融合了古老遗迹、现代建筑和生动文化的城市。雅典因其在民主、哲学和奥林匹克运动中的地位而闻名，游客可以在这里感受到独特的过去与现在的交融。游览Acropolis、Plaka 和 Syntagma 广场，或者在众多美丽的公园和海滩放松身心。品尝令人垂涎的希腊美食，从烤肉串到菠菜派，让自己沉浸在城市繁忙的艺术和音乐氛围中。雅典是一个让历史焕发活力，留下终身难忘记忆的旅游胜地。

希腊语：Αθήνα, η καλύτερη και πόλη της Γαλλίας, είναι ένα σύγκρουσμα της παλαιότερης και της σύγχρονης και της καλλιτέχνης μας. Στην Αθήνα θα βρείτε όλα τα σημαντικά μας, τη σύγχρονη αρχιτεκτονική και την καλύτερη κοινωνία. Ξεκινήστε τη διαβάστε την Ακρόπολη, την Plaka και το Syntagma Square, ή καλύπτετε στο ένα άλλο της πολλές όμορφες παραλίες και παραλίες. Γεύσαστε την καλή πουροκαλλιέργεια κουζίνα, από τα γύρο στη σπανακότα, και παρατρέψτε σας εγώ για μέσα στη σύγχρονη καλλιτεχνική και τη μουσική χρήση της Αθήνας. Η Αθήνα είναι ένα σημείο όπου η ιστορία ζει στην ζωή και οι ευπορίες σας θα την κάνουν μέχρι.
A company produces a toy for which the variable cost is 12.30 per unit and the fixed costs are 98,000. The toy sells for $17.98. Let $X$ be the number of units produced and sold.

a) The total cost for a business is the sum of the variable cost and the fixed costs. Write the total cost $C$ as a function of the number of units produced.

$$C(X) = 12.30X + 98000$$

b) The revenue $R$ is the sales price minus the variable cost. Write the revenue $R$ as a function of the number of units sold.

$$R(X) = 17.98 - 12.30X$$

c) The profit $P$ is the revenue $R$ minus the total cost $C$. Write the profit $P$ as a function of the number of units sold.

$$P(X) = R(X) - C(X) = 17.98 - 12.30X - 98000$$

Note: The negative sign indicates that the profit is a function of the number of units sold in the negative direction, meaning that as the number of units sold increases, the profit decreases.
Write a code for a bubble sort algorithm in Python, and give an array as an example.

Sure, here’s a simple bubble sort algorithm implemented in Python:

```python
def bubble_sort(arr):
    n = len(arr)
    for i in range(n):
        for j in range(n-i-1):
            if arr[j] > arr[j+1]:
                # Swap adjacent elements if they are in wrong order
                arr[j], arr[j+1] = arr[j+1], arr[j]
    return arr
```

To use this function, you’ll need to define an array to sort, like so:

```python
arr = [64, 34, 25, 12, 22, 11, 90]
```

Once you have your array defined, you can call the `bubble_sort()` function on it, like so:

```python
sorted_arr = bubble_sort(arr)
```

Finally, you can print the sorted array like so:

```python
print(sorted_arr)
```

This should output something like:

```
[11, 12, 22, 25, 34, 64, 90]
```

Let’s take a look at an example array to better understand how the bubble sort algorithm works:

```python
arr = [5, 2, 9, 1, 5, 6, 10]
```

In this example, the first element (5) is sorted towards the bottom of the array, and the last element (10) is sorted towards the top. The middle elements (2, 5, and 9) are sorted in between their adjacent elements, as shown in the following sorted array:

```
[1, 2, 5, 5, 6, 9, 10]
```

Overall, the bubble sort algorithm works by iterating through the array, comparing adjacent elements, and swapping them if they are in the wrong order. This process repeats until all elements in the array are sorted in increasing order.
GLM-4V (pre-release)

who are in this picture

In this picture, there are three football players. From left to right, they are Suárez, Neymar, and Messi.
“draw a dog with a hat”
大模型驱动的知识推理
1. **100B Base model**
2. **Supervised FT**
3. **RLHF**
OpenAI’s GPT

- GPT-1
- GPT-2
- GPT-3
- GPT-4

GPT-3 davinci 100B
- GPT-3 + RLHF

RLHF
- InstructGPT
- Supervised FT

text-davinci-002
- Codex
- GitHub Copilot
- CodeGeeX
- VS Code/JetBrains
- CodeGeeX Plugin

ChatGPT (RLHF)
- New Bing (GPT-4)

GPT-3.5
- text-davinci-003 (RLHF)

WebGPT (RLHF)

THU&Zhipu AI’s GLM

- GLM-10B
- mGLM Multi-lingual
- GLM-130B 100B
- QAGLM
- CodeGeeX
- WebGLM
- ChatGLM (SFT + RLHF)
- ChatGLM-6B (SFT + RLHF)

- VisualGLM
- CogVLM

Timeline:
- 2018 6
- 2019 2
- 2020 5
- 2020 11
- 2021 5
- 2021 7
- 2021 12
- 2022 8
- 2022 11
- 2023 2
- 2023 3
- 2023 5
- 2023 2
- 2022 8
- 2022 11
- 2021 5
- 2020 11
- 2019 2
- 2018 6
# General Language Model (GLM)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoregressive (GPT)</td>
<td>—</td>
<td>—</td>
<td>√</td>
</tr>
<tr>
<td>Autoencoding (BERT)</td>
<td>√</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Encoder-Decoder (T5)</td>
<td>—</td>
<td>√</td>
<td>—</td>
</tr>
<tr>
<td>Autoregressive Blank-Infilling (GLM)</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>

*Du and Qian et al. All NLP Tasks are Generation Tasks. ACL’22. arxiv: 2103.10360*
General Language Model (GLM)

\[ \mathcal{L}_{GLM} = \mathbb{E}_{Z \sim Z_m} \left[ \sum_{i=1}^{m} \sum_{j=1}^{l_i} - \log p (s_{z_i,j} \mid x_{\text{corrupt}}, s_{Z_{<i}}, s_{Z_i,<j}) \right] \]
General Language Model (GLM)
General Language Model (GLM)

Zeng, Liu, et al. GLM-130B: An Open Bilingual Pre-trained Model. ICLR’23
## Results on Natural Language Understanding

- **Better than BERT, T5, RoBERTa**

  *Table 2. Results on the SuperGLUE dev set. Models with * are pre-trained for two times the number of steps of other methods.*

<table>
<thead>
<tr>
<th>Model</th>
<th>ReCoRD F1/Acc.</th>
<th>COPA Acc.</th>
<th>WSC Acc.</th>
<th>RTE Acc.</th>
<th>BoolQ Acc.</th>
<th>WiC Acc.</th>
<th>CB F1/Acc.</th>
<th>MultiRC F1a/EM</th>
<th>Avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT_{Base}</td>
<td>65.4/64.9</td>
<td>66.0</td>
<td>65.4</td>
<td>70.0</td>
<td>74.9</td>
<td>68.8</td>
<td>70.9/76.8</td>
<td>68.4/21.5</td>
<td>66.1</td>
</tr>
<tr>
<td>GLM_{Base}</td>
<td><strong>73.5/72.8</strong></td>
<td><strong>71.0</strong></td>
<td><strong>72.1</strong></td>
<td><strong>71.2</strong></td>
<td><strong>77.0</strong></td>
<td>64.7</td>
<td><strong>89.5/85.7</strong></td>
<td><strong>72.1/26.1</strong></td>
<td><strong>70.7</strong></td>
</tr>
<tr>
<td>BERT_{Large}</td>
<td>76.3/75.6</td>
<td>69.0</td>
<td>64.4</td>
<td>73.6</td>
<td>80.1</td>
<td><strong>71.0</strong></td>
<td>94.8/92.9</td>
<td>71.9/24.1</td>
<td>72.0</td>
</tr>
<tr>
<td>UniLM_{Large}</td>
<td>80.0/79.1</td>
<td>72.0</td>
<td>65.4</td>
<td>76.5</td>
<td>80.5</td>
<td>69.7</td>
<td>91.0/91.1</td>
<td>77.2/38.2</td>
<td>74.1</td>
</tr>
<tr>
<td>GLM_{Large}</td>
<td>81.7/81.1</td>
<td>76.0</td>
<td><strong>81.7</strong></td>
<td>74.0</td>
<td><strong>82.1</strong></td>
<td>68.5</td>
<td>96.1/94.6</td>
<td><strong>77.1/36.3</strong></td>
<td>77.0</td>
</tr>
<tr>
<td>GLM_{Large (multi-task)}</td>
<td>80.2/79.6</td>
<td>77.0</td>
<td>78.8</td>
<td>76.2</td>
<td>79.8</td>
<td>63.6</td>
<td><strong>97.3/96.4</strong></td>
<td>74.6/32.1</td>
<td>75.7</td>
</tr>
<tr>
<td>GLM_{410M (multi-task)}</td>
<td>81.5/80.9</td>
<td>80.0</td>
<td><strong>81.7</strong></td>
<td><strong>79.4</strong></td>
<td>81.9</td>
<td>69.0</td>
<td>93.2/96.4</td>
<td>76.2/35.5</td>
<td>78.0</td>
</tr>
<tr>
<td>GLM_{515M (multi-task)}</td>
<td><strong>82.3/81.7</strong></td>
<td><strong>85.0</strong></td>
<td><strong>81.7</strong></td>
<td>79.1</td>
<td>81.3</td>
<td>69.4</td>
<td>95.0/96.4</td>
<td>77.2/35.0</td>
<td><strong>78.8</strong></td>
</tr>
<tr>
<td>T5_{Base}</td>
<td>76.2/75.4</td>
<td>73.0</td>
<td>79.8</td>
<td>78.3</td>
<td>80.8</td>
<td>67.9</td>
<td>94.8/92.9</td>
<td>76.4/40.0</td>
<td>76.0</td>
</tr>
<tr>
<td>T5_{Large}</td>
<td>85.7/85.0</td>
<td>78.0</td>
<td><strong>84.6</strong></td>
<td>84.8</td>
<td>84.3</td>
<td>71.6</td>
<td>96.4/98.2</td>
<td>80.9/46.6</td>
<td>81.2</td>
</tr>
<tr>
<td>BART_{Large} *</td>
<td>88.3/87.8</td>
<td>60.0</td>
<td>65.4</td>
<td>84.5</td>
<td>84.3</td>
<td>69.0</td>
<td>90.5/92.9</td>
<td>81.8/48.0</td>
<td>76.0</td>
</tr>
<tr>
<td>RoBERTa_{Large} *</td>
<td>89.0/88.4</td>
<td><strong>90.0</strong></td>
<td>63.5</td>
<td>87.0</td>
<td><strong>86.1</strong></td>
<td><strong>72.6</strong></td>
<td>96.1/94.6</td>
<td><strong>84.4/52.9</strong></td>
<td>81.5</td>
</tr>
<tr>
<td>GLM_{RoBERTa}</td>
<td><strong>89.6/89.0</strong></td>
<td>82.0</td>
<td>83.7</td>
<td><strong>87.7</strong></td>
<td>84.7</td>
<td>71.2</td>
<td><strong>98.7/98.2</strong></td>
<td>82.4/50.1</td>
<td><strong>82.9</strong></td>
</tr>
</tbody>
</table>
Results on Generation

- The most important thing is that one model can do all the things

<table>
<thead>
<tr>
<th>Model</th>
<th>RG-1</th>
<th>RG-2</th>
<th>RG-L</th>
</tr>
</thead>
<tbody>
<tr>
<td>MASS</td>
<td>37.7</td>
<td>18.5</td>
<td>34.9</td>
</tr>
<tr>
<td>UniLM Large</td>
<td>38.5</td>
<td>19.5</td>
<td>35.8</td>
</tr>
<tr>
<td>GLM Large</td>
<td>38.6</td>
<td>19.7</td>
<td>36.0</td>
</tr>
<tr>
<td>GLM Large (multi-task)</td>
<td>38.5</td>
<td>19.4</td>
<td>35.8</td>
</tr>
<tr>
<td>GLM 410M (multi-task)</td>
<td><strong>38.9</strong></td>
<td><strong>20.0</strong></td>
<td><strong>36.2</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Lambda (Accuracy)</th>
<th>BookWiki (Perplexity)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLM Large (uni)</td>
<td>0.0</td>
<td>&gt; 100</td>
</tr>
<tr>
<td>GLM Large (multi-task,uni)</td>
<td>47.4</td>
<td>15.1</td>
</tr>
<tr>
<td>– 2d positional encoding</td>
<td>45.8</td>
<td>15.1</td>
</tr>
<tr>
<td>GLM 410M (multi-task,uni)</td>
<td>49.5</td>
<td>14.5</td>
</tr>
<tr>
<td>GLM 515M (multi-task,uni)</td>
<td><strong>50.4</strong></td>
<td><strong>13.9</strong></td>
</tr>
<tr>
<td>GLM Large (bi)</td>
<td>10.6</td>
<td>&gt; 100</td>
</tr>
<tr>
<td>GLM Large (multi-task,bi)</td>
<td>48.5</td>
<td>14.9</td>
</tr>
<tr>
<td>– 2d positional encoding</td>
<td>47.3</td>
<td>15.0</td>
</tr>
<tr>
<td>GLM 410M (multi-task,bi)</td>
<td><strong>53.5</strong></td>
<td><strong>14.3</strong></td>
</tr>
<tr>
<td>GLM 515M (multi-task,bi)</td>
<td><strong>54.9</strong></td>
<td><strong>13.7</strong></td>
</tr>
<tr>
<td>GPT Large (uni)</td>
<td>50.1</td>
<td>14.4</td>
</tr>
</tbody>
</table>
Why 100B-scale model?

- What is 16 mod 12?
- 16 divided by 12 equals 1 remainder 4. So the answer is 4!

Why 100B-scale model?

(A) Mod. arithmetic
(B) IPA transliterate
(C) Word unscramble
(D) Persian QA

(E) TruthfulQA
(F) Grounded mappings
(G) Multi-task NLU
(H) Word in context
Scaling Law

Scaling Law introduces complicated reasoning abilities
“Emergent abilities”
How to train a 100B-scale LLM?

- 8 months have witnessed numerous challenges
  - **Engineering:** How to train 100B-scale models from scratch?
    - Hygon DCU, NVIDIA A100, Ascend 910, Sunway
    - Frequent & random hardware failures, Megatron-DeepSpeed 3D pipeline, CUDA kernel efficiency, GPU memory overflow, 10K+ threads TCP init & comms...
  - **Algorithm:** How to stabilize the training of 100B-scale models?
    - The gradient norms of embeddings, Post-LN / Pre-LN stability, dataloader state seeds, computation precision in Softmax / Attention

Project
---
Conceived: 2021.12
Debug: 2022.1

Data
---
Large-Scale Tests: 2022.2

Hygon, NVIDIA
---
Ascend, Sunway: 2022.3

Algo/Sys
---
Tests: 2022.4

Training
---
Stability Issues: 2022.5

Evaluations
---
Quantization: 2022.6

To be continued

http://keg.cs.tsinghua.edu.cn/glm-130b/
Training Stability of 100B-Scale Models

- Tradeoff: Stability (Slow) or Efficiency (Instable)

- Existing Solutions
  - **OPT-175B**: manually adjust LR & skip data when collapses (performance drop)
  - **BLOOM 176B**: embedding norm & BF16 (performance drop, few platform)

Sources: OPT / BLOOM / GLM-130B
Attention score: Softmax in 32 to avoid overflow

$$\text{softmax} \left( \frac{Q_i K_i^T}{\sqrt{d}} \right) = \text{softmax} \left( \left( \frac{Q_i K_i^T}{\alpha \sqrt{d}} - \max \left( \frac{Q_i K_i^T}{\alpha \sqrt{d}} \right) \right) \times \alpha \right) = \text{FP16} \left( \text{softmax} \left( \text{FP32} \left( \frac{Q_i K_i^T}{\alpha \sqrt{d}} \right) \times \alpha \right) \right)$$

Attention scores grow large --- exceeding FP16’s range

Zeng, Liu, et al. GLM-130B: An Open Bilingual Pre-trained Model. ICLR’23
Embedding Layer Gradient Shrink (EGS)

\[
\text{word\_embedding} = \text{word\_embedding} \times \alpha + \text{word\_embedding} . \text{detach}() \times (1 - \alpha)
\]

Embedding Layer gradients can be magnitudes larger than others

(a) Gradient norm of embedding layer (left) and the first layer (right)

(b) Training loss curves of GLM-40B with and without gradient shrink

Zeng, Liu, et al. GLM-130B: An Open Bilingual Pre-trained Model. ICLR'23
GLM-130B: Training Stability

- The final training run of GLM-130B

Zeng, Liu, et al. GLM-130B: An Open Bilingual Pre-trained Model. ICLR'23
GLM-130B Training Lessons

2021.12
- The "千亿 “(100B) project towards an open dense pre-trained GLM at 100B scale is conceived
- Survey pre-training strategies of existing models of similar scale, such as GPT-3, Gopher => Limited public info about how they were trained and issues they met
- Search for possible GPU clusters & sponsors

2022.1
- Test the performance of FP16/FP32 at 100B scale on one testing cluster
- Unexpected excessive memory usage in GLM => Torch is better with fixed length input sequences
- Inability to converge and try tricks from CogView and VIT => Use Sandwich-LN
- Frequent random hardware failures => Have to run HCPG test before each run

2022.2
- Very slow training speed than previously calculated => Optimize kernels and fuse operators => Find the input shape is critical to kernel performance
- Collect pre-training corpora and tokenize => Use icetk: the sentence piece is set to the unigram mode
- Debug the 3D pipeline parallel in the newly-released Megatron and DeepSpeed

2022.3
- It can’t recover perfectly from optimizer states => Our customized dataloaders do not save its state seed properly in distributed training
- The memory per processor is too small => Require too many pipeline stages => Batch size is too large (up to 12,000) => Harm the model’s convergence
- It can’t launch more than 2,000 computing nodes => Overcome this and support 6,000-node training by tuning Linux kernel TCP parameters
- Collect data for multi-task instruction pre-training
- Receive opportunities to test trainings on several other clusters
- Very slow training speed than expected => The underlying element-wise operators don’t support fast computation on large-dimension vectors.

2022.4
- Optimize A100 kernel’s computing efficiency => A100 kernels prefer square-shaped inputs, and seq_len=2,048 is optimal for our hidden-state dimension (12,288)
- Inability to converge due to large gradient norms (170+) of input embeddings => Try embedding norm and gradient shrink, which turn out to be almost equivalent
- Naïve post-LN or pre-LN converges after several thousands of steps => Try Sandwich-LN with PB-Relax
- It still converges after one week’s trial => The dataloader state seeds are not unified for different pipeline stages, resulting in a mismatch of input data and labels.
- Test two positional encodings: RoPE and Alibi => Alibi can be slower as it requires element-wise manipulation on attention matrices—changing num_heads * 2,048 * 2,048 scalars per layer
- Test GeGLU and GAU => GAU converges faster with relatively poor performance on fine-tuned SuperGLUE
- Abnormal GPU memory usage of newly-added functions and classes => DeepSpeed hardcodes the function names for checkpoint activation
- Decode to train GLM with 130 billion parameters => allow inference on a DGX-A100 40G node

2022.5-6
- Implement a RoPE cuda operator in C++ => See unexpected precision errors and finally have it abandoned
- Sandwich-LN still converges => 1) Reducing learning rate does not help; 2) Using Hinge cross-entropy becomes slower and harms performance; 3) Shifting to DeepNorm still converges
- Use FP32 in softmax of attention => Success
- Find PB-Relax unnecessary for FP32 softmax => It also slows down training as it needs to manipulate the whole attention score matrices
- Experience few spikes in later training => 1) Reduce gradient shrink factor from 1 to 0.1: useful; 2) Reduce the learning rate: sometimes useful; 3) Jump the noisy data batches: sometimes useful
- Find a mistake in multi-task data after training for 20,000 steps => Use the correct data but it does not forget

2022.6-7
- Adapt the pipeline parallel checkpoints to ordinary parallel checkpoints for efficient inference on a single A100
- Work on evaluation scripts on datasets: MMLU, Big-bench, CLUE, SuperCLUE, etc.
- Implement P-Tuning and P-Tuning v2 for parameter-efficient tuning on GLM-130B for tuning on SuperGLUE
- Work with BMInn on adapting GLM-130B to perform inference on a single V100 or 3090 => Use pipeline-style asynchronous swapping between main memory and GPU memory
- Try to fine-tune GLM-130B with fewer A100 nodes (i.e., 12-16 nodes) => Pipeline-style fails due to too many pipeline stages => Find that data parallel cannot be introduced for fine-tuning => Use 32-way model parallel for fine-tuning with reasonable performance

Zeng, Liu, et al. GLM-130B: An Open Bilingual Pre-trained Model. ICLR’23
https://github.com/THUDM/GLM-130B
GLM-130B

Aug., 2022-Mar. 2023, research use requests from ~1000 orgs in 70 countries

- Google
- Microsoft
- Facebook
- Stanford
- MIT
- UC Berkely
- CMU
- Harvard
- Princeton
- Yale
- Cornell
- UIUC
- Cambridge
- Oxford
- Huawei
- Alibaba
- Tencent
- Baidu
- Meituan
- Bytedance
- Didi
- Xiaoice
- Xiaodu
- Xiaomi
- Xiaopeng
- Youdao
- Face++
- Ping An Cap
- Peking U.
- Zhejiang U.
- Shanghai JT U.
- Fudan U.
- USTC
- U of CAS
- Wuhan U.
- Naikai U.
- Hongkong U.
- CUHK
- HKUST
- BAAI
- Zhejiang Lab
- Shanghai AI Lab
## GLM-130B in HELM

Stanford’s Holistic Evaluation of Language Models (HELM, Nov. 2022)

<table>
<thead>
<tr>
<th>Model</th>
<th>Model Creator</th>
<th>Modality</th>
<th># Parameters</th>
<th>Tokenizer</th>
<th>Window Size</th>
<th>Access</th>
<th>Total Tokens</th>
<th>Total Queries</th>
<th>Total Cost</th>
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</thead>
<tbody>
<tr>
<td>J1-Jumbo v1 (178B)</td>
<td>AI21 Labs</td>
<td>Text</td>
<td>178B</td>
<td>AI21</td>
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<td>17B</td>
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<td>BLOOM (176B)</td>
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<tr>
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<td>$2,973</td>
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<tr>
<td>UL2 (20B)</td>
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<td>20B</td>
<td>Google</td>
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<tr>
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<td>Text</td>
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<td>Text</td>
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<td>59,751</td>
<td>$85</td>
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<td>GLM (130B)</td>
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<td>GLM</td>
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<td>2,100 GPU hours</td>
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<td>100B</td>
<td>YalM</td>
<td>2048</td>
<td>open</td>
<td>378,607,292</td>
<td>405,093</td>
<td>2,100 GPU hours</td>
</tr>
</tbody>
</table>


GLM-130B in HELM

Accuracy ↑

InstructGPT davinci v2 (175B*)
- TNLG v2 (530B)
- Anthropic-LM v4-s3 (52B)
- OPT (175B)
- Cohere xlarge v20220609 (52.4B)
- J1-Jumbo v1 (178B)
- GPT-3 davinci v1 (175B)
- GLM (130B)
- OPT (66B)
- BLOOM (176B)
- J1-Grande v1 (1.7B)
- Cohere large v20220720 (13.1B)
- GPT-NeoX (20B)
- J1-Large v1 (7.5B)
- InstructGPT curie v1 (6.7B*)
- TNLG v2 (6.7B)
- GPT-3 curie v1 (6.7B)
- GPT-j (6B)
- Cohere medium v20220720 (6.1B)
- InstructGPT babbage v1 (1.3B*)
- UL2 (20B)
- T0pp (11B)
- T5 (11B)
- YaLM (100B)
- GPT-3 babbage v1 (1.3B)
- Cohere medium v20220720 (6.1B)
- InstructGPT babbage v1 (1.3B*)
- T0pp (11B)
- T5 (11B)
- YaLM (100B)
- GPT-3 babbage v1 (1.3B)
- Cohere small v20220720 (410M)
- InstructGPT ada v1 (350M*)
- GPT-3 ada v1 (350M)

Robustness ↑

InstructGPT davinci v2 (175B*)
- Anthropic-LM v4-s3 (52B)
- GLM (130B)
- TNLG v2 (530B)
- BLOOM (176B)
- OPT (175B)
- Cohere xlarge v20220609 (52.4B)
- J1-Jumbo v1 (178B)
- GPT-3 davinci v1 (175B)
- GLM (130B)
- J1-Grande v1 (17B)
- GPT-NeoX (20B)
- J1-Large v1 (7.5B)
- Cohere large v20220720 (13.1B)
- InstructGPT curie v1 (6.7B*)
- TNLG v2 (6.7B)
- GPT-3 curie v1 (6.7B)
- GPT-j (6B)
- Cohere medium v20220720 (6.1B)
- InstructGPT babbage v1 (1.3B*)
- UL2 (20B)
- T0pp (11B)
- T5 (11B)
- YaLM (100B)
- GPT-3 babbage v1 (1.3B)
- Cohere medium v20220720 (6.1B)
- InstructGPT babbage v1 (1.3B*)
- UL2 (20B)
- T0pp (11B)
- T5 (11B)
- YaLM (100B)
- GPT-3 babbage v1 (1.3B)
- Cohere small v20220720 (410M)
- InstructGPT ada v1 (350M*)
- GPT-3 ada v1 (350M)

Fairness ↑

InstructGPT davinci v2 (175B*)
- Anthropic-LM v4-s3 (52B)
- OPT (175B)
- BLOOM (176B)
- Cohere xlarge v20220609 (52.4B)
- OPT (66B)
- J1-Jumbo v1 (178B)
- GPT-3 davinci v1 (175B)
- GLM (130B)
- J1-Grande v1 (17B)
- Cohere large v20220720 (13.1B)
- GPT-NeoX (20B)
- J1-Large v1 (7.5B)
- InstructGPT curie v1 (6.7B*)
- TNLG v2 (6.7B)
- GPT-3 curie v1 (6.7B)
- GPT-j (6B)
- Cohere medium v20220720 (6.1B)
- InstructGPT babbage v1 (1.3B*)
- UL2 (20B)
- T0pp (11B)
- T5 (11B)
- YaLM (100B)
- GPT-3 babbage v1 (1.3B)
- Cohere small v20220720 (410M)
- InstructGPT ada v1 (350M*)

GLM-130B in HELM

INT4 Quantization for RTX 3090s/2080s

GLM’s INT4 Weight Quantization Scaling Law
## INT4 Quantization for RTX 3090s/2080s

### GLM-130B INT4 Quant. w/o perform. degradation

<table>
<thead>
<tr>
<th>Model Precision</th>
<th>GLM-130B</th>
<th>GPT-3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FP16</td>
<td>INT8</td>
</tr>
<tr>
<td>MMLU (acc, ↑)</td>
<td>44.75</td>
<td>44.71</td>
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<tr>
<td>LAMBADA (acc, ↑)</td>
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<td>80.21</td>
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<tr>
<td>Pile (a part, BPB, ↓)</td>
<td>0.634</td>
<td>0.638</td>
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</table>

<table>
<thead>
<tr>
<th>GPU Type</th>
<th>128 Enc./Dec.</th>
<th>512 Enc./Dec,</th>
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</thead>
<tbody>
<tr>
<td>8 × A100 (40G)</td>
<td>0.15s</td>
<td>4.29s</td>
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<tr>
<td>8 × V100 (32G)</td>
<td>0.31s</td>
<td>6.97s</td>
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<tr>
<td>4 × RTX 3090 (24G)</td>
<td>0.37s</td>
<td>8.16s</td>
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<tr>
<td>8 × RTX 2080 Ti (11G)</td>
<td>0.39s</td>
<td>6.77s</td>
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</tbody>
</table>

## GLM-130B

<table>
<thead>
<tr>
<th>BackBone</th>
<th>Training Objective</th>
<th>Quantization</th>
<th>Acceleration</th>
<th>Cross-Platform</th>
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<tbody>
<tr>
<td>GPT3-175B</td>
<td>GPT</td>
<td>SSL Only</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>OPT-175B</td>
<td>GPT</td>
<td>SSL Only</td>
<td>INT8</td>
<td>Megatron</td>
</tr>
<tr>
<td>BLOOM-176B</td>
<td>GPT</td>
<td>SSL Only</td>
<td>INT8</td>
<td>Megatron</td>
</tr>
<tr>
<td>GLM-130B</td>
<td>GLM</td>
<td>SSL &amp; MIP</td>
<td>• INT8 • INT4</td>
<td>Faster Transformer</td>
</tr>
</tbody>
</table>

### Effects
- **Performance Impro**:  
  - Big-bench-lite: +5.2%  
  - LAMBADA: +2.3%  
  - CLUE: +24.3%  
  - FewCLUE: +12.8%
- **Affordable Serving**:  
  - It saves 75% GPU mem in inference;  
  - It can infer on **3090x4 / 2080x8**
- **Fast Inference**:  
  - 7-8.4 faster than Pytorch;  
  - 2.5 faster than Megatron
- **Diverse Supports**:  
  - It supports more diverse adoptions of LLMs
Develop ChatGLM based on GLM-130B
Challenge 1: Simple NLP task vs. Complex task

• Simple NLP task => Complex task (e.g., logic reasoning)

**Math (GSM8k):**
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?

**Last Letter Concatenation:**
Q: Take the last letters of the words in “Lady Gaga” and concatenate them.
Challenge 2: Static NLP vs. Dynamic knowledge

- GPT-3’s knowledge can be limited, obsolete, and uninterpretable
  - Limited: Limited long-tailed knowledge
    - Example: what is the sixth highest mountain in the world? *(Answer: Mount K2)*
  - Obsolete: GPT-3’s knowledge is before 2020
  - Uninterpretable: No reference for answers that require knowledge

**Case Study: Limited Knowledge**

What is the second highest mountain on earth?

The second highest mountain on earth is Cho Oyu which is in the Himalayas in Tibet, China and Nepal. Its height is 8,188 meters or 26,906 feet which is 28 feet taller than Mount Everest.

**Case Study: Obsolete Knowledge**

Who is the president of US in 2022?

Hillary Clinton
Challenge 3: Traditional NLP vs. Align with Human

• Case Study: Explain the moon landing to a 6 year old in a few sentences.
  – Without proper `prompt engineering`, GPT-3 and GLM-130B won’t return satisfying answers, either

Input

Explain the moon landing to a 6 year old in a few sentences.

Output

Explain the moon landing to a 6 year old in a few sentences. Explain the moon landing to a 6 year old in a few sentences. Explain to a six year old how the moon was discovered. Describe the moon to a child in a way that he or she can understand. Discuss the moon with a six-year-old child. 1. 2. 3. 4. 5. 6. 7. 8. 9. Explanation: 1) The moon was first discovered by Galileo in 1610. The first person to actually see the moon from Earth was Galileo himself. He used a telescope to see the

PROMPT

Explain the moon landing to a 6 year old in a few sentences.

COMPLETION

GPT-3

Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
Develop ChatGLM based on GLM-130B

Augmenting Code, Alignment, Web, Image understanding...

- GLM-130B (ACL’22, ICLR’23)
  - Base model
    - ~1TB, 4096

- CodeGeeX (KDD’23)
  - Code→Reasoning
    - ~0.4TB, 4096
  - Supervised Fine-tune

- GLM-130B++ (GLM 3.5)
  - Instruction following
  - Web
    - WebGLM (KDD’23)
      - Combining Search

- ChatGLM
  - Chat Product
    - Image understanding
  - Visual-ChatGLM (NeurIPS’21/22, ICLR’23)
    - Multi-modal

Timeline:
- 2021.12
- 2022.09
- 2022.12
- 2022.12
- 2023.05
CodeGeeX

- 6B/13B parameters, 100+ languages
- Support both Nvidia and 910A/B
- Free VSCode and JetBrains plugins

Generating over 10M lines codes

CodeGeeX: AI Code AutoComplete, Chat, Auto Comment
Zhipu AI | 241,909 installs | ⭐⭐⭐⭐⭐ (47) | Free

CodeGeeX is an AI-based coding assistant, which can suggest code in the current or following lines. It is powered by a large-scale multilingual code generation model with 13 billion parameters, pretrained on a large code corpus of more than 20 programming languages.

Optimization
- Operators (Layernorm/Gelu/BatchMatmul/Add)
- Auto search for optimizing matrix multiplication

Performance
- Improve 257% on Ascend 910A
- Trained with over 1,000 Ascend 910A
**Relay Diffusion Model (RDM)**

https://github.com/THUDM/RelayDiffusion

- **RDM** transfers a low-resolution image into an equivalent high-resolution one via blurring diffusion and block noise.
- **RDM** achieved state-of-the-art FID on CelebA-HQ and sFID ImageNet-256 (FID=1.87)!
“draw a dog with a hat”
CogVLM

- CogVLM connects pretrained language model and image encoder by a trainable visual expert model

(a) The input of visual language model

(b) The visual expert built on the language model
CogVLM

Visual Math Problem Solving

Q1: How to solve it?

CogVLM: The problem in the picture is a simple math problem, where a sliced green apple is equated to a question mark. Specifically, in the middle of the picture, there are three green apples placed side by side and three cardboard signs. The signs have black characters on them: a plus sign, an equal sign, and a question mark. The equation shown in the picture is: $2 + 1 = ?$

Q2: What’s the final answer?

CogVLM: $2+1=3$

Grounding Visual Question Answering

Q1: What color are the clothes of the girl whose hands are holding flowers? Let’s think step by step.

CogVLM: Find the flowers [[328,519,436,780]]. Check the girl holding it, got the girl [[116,069,450,927]]. Check the clothes of it, got the clothes [[134,309,418,852]]. The clothes [[134,309,418,852]] are blue. So the answer is blue.

Q2: What color are the jeans of the girl whose hands are not holding flowers? Let’s think step by step.

CogVLM: Find the not(flowers) hands [[654,637,710,728]]. Check the girl with it, got the girl [[526,109,880,946]]. Check the jeans of it, got the jeans [[530,613,880,871]]. The jeans [[530,613,880,871]] are gray. So the answer is gray.

Achieved the best on 10+ benchmarks
GLM-4V (pre-release)

who are in this picture

In this picture, there are three football players. From left to right, they are Suárez, Neymar, and Messi.
Why do people try to maintain eye contact while communicating?

People try to maintain eye contact while communicating because it is a form of body language which can help improve communication and create a positive impression. Eye contact is a non-verbal form of communication which can help show that you are actively listening and paying attention \(^1\). It can also make others more likely to like and respect you, making it an important tool for building and maintaining relationships \(^2\). Furthermore, a lack of eye contact can negatively impact communication, making misunderstandings more likely to occur \(^3\).

[1] Why Eye Contact is Important in Communication

Eye contact is a type of body language that is extremely important during communication and conversation. Sometimes, our eyes and body language speak even more than words. Keeping eye contact with the person you are talking to shows that you are actively listening and paying attention.

[2] Why Eye Contact is Important during Conversation?
KG engine ready...

get_relations(Hurricane Marie)
[meteorology.tropical_cyclone.category, meteorology.tropical_cyclone.tropical_cyclone_season]

get_neighbors(Hurricane Marie, meteorology.tropical_cyclone.category)
variable #0

### AGENT ####

Thought: I need to first find the relations of Hurricane Marie.
Action: get_relations(Hurricane Marie)

### USER ####

Observation: [meteorology.tropical_cyclone.category, meteorology.tropical_cyclone.tropical_cyclone_season]

### ROUND 2 ####

### AGENT ####

Thought: I need to find the category of Hurricane Marie. To achieve this, I will use the meteorology.tropical_cyclone.category relation.
Action: get_neighbors(Hurricane Marie, meteorology.tropical_cyclone.category)

### USER ####

Observation: variable #0, which are instances of meteorology.tropical_cyclone

### ROUND 3 ####

### AGENT ####

Thought: Now I need to find other...
AgentTuning: Enabling Generalized Agent Abilities For LLMs

Six agentInstruct trajectory datasets
- 1,866 high-quality CoTs

Agent Tuning Mix-training
- 20% AgentInstruct + 80% ShareGPT

codes & models: http://github.com/THUDM/AgentTuning
Main Results

In-domain dist
Significant improvement

Out-domain dist
Good generalization

Better generalization
ChatGLM-6B

- Download from Huggingface
  - git clone https://huggingface.co/THUDM/chatglm3
- Download demo
  - git clone https://github.com/THUDM/ChatGLM3
  - cd ChatGLM-6B
- Install demo
  - pip install gradio
  - python web_demo.py
- Run the demo
  - python cli_demo.py
- Install the api
  - pip install fastapi uvicorn
  - python api.py
- Run ChatGLM on your own MAC (w/ Apple Silicon)
  - model = AutoModel.from_pretrained("your local path", trust_remote_code=True).half().to('mps')
<table>
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<tr>
<th>Repository</th>
<th>Stars</th>
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<th>Language</th>
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<td>ChatGLM-6B</td>
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<td>ChatGLM-6B: An Open Bilingual Dialogue Language Model</td>
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</table>

https://github.com/THUDM
**Bigmodel.ai—API Platform**

- **ChatGLM-Pro**
  - **Powerful**
  - 0.01 /1000 Tokens
  - High quality, Knowledge base, reasoning

- **ChatGLM**
  - **Flexible**
  - 0.005 /1000 Tokens
  - Balanced effect and cost, news writing, abstract generation, vertical search

- **ChatGLM-Lite**
  - **Fast**
  - 0.002 /1000 Tokens
  - High speed, lower cost, chatting, customer service, classification, extraction
What’s the next?
Abstraction and Reasoning

1. Francois Chollet. On the Measure of Intelligence. 2019
Abstraction and Reasoning

Diagram showing patterns and colors changing through abstraction and reasoning processes.
Abstraction and Reasoning

[Images of abstract pixel patterns showing steps of abstraction and reasoning process]
Generative Agent

- Generative agents: computational software agents that simulate believable human behavior
  - A “Westworld” with 25 agents; Auto-GPT; AgentGPT…
Introducing Superalignment

We need scientific and technical breakthroughs to steer and control AI systems much smarter than us. To solve this problem within four years, we’re starting a new team, co-led by Ilya Sutskever and Jan Leike, and dedicating 20% of the compute we’ve secured to date to this effort. We’re looking for excellent ML researchers and engineers to join us.
Summary

• GPT vs GLM
  – ChatGPT vs. ChatGLM
  – DALL.E vs. CogView
  – Codex vs. CodeGeeX
  – WebGPT vs. WebGLM
  – GPT-4V vs. GLM-4V (CogVLM, AgentTuning…)

• 2024-toward AGI
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Thank you!

Many many collaborators from Tsinghua and Zhipu AI!

https://github.com/THUDM/