

CogAgent: A Visual Language Model for GUI Agents

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Abstract

People are spending an enormous amount of time on digital devices through graphical user interfaces (GUIs), e.g., computer or smartphone screens. Large language models (LLMs) such as ChatGPT can assist people in tasks like writing emails, but struggle to understand and interact with GUIs, thus limiting their potential to increase automation levels. In this paper, we introduce CogAgent, an 18-billion-parameter visual language model (VLM) specializing in GUI understanding and navigation. By utilizing both low-resolution and high-resolution image encoders, CogAgent supports input at a resolution of 1120×1120 , enabling it to recognize tiny page elements and text. As a generalist visual language model, CogAgent achieves the state of the art on five text-rich and four general VQA benchmarks, including VQAv2, OK-VQA, Text-VQA, ST-VQA, ChartQA, infoVQA, DocVQA, MM-Vet, and POPE. CogAgent, using only screenshots as input, outperforms LLM-based methods that consume extracted HTML text on both PC and Android GUI navigation tasks—Mind2Web and AITW, advancing the state of the art. The model and codes are available at <https://github.com/THUDM/CogVLM>.

1. Introduction

Autonomous agents in the digital world are ideal assistants that many modern people dream of. Picture this scenario: You type in a task description, then relax and enjoy a cup of coffee while watching tasks like booking tickets online, conducting web searches, managing files, and creating PowerPoint presentations get completed automatically.

Recently, the emergence of agents based on large language models (LLMs) is bringing us closer to this dream. For example, AutoGPT [33], a 150,000-star open-source project, leverages ChatGPT [29] to integrate language un-

derstanding with pre-defined actions like Google searches and local file operations. Researchers are also starting to develop agent-oriented LLMs [7, 42]. However, the potential of purely language-based agents is quite limited in real-world scenarios, as most applications interact with humans through Graphical User Interfaces (GUIs), which are characterized by the following perspectives:

- Standard APIs for interaction are often lacking.
- Important information including icons, images, diagrams, and spatial relations are difficult to directly convey in words.
- Even in text-rendered GUIs like web pages, elements like canvas and iframe cannot be parsed to grasp their functionality via HTML.

Agents based on visual language models (VLMs) have the potential to overcome these limitations. Instead of relying exclusively on textual inputs such as HTML [28] or OCR results [31], VLM-based agents directly perceive visual GUI signals. Since GUIs are designed for human users, VLM-based agents can perform as effectively as humans, as long as the VLMs match human-level vision understanding. In addition, VLMs are also capable of skills such as extremely fast reading and programming that are usually beyond the reach of most human users, extending the potential of VLM-based agents. A few prior studies utilized visual features merely as auxiliaries in specific scenarios, e.g. WebShop [39] which employs visual features primarily for object recognition purposes. With the rapid development of VLM, can we naturally achieve universality on GUIs by relying solely on visual inputs?

In this work, we present CogAgent, a visual language foundation model specializing in GUI understanding and planning while maintaining a strong ability for general cross-modality tasks. By building upon CogVLM [38]—a recent open-source VLM, CogAgent tackles the following challenges for building GUI agents:

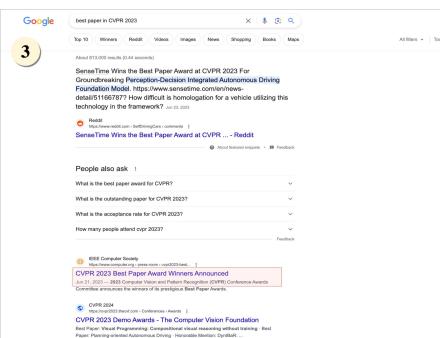
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 User: Could you guide me through the steps to “search for the best paper in CVPR 2023”?



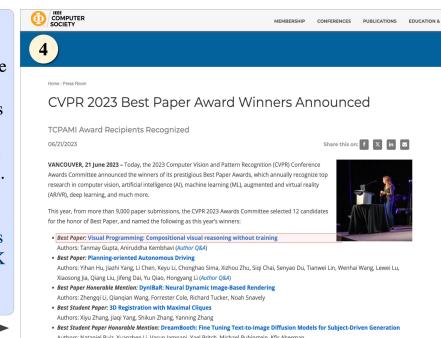
CogAgent: Move the cursor to the Google Search box located approximately at the center of the screen, then type 'best paper in CVPR 2023'.
[Operation]: [searchbox] Search -> TYPE: best paper in CVPR 2023 at the box [[250,479,750,540]]



CogAgent: Click on the area of the screen that corresponds to the 'CVPR 2023 Best Paper Award Winners Announced' link to navigate to the details of the winning papers.
[Operation]: [div] CVPR 2023 Best Paper Award Winners Announced -> CLICK at the box [[168,775,656,829]]



CogAgent: Press the enter key on the keyboard while the cursor is inside the Google Search box to initiate the search for 'best paper in CVPR 2023'.
[Operation]: Press Enter



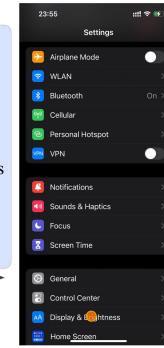
CogAgent: Move the cursor over the box that represents the link for 'Best Paper: Visual Programming: Compositional visual reasoning without training', and click.
[Operation]: [link] Best Paper: Visual Programming: Compositional visual reas... -> CLICK at the box [[087,675,817,695]]

Computer Agent

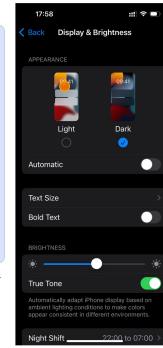
 User: Could you guide me through the steps to “change the display mode to light mode”?



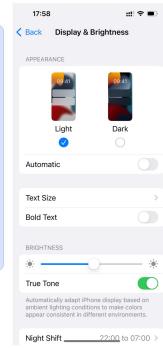
CogAgent: Touch the area on the screen where the 'Settings' icon is located. This action aims to open the settings menu where you can proceed with changing the phone's display mode to light mode.
[Operation]: tap [[396,587]]



CogAgent: Touch the area on the screen where the 'Display & Brightness' text is located. This action aims to open the display settings where you can proceed with changing the light mode.
[Operation]: tap [[450,911]]



CogAgent: Touch the area on the screen that corresponds to the 'Light' option under the 'APPEARANCE' section. This action aims to switch the display mode from dark to light.
[Operation]: tap [[305,234]]



Smartphone Agent

 User: How many likes and quotes does the tweet get?

CogAgent: The tweet gets 548 likes and 14 quotes.

 User: Why does this tweet have so many likes?

CogAgent: The tweet has many likes because it is from a well-known TV show, 'Friends', and the news of Central Perk Coffeehouse coming to Boston is likely exciting for fans.

 User: What are the recommended steps for “posting a reply ‘Brilliant!’”?

CogAgent: [Plan]: 1. Locate the reply button at the bottom of the screen.
 2. Click on the 'Post your reply' button to bring up the keyboard.
 3. Type in the text 'Brilliant!' into the reply field.
 4. Submit the reply by pressing the send or post button on the keyboard.
[Next Action]: Tap on the 'Post your reply' button located towards the bottom center of the current screen view.



 User: If you choose the fastest route, how long does it take from University of Florida to Hollywood? How far is it?

CogAgent: It takes 4 hours and 34 minutes from University of Florida to Hollywood. The distance is approximately 516 km.

 User: What are the recommended steps for “checking for the estimated time if departing at 8 a.m. tomorrow morning”?

CogAgent: [Plan]: 1. Access the time settings to change departure time.
 2. Update the departure date and time to tomorrow morning at 8 a.m.
 3. View the updated estimated time for the trip.
[Next Action]: Click on the 'Now' button next to 'Drive' to start changing the trip details.

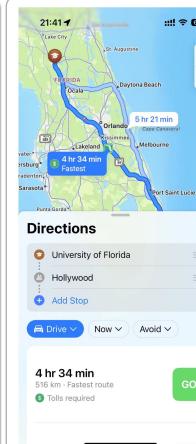


Figure 1. Samples of visual agents generated by CogAgent. More samples are demonstrated in the Appendix.

- **Training Data.** Most current VLMs are pre-trained on datasets like LAION [32], consisting of natural images on the Web. However, we notice that the GUI images share a different distribution from natural images. We thus construct a large-scale annotated dataset about GUIs and OCR for continual pre-training.
- **High-Resolution vs. Compute.** In GUIs, tiny icons and text are ubiquitous, and it is hard to recognize them in commonly-used 224×224 resolution. However, increasing the resolution of input images results in significantly long sequence length in language models. For example, a 1120×1120 image corresponds to a sequence of 6400 tokens if the patch size is 14, demanding excessive training and inference compute. To address this, we design a cross-attention branch that allows for a trade-off between the resolution and the hidden size within a proper computation budget. Specifically, we propose to combine the original large ViT [12] (4.4B parameters) used in CogVLM [38] and a new small *high-resolution cross-module* (with image encoder of 0.30B parameters) to jointly model visual features.

Our experiments show that:

- CogAgent tops popular GUI understanding and decision-making benchmarks, including AITW [31] and Mind2Web [10]. To the best of our knowledge, this is the first time that a generalist VLM can outperform LLM-based methods with extracted structured text.
- Though CogAgent focuses on GUIs, it achieves state-of-the-art generalist performance on nine visual question-answering benchmarks including VQAv2 [1], OK-VQA [23], TextVQA [34], ST-VQA [4], ChartQA [24], infoVQA [26], DocVQA [25], MM-Vet [41], and POPE [19].
- The separated design of high- and low-resolution branches in CogAgent significantly lows the compute cost for consuming high-resolution images, e.g., the number of the floating-point operations (FLOPs) for CogAgent-18B with 1120×1120 inputs is less than half that of CogVLM-17B with its default 490×490 inputs.

CogAgent is open-sourced at <https://github.com/THUDM/CogVLM>. It represents an effort to promote the future research and application of AI agents, facilitated by advanced VLMs.

2. Method

In this section, we will first introduce the architecture of CogAgent, especially the novel high-resolution cross-module,

and then illustrate the process of pre-training and alignment in detail.

2.1. Architecture

The architecture of CogAgent is depicted in Fig. 2. We build our model based on a pre-trained VLM (on the right side of the image), and propose to add a cross-attention module to process high-resolution input (on the left side of the image). As our base VLM, We select CogVLM-17B [38], an open-sourced and state-of-the-art large vison-language model. Specifically, We employ EVA2-CLIP-E [35] as the encoder for low-resolution images (224×224 pixels), complemented by an MLP adapter that maps its output into the feature space of the visual-language decoder. The decoder, a pre-trained language model, is enhanced with a visual expert module introduced by Wang et al. [38] to facilitate a deep fusion of visual and language features. The decoder processes a combined input of the low-resolution image feature sequence and text feature sequence, and autoregressively outputs the target text.

Similar to most VLMs, the original CogVLM can only accommodate images of relatively low resolution (224 or 490), which hardly meets the demands of GUI where the screen resolution of computers or smartphones is typically 720p (1280×720 pixels) or higher. It is a common problem among VLMs, e.g. LLaVA [21] and PALI-X [8] are pre-trained at a low resolution of 224×224 on the general domain. The primary reason is that high-resolution image brings prohibitive time and memory overhead: VLMs usually concatenate text and image feature sequence as input to the decoder, thus the overhead of self-attention module is quadratic to the number of visual tokens (patches), which is quadratic to the image's side length. There are some initial attempts to reduce costs for high-resolution images. For instance, Qwen-VL [2] proposes a position-aware vision-language adapter to compress image features, but only reduces sequence length by four and has a maximum resolution of 448×448 . Kosmos-2.5 [22] adopts a Perceiver Resampler module to reduce the length of the image sequence. However, the resampled sequence is still long for self-attention in the large visual-language decoder (2,048 tokens), and can only be applied to restricted text recognition tasks.

Therefore, we propose a novel *high-resolution cross-module* as a potent complement to the existing structure for enhancing understanding at high resolutions, which not only maintains efficiency confronting high-resolution images, but also offers flexible adaptability to a variety of visual-language model architectures.

2.2. High-Resolution Cross-Module

The structural design of *high-resolution cross-module* is mainly based on the following observations:

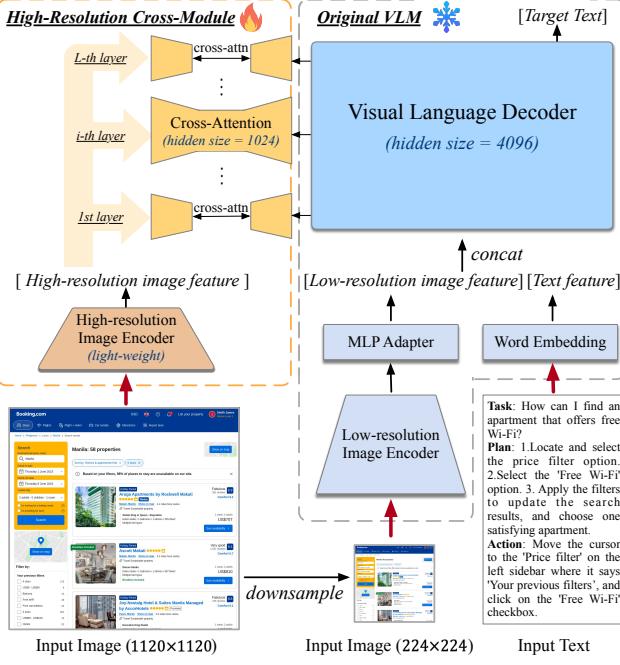


Figure 2. Model architecture of CogAgent. We adopt CogVLM as the original VLM.

1. At a modest resolution such as 224×224 , images can depict most objects and layouts effectively, yet the resolution falls short in rendering text with clarity. Hence, our new high-resolution module should emphasize text-related features, which are vital for understanding GUIs.
2. While pre-trained VLMs in general domain often need large hidden sizes (e.g. 4,096 in PALI-X and CogVLM, 5,120 in LLaVA), VLMs tailored for text-centered tasks like document OCR require smaller hidden sizes to achieve satisfying performance (e.g. 1,536 in Kosmos-2.5 and Pix2Struct [16]). This suggests that text-related features can be effectively captured using smaller hidden sizes.

As shown in Fig. 2, the high-resolution cross-module acts as a new branch for higher-resolution input, which accepts images of size 1120×1120 pixels in our implementation. Different from the original low-resolution input branch, the high-resolution cross-module adopts a much smaller pre-trained vision encoder (visual encoder of EVA2-CLIP-L [35] in our implementation, 0.30B parameters), and uses cross-attention of a small hidden size to fuse high-resolution image features with every layer of VLLM decoder, thus reducing the computational cost. To be concrete, for an input image, it is resized to 1120×1120 and 224×224 and fed into the high-resolution cross-module and the low-resolution branch respectively, then encoded into image feature sequences X_{hi} and X_{lo} with two distinct-sized

image encoders in parallel. The visual language decoder retains its original computations, while the only change is to integrate a cross-attention between X_{hi} and hidden states in every decoder layer.

Formally, suppose that the input hidden states of the i -th attention layer in the decoder are $X_{\text{in}_i} \in \mathbb{R}^{B \times (L_{I_{\text{lo}}} + L_T) \times D_{\text{dec}}}$, and the output hidden states of cross-module’s image encoder are $X_{\text{hi}} \in \mathbb{R}^{B \times (L_{I_{\text{hi}}}) \times D_{\text{hi}}}$, where B is the batch size, $L_{I_{\text{lo}}}$, $L_{I_{\text{hi}}}$ and L_T are the lengths of the low-resolution image, high-resolution image and text sequences, D_{dec} and D_{hi} is the hidden size of the decoder and high-resolution encoder’s output respectively. Each layer’s attention procedure can be formulated as

$$X'_i = \text{MSA}(\text{layernorm}(X_{\text{in}_i})) + X_{\text{in}_i}, \quad (1)$$

$$X_{\text{out}_i} = \text{MCA}(\text{layernorm}(X'_i), X_{\text{hi}}) + X'_i, \quad (2)$$

where MSA and MCA represent multi-head self-attention with visual expert and multi-head cross-attention, while X'_i and X_{out_i} represent their respective output features with the residual connection. To implement cross-attention between them, we add learnable transformation matrices $W_{K_{\text{cross}}}^i, W_{V_{\text{cross}}}^i \in \mathbb{R}^{D_{\text{hi}} \times D_{\text{cross}}}$ to get $K_{\text{cross}}^i = X_{\text{hi}} W_{K_{\text{cross}}}^i$, $V_{\text{cross}}^i = X_{\text{hi}} W_{V_{\text{cross}}}^i \in \mathbb{R}^{L_{I_{\text{hi}}} \times D_{\text{cross}}}$, and $W_{Q_{\text{cross}}}^i \in \mathbb{R}^{D_{\text{dec}} \times D_{\text{cross}}}$ to get $Q_{\text{cross}}^i = X'_i W_{Q_{\text{cross}}}^i \in \mathbb{R}^{(L_{I_{\text{lo}}} + L_T) \times D_{\text{cross}}}$ in every decoder layer. With the residual connection in Eq. 2, the cross-attention with high-resolution images can be perceived as a complement to the features of low-resolution images, thereby effectively utilizing the previous pre-trained model in low resolution.

Computational complexity. Let the number of attention head be H_{cross} and H_{dec} in cross-attention and self-attention, and the dimension of each head be $d_{\text{cross}} = D_{\text{cross}} / H_{\text{cross}}$ and $d_{\text{dec}} = D_{\text{dec}} / H_{\text{dec}}$. If using our high-resolution cross-module, the computational complexity of attention is

$$\begin{aligned} T_{\text{improved}} = \mathbf{O}((L_{I_{\text{lo}}} + L_T)L_{I_{\text{hi}}}H_{\text{cross}}d_{\text{cross}} \\ + (L_{I_{\text{lo}}} + L_T)^2H_{\text{dec}}d_{\text{dec}}). \end{aligned} \quad (3)$$

Note that d_{cross} and H_{cross} can be flexibly adjusted according to computational budget and model performance. If not utilizing the high-resolution cross-module and directly substituting low-resolution images with high-resolution ones, the computational complexity would be

$$T_{\text{original}} = \mathbf{O}((L_{I_{\text{hi}}} + L_T)^2H_{\text{dec}}d_{\text{dec}}). \quad (4)$$

In our implementation, $d_{\text{cross}} = 32$, $H_{\text{cross}} = 32$, and we inherit $d_{\text{dec}} = 128$, $H_{\text{dec}} = 32$ from CogVLM-17B. Both high- and low-resolution encoders patchify images with 14×14 -pixel patches, thus $L_{I_{\text{hi}}} = 6400$, $L_{I_{\text{lo}}} = 256$. Our method leads to at least $\frac{L_{I_{\text{hi}}} + L_T}{L_{I_{\text{lo}}} + L_T} = \frac{6400 + L_T}{256 + L_T} \times$ acceleration which is a stringent lower bound (refer to Appendix for detailed derivation), and reduces memory overhead at the same time.

2.3. Pre-training

To enhance the model’s ability to comprehend high-resolution images and adapt it for GUI application scenarios, we focus our pre-training efforts on the following aspects: the capability to recognize texts of various sizes, orientations, and fonts in high-resolution images, the grounding ability of text and objects in the image, and a specialized understanding capability for GUI imagery such as web page. We divide our pre-train data into three parts based on the aforementioned aspects, with samples in the Appendix. All the pre-training data are derived from publicly available datasets. The construction methods are detailed below.

Text recognition. Our data includes (1) Synthetic renderings with text from language pre-training dataset (80M). This is similar to the Synthetic Document Generator in Kim et al. [15], with text of varying font, size, color and orientation, and diverse image background from LAION-2B [32]. (2) Optical Character Recognition (OCR) of natural images (18M). We collect natural images from COYO [6] and LAION-2B [32] and employ Paddle-OCR [13] to extract the texts and their bounding boxes, and filter out images with no text boxes. Paddle-OCR may introduce some errors, which can be ameliorated through integration with other pre-training datasets and subsequent fine-tuning processes. (3) Academic documents (9M). We follow Nougat [5] to construct image-text pairs including text, formula and tables from the source code (LaTeX) release on arXiv. For (1)(3), we apply the same data augmentation as Nougat which includes erosion, gaussian noise, gaussian blur, image compression, and elastic transform, etc. For (2), we additionally employed more aggressive rotation and flipping data augmentation techniques, thereby enhancing the model’s robustness in recognizing text.

Visual grounding. It is imperative for GUI agents to possess the capability to accurately comprehend and locate diverse elements within images. Therefore, we incorporated a range of grounding data into pre-training. We follow CogVLM [38] to use a constructed visual grounding dataset of 40M images with image-caption pairs sampled from LAION-115M [18], which associate entities in the caption with bounding boxes to indicate their positions. The format of the bounding box is $[[x_0, y_0, x_1, y_1]]$, where (x_0, y_0) and (x_1, y_1) represent the coordinates of upper-left and lower-right corners which are normalized to [000, 999]. If multiple objects are indicated by a single noun phrase, their boxes are separated by semicolons in double square brackets. We have also collected grounding data on web page elements, which will be introduced in the next part.

GUI imagery. Our approach innovatively addresses the scarcity and limited relevance of GUI images in datasets like LAION and COYO, which predominantly feature natural images. GUI images, with their distinct elements such as input fields, hyperlinks, icons, and unique layout charac-

teristics, require specialized handling. To boost the model’s capability in interpreting GUI imagery, we have conceptualized two pioneering GUI grounding tasks: (1) GUI Referring Expression Generation (REG) – where the model is tasked with generating HTML code for DOM (Document Object Model) elements based on a specified area in a screenshot, and (2) GUI Referring Expression Comprehension (REC) – which involves creating bounding boxes for given DOM elements. To facilitate robust training in GUI grounding, we have constructed the CCS400K (Common Crawl Screenshot 400K) dataset. This extensive dataset is formed by extracting URLs from the latest Common Crawl data, followed by capturing 400,000 web page screenshots. Alongside these screenshots, we compile all visible DOM elements and their corresponding rendered boxes using Playwright¹, supplementing the dataset with 140 million REC and REG question-answer pairs. This rich dataset ensures comprehensive training and understanding of GUI elements. To mitigate the risk of overfitting, we employ a diverse range of screen resolutions for rendering, selected randomly from a list of commonly used resolutions across various devices. Additionally, to prevent the HTML code from becoming overly extensive and unwieldy, we perform necessary data cleaning by omitting redundant attributes in the DOM elements, following the method outlined in [16].

We also incorporate publicly available text-image datasets including LAION-2B and COYO-700M (after removing the broken URLs, NSFW images, and images with noisy captions and political bias) during pre-training.

We pre-train our CogAgent model for a total of 60,000 iterations with a batch size of 4,608 and a learning rate of 2e-5. We freeze all parameters except the newly added high-resolution cross-module for the first 20,000 steps, resulting in a total number of 646M (3.5%) trainable parameters, then additionally unfreeze the visual expert in CogVLM for the next 40,000 steps. We warm up with curriculum learning by first training on easier text recognition (synthetic renderings and OCR on natural images) and image captioning, then sequentially incorporating harder text recognition (academic document), grounding data and web page data, as we observed that it leads to faster convergence and more stable training in our preliminary experiments.

2.4. Multi-task Fine-tuning and Alignment

To enhance our model’s performance for diverse tasks and ensure it aligns with free-form human instructions in the GUI setting, we further fine-tune our model on a broad range of tasks. We manually collected over two thousand screenshots from mobile phones and computers, each annotated with screen elements, potential tasks, and methods of operation in the question-answering format by human annotators (details illustrated in the Appendix). We also utilize

¹<https://playwright.dev>

Mind2Web [10] and AITW [31], datasets focusing on web and Android behaviors which comprise tasks, sequences of actions and corresponding screenshots, and convert them into a natural language question-and-answer format using GPT-4. Besides, we incorporate multiple publicly available visual question-answering (VQA) datasets encompassing a variety of tasks into our alignment dataset. We unfreeze all model parameters during this stage and train for 10k iterations with a batch size of 1024 and a learning rate of 2e-5.

3. Experiments

To evaluate the foundational capabilities and GUI-related performance of our model, we conduct extensive experiments on a broad range of datasets. First, we conduct evaluations on eight VQA benchmarks, as well as MM-Vet [41] and POPE [19], which validate our model’s enhanced ability in visual understanding, especially on those that are reliant on text recognition. Then we evaluate our model on Mind2Web and AITW datasets, as the representative of two major GUI scenarios — computers and smartphones.

3.1. Foundational Visual Understanding

We first extensively evaluate CogAgent’s foundational visual understanding capability across eight VQA benchmarks, covering a wide range of visual scenes. The benchmarks can be divided into two categories: general VQA, including VQAv2 [1] and OK-VQA [23], and text-rich VQA, including TextVQA [34], OCR-VQA [27], ST-VQA [4], DocVQA [25], InfoVQA [26] and ChartQA [24]. The latter category emphasizes the understanding of visually-situated text, including documents, charts, photographs containing text, etc. Contrary to models individually fine-tuned for optimal performance on each downstream task, our model is fine-tuned collectively on all datasets simultaneously, yielding a single generalist model which is then evaluated across all datasets. The goal of generalist evaluation is to better mirror real-world situations of visual agents where typically a single model is used, and to demonstrate the model’s versatility and robustness across tasks.

The results are presented in Tab. 1. For general VQA, CogAgent achieves state-of-the-art generalist results on both datasets. For text-rich VQA, CogAgent achieves state-of-the-art results on 5 out of 6 benchmarks, significantly surpassing generalist competitors (TextVQA+8.0, ChartQA+2.1, InfoVQA+2.3, DocVQA+16.2), even outperforming the task-specific state-of-the-art models on TextVQA(+4.7), STVQA(+0.6) and DocVQA(+1.6). Notably, compared to the generalist results of CogVLM which CogAgent is initially based on, CogAgent demonstrates certain improvements on both general and Text-rich VQA tasks, suggesting the efficacy of our proposed model architecture and training methods.

Furthermore, we conducted zero-shot tests of our model on the challenging MM-Vet [41] and POPE [19] datasets, both of which are instrumental in gauging the multi-modal capabilities and the generalization performance in complex tasks including conversation question-answering, detailed descriptions, complex reasoning tasks. MM-Vet is designed with six core tasks to assess multi-modal models’ proficiency in handling intricate assignments, and POPE-adversarial models on their susceptibility to hallucinations. Our experimental results, as detailed in Table 2, showcase that our model significantly outperforms other existing models in both datasets. Notably, on the MM-Vet dataset, our model achieved a remarkable score of 52.8, surpassing the closest competitor, LLaVA-1.5, by a substantial margin (+16.5). On the POPE-adversarial evaluation, our model attained a score of 85.9, demonstrating superior handling of hallucinations compared to other models.

These results indicate CogAgent’s robust performance in foundational visual understanding, especially in the interpretation of images with embedded text. With these core competencies, the model can be feasibly applied to various visual agent tasks across different GUI environments.

3.2. GUI Agent: Computer Interface

We evaluate CogAgent on Mind2Web, a dataset for web agents that includes over 2,000 open-ended tasks collected from 137 real-world websites across 31 domains. Each entry in the dataset comprises a high-level task description, a sequence of actions, and webpage snapshots in a variety of formats, including HTML and screenshots. Given task description, current webpage snapshot and previous actions as inputs, agents are expected to predict the subsequent action. We follow the setting of Deng et al. [10] in our experiments, and report step success rate (step SR) metric. Further details are attached in the Appendix.

Several language models were evaluated on this benchmark. For instance, AgentTuning [42] and MindAct [10] evaluated Llama2-70B and Flan-T5-XL in a fine-tuned setting, and GPT-3.5 and GPT-4 in a in-context learning setting. However, limited by the input modality of language models, these models could only use heavily cleansed HTML as the representation of screen inputs. To the best of our knowledge, no visually-based web agents have been experimented with on this benchmark.

We fine-tune our model on the train set and evaluate on three out-of-domain subsets, i.e. cross-website, cross-domain, and cross-task. We additionally fine-tune LLaMA2-7B and LLaMA2-70B as the baseline of fine-tuned LLMs, and adopt the same HTML cleansing process as Deng et al. [10] to construct HTML input. The results are presented in Sec. 3.2. Compared to other methods, our approach achieved significant performance improvements across all three subsets, surpassing LLaMA2-70B, which

Method	General VQA				Text-rich VQA			
	VQAv2	OKVQA	OCRVQA	TextVQA	STVQA	ChartQA	InfoVQA	DocVQA
<i>task-specific fine-tuning models</i>								
Pix2Struct [16]	-	-	-	-	-	58.6	40.0	76.6
BLIP-2 [18]	82.2	59.3	72.7	-	-	-	-	-
PALI-X-55B [8]	<u>86.0</u>	<u>66.1</u>	75.0	71.4	79.9	<u>70.9</u>	<u>49.2</u>	80.0
CogVLM _{task-specific} [38]	84.7	64.7	74.5	69.7	-	-	-	-
<i>generalist models</i>								
UReader [40]	-	57.6	-	-	-	59.3	42.2	65.4
Qwen-VL [2]	79.5	58.6	75.7	63.8	-	65.7	-	65.1
Qwen-VL-chat [2]	78.2	56.6	70.5	61.5	-	66.3	-	62.6
Llava-1.5 [20]	80.0	-	-	61.5	-	-	-	-
Fuyu-8B [3]	74.2	60.6	-	-	-	-	-	-
CogVLM _{generalist} [38]	83.4	58.9	74.1	68.1	-	-	-	-
CogAgent (Ours)	83.7	61.2	75.0	76.1	80.5	68.4	44.5	81.6

Table 1. **Performance on Visual Question Answering benchmarks.** Bold text indicates the best score among the generalist category, and underlined text represents the best score across both generalist and task-specific categories.

is nearly 4× the scale of CogAgent, by 11.6%, 4.7%, and 6.6%, respectively. This reflects not only the capability of our model but also the advantages of employing a visual agent in computer GUI scenarios.

3.3. GUI Agent: Smartphone Interface

To evaluate our model on diverse smartphone interfaces and tasks, we utilize Android in the Wild (AITW) dataset [31], a large-scale dataset for Android device agents. It comprises 715k operation episodes, covering 30k distinct task instructions, four Android versions, and eight device types featuring varying screen resolutions. Each episode in the dataset consists of a goal described in natural language, followed by a sequence of actions and corresponding screenshots. The training target is to predict the next action based on the given goal, historical actions, and the screenshot. AITW considers a wide range of action types, including tapping, swiping, typing, going home, going back, entering, etc. For each action, models are required to predict the exact action type; for tap, swipe and type, models are further required

Method	LLM	MM-Vet	POPE _{adv}
BLIP-2 [18]	Vicuna-13B	22.4	-
Otter [17]	MPT-7B	24.7	-
MiniGPT4 [44]	Vicuna-13B	24.4	70.4
InstructBLIP [9]	Vicuna-13B	25.6	77.3
LLaVA [21]	LLaMA2-7B	28.1	66.3
LLaMA-Adapter v2 [14]	LLaMA-7B	31.4	-
DreamLLM [11]	Vicuna-7B	35.9	76.5
LLaVA-1.5 [20]	Vicuna-13B	36.3	84.5
Emu [36]	LLaMA-13B	36.3	-
CogAgent (Ours)	Vicuna-7B	52.8	85.9

Table 2. **Evaluation of CogAgent on conversational style QA and hallucination assessment.** Regarding the POPE dataset, we use its adversarial subset for this evaluation.

Method	cross-task	cross-website	cross-domain	overall
<i>Representations of screen inputs: HTML</i>				
GPT-3.5[29](few-shot)	18.6	17.4	16.2	17.4
GPT-4[30] [†] (few-shot)	36.2	30.1	26.4	30.9
Flan-T5XL [10]	52.0	38.9	39.6	43.5
LLaMA2-7B[37]	52.7	47.1	50.3	50.1
LLaMA2-70B[37]	55.8	51.6	55.7	54.4
<i>Representations of screen inputs: Image</i>				
CogAgent (Ours)	62.3	54.0	59.4	58.2

Table 3. **Performance on Mind2Web.** [†] denotes element selection from top-10 element candidates, others from top-50, following Deng et al. [10]. Results for GPT-3.5 and GPT-4 are from Deng et al. [10].

Method	GoogleApp	Install	WebShop	General	Single	Overall
<i>Representations of screen inputs: textual description (OCR+icon)</i>						
GPT-3.5[29](few-shot)	10.47	4.38	8.42	5.93	9.39	7.72
LLaMA2-7B[37] [†]	30.99	35.18	19.92	28.56	27.35	28.40
<i>Representations of screen inputs: image</i>						
Auto-UIUnified[43]	71.37	76.89	70.26	68.24	84.58	74.27
CogAgent (Ours)	74.95	78.86	71.73	65.38	93.49	76.88

Table 4. **Performance on Android in the Wild (AITW) dataset.** [†] represents models individually fine-tuned on each subset, while others are unified models across all subsets. The results of LLaMA2 and GPT-3.5 are from Zhan and Zhang [43].

to predict the position, direction, and content to be typed, respectively.

We conduct comparisons with two kinds of baselines: language models using the textual description of UI elements provided by the original dataset (text OCR and icon) as the representations of screen inputs², and visual-language

²Some Android applications may have View Hierarchy which is more friendly to language-based agents, but most of them tend to be poor quality or missing altogether. Therefore, as a large-scale, general-purpose dataset, AITW retained the results of OCR detection and icon detection as textual

models using images as the screen inputs. We simultaneously fine-tuned on all the subsets, yielding a unified model which is then evaluated on all test sets. As the GoogleApps subset is 10-100 times larger than other subsets, we downsample it to 10% to avoid data imbalance.

Results are shown in Tab. 4. CogAgent achieves state-of-the-art performance compared to all previous methods. In comparison to language-based methods, our model surpasses both baselines by a large margin. In comparison to the visual-language baseline, Auto-UI, our model achieves +2.61 improvements in the overall performance. In instances of inaccuracies, we randomly sample hundreds of cases, and upon reassessment, more than 40% are determined to be correct (refer to the appendix for details). This diversity arises from the multiple valid pathways inherent in mobile interactions, resulting in a range of responses.

4. Ablation Study

To thoroughly comprehend the impact of various components in the methodology, we conduct ablation studies on two aspects, model architecture and training data. The evaluation is conducted on diverse datasets, including multiple VQA datasets (STVQA, OCRVQA, DocVQA) and a web agent dataset (Mind2Web). For VQA datasets, we fine-tune the model on four datasets together for 3,000 iters with a batch size of 1,280, and report the generalist score; for Mind2Web, models are fine-tuned for 2,400 iters with a batch size of 128 and use top-10 setting. Training iterations are fewer than those in the main experiment, aiming to control variables within the constraints of a limited budget.

4.1. Model Architecture

To ascertain the efficacy of the high-resolution cross-module, we compare it with directly increasing the resolution using the original model architecture of CogVLM, and ablate on two perspectives: computational efficiency and model performance.

To measure computational overhead, we use floating point operations (FLOPs) as the metric, and conduct experiments on multiple resolutions including 224, 490, 756, and 1120. From Fig. 3 we can see that, as the image resolution increases, models that use a high-resolution cross-module experience only a modest rise in computational overhead, demonstrating an almost linear relationship with the number of image patches. In contrast, using the original model structure, i.e. CogVLM, leads to a significant increase in the number of FLOPs at higher resolutions. Its FLOPs can even be more than 10 times higher compared to employing a cross-module at a resolution of 1120, which is the resolution utilized by CogAgent.

representations of screenshots.

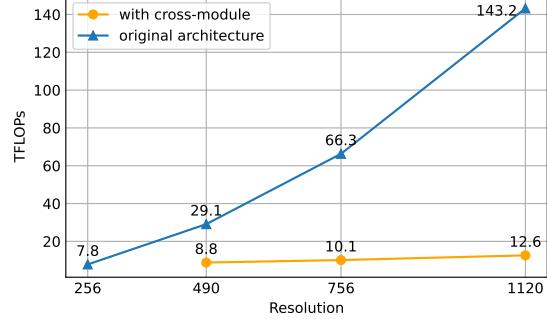


Figure 3. Comparison of FLOPs during forward propagation for different model architectures and resolutions.

We further compare the model performance in Tab. 5, which indicates that models with high-resolution cross-module at the resolution of 756 require only 1/2 of the computational resources used by the original structure at the resolution of 490, while delivering significantly better performance. Additionally, the high-resolution cross-module allows for further increasing models’ acceptable resolution within a limited computational budget, thereby yielding additional performance improvements.

	high-res	base	cross	STVQA	OCRVQA	DocVQA	Mind2Web	training time/it (s)	TFLOPs
	res	res	res						
✗	224	—	48.0	70.2	28.6	34.6	2.36	7.77	
✗	490	—	68.1	74.5	57.6	40.7	6.43	29.14	
✓	224	756	73.6	74.2	62.3	40.7	3.57	10.08	
✓	224	1120	78.2	75.9	74.1	41.4	5.17	12.56	

Table 5. Ablation study on model architecture. Training time is evaluated on A800 with the batch size of 8. Models are pre-trained with Caption+OCR data.

4.2. Pre-train Data

	pre-train data	base	res	cross	res	STVQA	OCRVQA	DocVQA	Mind2Web
Cap		490	—	—	—	68.1	74.5	57.6	38.6
Cap+OCR		490	—	—	—	72.5	75.0	59.8	40.7
Cap+OCR		224	1120	—	—	78.2	75.9	74.1	41.4
All		224	1120	—	—	79.4	75.6	76.4	54.2

Table 6. Ablation study on pre-train data with sequentially added image captioning, OCR and other pre-train data.

We further conduct an ablation study on pre-training data, which is an integral part of training visual agents. Building upon the image-caption data commonly used in visual-language training, we sequentially add OCR data (denoted as Cap+OCR), as well as GUI and grounding data (denoted as All). The results in Tab. 6 indicate that each part of data broadly contributes to enhanced performance. Notably, web and grounding data have a significant impact on the Mind2Web dataset, underscoring the importance of

constructing domain-specific pre-train data in the training of GUI agents.

5. Conclusion

We introduce CogAgent, a VLM-based GUI agent with enhanced pre-train data construction and efficient architecture for high-resolution input. CogAgent achieves state-of-the-art performance on a wide range of VQA and GUI benchmarks, and will be open-sourced.

CogAgent is an initial exploration of VLM-based GUI agent, and still has some shortcomings, e.g. imprecise output coordinates and incapability of processing multiple images, necessitating further research.

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Appendix

1. Details of Training Configurations

We report the detailed training settings of CogAgent in Table 7, and model configurations of CogAgent in Table 8.

Configurations	Pre-train	Multi-task
Total steps	60,000	10,000
Warmup steps	500	500
Batch size	4,608	1,024
Learning rate		2×10^{-5}
Learning rate decay		Cosine
Weight decay		0.05
Dropout ratio		0.1
Adam ϵ		1×10^{-5}
Adam β		(0.9, 0.95)

Table 7. Training settings of pre-training and multi-task fine-tuning.

VLM decoder	
Architecture	Vicuna-1.5-7B + visual expert
Layers	32
Hidden size	4,096
Attention heads	32
Low-resolution visual encoder	
Architecture	EVA2-CLIP-E
Input resolution	224×224
Patch size	14×14
High-resolution visual encoder	
Visual encoder	EVA2-CLIP-L
Input resolution	1120×1120
Patch size	14×14
Cross Attention	
Hidden size	1,024
Attention heads	32

Table 8. Model configurations of CogAgent.

2. Details of Evaluation Datasets

In this section, we will provide a detailed overview of the datasets used in our evaluations .

2.1. General VQA

- **VQAv2 [1].** VQAv2 is designed for visual question answering with natural images, covering a wide range of question types including yes/no, numerical counting, and more open-ended inquiries. The dataset comprised of a collection exceeding 200,000 images, paired with more than 1.1 million questions. Each question is paired with 10 answers annotated by different annotators.
- **OK-VQA [23].** OK-VQA (Outside Knowledge Visual Question Answering) dataset is constructed to evaluate visual question-answering skills that require external knowledge. Models need to combine image content and common sense to answer questions. The dataset includes 14,055 open-ended questions, each accompanied by 5 ground truth answers.
- **MM-Vet [41].** MM-Vet is designed to evaluate the overall capability of generalist visual language models in a zero-shot manner. It integrates 6 core VL capabilities to solve complex tasks (including recognition, OCR, knowledge, language generation, spatial awareness, and math), and explores 16 distinct integrations resulting from the combination of these capabilities. As for evaluation metrics, it utilizes a language model-based evaluator tailored for open-ended responses.
- **POPE [19].** POPE (Polling-based Object Probing Evaluation) is a dataset constructed to assess the object hallucination problem in large visual language models. It employs a polling-based object probing method, transforming hallucination assessment into a binary classification challenge. This is achieved by prompting large vision-language models (LVLMs) with straightforward Yes-or-No queries regarding the objects in question (for example, "Is there a car in the image?"). Our evaluation is conducted under the dataset's most challenging setting: the adversarial setting.

2.2. Text-rich VQA

- **OCR-VQA [27].** OCR-VQA dataset comprises 207,572 images of book covers, paired with more than 1 million question-answer pairs. The questions inquire about book information including title, edition, year, author, and genre of the book, which requires text recognition and comprehension abilities.
- **TextVQA [34].** TextVQA is a benchmark of visual reasoning based on text in images. Models need to

Task	Dataset	Description	Split	Metrics
General VQA	VQAv2	VQA on natural images.	test-dev	VQA Score(↑)
	OK-VQA	VQA on natural images requiring outside knowledge.	val	VQA Score (↑)
	MM-Vet	Conversational style VQA on integrated capabilities.	test	GPT-4 score(↑)
	POPE	VQA for hallucination assessment. The adversarial setting is used.	test	F1 score(↑)
Text-rich VQA	OCR-VQA	VQA on images of book covers.	test	EM (↑)
	TextVQA	VQA on natural images containing text.	test	VQA Score (↑)
	ST-VQA	VQA on natural images requiring textual understanding.	test	ANLS (↑)
	ChartQA	VQA about charts with visual and logical reasoning.	test	VQA Score (↑)
	InfoVQA	VQA on infographics.	test	ANLS (↑)
	DocVQA	VQA on document images.	test	ANLS (↑)
GUI Agent	Mind2Web	Web behavior prediction given snapshots and historical actions.	test	step SR (↑)
	AITW	Android behavior prediction given snapshots and historical actions.	test	Matching Score (↑)

Table 9. Summary of the evaluation benchmarks.

incorporate the textual information in the images and reason over it to answer TextVQA questions. It comprises a total of 28,408 images and 45,336 questions.

- **ST-VQA [4].** ST-VQA is designed to emphasize the significance of exploiting the semantic information present within images in textual form during the VQA process. It comprises tasks of diverse difficulties, for which recognizing the scene text and performing necessary reasoning is required to generate the answer. The dataset comprises 23,038 images sourced from multiple public datasets and 31,791 question-answer pairs.
- **ChartQA [24].** ChartQA is a benchmark of question-answering about logical and visual reasoning on charts. It consists of 20,882 charts curated from four different online sources, 9,608 manual written questions, as well as 23,111 questions automatically generated with T5 according to human-written chart summaries.
- **InfographicVQA(InfoVQA) [26].** The task of InfoVQA is to answer questions centering on a given infographic image. The answers to most questions can be extracted from the given documents, while the answers to a small percentage of questions are not extractive. There are 5K Images collected from the Internet and 30K manually annotated questions in the dataset.
- **DocVQA [25].** DocVQA focuses on question-answering given a document image. The answer for questions is often a span of text from the given documents. There are 12K images and 50K manually annotated questions in the datasets.

2.3. GUI Agent

CogAgent is evaluated on two GUI agent datasets, Mind2Web and Android in the Wild (AITW), corresponding to computer agent and smartphone agent respectively.

- **Mind2Web [10].** Mind2Web is designed to develop and evaluate web agents capable of executing intricate tasks on various websites based on language directions. While existing datasets for web agents commonly rely on simulated or overly simplified web data, Mind2Web utilizes real-world websites and is annotated by human annotators. It gathers data from 137 websites covering 31 domains, and collects over 2,000 open-ended tasks, each accompanied by a crowd-sourced action sequence.

In mind2web, evaluated agents are asked to accomplish a designated task on a chosen website by performing a sequence of actions. Each instance (i.e. a specific task) in Mind2Web contains a task description, action sequence, and webpage snapshots. Each action in the sequence is a (Target element, Operation) pair, and Operation includes Click, Type (with additional value), and Select (with additional value). Each action is paired with the concurrent webpage snapshots in a variety of formats including raw HTML code, DOM tree, screenshot, etc. As for CogAgent, we choose screenshot images as the input representation of websites; as for other language-based agents, HTML is chosen as the input representation.

Following Deng et al. [10] and Zeng et al. [42], we formalize the problem as: first choose the target webpage element among top-k ($k=10$ or 50) candidates, then predict specific operations. The top-k candidates are provided by the candidate generation model in Deng et al. [10]. Step success rate (step SR) is reported on 3 out-of-domain test sets (cross-website, cross-domain,

cross-task) as metric. Only predictions with the same target element and operation as the ground truth are regarded as correct.

- **Android in the Wild (AITW) [31].** AITW is constructed to develop and evaluate Android device-control systems that are capable of understanding and acting upon human natural language instructions by directly manipulating the device’s user interface. This dataset significantly surpasses others in its category in terms of size, encompassing 715k episodes across 30k distinct instructions, and covering four Android versions (v10–13). It also includes eight types of devices, ranging from Pixel 2 XL to Pixel 6, each with different screen resolutions. AITW consists of five subsets: GoogleApps, Install, WebShopping, General, and Single. The subsets have distinct tasks, while are in the same data format. Each episode (i.e. action sequence) comprises three components: a goal instruction provided in natural language, a user action sequence, and a corresponding screenshots sequence.

As for screenshots, AITW only provides screenshot images and does not provide tree-based representations of UI. This is because a large portion of them in Smartphone applications are of low quality or even do not exist, and adopting the tree-based representation would strongly limit agents’ applications. For visual agents, screenshots are provided to the agents in image format; for language-model-based agents evaluated by Zhan and Zhang [43], the textual representations of OCR and icons formatted in HTML syntax are provided. As for actions, AITW considers a variety of action types including tapping, swiping, typing, going home, going back, entering, etc. For each action, models are required to predict the exact action type; for tap, swipe and type, models are further required to predict the position, direction, and content to be typed, respectively. The detailed standard for computing matching scores is provided in Rawles et al. [31].

3. Derivation of Acceleration for High-Resolution Cross-Module

Suppose that $L_{I_{lo}}$, $L_{I_{hi}}$ and L_T are the lengths of the low-resolution image, high-resolution image and text sequences. Let H_{cross} , H_{dec} be the number of attention heads in cross-attention and self-attention, and d_{cross} , d_{dec} be the dimension of each attention head.

If using our high-resolution cross-module, the computational complexity of attention is

$$T_{\text{improved}} = \mathbf{O}((L_{I_{lo}} + L_T)L_{I_{hi}}H_{cross}d_{cross} + (L_{I_{lo}} + L_T)^2H_{dec}d_{dec}). \quad (5)$$

If not utilizing the high-resolution cross-module and directly substituting low-resolution images with high-resolution ones, the computational complexity would be

$$T_{\text{original}} = \mathbf{O}((L_{I_{hi}} + L_T)^2H_{dec}d_{dec}). \quad (6)$$

The reduction factor of the computational complexity in attention, $T_{\text{original}}/T_{\text{improved}}$, equals to

$$\frac{(L_{I_{hi}} + L_T)^2H_{dec}d_{dec}}{(L_{I_{lo}} + L_T)L_{I_{hi}}H_{cross}d_{cross} + (L_{I_{lo}} + L_T)^2H_{dec}d_{dec}} \quad (7)$$

$$= \frac{L_{I_{hi}} + L_T}{L_{I_{lo}} + L_T} \frac{(L_{I_{hi}} + L_T)H_{dec}d_{dec}}{L_{I_{hi}}H_{cross}d_{cross} + (L_{I_{lo}} + L_T)H_{dec}d_{dec}} \quad (8)$$

$$= \frac{L_{I_{hi}} + L_T}{L_{I_{lo}} + L_T} \frac{(L_{I_{hi}} + L_T)\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}}}{L_{I_{hi}} + (L_{I_{lo}} + L_T)\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}}} \quad (9)$$

- **Case 1:** $L_{I_{lo}}, L_T \ll L_{I_{hi}}$.

Given that $L_{I_{lo}}$ is much smaller than $L_{I_{hi}}$, when L_T also satisfies being much smaller than $L_{I_{hi}}$, both $\frac{L_{I_{lo}}}{L_{I_{hi}}}$ and $\frac{L_T}{L_{I_{hi}}}$ become first-order small quantities. If conducting a 0-th order approximation for the complexity reduction factor, we obtain:

$$\frac{T_{\text{original}}}{T_{\text{improved}}} = \frac{L_{I_{hi}}(1 + \frac{L_T}{L_{I_{hi}}})}{L_{I_{lo}} + L_T} \frac{L_{I_{hi}}(1 + \frac{L_T}{L_{I_{hi}}})\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}}}{L_{I_{hi}}(1 + \frac{L_{I_{lo}} + L_T}{L_{I_{hi}}}\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}})} \quad (10)$$

$$= \frac{L_{I_{hi}}(1 + \frac{L_T}{L_{I_{hi}}})}{L_{I_{lo}} + L_T} \frac{(1 + \frac{L_T}{L_{I_{hi}}})\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}}}{1 + \frac{L_{I_{lo}} + L_T}{L_{I_{hi}}}\frac{H_{dec}d_{dec}}{H_{cross}d_{cross}}} \quad (11)$$

$$\approx \frac{L_{I_{hi}}}{L_{I_{lo}} + L_T} \quad (12)$$

- **Case 2:** Our implementation.

In our implementation, $d_{cross} = 32$, $H_{cross} = 32$, and we inherits $d_{dec} = 128$, $H_{dec} = 32$ from CogVLM-17B. Both high- and low-resolution encoders patchify images with 14×14 -pixel patches, thus $L_{I_{hi}} = 6400$, $L_{I_{lo}} = 256$. Subsitute the values to Eq. (9), we obtain

$$\frac{T_{\text{original}}}{T_{\text{improved}}} = \frac{6400 + L_T}{256 + L_T} \frac{4(6400 + L_T)}{6400 + 4(256 + L_T)} \quad (13)$$

$$> \frac{6400 + L_T}{256 + L_T} \quad (14)$$

That is to say, our method leads to at least $\frac{L_{I_{hi}} + L_T}{L_{I_{lo}} + L_T} = \frac{6400 + L_T}{256 + L_T} \times$ acceleration which is a stringent lower bound. Taking pre-training as an example, with L_T typically below 512 in earlier stages, our high-resolution cross-module can get an over $25 \times$ reduction in computational cost.

4. Performance Analysis on AITW

Android in the Wild (AITW) dataset is a large-scale dataset for Android device agents. Our analysis centers on instances where the CogAgent's responses diverge from the annotated ground truth, focusing on these discrepancies.

In our analysis, we conducted a sampling and manual verification of cases where there was a discrepancy between the model's responses and the labeled answers. We sampled instances and discovered that in 42% of these, the model's response actually represented an alternative correct method, rather than an error. This phenomenon is common due to the multiplicity of ways to accomplish a function on a smartphone. For example, many phones are equipped with both Google's app and a Google search bar, and searches can be conducted using either. During the use of smartphones, human users may exhibit simultaneous needs for both in-depth exploration and extensive browsing. For example, when browsing news, CogAgent might identify relevant results on the current page and select them immediately, while some users may prefer to scroll through the entire page first. Furthermore, the data collection for annotations might involve redundant or overly detailed steps, whereas CogAgent can directly find the most efficient path. Fig. 4 illustrates these typical examples of multiple correct answers.

Given the nature of smartphone usage, wherein accomplishing a task often involves multiple viable paths, it is advisable for future studies to explore a virtual environment with an evaluation of the accuracy of task completion following a sequence of actions, aligning more closely with real-world human usage scenarios.

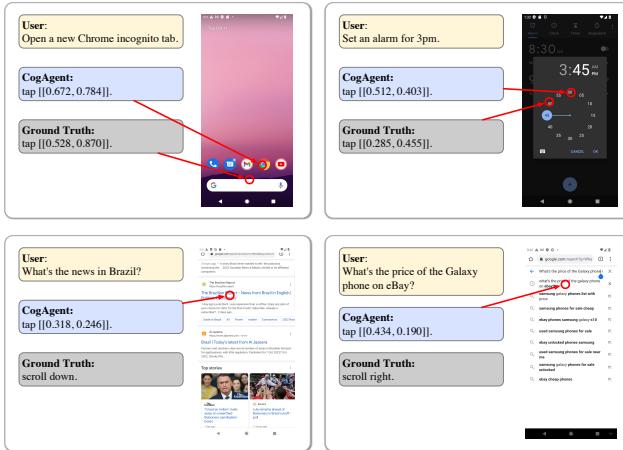


Figure 4. Instances in the AITW dataset where CogAgent provides accurate responses that differ from the annotated ground truth.

5. Samples of Pre-train Data

Samples of pre-train data are listed in this section, including data for text recognition (Fig. 5), visual grounding (Fig. 6), and webpage-html pairs (Fig. 7).

has kept nine players that featured in last year's FIBA Basketball World Cup. While 36-year-old Eduardo Mingas is set to play his sixth consecutive African Championship, Roberto Fortes who has featured for Angola in consecutive World Championships, will make his AfroBasket debut in Tunis from 19 - 30 August. Fortes stood out throughout the training camp, having helped Angola beat Venezuela in

being about a half hour from the city's center. I was struck by how lovely it was, until I learned one couldn't eat the fish, and it wasn't a good idea to do too much swimming radiation being a prob Halladay no-hitter came in the first post season start of his career Roy Halladay of the Phillies pitched the second no-hitter in Major League Baseball postseason history on Wednesday as the Philadelphia Phillies beat the Cincinnati Reds 4-0 in their National League



$$g'(y) := \frac{f(x)}{\sqrt{\tilde{d}_{\lambda,h}(x)}} - \frac{f(y)}{\sqrt{\tilde{d}_{\lambda,h}(y)}} \quad L^p \rightarrow L^p_{(2n-1)/p'}$$

$$\gamma = 6.96 \times 10^8 \text{ m}$$

$$\kappa^2 = -\frac{1}{2} \nabla^\mu \chi^\nu \nabla_\mu \chi_\nu$$

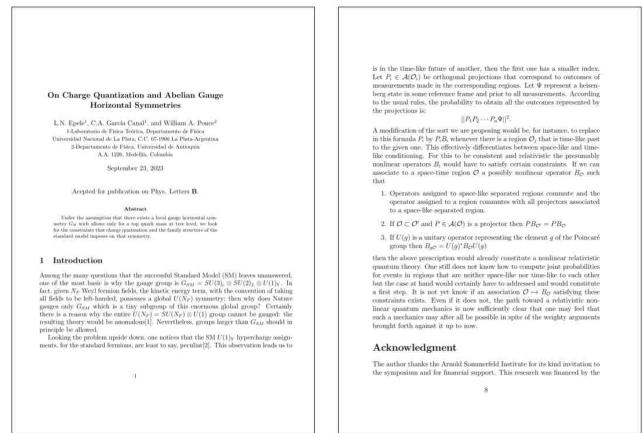


Figure 5. Samples of pre-train data for text recognition.



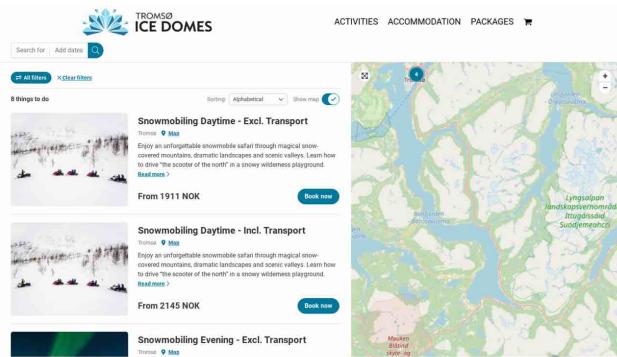
A bride [[592,179,866,956]] and groom [[717,160,862,882]] standing near the water [[425,426,990,898]] at sunset.



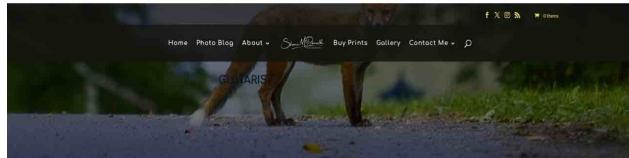
Chicken and rice dish [[301,160,997,792]] in a pan [[282,107,998,839]], with spoons [[091,476,630,953]] and plate [[002,004,258,374]] next to it.



A bluebird [[302,413,640,752]] sitting on a branch coffee mugs [[279,588,677,804]].



[Box] [[30, 281, 870, 445]]



[Box] [[190, 510.203125, 1088.21875, 682.703125]]

[HTML] <p>n WordPress via the Jetpack plugin publish reports on your blogs which are very interesting. If you have a WordPress blog and you have not yet installed Jetpack then you really should as there are some great features including the 'Publicize' feature where you can auto-update your Facebook, Twitter and Google+ accounts with your posts. My [...]</p>

Figure 6. Samples of pre-train data for visual grounding.

Figure 7. Samples of webpage-html pairs.

6. Details of Fine-Tuning Data

6.1. Human annotation

To enable CogAgent to function as an agent on various apps and websites, we assembled a team of over ten annotators to collect and label screenshots. To ensure the quality of the annotations and prevent overly simplistic, homogenized content, the annotation process was divided into two phases.

In the first phase, annotators were required to independently select from a pool of apps and websites, and capture screenshots of pages strongly relevant to the main function of that app/website, with no less than 20 screenshots for each app/website. Subsequently, for each screenshot, the annotators would label them according to the following aspects:

1. **Five buttons.** List the names of five clickable buttons from the screenshots. The types of buttons should be diverse.
2. **Three clickable areas.** List three clickable areas from the screenshots, e.g. text boxes, search boxes, clickable images, hyperlinks, etc.
3. **Two questions extracting information from the image.** Ask questions involving the textual information in the images. For instance, “In what year did the user in the image register?” .
4. **One operation requirement.** What function of the webpage/app would you use in this interface? For example, adding the comment: “cool!”. The requirement shouldn’t be vague such as “adding comment”.

In the second phase, annotators are required to provide grounding annotation for the questions and operational methods proposed in the first phase (the aforementioned parts 3 and 4). For example, for Figure 8, a possible annotation would be:

1. **Buttons:** Back; Search; Subscribed; Home; Library.
2. **Clickable areas:** Avatar in the middle top; Video preview in the middle bottom; Personal profile.
3. **Question 1:** Based on the page, how many followers does this author have?

Answer: According to the personal profile at the top [[013,568,802,188]], this author has 4.97M followers.

Question 2: Based on the page, how many videos has this author posted?

Answer: According to the personal profile at the top [[013,568,802,188]], this author has posted 502 videos.

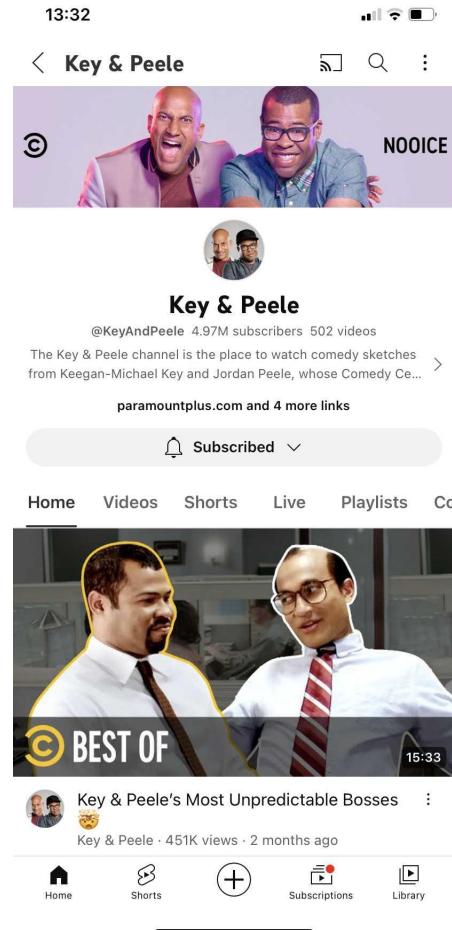


Figure 8. Samples of human-collected screenshot.

4. **Operation requirement:** Based on the page, write out the steps to complete the following function: Follow this author.

Answer: Click on Subscribed [[049,826,728,078]] to follow this author.

6.2. Conversion of Agent Datasets

To convert Mind2Web to natural language with GPT4, we use the following prompt:

Imagine that you are a robot operating a computer. Like how humans operate the computer, you can move the mouse, click with the mouse, or type some texts with the keyboard.

Your ultimate task is: “Find the lowest-priced round trip flight with hotel on May 2 from Kathmandu, Nepal KTM to Shanghai, China PVG and return on May 5. Book a double room and check out with the default flights.”

You are given previous actions: (format: element → operation)

1. [link] Flight + Hotel → CLICK,
2. [textbox] Where from? → TYPE: KATHMANDU,
3. [div] Tribhuvan Intl Airport (KTM), Nepal → CLICK,
4. [textbox] Where to? → TYPE: SHANGHAI,
5. [div] Pudong Intl Airport (PVG), China → CLICK,
6. [span] Sat 8 Apr - Sat 15 Apr → CLICK,
7. [checkbox] 2 May 2023 → CLICK,
8. [checkbox] 5 May 2023 → CLICK,

Furthermore, you **secretly** know the following steps of action. **(But you have to pretend this is the result of your derivation and you don't know it before)**

1. [button] Search → CLICK,
2. [button] Recommended → CLICK,
3. [div] Lowest Price → CLICK,
4. [svg] → CLICK,
5. [button] Choose your room → CLICK,
6. [button] Book Business Double Room A → CLICK,
7. [svg] → CLICK,
8. [svg] → CLICK,
9. [button] Choose → CLICK

Please formulate an operational guide for future operations for solving the task. The guide includes:

1. Plan: A **multi-step future** plan that does not involve low-level operations **(start from current screen and action, DON'T include previous actions)**, steps indexed by numbers. **Be sure to pretend that you don't know the future interface and actions, and don't know the elements not existing on the current screen)**

2. Action: The specific **immediate** action that needs to be taken (Corresponding to the **very next action**) [button] Search → CLICK at the box **{“x_left”: 0.876, “y_left”: 0.308, “width”: 0.063, “height”: 0.034}**), which should be detailed enough to directly control the operation, such as specifying the exact location (or box) to click, the exact content of the text to type, the item to select.

Output Format: A JSON dictionary strictly following the format:

```
{
  "plan": "...<Your Plan Here>",
  "action": "...<Your Action Here>",
  "operation": "[button] Search → CLICK at the box \"x_left\": 0.876, \"y_left\": 0.308, \"width\": 0.063, \"height\": 0.034"
}
```

Please do not output any content other than the JSON format. Don't mention elements that only appear in HTML such as svg, div.

The returned answer from GPT-4 would be:

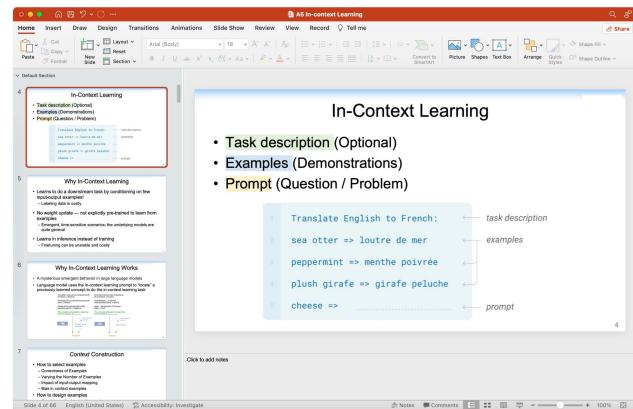
{ “plan”: “1. After searching, you’ll see a list of flight and hotel packages. 2. Review the recommended options, usually highlighted for convenience. 3. Focus on finding the lowest priced option. You might need to navigate through various sorting or filtering features to do this. 4. Once you’ve found the lowest priced option, select it to view more details. 5. In the detailed view, you’ll have to choose your room type. Look for options that fit your requirements, like a business double room. 6. After selecting the room, proceed to finalize your booking. This might involve confirming your choice and entering any required information. 7. Review all the details carefully before finalizing the booking to ensure everything is correct.”,

“action”: “Click the ‘Search’ button to proceed with the search based on the entered criteria. This button is located towards the right side of the screen.”,

“operation”: “[button] Search → CLICK at the box {“x_left”: 0.876, “y_left”: 0.308, “width”: 0.063, “height”: 0.034}” }

7. More Generated Samples of CogAgent

To further demonstrate the capabilities of CogAgent, we provide additional generated samples in this section.



User: Could you provide instructions for "Insert a new slide named "In-Context Learning: Details" with a Two Content layout after the current slide."?

CogAgent: Plan: 1. Click on the 'New Slide' button to start a new slide from scratch.

2. Once the new slide is open, click on the 'Home' tab if not already selected.

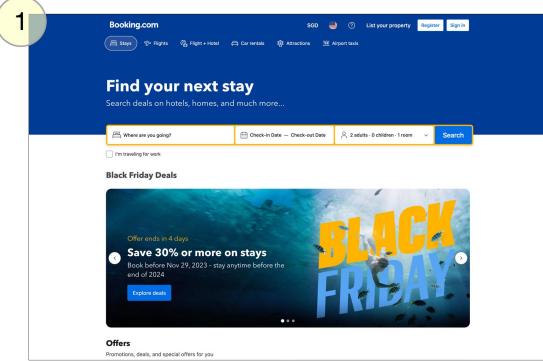
3. In the Home tab, find and select the 'Two Content Layout' option.

4. Type in the title for the new slide as 'In-Context Learning: Details'.

5. Save the new slide with the correct layout and title.
Next Action: Move the cursor over the 'New Slide' button located at the specified coordinates on the screen and perform a left mouse click.

Figure 9. More generated samples of CogAgent.

User: What's the proper procedure for "Book a room of the lowest price in New York on Dec 1st"? (with grounding)



- Plan:** 1. Type 'New York' into the search box to specify the destination.
2. Select the correct New York location from the auto-suggested list.
3. Adjust the check-in and check-out dates to December 1st, respectively.
4. Execute the search by clicking the 'Search' button.

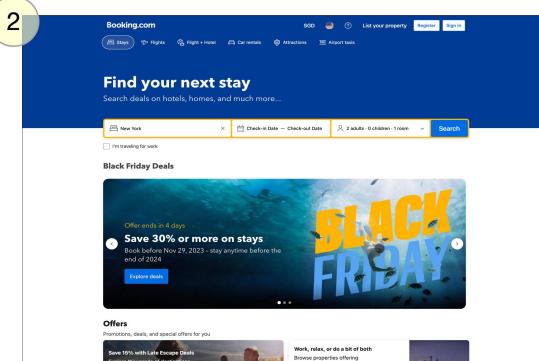
5. Once the results are displayed, sort them by price, selecting the lowest first.

6. Review the options and select the room offer that is the lowest priced.

7. Proceed to book the selected room following the website's booking procedure.

Next Action: Type 'New York' into the textbox located at the coordinates '{x_min: 0.175, y_min: 0.309, width: 0.28, height: 0.047}' on the screen.

Grounded Operation: [textbox] Where are you going? -> TYPE: New York at the box [[175,309,455,356]]



- Plan:** To book the lowest priced room in New York on Dec 1st, the next steps would involve:
1. Adjusting the check-in and check-out dates to December 1st, respectively.

2. Executing a search for available rooms.

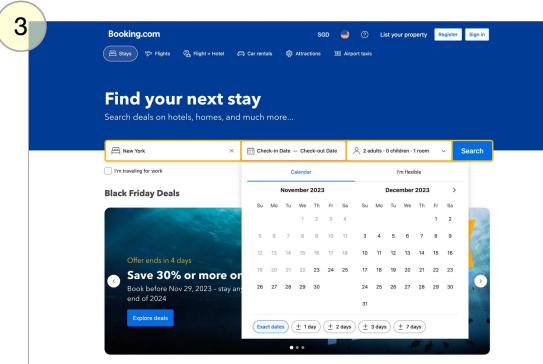
3. Sorting the search results by price, from low to high.

4. Selecting the room offer with the lowest price.

5. Proceeding to book the chosen room.

Next Action: Click on the 'Check-in Date' textbox at the specified coordinates to bring up the date selection interface.

Grounded Operation: [checkbox] Check-in Date -> CLICK at the box [[438,309,549,357]]



- Plan:** 1. Confirm the checkout date by clicking on the appropriate date, which in this case is 1 December 2023.

2. Initiate the search for hotels by clicking the 'Search' button to find available rooms.

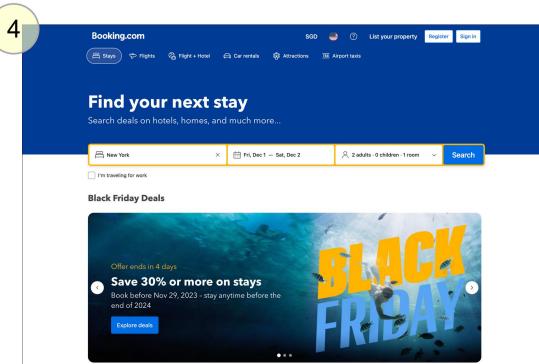
3. Once the results are displayed, sort the list of hotels by price, selecting the option to order them from the lowest to highest price.

4. Review the sorted list and select the hotel offering the lowest price.

5. Proceed to book the selected hotel room following the website's booking procedure.

Next Action: Click on the calendar box corresponding to the date 1 December 2023 to set it as the checkout date.

Grounded Operation: [gridcell] 1 December 2023 -> CLICK at the box [[739,564,776,611]]



- Plan:** 1. Click the Search button to initiate the search with the current criteria.

2. Once the search results are displayed, sort the listings by price, selecting the option to order them from low to high.

3. Review the sorted list and select the room offer that is the lowest in price.

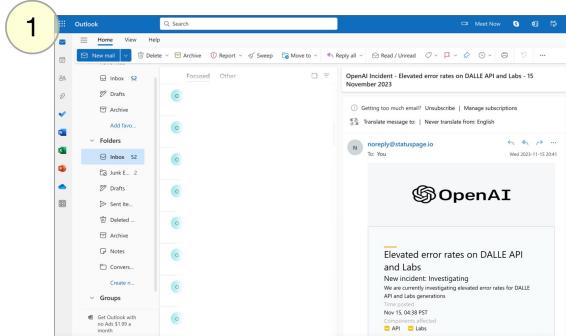
4. Click on the 'Book' button for the chosen offer to proceed with the reservation process.

Next Action: Click the Search button located at the bottom right of the search parameters box to execute the search for hotels in New York from December 1st to December 2nd for 2 adults and 0 children in 1 room.

Grounded Operation: [button] Search -> CLICK at the box [[798,367,875,424]]

Figure 10. More generated samples of CogAgent.

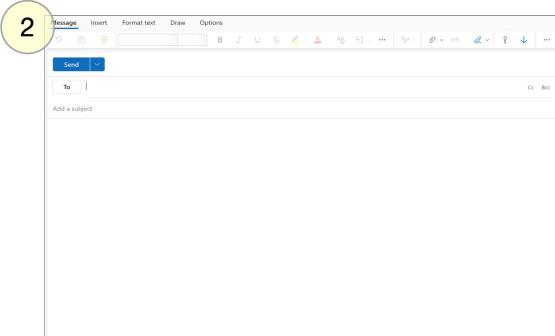
User: Could you guide me through the steps to "Write an email to cvpr2024@gmail.com, with subject of 'I'm CogAgent', and the main body of 'Here is CogAgent sending the email.' " ?



CogAgent:

1. Click on the 'New email' button to start a new email.
2. Enter the recipient's email address in the 'To:' field.
3. Enter the subject in the 'Subject:' field.
4. Type the main body of the email in the 'Body' text area.

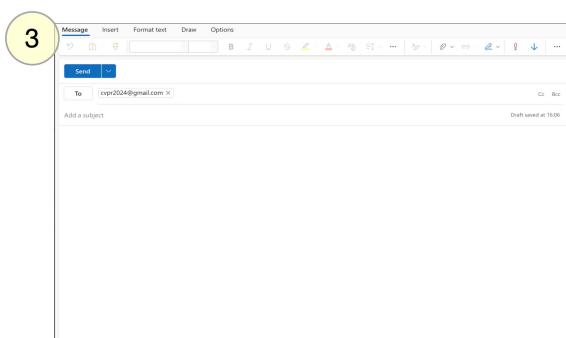
Next Action: Click on the 'New mail' button located at the top left corner of the screen, within the Outlook interface.



CogAgent:

1. Type the email address into the 'To' field.
2. Enter the subject line in the 'Subject' field.
3. Use the keyboard to type the main body of the email.

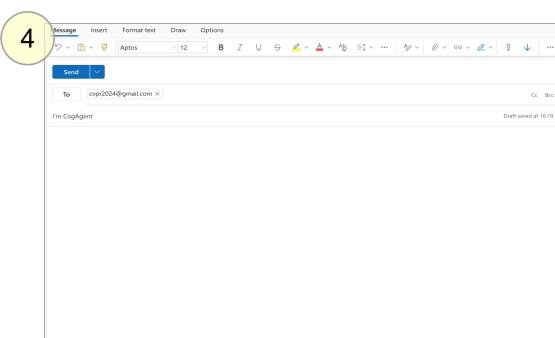
Next Action: Move the cursor to the 'To' textbox, click on it to focus on it, and type 'cvpr2024@gmail.com'.



CogAgent:

1. Type the subject line into the 'Subject' field.
2. Enter the main body of the email in the large text area below the subject line.
3. Use the 'Send' button to send the email.

Next Action: Click on the 'Subject' textbox, which is currently highlighted and type 'I'm CogAgent'. Then, use the keyboard to type the rest of the message in the large text area below it.



CogAgent:

1. Click on the text area to bring up the keyboard if it's not already active.
2. Type the main body of the email, 'Here is CogAgent sending the email.'
3. Find and click the 'Send' button to send the email.

Next Action: Move the cursor to the text area where the message content needs to be typed and type 'Here is CogAgent sending the email.'

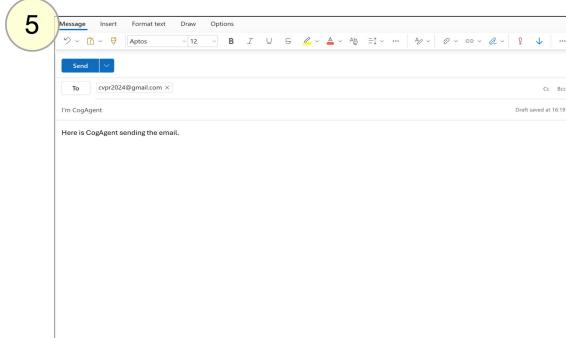


Figure 12. More generated samples of CogAgent.

User: Could you guide me through the steps to "Listen to the music named You Raise Me Up." ?

1

CogAgent:
Plan: 1. Locate the Music app icon.
 2. Open the app to find the music library.
 3. Search for 'You Raise Me Up' by using the search function within the app.
Next Action: Click on the Music app icon located in the second row from the bottom, third column from the left.

2

CogAgent:
Plan: 1. Tap on the search bar at the top of the screen.
 2. Enter the song title into the search field.
 3. Execute the search by pressing the search button or enter key on the keyboard.
Next Action: Move the cursor to the search bar and click it to activate the text entry mode for typing in the song name 'You Raise Me Up'.

3

CogAgent:
Plan: 1. Tap on the search bar at the top of the screen.
 2. Enter the text 'You Raise Me Up' into the search field.
 3. Execute the search by pressing the search button or enter key on the keyboard.
Next Action: Click on the search bar where it says 'Artists, Songs, Lyrics, and...', then type 'You Raise Me Up'.

4

CogAgent:
Plan: 1. Identify the search bar at the top of the screen.
 2. Review the list of songs that appear as a result of the search query.
Next Action: Look at the search results section just below the search bar to find the song 'You Raise Me Up'.

Figure 13. More generated samples of CogAgent.



User: What's shown in this picture? Describe in detail.

CogAgent: The screenshot shows a character standing in the game Genshin Impact, looking at a teleport waypoint. The HUD displays various elements: on the top left is a mini-map with icons indicating different locations; on the top right are character portraits and health bars for Raiden Shogun, Bennett, and Kaedehara Kazuha, along with an UID number; below these is a quest prompt 'Go to Merusea Village' with a distance indicator of 284m; in the center is the glowing Teleport Waypoint; at the bottom are the character's level (Lv. 90), health points (25123/3461), stamina (623), and other game UI elements like food, a key, and a compass.

User: I'm looking for guidance on how to "Go to the teleport waypoint"?

CogAgent: Plan: 1. Identify the direction to the teleport waypoint from the current location on the map.

2. Navigate through the environment or use in-game transportation methods to reach the destination. 3. Confirm arrival at the teleport waypoint and prepare for the next step of the journey within Genshin Impact.

Next Action: Move the cursor over the 'Teleport Waypoint' icon located towards the center right of the screen, just above the character's feet, and left-click to activate it.

Grounded Operation: [generic] Teleport Waypoint -> CLICK at the box [[506,497,686,547]]

User: Who are the teammates on the current mission?

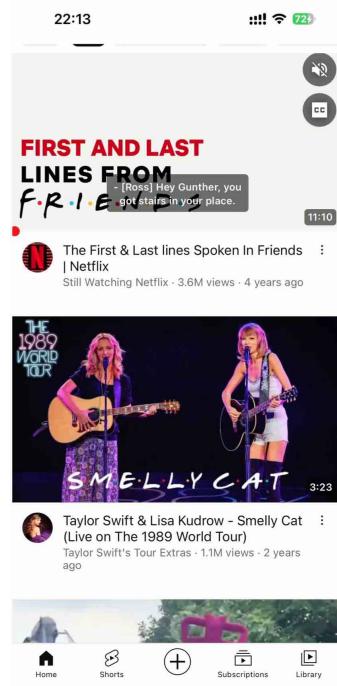
CogAgent: The teammates on the current mission are Raiden Shogun, Bennett, and Kaedehara Kazuha.

User: I'm looking for guidance on how to "Find out how to view a detailed map"?

CogAgent: Plan: 1. Identify the map icon on the screen.

2. Click on the map icon to open the detailed map view.

Next Action: Move the cursor over the top left corner of the screen and click on the compass-like icon with 'N' inside it.



User: When did the Smelly Cat video post?

CogAgent: The Smelly Cat video post was made 2 years ago.

User: How long is the Smelly Cat video?

CogAgent: The Smelly Cat video is 3 minutes and 23 seconds long.

User: What should I do if I want to watch the Smelly Cat video (in the middle of the screen) and share it with my friend Rena?

CogAgent: Plan: 1. Play the Smelly Cat video by Taylor Swift & Lisa Kudrow to ensure it is fully loaded and ready for viewing.

2. Locate the share icon on the screen, which is typically represented by a symbol such as a paper airplane or an arrow pointing outwards from a box.

3. Tap the share icon to open sharing options.

4. Find and select the option to send via messaging app, like WhatsApp, to share the video with friends.

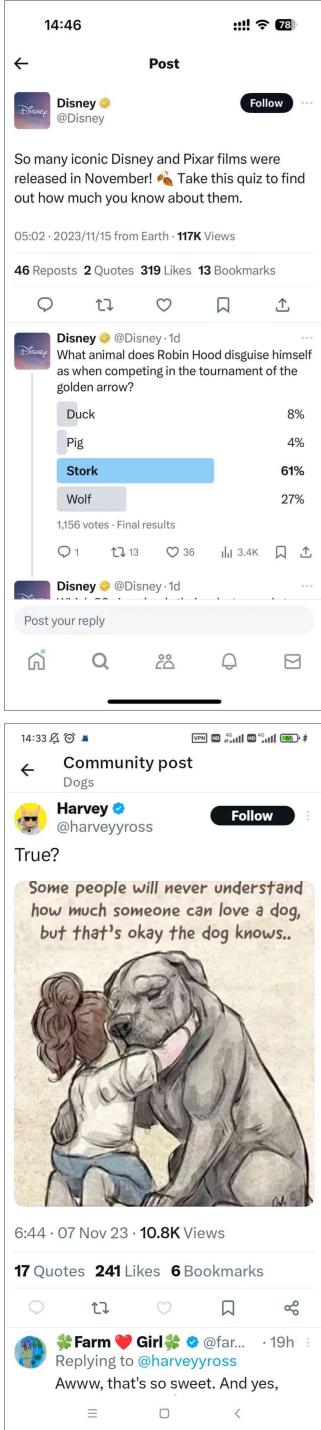
5. In the messaging app, locate the contact named Rena.

6. Send the video link to Rena through the messaging app.

Next Action: Touch the area in the middle of the screen where the 'Smelly Cat' thumbnail is displayed, corresponding to [Live on The 1989 World Tour] by Taylor Swift & Lisa Kudrow - Smelly Cat. This action is intended to start playing the video.

Grounded Operation: tap [[701,498]]

Figure 14. More generated samples of CogAgent.



User: Describe the image in detail.

CogAgent: The image is a screenshot of Twitter posts from the official Disney account. In the first post, there's an emoji-filled statement that reads 'So many iconic Disney and Pixar films were released in November! Take this quiz to find out how much you know about them.' This tweet was posted on 2023/11/15 at 05:02 and has received 46 reposts, 2 quotes, 319 likes, and 13 bookmarks. Below it, another tweet states 'What animal does Robin Hood disguise himself as when competing in the tournament of the golden arrow?' with multiple choice options like Duck, Pig, Stork, Wolf.

User: Which option has the highest number of votes?

CogAgent: The 'Stork' option has the highest number of votes with 61%.

User: How can I "Follow Disney's Twitter account"?

CogAgent: Plan: 1. Locate the 'Follow' button on the screen.
2. Click the 'Follow' button to follow Disney's Twitter account.

Next Action: Move the cursor over the 'Follow' button next to the Disney logo and click it.

User: Describe the image in detail.

CogAgent: The image showcases a tweet from an account named 'Harvey' with the handle '@harveyyross'. The tweet contains an illustration of a young girl hugging a large dog. Above this, there is another text that reads: 'Some people will never understand how much someone can love a dog, but that's okay the dog knows...'. Below the illustration, there are statistics showing the tweet has been viewed 10.8K times, liked by 241 users, retweeted 6 times, and bookmarked by 6 users. Additionally, there is a reply to this tweet from an account named 'Farm Girl' with the handle '@far...', which says: 'Awww, that's so sweet. And yes,' indicating agreement or appreciation for the original message.

User: Does the tweet have any reply? What is it?

CogAgent: Yes, there is a reply to the tweet from an account named 'Farm Girl' with the handle '@far...'. The reply reads: 'Awww, that's so sweet. And yes,' indicating agreement or appreciation for the original message.

Figure 15. More generated samples of CogAgent.



User: Describe the screen in detail.

CogAgent: The picture shows a mobile phone screen with various icons arranged in a grid. There are 24 app icons on the screen, including three cute cartoon bears at the bottom of the screen. These bears have different expressions and colors. In addition to the app icons, there is also a digital clock displaying "11:15" at the top left corner of the screen.

User: What apps do I have?

CogAgent: The apps on the phone are divided into two categories: system apps and third-party apps. System apps include "FaceTime", "Calendar", "Photos", "Mail", "Clock", "Maps", "Weather", "Notes", "Reminders", "Stocks", "Videos", "iTunes Store", "App Store", "Books", "Health", "Home", "Music", and "Moji Weather". Third-party apps include "Q Search" and other unidentified apps, which cannot be identified from their icons alone.

User: What should I do if I want to see photos taken 2 days ago?

CogAgent: You should tap on the "Photos" app, and it will display all your photos. If you want to see photos taken 2 days ago, you can select a date from the options at the top of the screen or use the search function in the Photos app to find specific photos.

User: If I want to take a photo, what should I do?

CogAgent: You should tap on the "Camera" app to take a photo.

User: What should I do if I want to call Susan?

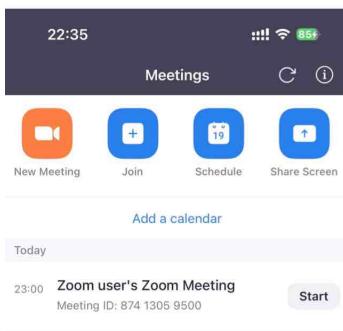
CogAgent: You should tap on the "Phone" app to call Susan.

User: How can I know Susan's number?

CogAgent: You can call Susan by searching for her number in the phone's contact list or on your phone's address book. If you have saved her number, you can directly dial it from there.

User: What should I do if I want to download youtube?

CogAgent: You should tap on the "App Store" app, and then search for YouTube in it. Once you find the official YouTube app, you can download and install it to watch videos.



User: Is there a preferred method for "Join another zoom meeting with id 13572468"?

CogAgent: **Plan:** 1. Identify and select the 'Join' option for an existing or new meeting ID.

2. Enter the specific Meeting ID when prompted to join a particular Zoom meeting.

3. Confirm any additional required details such as passcodes if necessary, and then join the meeting successfully.

Next Action: Tap on the 'Join' button located in the middle of the screen, which corresponds to the coordinates [x,y]=[0.456,0.18]. This action is intended to initiate the process of joining a Zoom meeting.

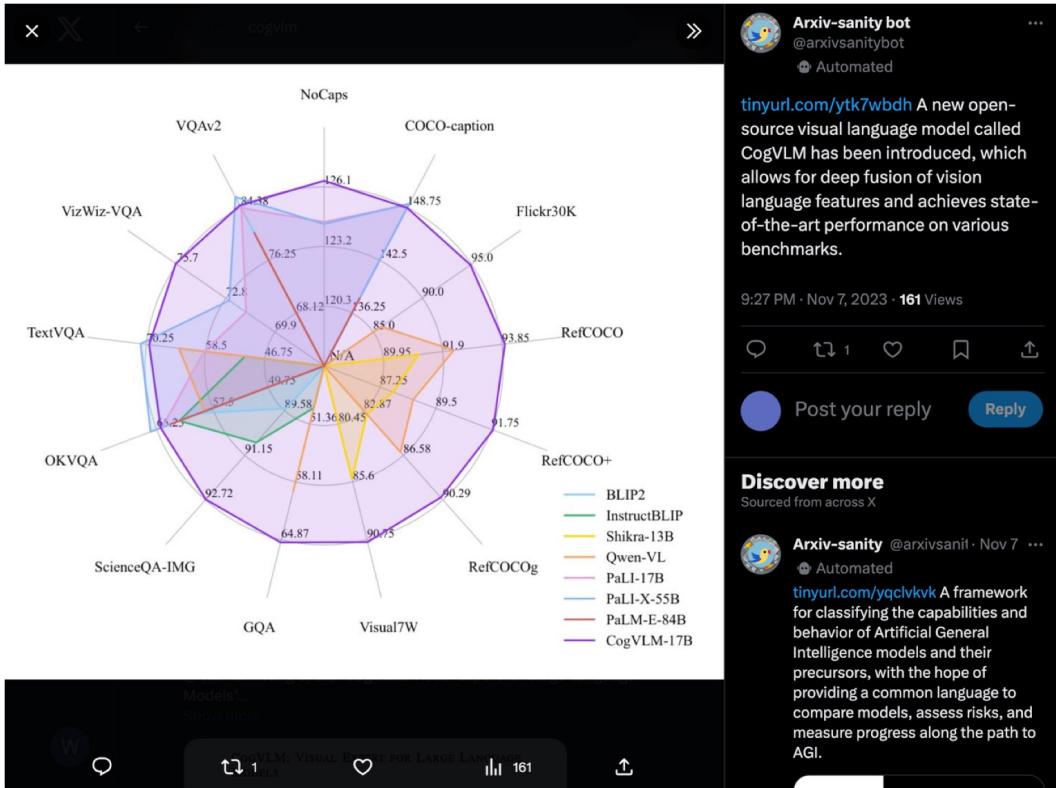
Grounded Operation: tap [[456,180]]

User: In how many minutes will the next meeting start? Please think step by step.

CogAgent: The next meeting will start in 23 minutes. This is determined by subtracting the current time (22:35) from the scheduled start time of the meeting (23:00).



Figure 16. More generated samples of CogAgent.



User: What's the performance on CogVLM-17B on Visual7W?

CogAgent: The performance on CogVLM-17B on Visual7W is 90.75.

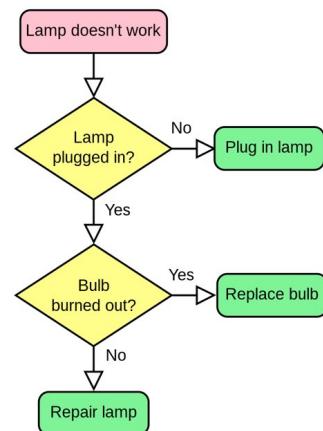
User: What's Arxiv-sanity's comment?

CogAgent: Arxiv-sanity's comment is: 'A new open-source visual language model called CogVLM has been introduced, which allows for deep fusion of vision language features and achieves state-of-the-art performance on various benchmarks.'



User: I am getting one funghi pizza and one prosciutto pizza. How much should I pay in total?

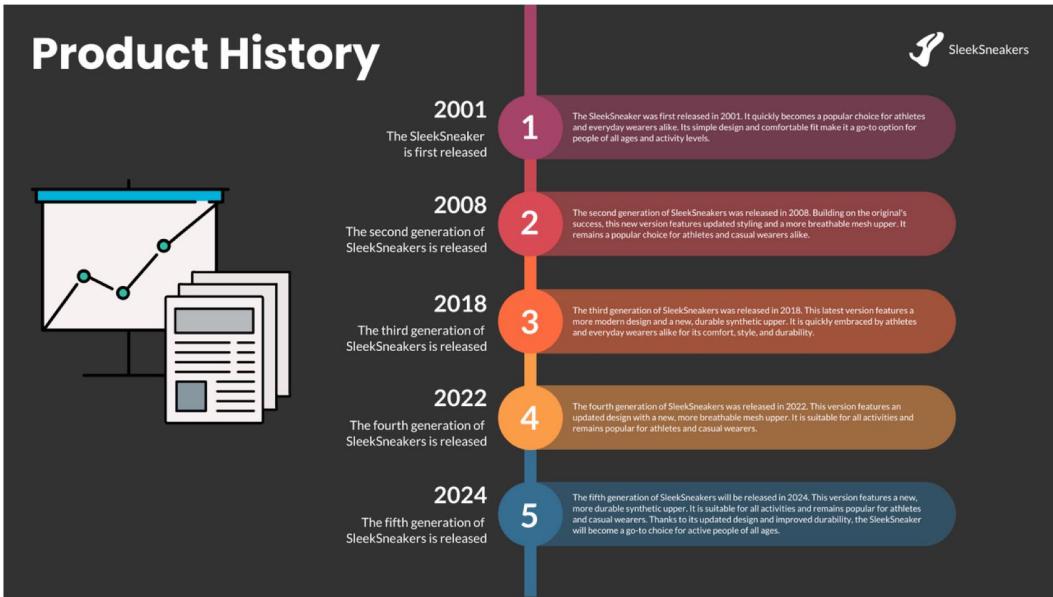
CogAgent: The funghi pizza costs 6,90€ and the prosciutto pizza costs 7,90€. Therefore, the total cost for both pizzas would be 14,80€.



User: What is the solution if the lamp is plugged in and the bulb has burned out?

CogAgent: If the lamp is plugged in and the bulb has burned out, the solution is to 'Replace bulb'.

Figure 17. More generated samples of CogAgent.



User: Describe this image.

CogAgent: The image is a timeline showcasing the product history of 'SleekSneakers'. It starts from 2001, where 'The SleekSneaker' was first released, and ends in 2024, where the fifth generation of SleekSneakers was released. The timeline highlights key milestones, such as the introduction of the second generation of SleekSneakers in 2008, the fourth generation in 2022, and the fifth generation in 2024. Each milestone is accompanied by a brief description.

User: Read the content in 2022.

CogAgent: In 2022, the fourth generation of SleekSneakers was released. This version features an updated design with a new, more breathable mesh upper. It is suitable for all activities and remains popular for athletes and casual wearers.



User: In which country was this photo taken?

CogAgent: The photo was taken in Australia, as the Australian Open is one of the major tennis tournaments held there.



User: Who is the person on the left?

CogAgent: The person on the left is Keira Knightley.

Figure 18. More generated samples of CogAgent.

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43 [†]
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PreLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	19.38	4.49

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except [†] reported on the test set).

User: Convert it to the markdown format.

CogAgent: | method | top-1 err. | top-5 err. |

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	18.43	1
GoogLeNet [44] (ILSVRC'14)	7.89	1
VGG [41] (v5)	24.4	7.1
PreLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	19.38	4.49

Dataset 1

Department	Name	Salary
Administration	Emily	\$2,000
Finance	Nick	\$1,800
Marketing	John	\$2,600
Marketing	Gloria	\$1,800
Administration	Jane	\$2,500
Finance	Max	\$2,000
Administration	Tyler	\$3,000
Finance	Wilkins	\$2,500
Marketing	Miles	\$2,800
Administration	Sabine	\$1,900

User: Based on the table, how much is Wilkins earning?

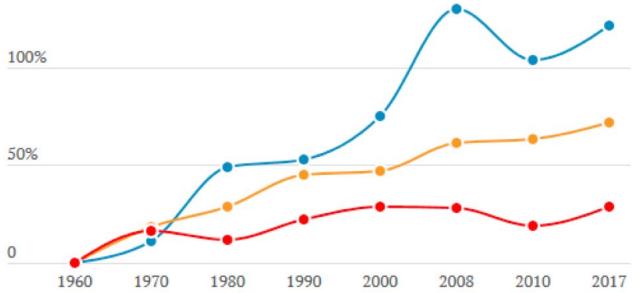
CogAgent: Wilkins is earning \$2,500.

US Nationwide:

● Median House Price ● Median Gross Rent per Month
● Median Household Income

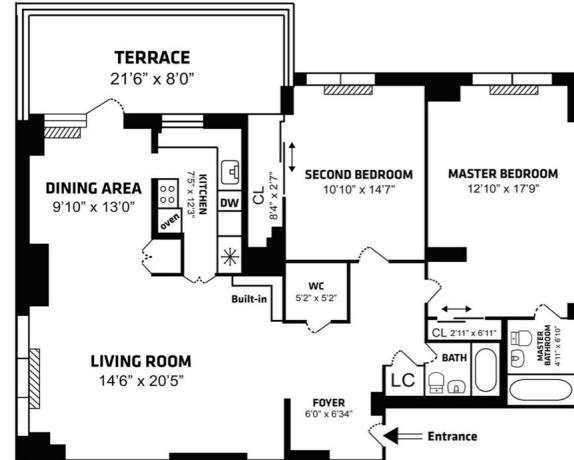
Growth rate:

150%



User: Which year has the highest growth rate of median house price?

CogAgent: The year 2008 has the highest growth rate of median house price, which is 150%.



User: What are the appliances in the kitchen in this floorplan?

CogAgent: The kitchen in this floorplan has a built-in oven, a built-in dishwasher, and a built-in microwave.

Figure 19. More generated samples of CogAgent.