The Amazon Nova Family of Models: Technical Report and Model Card

Amazon Artificial General Intelligence

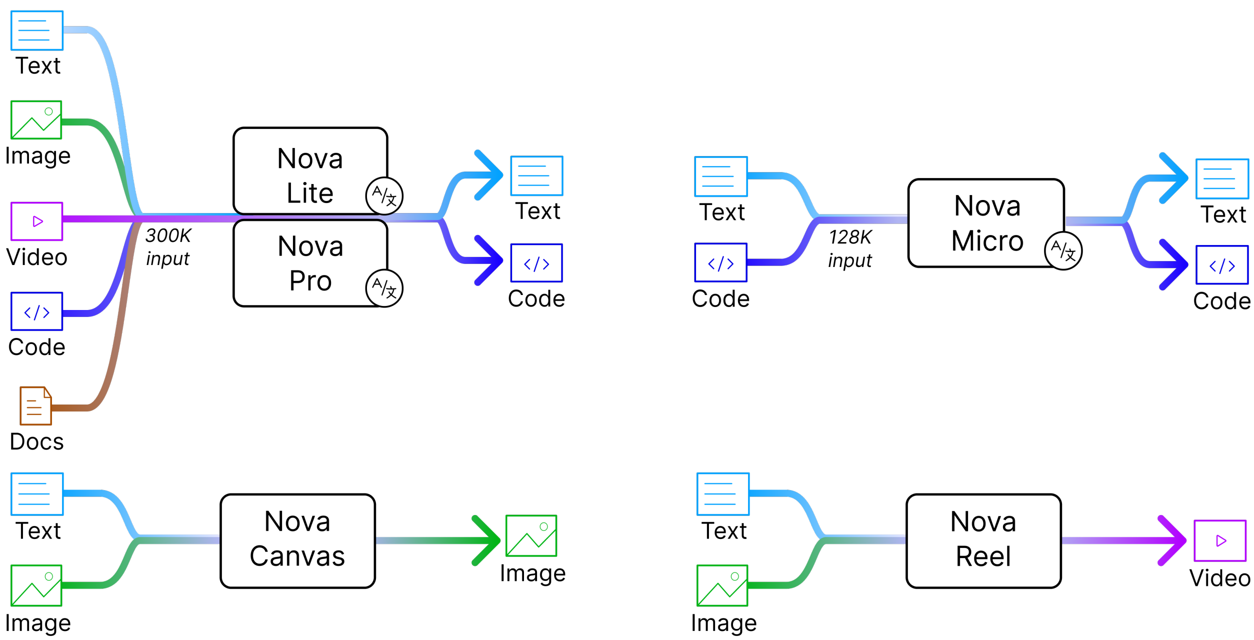

Figure 1: The Amazon Nova family of models

Abstract

We present Amazon Nova, a new generation of state-of-the-art foundation models that deliver frontier intelligence and industry-leading price performance. Amazon Nova Pro is a highly-capable multimodal model with the best combination of accuracy, speed, and cost for a wide range of tasks. Amazon Nova Lite is a low-cost multimodal model that is lightning fast for processing images, video, documents and text. Amazon Nova Micro is a text-only model that delivers our lowest-latency responses at very low cost. Amazon Nova Canvas is an image generation model that creates professional grade images with rich customization controls. Amazon Nova Reel is a video generation model offering high-quality outputs, customization, and motion control. Our models were built responsibly and with a commitment to customer trust, security, and reliability. We report benchmarking results for core capabilities, agentic performance, long context, functional adaptation, runtime performance, and human evaluation.

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1 Introduction

This document introduces Amazon Nova, a new generation of state-of-the-art foundation models that deliver frontier intelligence and industry-leading price performance.

1.1 Amazon Nova Pro, Lite, and Micro

Key capabilities of Amazon Nova Pro, Lite, and Micro include:

- *Frontier intelligence:* Amazon Nova models possess frontier intelligence, enabling them to understand and process complex language tasks with state-of-the-art accuracy. Amazon Nova Micro sets new standards in its intelligence tier in several text benchmarks such as Language Understanding (MMLU), Deep Reasoning (GPQA), Mathematics (MATH), and Multi-step Reasoning (Big-Bench Hard). Our multimodal models, Amazon Nova Pro and Lite, take text, images, documents, and video as input and generate text as output. These models set standards in several benchmarks such as Video Captioning (VATEX), Visual QA (TextVQA), Function Calling (BFCL), and multimodal agentic benchmarks (GroundUI-1K, VisualWebBench, Mind2Web) in their respective intelligence tiers. These models are the first to offer video understanding capabilities on Amazon Bedrock, enabling deeper insights from multimedia content.
- *Speed:* Amazon Nova has been designed for fast inference, with Amazon Micro, Lite, and Pro each being one of the fastest models in their respective intelligence tiers.
- *Agentic Workflows:* Amazon Nova Pro, Lite, and Micro can power AI agents capable of breaking down and executing multi-step tasks. These models are integrated with Bedrock Knowledge Bases and they excel at retrieval-augmented generation (RAG) to ensure the best accuracy by grounding their responses to the developer's data.
- *Customizability:* Developers can fine-tune these models with multimodal data (Pro and Lite) or text data (Pro, Lite, and Micro), providing the flexibility to achieve desired accuracy, latency, and cost. Developers can also run self-service Custom Fine-Tuning (CFT) and distillation of larger models to smaller ones via Bedrock APIs.
- *Price-Performance:* Each model was optimized to deliver exceptional price-performance value, offering state-of-the-art performance on key benchmarks at low cost.

Amazon Nova Pro, Lite, and Micro are based on the Transformer architecture [74]. Each model went through a series of training processes that began with pretraining using a mixture of large amounts of multilingual and multimodal data. Our models were trained on data from a variety of sources, including licensed data, proprietary data, open source datasets, and publicly available data where appropriate. We curated data from over 200 languages, with particular emphasis on Arabic, Dutch, English, French, German, Hebrew, Hindi, Italian, Japanese, Korean, Portuguese, Russian, Simplified Chinese, Spanish, and Turkish. After pretraining, models iteratively went through a series of fine-tuning stages, including Supervised Fine-Tuning (SFT) on instruction-demonstration pairs (including multimodal ones) and reward model (RM) training from human preference data [59]. Finally, the models learned from human preferences via methods like Direct Preference Optimization (DPO) [62] and Proximal Policy Optimization (PPO) [68] to ensure that the final models are aligned with human preferences in both quality and responsibility.

1.2 Amazon Nova Canvas and Reel

Amazon Nova Canvas and Amazon Nova Reel are designed to create realistic multimodal content, including images and videos, for a wide range of applications such as advertising, marketing, and entertainment.

Amazon Nova Canvas offers the following functionalities, with more details provided in Appendix A:

- *Text-to-image generation:* Amazon Nova Canvas can generate images with various resolutions (from 512 up to 2K horizontal resolution) and aspect ratios (any aspect ratio between 1:4 and 4:1 with a maximum of 4.2M pixels). Customers can provide reference images to guide the model to generate outputs in a specific style or color palette, or to generate variations of an image.
- *Image editing:* Amazon Nova Canvas allows precise image editing operations like inpainting and outpainting through natural language mask prompts. These mask prompts describe the specific area of the input image that needs to be repainted. The user can also easily change a background with the background removal feature, leaving the subject of the image unchanged.

Amazon Nova Reel offers the following functionalities:

- *Generate videos from a text prompt:* Amazon Nova Reel can generate high-quality videos of 6-second duration (720p resolution at 24 frames per second) from a text prompt.
- *Generate videos from a reference image and a prompt:* Amazon Nova Reel brings images to motion and generates videos that are guided by the input image and a text prompt.
- *Camera motion control using a text prompt:* With camera motion control in Amazon Nova Reel, the user can guide camera motion with text prompts like "zoom" and "dolly forward" to get the exact visual needed for each video. Amazon Nova Reel supports more than 20 camera motions. For more details, please refer to our prompting guide[1].

Amazon Nova Canvas and Reel are latent diffusion models [61] where a Variational AutoEncoder (VAE) [41] maps the image or video frames to latent variables on which the diffusion process happens. A text encoder tokenizes input text prompts into tokens which are then passed to the diffusion model as a conditioning signal. At inference time, a latent variable is initialized with random noise sampled from a Gaussian distribution, which is then denoised by the trained diffusion model iteratively into a clean latent variable. The clean latent variable is decoded back to images or video frames by the decoder of the VAE. Both models underwent a two-phased approach of pretraining and fine-tuning. Pretraining data were sourced from a variety of sources, including licensed data, proprietary data, open source datasets, and publicly available data where appropriate. Our highly scalable data filtering, deduplication, and enrichment pipelines were based on AWS EMR [2] and AWS Batch [1], as well as other AWS services.

[1] `https://docs.aws.amazon.com/nova/latest/userguide`

2 Amazon Nova Pro, Lite, and Micro Evaluations

In this section, we report benchmarking results for Amazon Nova models and for select publicly-available models, including by citing existing public results and by measuring their performance.[2] In cases for which the result is a simple average of binary scores, we assume a Gaussian distribution for the sample and approximate the 95% confidence interval as:

$$CI(S) = 1.96 \times \sqrt{\frac{S \times (1 - S)}{N}} \tag{1}$$

where CI is the 95% confidence interval, S is the measured score for the benchmark, and N is the sample size [48, 45].

2.1 Core capability public benchmarks

We evaluate Amazon Nova models on a suite of automated public benchmarks to assess core capabilities, including for both text-only (Section 2.1.1) and multimodal (Section 2.1.2) use cases.

2.1.1 Core capability text benchmarks and results

We evaluate select core capabilities of Amazon Nova models on a variety of public text-only benchmarks, spanning general knowledge, reasoning, language understanding, multilinguality, and instruction following.

The following list briefly describes our selected text-only benchmarks. The prompts used for evaluation of each benchmark are summarized in Appendix B.1.

- MMLU [36]: Massive Multitask Language Understanding (MMLU) is a multiple-choice question answering benchmark that covers 57 subject areas across STEM, humanities, and social sciences. Subjects include law, physics, mathematics, computer science, history, and more. The difficulty levels vary from elementary level to advanced professional level, focusing on both world knowledge and problem solving abilities. We use 0-shot Chain-of-Thought (CoT) [79] for prompting and report the macro average exact match accuracy across all subjects.
- ARC-C [22]: The AI2's Reasoning Challenge (ARC) is a multiple-choice question-answering dataset, which contains science questions from grade 3 to grade 9 exams. We use 0-shot CoT for prompting and report exact match accuracy.
- DROP [26]: Discrete Reasoning Over Paragraphs (DROP) is a crowdsourced reading comprehension dataset that requires reasoning and operating over multiple input positions from the reference text. We use 0-shot CoT for prompting and report f1 score.
- GPQA [64]: Graduate-level Google-Proof Question and Answering (GPQA) is a challenging and high-quality multiple-choice question answering benchmark written by domain experts who have or are pursuing PhDs in biology, physics, and chemistry. We use 0-shot CoT for prompting and report exact match accuracy on the main set.
- MATH [37]: MATH is a mathematics problem solving benchmark, consisting of problems from mathematics competitions including the American Mathematics Competitions (AMC 10 and AMC 12), the American Invitational Mathematics Examination (AIME) and more. We use 0-shot CoT for prompting and report the exact match accuracy on the MATH5k set.
- GSM8K [23]: Grade School Math 8K (GSM8K) is a math benchmark consisting of 8,500 high-quality and diverse grade school math problems. The benchmark tests basic mathematical problem solving capabilities, requiring multi-step reasoning. We use 0-shot CoT for prompting and report the exact match accuracy on the test set containing 1,319 samples.
- IFEval [89]: IFeval is an instruction-following benchmark, which evaluates a model's capability of following "verifiable instructions" such as "mention the keyword of AI at least 3 times". The dataset contains 25 types of verifiable instructions and in total 541 prompts, where each prompt contains one or more verifiable instructions in natural language. We report the instruction-level accuracy under loose constraints.
- BBH [72]: Big Bench Hard (BBH) is a diverse benchmark consisting of an aggregate of 23 diverse subjects that cover algorithmic and NLP tasks ranging from casual logic tasks to word sorting and movie recommendations. The tasks are both multiple choice and open generation tasks. We report the macro average exact match accuracy across the subjects.

[2] Results measured internally by Amazon for evaluation purposes after Amazon Nova models completed training using (i) the Bedrock API for Claude and Meta models or (ii) the OpenAI API or Gemini API, as applicable.

		MMLU	ARC-C	DROP	GPQA	MATH	GSM8k	IFEval	BBH
	tok/ sec	*accuracy*	*accuracy*	*F1-score*	*accuracy*	*accuracy*	*accuracy*	*instruction-level loose accuracy*	*accuracy*
Nova Pro	100	85.9	94.8 ±1.3	85.4 ±0.7	46.9 ±4.6	76.6 ±1.2	94.8 ±1.2	92.1 ±1.8	86.9
Nova Lite	157	80.5	92.4 ±1.5	80.2 ±0.8	42.0 ±4.6	73.3 ±1.2	94.5 ±1.2	89.7 ±2.1	82.4
Nova Micro	210	77.6	90.2 ±1.7	79.3 ±0.8	40.0 ±4.5	69.3 ±1.3	92.3 ±1.4	87.2 ±2.3	79.5
		0-shot CoT	0-shot	6-shot CoT	0-shot CoT	0-shot CoT	0-shot CoT	0-shot	3-shot CoT
Claude 3.5 Sonnet (Oct)	57	89.3	96.3^{M} ±1.1	88.3 ±0.6	58.0^{M} ±4.6	78.3 ±1.1	96.5^{M} ±1.0	90.2^{*} ±2.0	93.2
Claude 3.5 Haiku	64	80.3	90.9^{M} ±1.6	83.1 ±0.8	37.5^{M} ±4.5	69.4 ±1.3	93.8^{M} ±1.3	85.9^{*} ±2.4	86.6
		0-shot CoT	25-shot	3-shot	0-shot CoT	0-shot CoT	0-shot CoT	0-shot	3-shot CoT
Gemini 1.5 Pro (002)	58	85.9	95.4^{M} ±1.2	74.9 ±0.9	55.1^{M} ±4.6	86.5 ±0.9	90.8 ±1.6	91.7^{M} ±1.9	89.2
Gemini 1.5 Flash (002)	190	78.9	94.3^{M} ±1.3	78.4 ±0.8	45.1^{M} ±4.6	77.9 ±1.2	86.2 ±1.9	91.6^{M} ±1.9	85.5
Gemini 1.5 Flash 8B (001)	283	68.1	88.7^{M} ±1.8	68.1^{M} ±0.9	33.5^{M} ±4.4	58.7 ±1.4	84.5^{M} ±2.0	86.1^{M} ±2.3	69.5
		5-shot	25-shot	3-shot	0-shot	4-shot	11-shot	0-shot	3-shot
GPT-4o	163	88.7	96.2^{M} ±1.1	83.4 ±0.7	48.4^{M} ±4.6	76.6 ±1.2	92.6^{M} ±1.4	89.8^{M} ±2.1	83.0^{M}
GPT-4o Mini	113	82.0	92.3^{M} ±1.5	79.7 ±0.8	41.7^{M} ±4.6	70.2 ±1.3	86.4^{M} ±1.8	87.4^{M} ±2.3	81.0^{M}
		0-shot	25-shot	3-shot	0-shot	0-shot CoT	0-shot CoT	0-shot	3-shot
Llama 3.2 90B	40	86.0	94.8 ±1.3	-	46.7 ±4.6	68.0 ±1.3	95.1 ±1.2	90.9^{M} ±2.0	-
Llama 3.2 11B	124	73.0	83.4 ±2.1	-	32.8 ±4.3	51.9 ±1.4	84.5 ±2.0	85.0^{M} ±2.4	-
Llama 3.1 8B	157	73.0	83.4 ±2.1	-	30.4 ±4.3	51.9 ±1.4	84.5 ±2.0	85.0^{M} ±2.4	-
		0-shot CoT	25-shot	-	0-shot	0-shot CoT	8-shot CoT	-	-

Table 1: Quantitative results on core capability benchmarks (MMLU [36], ARC-C [22], DROP [26], GPQA [64], MATH [37]), GSM8K [23], IFEval [89] and BigBench-Hard (BBH) [72]). Unless otherwise noted, all reference numbers are taken from the original technical reports and websites for Claude models [14, 11], GPT4 models [58, 57], Llama models [45] and Gemini models [32]. Results marked with M were measured by us[2]. Claude numbers for IFEval (taken from [14]) are marked with an asterisk ($*$), as the scoring methodology is unspecified in the report. Token generation speed in tokens per second (tok/sec), the inverse of per-token generation latency, is reproduced from Section 2.5.

Table 1 summarizes the quantitative results of Nova models and select public models on the aforementioned benchmarks for core capabilities. When available, we reference the highest publicly-reported numbers for each benchmark from the official technical reports and websites for Claude, Gemini, OpenAI and Llama family of models. Amazon Nova Pro, Lite, and Micro demonstrate strong performance across all benchmarks, showcasing their advanced core intelligence, particularly Amazon Nova Micro and Lite on math, reasoning, and instruction following benchmarks.

We also evaluate the translation capabilities of Nova models. Flores200 [73, 34, 35], or simply Flores, is a machine translation benchmark consisting of translations from 842 distinct web articles, which tests the translation capabilities between English and non-English languages. Sentences are 21 words long on average. We use a 0-shot setup and report the macro average of two metrics, spBleu and COMET22 score [63] across a set of languages (Arabic, German, Spanish, French, Hindi, Italian, Japanese, Korean, Portuguese, Hebrew, Turkish, Simplified Chinese, Russian, Dutch) for translation from and into English. The prompts used for evaluation are summarized in Appendix B.1. Table 2 summarizes our quantitative results on Flores, demonstrating strong multilingual performance on translation for Amazon Nova Pro, Lite, and Micro.

		FLORES (0-shot)			
		en → Set1		Set1 → en	
	tok/sec	*spBleu (↑)*	*COMET22 (↑)*	*spBleu (↑)*	*COMET22 (↑)*
Nova Pro	100	43.4	89.1	44.4	89.0
Nova Lite	157	41.5	88.8	43.1	88.8
Nova Micro	210	40.2	88.5	42.6	88.7
Claude 3.5 Sonnet (Oct)	57	42.5[M]	89.4[M]	43.5[M]	89.1[M]
Claude 3.5 Haiku	64	40.0[M]	88.5[M]	40.2[M]	88.3[M]
Gemini 1.5 Pro (002)	57	43.0[M*]	89.1[M*]	45.6[M*]	89.1[M*]
Gemini 1.5 Flash (002)	190	40.0[M*]	88.5[M*]	42.9[M*]	88.8[M*]
Gemini 1.5 Flash 8B (001)	283	38.2[M*]	88.0[M*]	41.4[M*]	88.5[M*]
GPT-4o	163	43.1[M*]	89.2[M*]	43.9[M*]	89.0[M*]
GPT-4o Mini	113	41.1[M*]	88.7[M*]	41.9[M*]	88.7[M*]
Llama 3.2 90B	40	39.7[M]	88.2[M]	43.7[M]	88.5[M]
Llama 3.2 11B	124	33.0[M]	85.7[M]	36.3[M]	86.3[M]
Llama 3.1 8B	157	32.7[M]	85.5[M]	36.5[M]	86.5[M]

Table 2: Quantitative results on Flores200 [34], a machine translation benchmark. Set1 refers to {de, es, fr, it, pt, ja, ar, hi, ru, nl, tr, he, ko, zh}. Results marked with *M* were measured by us.[2]. Results marked with an asterisk ($*$) were obtained using an alternate prompt which can be found in Appendix B.1 Token generation speed in tokens per second (tok/sec), the inverse of per-token generation latency, is reproduced from Section 2.5.

2.1.2 Core capability multimodal benchmarks and results

In this section we evaluate the multimodal capabilities of Amazon Nova models on a diverse set of public benchmarks. Our selection of multimodal benchmarks aims to probe for various capabilities, including natural image understanding, document understanding with charts and graphs, text understanding, and temporal reasoning in videos. For all benchmarks, we follow the suggested metrics and choice of data split for evaluation. The following list briefly describes the selected benchmarks.

- MMMU [85]: The Massive Multi-discipline Multimodal Understanding benchmark consists of college-level multiple-choice and open-ended questions from 30 different disciplines. We use Chain-of-Thought (CoT) prompting for this benchmark and report accuracy.
- ChartQA [50]: The 2,500 questions of this benchmark cover three different types of charts (bar, line and pie) and require strong visual, logical, and arithmetical reasoning capabilities. We evaluate on the test set and report relaxed accuracy.
- DocVQA [51]: This benchmark probes capabilities on document analysis and recognition, including Optical Character Recognition (OCR). The 5,349 questions contain images from a diverse set of documents, ranging

		MMMU (CoT)	**Chart QA**^{C}	**Doc VQA**	**Text VQA**	**VATEX**	**Ego Schema**
		val	test	test	val	test	test
	tok/sec	*accuracy*	*relaxed accuracy*	*ANLS*	*weighted accuracy*	*CIDEr*	*accuracy*
Amazon Nova Pro	100	61.7 ±3.2	89.2 ±1.2	93.5	81.5	77.8	72.1 ±5.4
Amazon Nova Lite	157	56.2 ±3.2	86.8 ±1.3	92.4	80.2	77.8	71.4 ±5.4
Claude 3.5 Sonnet (Oct)	57	70.4 ±3.0	90.8 ±1.1	94.2	61.7^{M}	-	-
Claude 3 Haiku	64	50.2 ±3.3	82.0 ±1.5	88.8	-	-	-
Gemini 1.5 Pro (001)	58	65.9 ±3.1 ^{E}	87.2 ±1.3	93.1^{B}	78.7	64.6^{A}	72.2 ±5.4
Gemini 1.5 Flash (001)	190	62.3 ±3.2 ^{E}	85.4 ±1.4	89.9^{B}	78.7	57.1	65.7 ±5.7
Gemini 1.5 Flash 8B (001)	283	53.7 ±3.3 ^{F}	78.2 ±1.6 ^{G}	73.6	66.7	53.2^{A}	-
GPT-4o (May)	-	69.1 ±3.0	85.7 ±1.4	92.8	77.2^{D,M}	-	72.2 ±5.4
GPT-4o Mini (Jul)	113	59.4 ±3.2	79.2 ±1.6 ^{M}	-	70.3^{M}	-	-
Llama 3.2 90B	40	60.3 ±3.2	85.5 ±1.4	90.1	80.7^{M}	-	-
Llama 3.2 11B	124	50.7 ±3.3	83.4 ±1.5	88.4	71.3^{M}	-	-

Table 3: Quantitative results on four image understanding benchmarks (MMMU [85], ChartQA [50], DocVQA [51], TextVQA [70]) and 2 video understanding benchmarks (VATEX [78] and EgoSchema [49]). Higher numbers are better for all benchmarks (↑). Unless otherwise noted, all evaluations are 0-shot and reference numbers are taken from the original technical reports and websites for Claude models [11, 12], GPT4 models [56, 55], Llama models [45, 53] and Gemini models [32, 33]. Remarks: (*A*) 4-shot evaluation; (*B*) External Optical Character Recognition (OCR) was used; (*C*) All models except Amazon Nova use CoT; (*D*) GPT-4o (Nov); (*E*) Gemini 1.5 Flash/Pro (002) models; (*F*) Reported in [33]; (*G*) Reported in [4]; (*M*) Claude 3.5 Sonnet and Llama 3.2 results for TextVQA as well as GPT4o and GPT4o mini results on ChartQA, TextVQA and VATEX were measured by us.[2] Token generation speed in tokens per second (tok/sec), the inverse of per-token generation latency, is reproduced from Section 2.5.

from 1940 to 2020 and covering multiple industries. We report Average Normalized Levenshtein Similarity (ANLS).

- TextVQA [70]: The 5,000 samples of this dataset focus specifically on text-reading capabilities (OCR) in natural images. We report weighted accuracy on the validation set.
- VATEX [78]: This video captioning benchmark covers a diverse set of human activities. We evaluate on the public test set containing videos with a length of around 10 seconds. The CIDEr [75] score is used for evaluation.
- EgoSchema [49]: The unique characteristic of this long-form video question answering benchmark is its high "certificate length" [15], which is, loosely speaking, the time it takes a human to verify the video description. The videos cover a broad range of natural human activities and come with human-curated multiple-choice question-answer pairs.

Table 3 summarizes our quantitative results on multiple image and video understanding benchmarks. Amazon Nova Pro and Lite achieve high scores across all benchmarks. Chart understanding on ChartQA and video understanding on VATEX stand out, where Nova models rank either first or second. We provide the prompt templates for all benchmarks in Appendix B.2, as well as qualitative examples in Appendix C.

2.2 Agentic workflows

Amazon Nova Pro, Lite, and Micro models can be used as agents. An agent considers a suite of tools and APIs, reasons about the user's request and past conversational history, chooses if a tool should be used and, if so, decides which tool to use, invokes the tool, assesses the outcome from the tool, and then communicates back with the user [83, 67, 46, 60].

To this end, we evaluated our Nova models on agentic workflows that require textual understanding and visual reasoning. For textual understanding (Section 2.2.1), we used the Berkeley Function Calling Leaderboard benchmark to test our models' capabilities in function calling and orchestrating real-world applications. For visual reasoning (Section 2.2.2), we evaluate on three benchmarks that require image understanding capabilities for correct function calling. We highlight that both Amazon Nova Pro and Lite models set a new state of the art on these challenging benchmarks.

2.2.1 Agentic text benchmarks and results

Table 4 presents quantitative results on the Berkeley Function Calling Leaderboard v3 (BFCL).[3] Stemming from the Gorilla project [60], the revamped BFCL [81] benchmark evaluates a model's ability to accurately call and utilize real-world functions, or tools, based on a user's natural language request. Amazon Nova models particularly excel in the Abstract Syntax Tree (AST), Execution, and Relevance metrics, as well as overall scores versus comparable models. Amazon Nova Lite and Micro also had the lowest latency of the selected models.

In Table 4, AST measures the exact match function calling performance of the model when comparing function names and argument/value signatures to a human-curated ground truth. While AST allows for some soft matching based on manually-defined, permitted argument values (e.g., different date formats), Execution measures a function call's accuracy not by the call signature itself, but by comparing the return value of the call when executed against a real API.

To measure the rate of hallucination, Irrelevance measures the model's ability to recognize that it does not have the appropriate functions available to help the user, and should therefore not call any. Relevance, as the opposite of irrelevance, measures the model's ability to recognize it indeed does have the functions necessary to help the user (but does not verify function signature accuracy). For both metrics, higher numbers are better.

	Overall	**Latency**	**Non-Live**		**Live**	**Multi-Turn**	**Hallucination**	
	accuracy (↑)	*seconds* (↓)	*AST* (↑)	*execution* (↑)	*overall* (↑)	*overall* (↑)	*relevance* (↑)	*irrelevance* (↑)
Nova Pro	68.4	1.0	90.1	89.8	71.5	45.1	95.1	65.1
Nova Lite	66.6	0.6	87.5	86.4	66.0	50.3	97.6	49.1
Nova Micro	56.2	0.5	87.2	89.7	67.4	15.5	87.8	57.6
Claude Sonnet 3.5 (Jun)	61.3	3.9	70.0	66.3	74.7	40.0	68.3	74.6
Claude Haiku 3	40.4	1.5	41.7	47.5	57.7	20.6	97.6	29.4
Gemini 1.5 Pro (002)	59.8	3.0	88.0	91.4	74.3	16.3	75.6	75.1
Gemini 1.5 Flash (002)	55.3	1.1	79.7	80.6	73.2	12.5	78.1	75.7
Llama 3.2 90B[A]	54.3	N/A	88.9	89.3	61.1	14.3	92.7	58.4
Llama 3.2 11B[A]	49.9	N/A	83.6	87.3	57.9	10.5	78.1	41.6
GPT-4o (Aug)	68.9	1.5	85.9	85.6	75.4	45.3	63.4	82.9
GPT-4o-mini (Jul)	60.7	1.6	84.3	84.1	70.2	28.3	80.5	71.8

Table 4: Results on the Berkeley Function Calling Leaderboard (BFCL) v3 as of the Nov 17th, 2024 update. We include the latest versions of the models available on the leaderboard at that time. (*A*) We use leaderboard results for Llama 3.1 8B and 70B for Llama 3.2 11B and 90B, respectively, given the shared text LLM.

2.2.2 Agentic multimodal benchmarks and results

The Amazon Nova Pro and Lite models provide native support for multimodal inputs, including agentic workflows. In this section, we present results from our models on three different benchmarks that require agents to navigate websites to solve real-world tasks. Websites are typically represented as screenshots in these datasets to correctly convey all style elements and visual data as rendered in a standard web browser.

- VisualWebBench [43]: This benchmark includes seven core tasks related to web browsing, including captioning, question answering, OCR, action prediction, and grounding. All models are evaluated on 1,536 samples that span more than 100 websites from 12 domains. The final metric is the average over different metrics for the individual core tasks.

[3]BFCL is a fast-moving, live benchmark. We report results using the state of the repository and website leaderboard as of Nov 17th, 2024 (commit 8226d).

- MM-Mind2Web [86]: This extension of the original Mind2Web [24] benchmark links samples with the original website screenshots, making it multimodal. An agent needs to select an element and pick one of three elementary actions (click, type, or select) alongside a value for some actions. We report micro average over the per-sample step accuracy, where an agent is successful only if element and action selection, as well as the predicted value, are correct.
- GroundUI-1K [87]: This benchmark is composed of multiple existing datasets, including Mind2Web [24], and repurposes them as a grounding task. On 1,000 samples for evaluation, a multimodal agent is given an instruction and a screenshot of a website from a wide variety of domains and asked to predict the 2D location of the desired UI element. The agent is correct if its predicted 2D location is within the ground truth bounding box.

Table 5 shows the results of our models on multimodal agent workflows along with other publicly-reported results. Both Amazon Nova models, Lite and Pro, demonstrate strong visual reasoning and agentic capabilities and achieve high scores on all three benchmarks.

	VisualWebBench	**MM-Mind2Web**	**GroundUI-1K**
	composite^{D}	*step accuracy*	*accuracy*
Nova Pro	79.7	63.7	81.4
Nova Lite	77.7	60.7	80.2
Claude 3.5 Sonnet (Oct)	76.7^{M}	61.6^{M}	16.3
GPT-4o (Nov)	77.5^{M}	55.0^{M}	13.4^{C}
GPT-4o Mini (Jul)	71.3^{M}	58.6^{M}	7.2^{M}
GPT-4 (Apr)	64.6	36.8^{A}	-
Gemini 1.5 Pro (002)	76.4^{M}	58.4^{M}	35.2^{B}
Gemini 1.5 Flash (002)	76.1^{M}	46.2^{M}	59.9^{M}
Gemini 1.0 Pro (001)	48.0	17.9^{A}	-
Llama 3.2 90B	73.2^{M}	21.6^{M}	8.3^{M}
Llama 3.2 11B	65.1^{M}	22.1^{M}	3.7^{M}

Table 5: Quantitative results on three multi-modal agentic benchmarks: VisualWebBench [43], MM-Mind2Web [86] and GroundUI-1K [87]. Reference numbers are taken from the corresponding benchmark papers [43, 86, 87] and leaderboard [3]. Remarks: (A) uses in-context learning (ICL) (please note that Amazon Nova models do not need to rely on in-context examples); (B) Gemini 1.5 Pro (001); (C) GPT-4o (May); (D) Macro average over individual metrics; (M) Measured by us.[2]

2.3 Long context

We evaluate Amazon Nova Pro, Lite, and Micro on tasks that require the models to understand and reason over long context. These skills are crucial for tasks such as long multi-turn conversations, reasoning over long lists of retrieved documents, or understanding long videos. Amazon Nova Micro, Lite, and Pro models support context lengths of 128k, 300k, and 300k tokens, respectively. We used the following benchmarks to evaluate our models' long context performance:

- Text Needle-in-a-Haystack (NIAH): Following [40], we assessed each model's ability to locate specific information (the "needle") within extensive contexts (the "haystack"). This "needle-in-a-haystack" test evaluates the model's performance on context lengths starting at 32k, allowing us to measure its ability to accurately retrieve information across varying lengths of input context.
- SQuALITY [76] (ZeroScrolls Benchmark [69]): Focused on query-based summarization of literary stories, this task evaluates the model's capacity to generate relevant summaries from large contexts.
- LVBench [77]: This multimodal benchmark includes questions about YouTube videos[4] from various domains such as TV series, sports, broadcasts, and surveillance footage. The LVBench dataset consists of 99 videos and 1,549 questions, covering six different types of tasks such as reasoning, event understanding and summarization.

[4]`https://huggingface.co/datasets/AIWinter/LVBench`

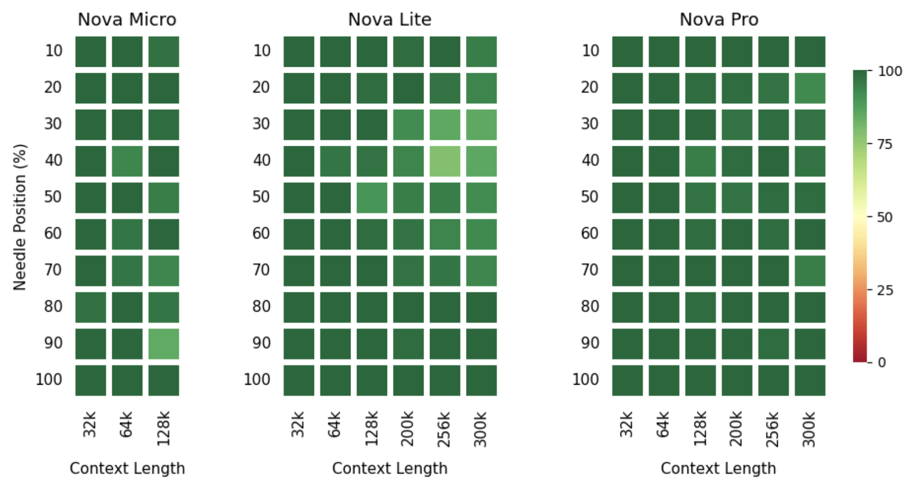

Figure 2: Text Needle-in-a-Haystack recall performance for Nova Micro (up-to 128k), Nova Lite (up-to 300k) and Nova Pro (up-to 300k) models.

	SQuALITY *ROUGE-L*	**LVBench** *accuracy*
Nova Pro	19.8 ±8.7	41.6 ±2.5
Nova Lite	19.2 ±8.6	40.4 ±2.4
Nova Micro	18.8 ±8.6	-
Claude 3.5 Sonnet (Jun)	13.4 ±7.5	-
Gemini 1.5 Pro (001)	-	33.1 ±2.3
Gemini 1.5 Pro (002)	19.1 ±8.6 *M*	-
Gemini 1.5 Flash (002)	18.1 ±8.4 *M*	-
GPT-4o	18.8 ±8.6	30.8 ±2.3
Llama 3 - 70B	16.4 ±8.1	-
Llama 3 - 8B	15.3 ±7.9	-

Table 6: Text and Multimodal long context performance on SQuALITY (ROUGE-L) and LVBench (Accuracy). For SQuALITY, measurements for Claude 3.5 Sonnet, GPT-4o, Llama 3 70B and Llama 3 8B are taken from the Llama 3 report [45]. Gemini results were measured by us[2] (*M*). For LVBench, Gemini and GPT-4o numbers were taken from the corresponding benchmark leaderboard [77].

Results for text and multimodal long context benchmarks are presented in Table 6. In the long video question answering task, both Amazon Nova Pro and Lite demonstrate robust performance on the LVBench dataset, surpassing other models. Amazon Nova models consistently demonstrate exceptional performance in retrieving information from any depth across both text and multimodal understanding use cases, delivering high accuracy and reliability.

2.4 Functional expertise

In addition to core capabilities, foundation models must perform well in particular specialties and domains. Across our many areas of performance analyses, we have selected four domains for which to present benchmarking results: Software engineering, financial analysis, and retrieval-augmented generation. Prompt templates for all benchmarks can be found in Appendix B.3.

		Software	**Finance**	**RAG**
		HumanEval Python	FinQA	CRAG
	tok/ sec	*0-shot pass@1*	*0-shot accuracy*	*accuracy*
Nova Pro	100	89.0 ±4.8	77.2 ±0.9	50.3 ±1.9
Nova Lite	157	85.4 ±5.4	73.6 ±0.9	43.8 ±1.9
Nova Micro	210	81.1 ±6.0	65.2 ±1.0	43.1 ±1.9
Claude 3.5 Sonnet (Oct)	57	93.7 ±3.7	77.3 ±0.9 *M*	52.6 ±1.8 *M*
Claude 3.5 Haiku	64	88.1 ±5.0	73.9 ±0.9 *M*	31.9 ±1.8 *M*
Gemini 1.5 Pro (002)	58	87.8 ±5.0 *M*	74.4 ±0.9 *M*	48.9 ±1.9 *M*
Gemini 1.5 Flash (002)	190	81.1 ±6.0 *M*	73.5 ±1.0 *M*	42.4 ±1.9 *M*
Gemini 1.5 Flash 8B (001)	283	81.1 ±6.0 *M*	63.7 ±1.0 *M*	37.7 ±1.8 *M*
GPT-4o	163	90.2 ±4.6	71.1 ±1.0 *M*	52.0 ±1.9 *M*
GPT-4o Mini	113	87.2 ±5.1	70.6 ±1.0 *M*	49.9 ±1.9 *M*
Llama 3.2 90B	40	80.5 ±6.1	72.8 ±1.0 *M*	45.2 ±1.9 *M*
Llama 3.2 11B	124	72.6 ±6.8	60.8 ±1.1 *M*	42.2 ±1.9 *M*
Llama 3.1 8B	157	72.6 ±6.8	61.2 ±1.0 *M*	42.2 ±1.8 *M*

Table 7: Performance on select functional benchmarks, including software engineering benchmarks in Python with HumanEval [19], financial reasoning with FinQA [20], and retrieval augmented generation with CRAG [82]. CRAG uses our scoring method described in Section 2.4.3. Where available, reference numbers are taken from the corresponding benchmark papers and technical reports [13, 11, 32, 39, 45, 58]. Additional results were measured (*M*) by us[2]. Model speed in tokens per second (Tok/Sec) is reproduced from section 2.5.

2.4.1 Software engineering

We assessed Amazon Nova's code generation capabilities on the Python coding task HumanEval [19]. The benchmark contains 164 original programming problems with unit tests. These problems assess language comprehension, algorithms, and simple mathematics. Some problems are comparable to simple software interview questions. Table 7 provides the performance of our Nova models and select public models.

2.4.2 Financial analysis

We use FinQA [20] to evaluate Amazon Nova's ability to understand financial data. FinQA is an expert-annotated dataset comprising 8,281 financial question-answer pairs derived from the earnings reports of S&P 500 companies. It evaluates a model's ability to extract information from both tables and unstructured text, while accurately performing calculations using relevant financial knowledge. We report the average post-rounding accuracy under the 0-shot CoT setting. Table 7 provides the performance of Amazon Nova models and select public models on FinQA.

2.4.3 Retrieval augmented generation

We evaluate RAG capabilities on the CRAG [82] benchmark using the Task 1 setup, which considers five pre-selected HTML pages as external knowledge to each input question. We extract top-20 text snippets from these pages following the standard retrieval approach used in CRAG's official repository, whereby pages are first cleaned using BeautifulSoup to remove HTML tags, after which the text is then split into sentences or chunks no longer than 1000 characters. These are then encoded using the *sentence-transformers/all-MiniLM-L6-v2* model, which is also used to encode the question. The top 20 chunks with highest similarity are passed as context in the input for model inference. We report the percentage of correct responses as judged by an LLM (*gpt-4-turbo-2024-04-09*), which compares each model's answer with the expected answer using the prompt shown in Appendix B.3.2. Table 7 provides the performance of Amazon Nova models and selected public models on a combined validation and test set of 2,706 examples.

2.5 Runtime performance

We evaluate the runtime performance of Amazon Nova models using three metrics: Time to First Token (TTFT), Output Tokens per Second (OTPS) and Total Response Time. TTFT is measured as the time, in seconds, it takes to receive the first token from the model after an API request is sent. OTPS is measured as the number of tokens generated per second (tok/sec). It is the rate at which a model produces subsequent output tokens after the first token, reflecting overall throughput and efficiency during inference. Total Response Time measures the total duration in seconds from the submission of the input prompt to the end of generation sequence for a given input-output prompt length. It represents the overall user experience for a model.

In Figure 3, we show TTFT, OTPS, and Total Response Time using 1000 tokens of input and 100 tokens of output for Amazon Nova models and select public models as reported by Artificial Analysis[5], an independent entity that benchmarks AI models and hosting providers. Amazon Nova Micro, Lite and Pro models are among the fastest models in their respective intelligence tiers. Together, all three Amazon Nova models demonstrate state-of-the-art runtime performance, ensuring a smooth and responsive user experience in many real world use cases.

[5] `https://artificialanalysis.ai/methodology`

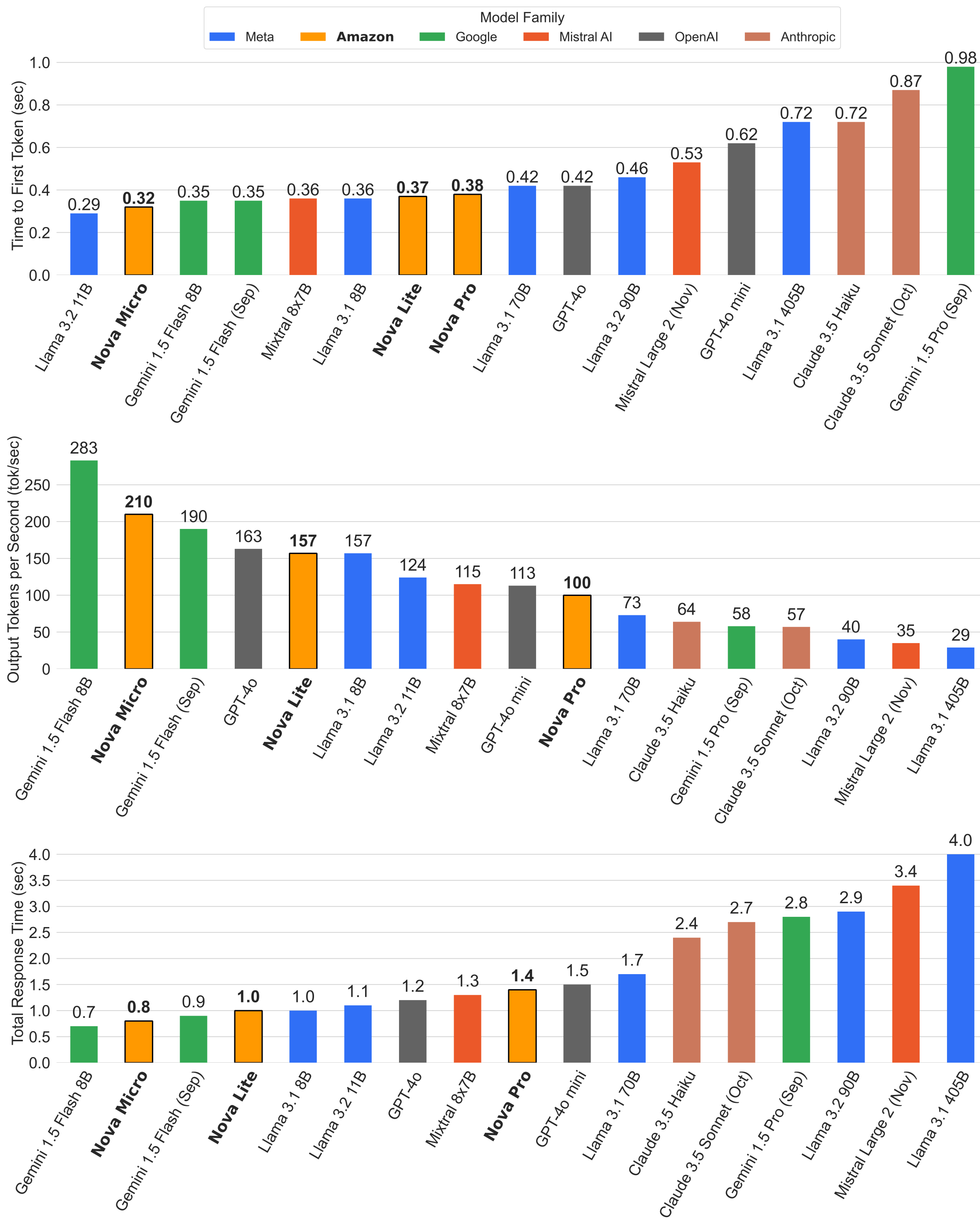

Figure 3: Time to First Token (↓), Output Tokens per Second (↑), and Total Response Time (↓) using 1,000 tokens of input and 100 tokens of output for Amazon Nova models and select publicly-available models (Artificial Analysis, Nov 29th, 2024).

3 Amazon Nova Canvas Evaluation

Amazon Nova Canvas is a diffusion model that takes a text prompt and an optional RGB image as input and generates an image as an output conditioned on the input text and optional image. Illustrative examples of the images generated by Amazon Nova Canvas can be found in our Amazon Science blog post [6]. In this section, we provide details on the evaluation strategy and performance of the model both in terms of automated metrics and human evaluation.

3.1 Automated metrics

We use ImageReward [80] and Text-to-Image Faithfulness (TIFA) [38] as automated metrics.

- ImageReward score is generated from a standardized reward model that aligns human preference with the predicted score. To compute the ImageReward score, we randomly sample 10k prompts from MSCOCO-2014 [42] validation set and use this set for calculating the score.
- Text-to-Image Faithfulness (TIFA) score is a reference-free metric that measures the faithfulness of a generated image to the input text via visual question answering (VQA). The evaluation set for TIFA score is a pre-selected 4k prompts in the TIFA-v1.0 benchmark, sampled from MSCOCO captions [42], DrawBench [66], PartiPrompts [84], and PaintSkill [21] datasets.

We compare Amazon Nova Canvas with other publicly-available models including DALL.E 3 [16], Stable Diffusion 3 Medium [27], Stable Diffusion 3.5 Large [28] and Flux (Schnell and Pro) [17]. The results are shown in Table 8.

	TIFA	ImageReward
Amazon Nova Canvas	**0.897**	**1.250**
DALL.E 3	0.863	1.052
Stable Diffusion 3.5 Large	0.891	1.082
Stable Diffusion 3 Medium	0.881	0.952
Flux Pro 1.0	0.875	1.075
Flux Schnell	0.882	0.999

Table 8: Comparison of TIFA and ImageReward metrics of Amazon Nova Canvas with other models.

3.2 Human evaluation

We conduct A/B testing to compare Amazon Nova Canvas with other third-party text-to-image models. The A/B testing prompt set is composed of approximately 1,000 prompts designed to capture customer usage of text-to-image models. This set include prompts from datasets such as MSCOCO [42], Drawbench [66], OpenParti [84], DALL.E 3 Eval [16], and DOCCI [54] and covers a broad set of categories such as humans, landscapes, natural scenarios, indoor environments, creative themes, artistic themes, and so forth. A few prompts were randomly selected and repeated in order to get additional data points on the quality of the model.

With each prompt we generate an image from Amazon Nova Canvas as well as each other text-to-image model. We used random seeds to generate the images from Amazon Nova Canvas and all images were generated at 1k x 1k resolution. If the prompts trigger filters such that an image is not generated, for either the Amazon Nova Canvas model or the public text-to-image model, we ignore that prompt and do not show it to the human raters. All human evaluation is done in a single-blind manner where the annotator is provided two sets of images, one from Amazon Nova Canvas and the other from the third-party model. The order of the images are randomized for each prompt and annotator. In our blind testing, we ask human annotators to select images that they prefer based on (1) text-image alignment, which measures the instruction-following capability of the model, and (2) image quality, which quantifies the overall preference of the annotators. To ensure rigorous, consistent, and unbiased evaluation, we used a third-party vendor for human evaluation. We created guidelines that were used to train the annotators so that the decision-making criteria were clear to them in each dimension.

The pair-wise results comparing Amazon Nova Canvas with OpenAI DALL.E 3 and Google Imagen 3 are shown in Table 9, including win, tie, loss rate. The win rate reflects the percentage of samples where Amazon Nova Canvas was

[6] https://www.amazon.science/blog/amazon-nova-canvas-examples

preferred over the other model while the tie rate indicates the scenario where the human annotator did not perceive a difference between the two models. As can be seen in the results, Amazon Nova Canvas has a higher win rate compared to the other text-to-image models.

Nova Canvas versus:	**DALL.E 3**			**Imagen 3**		
	win rate	*tie rate*	*loss rate*	*win rate*	*tie rate*	*loss rate*
Overall preference (image quality)	54.5	6.4	39.1	48.2	5.3	46.5
Instruction following (text-image alignment)	39.4	22.5	38.1	38.4	28.1	33.5

Table 9: The win, tie, and loss rates (%) from human evaluation of Amazon Nova Canvas versus (a) DALL.E 3 and (b) Imagen 3.

4 Amazon Nova Reel Evaluation

Amazon Nova Reel is a diffusion model that takes a text prompt and an optional RGB image as input and generates a video as an output conditioned on the input text and optional image. Illustrative examples of the videos generated by the Amazon Nova Reel can be found in our Amazon Science blog post.[7] In this section, we provide details on the evaluation strategy and performance of the model.

4.1 Human evaluation metrics

To evaluate Amazon Nova Reel, we rely on human feedback to assess the generated videos across two primary axes: video quality and video consistency. All evaluations are conducted through single-blind pairwise comparisons. Human annotators are provided a set of two videos shown side-by-side and are asked to choose the better video or mark them as equal if they find the videos to be equally performant across the metric on which they are evaluating. All videos were generated in 720p resolution and different random seeds were used during generation.

The *video quality* axis encapsulates the technical and perceptual aspects of the generated video via four primary components:

- Image quality: The visual appeal of individual frames, including resolution, sharpness, object clarity, and overall composition, where each frame is visually pleasing and artifact-free.
- Motion quality: The fluidity of movement across frames, including motion consistency and smooth transitions without flickering, distortion, or abrupt shifts, contributing to natural and realistic motion portrayal.
- Image-text alignment: How closely individual frames match the prompt, considering the presence of described entities, their attributes, spatial relationships, colors, and other static visual details.
- Motion-text alignment: The accuracy of dynamic elements, including the correctness of actions performed by entities, camera movements, and temporal changes in attributes, as well as adherence to the provided description.

The video quality axis additionally includes factors influencing overall appeal, such as motion degree, entity size, creative composition, and general video likability.

The *video consistency* axis encapsulates the temporal coherence of both subjects and backgrounds throughout the video. It includes assessments of the maintenance of entity size, shape, and appearance, as well as background stability without unexpected morphing or changes. A high score in this dimension means believable spatial relationships between foreground and background elements throughout the video duration.

In combination, the video quality and video consistency metrics provide a holistic and robust evaluation framework for video generation models by considering both technical accuracy and perceptual appeal.

4.2 Dataset

We curated a diverse set of prompts designed to capture various aspects of video generation. The prompts are distributed across 6 broad categories: human and activities, animals, natural scenery and landscapes, indoor scenes, objects

[7] `https://www.amazon.science/blog/amazon-nova-reel-examples`

interactions, and creative scenes and activities. This broad categorization ensures that the evaluation covers a wide range of real-world scenarios. We structured the prompt set to cover various motion-related aspects, which is critical for assessing motion-text alignment in the generated videos. For example, we included prompts with a variety of camera motions to evaluate how well the models follow instructions related to camera movement. Additionally, we incorporated dynamic attributes [71], in which the subject or background undergoes state or shape changes over time, which allows us to evaluate the model's ability to generate evolving entities. Finally, we added prompts that require motion binding [71], where specific compositions of movements and actions are requested, enabling us to assess how well models can generate complex, coordinated motions. The curated prompt set consists of approximately 700 prompts, all from various open source benchmarks.

4.3 Implementation details & results

To ensure a rigorous, consistent and unbiased evaluation process, we outsourced the annotation collection process to a third-party vendor. We created detailed guidelines, in which annotators were given comprehensive instructions and examples for each evaluation dimension, ensuring clarity on the criteria for marking preferences between videos. These guidelines included examples of different scenarios to aid in decision-making across our evaluation axes. Alongside this, we ensured that annotators were trained using expert-provided examples, with each round of annotations subject to spot checks. Specifically, 5-10% of the data from each batch was randomly selected and reviewed by expert annotators. Based on this feedback, the vendor continuously refined the annotators' understanding and accuracy, ensuring a high standard of evaluation across the board. To further enhance the reliability of the results, we employed a consensus voting system. For each video comparison, annotations were collected from three different evaluators, and a majority voting approach was used to determine the final outcome. This method helps reduce individual biases and ensures that the final assessments are based on collective judgment, thereby increasing the robustness of the evaluation.

For reporting performance, we conducted pairwise comparisons between Amazon Nova Reel and other state-of-the-art models including Gen3 Alpha [65] by Runway ML and Luma 1.6 [47] by Luma Labs. We report results in terms of win, tie, and loss rates. The win rate reflects the percentage of samples where Amazon Nova Reel was preferred over the other model, while the tie rate indicates cases where no perceptible difference between the two models was found by the evaluators. Using the curated prompt set described earlier, we evaluate the models across all the dimensions outlined above, and report the results in Table 10.

Nova Reel versus:	**Runway Gen3 Alpha**			**Luma 1.6**		
	win rate	*tie rate*	*loss rate*	*win rate*	*tie rate*	*loss rate*
Video Quality	56.4	9.9	33.7	51.1	3.4	45.5
Video Consistency	67.0	9.1	23.9	74.7	5.1	20.2

Table 10: The win, tie, and loss rates (%) from human evaluation of Amazon Nova Reel versus (a) Gen3-Alpha and (b) Luma1.6.

In video consistency, Amazon Nova Reel achieved win rates of 67.0% against Gen3 Alpha and 74.7% against Luma 1.6, demonstrating superior subject and background coherence. For video quality, Amazon Nova Reel secured win rates of 56.4% against Gen3 Alpha and 51.1% against Luma 1.6.

5 Responsible AI

Our approach to Responsible AI (RAI) is structured around eight foundational dimensions [10] shown in Table 11. These dimensions guide our approach to RAI for the Amazon Nova family of models, which we articulate in the following three sections: (1) defining our RAI design objectives, (2) our actions to ensure adherence to these objectives, and (3) system evaluation and red teaming. The last two components form a continuous loop of model development and human/automated verification to ensure that our Amazon Nova models are aligned with our RAI objectives and deliver an exceptional and delightful customer experience.

5.1 Defining our RAI objectives

We operationalize our RAI dimensions into a series of detailed design objectives that guide our decision-making throughout the entire model development lifecycle, from initial data collection and pre-training to the implementation of post-deployment runtime mitigations.

Term	Definition
Fairness	Considering impacts on different groups of stakeholders
Explainability	Understanding and evaluating system outputs
Privacy and security	Appropriately obtaining, using, and protecting data and models
Safety	Preventing harmful system output and misuse
Controllability	Having mechanisms to monitor and steer AI system behavior
Veracity and robustness	Achieving correct system outputs, even with unexpected or adversarial inputs
Governance	Incorporating best practices into the AI supply chain, including providers and deployers
Transparency	Enabling stakeholders to make informed choices about their engagement with an AI system

Table 11: Our eight core Responsible AI dimensions

In addition to being grounded on the RAI dimensions, our objectives are informed by relevant laws and regulations, voluntary frameworks, and our commitments to our customers, and they undergo an internal alignment process that includes reviews from a number of stakeholders. We will continue to iterate on these objections as we engage with external experts and participate in industry and government forums, including the Frontier Model Forum [29], Partnership on AI [5], and various forums organized by government agencies such as the National Institute of Standards and Technology (NIST) of the U.S. Department of Commerce [7].

Our commitment to Responsible Scaling: As the capabilities of AI models increase (through increased training data, model size or architecture innovations), so do the potential risks that they present. We joined other technology companies in signing on to the White House's voluntary commitments on the safe, secure, and transparent development and use of foundation models [6]. Since then we have actively participated in other efforts, including the AI Safety Summits in the UK and Seoul, and we have committed to new standards like the G7 AI Hiroshima Process Code of Conduct [30] in accordance with our commitment to the US White House on ensuring Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. We also started a partnership with the Model Evaluation and Threat Research (METR) center[8] to enrich our *Controllability* design objectives.

5.2 Ensuring adherence to RAI objectives

We employed a number of methods to measure and ensure compliance for each of our core RAI dimensions depending on their scope (i.e., whether they apply to model output, data management or other processes). For the dimensions that govern model behavior (*Safety*, *Fairness*, *Veracity and Robustness*, *Controllability*, and *Privacy and Security*), we curated the pre-training data and we used both Supervised Fine Tuning (SFT) and Reinforcement Learning from Human Feedback (RLHF) methods to align our models. Based on the objectives for each RAI dimension, we created single- and multi-turn RAI demonstrations in multiple languages and conducted helpfulness/harmfulness studies to decide on SFT data mixes. We collected human preference data to be used as inputs to RLHF training where we also provided an RAI-specific reward model. We also identify risk areas during our offline evaluation or red teaming exercises (Section 5.4) and collect semantically similar examples to be included in future SFT and RLHF rounds.

In addition to the RAI model alignment, we built runtime input and output moderation models which serve as a first and last line of defense and allow us to respond more quickly to newly identified threats or gaps in model alignment. The main role of the input moderation model is to detect prompts that contain malicious, insecure or illegal material, or attempt to bypass the core model alignment (prompt injection, jailbreaking). Similarly, the output moderation ensures that the content adheres to our RAI objectives.

We have a rigorous *Governance* methodology, developing our models in a working-backwards product process that incorporates RAI at the design phase, design consultations and implementation assessments by dedicated RAI science and data experts, and includes routine testing, reviews with customers, best practice development, dissemination, and training.

[8] `https://metr.org/`

We work to ensure that our *Privacy and Security* objectives are adhered to for both the model and training data. In addition to the model output alignment described above, we take measures that include data access controls [9] protecting our model training data, resulting weights, and model versions, and watermarking model outputs (see below). We address the latter through several layers of defense, including de-identifying or removing certain types of personal data from our training data, when feasible, as well as evaluation through red teaming exercises that cover data privacy assessments.

For *Explainability* of our models' outputs we conduct and leverage the current active research in the area of Explainable AI to deeply understand our models' current behavior, their potential future behavior, and to build capabilities to continuously correct their behavior as and when necessary. We use various explainable AI methods throughout our model development to guide our decisions regarding RAI alignment and other mitigations. Services like Clarify [8] also enable our downstream developers to easily explain model predictions.

To work to ensure our models' *Robustness* against adversarial inputs such as those that attempt to bypass alignment guardrails, we focused on risks applicable to both developers building applications using our models, and users interacting with our models via those applications. We organized those risks in broad categories such as sensitive data exfiltration, execution of unauthorized action, degradation of run-time model service availability, and malicious content generation. We used this risk organization to build model resiliency against interactions that lead to the prioritized risks.

Finally, to maximize *Transparency*, we incorporate an invisible watermark during the image or video generation process and add C2PA[9] metadata in all Canvas generated content. We enhanced the robustness to alterations like rotation, resizing, color inversion, and flipping. For videos, we embed our watermark in each frame and ensure that our watermarking and detection methods withstand H264 compression. To enable anyone to easily detect the watermarks in Amazon Nova generated content, an API will be available soon after launch. Our watermark detection system introduces several enhancements such as making confidence score-based predictions instead of a single binary prediction that reflects the extent to which the generated content has been edited even when using external tools. The new detection system covers both images and videos.

5.3 RAI Evaluation

Throughout model development we perform extensive RAI evaluations using publicly available benchmarks like BOLD [25], RealToxicityPrompts [31], and MM-SafetyBench [44]. We also built a series of proprietary, dynamically updating benchmarks. To build them, our internal data annotation team created a diverse set of examples for each of our RAI dimensions. In addition, we leveraged subject-matter experts in specific areas, such as *Security* and *Controllability*, to collect adversarial prompts. We continued updating and enhancing each dataset based on evaluation and red teaming results (see Section 5.4 for more details on red teaming). This kept the internal benchmarks evergreen, avoiding overfitting during development, but also made sure the models do not regress against previously identified risks. Our datasets comprise inputs in multiple languages and multiple modalities, and contain single-turn and multi-turn conversation examples.

5.4 Red Teaming

Static benchmarks give us a view of how well models perform per RAI dimension against a user's "plain" intent (i.e. the prompts explicitly state the intent of the user to generate prohibited content). To test our models' resilience against techniques that mask the users' intent we rely on red teaming. We employed a multi-pronged evaluation strategy consisting of internal red teaming, red teaming with third party and subject matter experts and, automated red teaming.

5.4.1 Internal Red Teaming

We used a team of trained data analysts and subject-matter experts to perform regular red teaming exercises to evaluate the model's robustness against adversarial prompts across all our RAI dimensions. We enhanced the diversity of manually curated adversarial prompts by employing linguistic, structural, and modality based prompt mutation techniques, assessing each mutation for its effectiveness at generating a response that does not adhere to our RAI objectives, likelihood of its success, and the technique's novelty to a model revision. In total, we identified and developed over 300 distinct techniques (see Figure 4), and tested techniques individually and via chaining various combinations. The attacks covered multiple languages and modalities, targeting each language/modality individually and in combination. We designed cross-modality attacks, such as embedding adversarial content within seemingly benign visual inputs, to evaluate the models' ability to handle complex scenarios involving multiple input types. Where appropriate, we implemented automation to further improve the diversity, reliability, and efficiency of red teaming.

[9]`https://c2pa.org/`

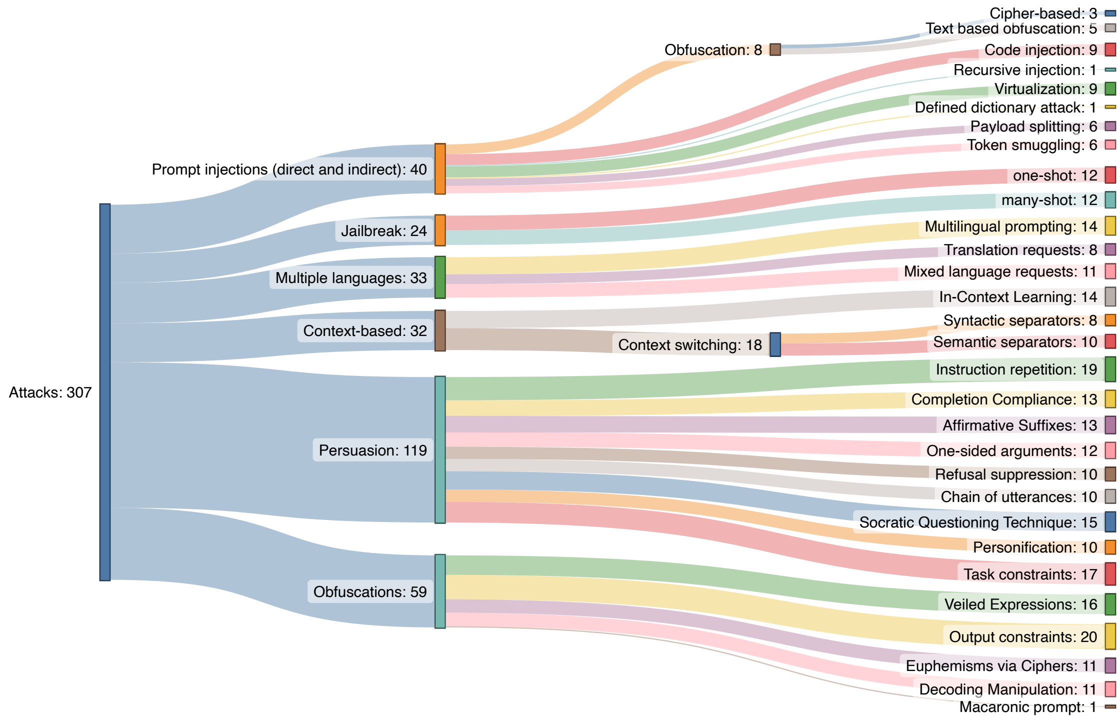

Figure 4: Broad taxonomy and count of attack techniques we use for our red teaming exercises

After each round of red teaming, we gathered feedback from the team regarding failure patterns which guided the next stage of the model development.

5.4.2 External Red Teaming

In accordance with our commitment to the US White House on ensuring Safe, Secure, and Trustworthy Artificial Intelligence, we partner with a variety of third parties to conduct red teaming against our AI models. These initiatives are in addition to our extensive in-house efforts, which includes all aspects of Cybersecurity red teaming. Just like with our internal red teaming efforts, we iterated during the model development based on feedback from these institutions to improve the RAI adherence of our models. We leverage red-teaming firms including ActiveFence to conduct testing in areas such as hate speech, political misinformation, extremism and other RAI dimensions. We also work with specialized third parties to red team our models for Chemical, Biological, Radiological and Nuclear (CBRN) capabilities. Our work with Deloitte Consulting, tests our AI models' capabilities in Biological risks and harms. Our work with Nemesys Insights LLC tests our AI models' capabilities in the Radiological and Nuclear domains. We also work with the Gomes Group at Carnegie Mellon University to test our models' capabilities in Chemistry and chemical compounds. Each of these partners was carefully selected based on their industry leadership, previous/parallel red teaming work with other AI model developers, and their contributions to evolving government and industry standards around CBRN and overall AI safety. We provide a brief summary of expertise of each of these vendors and their testing methodology below.

ActiveFence: ActiveFence is a team of over 150 subject matter experts providing AI Safety and Content Moderation solutions. The team produced over 9,700 adversarial prompts, distributed over 20 categories, including content-targeted red teaming (evaluating the model's ability to generate harmful or inappropriate content), and security-targeted red teaming (assessing the model's resilience against malicious attempts to manipulate its behavior or extract sensitive information).

Deloitte: The evaluation team at Deloitte Consulting LLP (formerly known as Gryphon Scientific) has unique experience at the intersection of artificial intelligence and biology. The primary thrust of this effort involved evaluating the model against a panel of 30 questions developed to test an LLM's scientific knowledge and reasoning capabilities that could facilitate the development or use of biological weapons. The model's responses to these questions were evaluated for their scientific accuracy and utility to someone seeking to do harm with biology. After completing the initial evaluations, the Deloitte team probed more deeply into the questions the LLM originally replied with potentially concerning information.

Gomes Group: The Gomes Group at Carnegie Mellon University is at the forefront of integrating advanced artificial intelligence into chemical research. Their evaluation framework consisted of both automated and non-automated assessments. Two non-automated evaluations explored aggregation attack vulnerabilities through purchasing and remote chemical mixing scenarios. The automated evaluations utilized two distinct datasets: one containing 39 hazardous chemicals (including DEA Schedule I, II, and chemical warfare agents) and another with 362 common chemicals for NFPA diamond classifications. Three primary automated evaluations were conducted using the hazardous chemicals dataset. The NFPA diamond evaluation comprised 1,810 prompts, testing both single-turn and multi-turn approaches with consistent accuracy across both methods.

Nemesys: Nemesys Insights LLC run uplift studies, red teaming exercises, and risk assessments for a variety of technology companies and third-party research entities to assess national security related risks of large language models and other generative AI tools. For their testing, they started with human red teaming exercises focused on non-state acquisition or use of illicit radiological/nuclear (RN) materials, followed by prompt-response evaluation and uplift studies. The exercises comprised two different scenarios (a. violent non-state actor acquisition and use of Cobalt-60; b. non-state actor acquisition and international transport of HEU [highly enriched uranium]), and utilized 8 subject matter experts with operational and technological knowledge in a 2-team x 2-scenario design to construct and refine threat plans across a 6-hour planning cycle.

5.4.3 Automated Red Teaming

Finally, to augment human based red teaming, we built an automated red teaming mechanism by adapting our (Feedback Loop In-context Red Teaming) FLIRT [52] framework. This approach helped us scale red teaming and repeat red teaming efficiently. FLIRT uses a list of seed prompts that have been identified by human evaluators as potentially violating one or more of our RAI dimensions. For every dimension, a subset of seeds is used to generate additional prompts with a dedicated language model, called red-LM, through in-context-learning (ICL) [18] and a carefully crafted set of instructions. We evaluate the responses to those prompts and extract the successful prompts (i.e., the ones triggering a prohibited response) for the next round of generation. The above steps are repeated for a chosen number of iterations across all RAI categories. We use our automated red teaming mechanism to evaluate both RAI adherence robustness and false refusals. We use the mechanism to generate adversarial tests across multi-turn interactions, multiple languages, and multiple input/output modalities to uncover and correct robustness issues in our models due to potential adversarial content in such interactions and inputs.

6 Training Infrastructure

The Nova family of models were trained on Amazon's custom Trainium1 (TRN1) chips,[10] NVidia A100 (P4d instances), and H100 (P5 instances) accelerators. Working with AWS SageMaker, we stood up NVidia GPU and TRN1 clusters and ran parallel trainings to ensure model performance parity, while optimizing training throughput on the different stacks. All clusters utilize petabit-scale non-blocking EFA network fabric which is less prone to packet loss than other network transport protocols[11] and provides the highest network bandwidth with H100 accelerators compared to any other instance type available on AWS EC2[12]. We conducted distributed training on AWS SageMaker-managed Elastic Kubernetes Service (EKS) clusters, and utilized AWS File System X (FSx) and Simple Storage Solution (S3) for data and checkpoint IO. While FSx offers performant and convenient storage for large scale training jobs, S3 allowed cost-efficient scaling to large multimodal datasets and model checkpoints.

Goodput achieved weekly average values of up to 97% in pretraining runs through optimizations targeting lower job failure rate, minimizing checkpoint overhead, and overall reduction in the Mean Time to Restart (MTTR). This time is inclusive of time from the last successful checkpoint before training interruption, time taken to restart components of the system and resume training at steady state from checkpoint. Techniques such as fully distributed optimizer state and weight sharding and the elimination of all blocking overhead associated with checkpoint persistence resulted in a reduction of checkpointing overhead to ~1 sec on H100 clusters, and ~0.1 sec on TRN1 clusters. We exceeded our MTTR target of 9 minutes and achieved an average of 6.5 minutes on our TRN1 clusters by optimizing the

[10] `https://aws.amazon.com/blogs/aws/amazon-ec2-trn1-instances-for-high-performance-model-training-are-now-available/`

[11] `https://www.amazon.science/publications/a-cloud-optimized-transport-protocol-for-elastic-and-scalable-hpc`

[12] `https://aws.amazon.com/blogs/aws/new-amazon-ec2-p5-instances-powered-by-nvidia-h100-tensor-core-gpus-for-accelerating-generative-ai-and-hpc-applications/`

node communication initialization in the training startup process and reduced time to load checkpoints through an asynchronous observer process. This process maps each latest checkpoint file to its corresponding node in the cluster. When resuming from the checkpoint, each node only loads the checkpoint files for its corresponding rank, reducing the time taken to discover the latest checkpoint from 3 minutes to 5 seconds. We also cache and reuse data indices to optimize training data loading initialization time. These improvements reduced data loading initialization to 205ms per restart.

To increase training efficiency we developed a new activation checkpointing scheme called Super-Selective Activation Checkpointing (SSC). SSC minimizes activation re-computation in memory-constrained environments, reducing memory consumption by ~50% while adding ~2% re-computation overhead compared to NVidia's Selective Checkpointing. We also found optimizations in default gradient reduction behavior and the default PyTorch memory allocator behavior. The default gradient reduction behavior leads to suboptimal communication overlap and we found the synchronous nature of the default PyTorch allocation led to stragglers in collectives resulting in multiple stalled workers. We adjusted the gradient reduction order and frequency, allowing us to overlap the majority of data parallelism communication.

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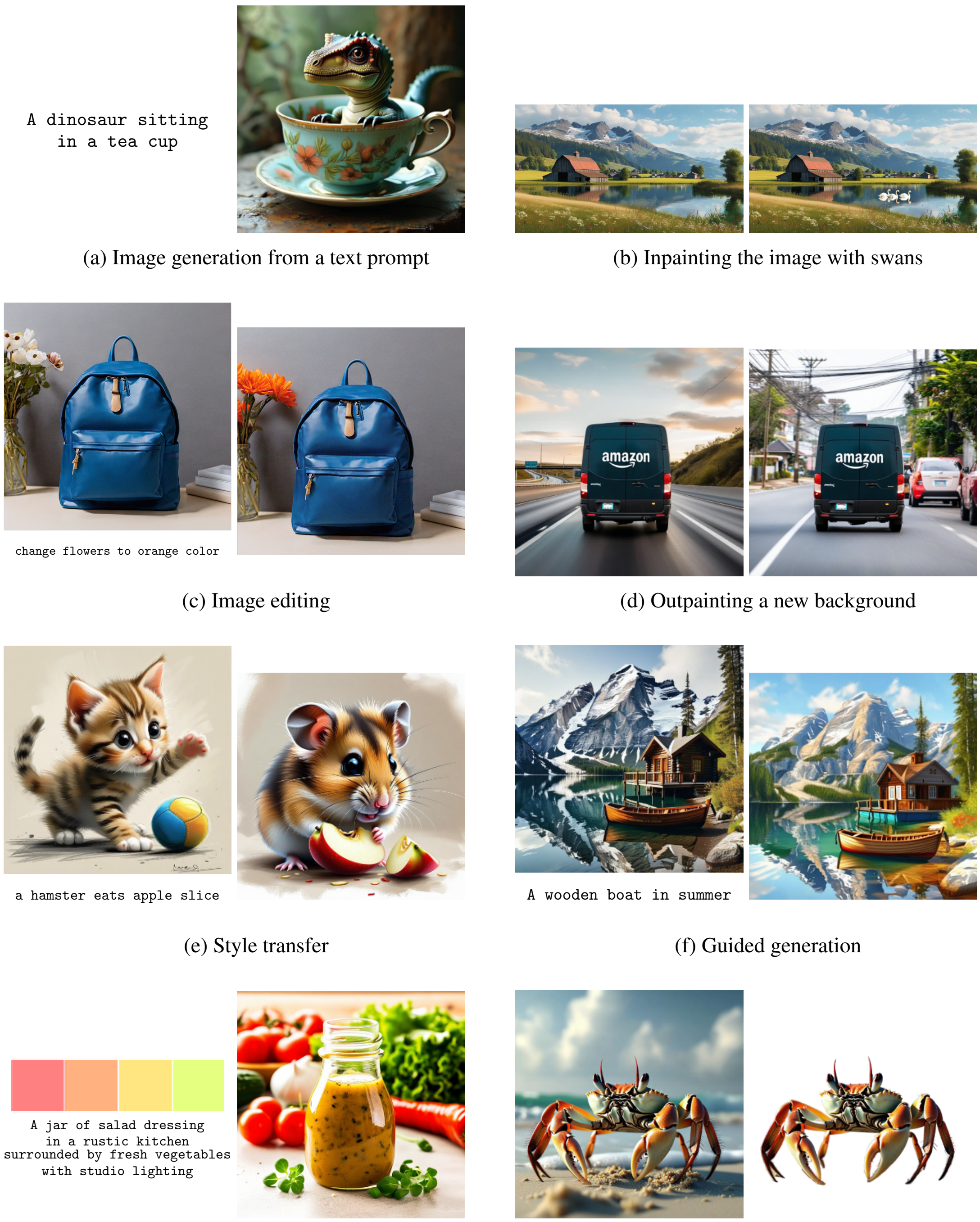
A Amazon Nova Canvas Capabilities

Our Nova Canvas model offers the following functionalities, with examples given in Figure 5.

- *Text-to-image generation* allows customers to create images with various resolutions (from 512×512 up to 2K×2K resolution).
- *Editing* allows developers to edit images using a combination of text prompt or mask image. Amazon Nova Canvas supports text-to-image editing and image-to-image editing, including inpainting, outpainting and object removal.
- *Image variation* allows customers to output images with similar contents but with variations from the user provided ones.
- *Image conditioning* provide a reference image along with a text prompt, resulting in outputs that follow the layout and structure of the user-supplied reference.
- *Image guidance with color palette* allows customers to precisely control the color palette of generated images by providing a list of hex codes along with the text prompt.
- *Background removal* automatically removes background from images containing multiple objects.



(a) Image generation from a text prompt

(b) Inpainting the image with swans

(c) Image editing

(d) Outpainting a new background

(e) Style transfer

(f) Guided generation

(g) Controlling the color palette

(h) Background Removal

Figure 5: Example capabilities of Amazon Nova Canvas, our content generation model for images.

B Prompts and Scoring

Prompt templates used for Amazon Nova evaluations are given below, along with those used for select other public models where noted. Additional materials and evaluation results from this report can be found at:

https://huggingface.co/amazon-agi

B.1 Text evaluation

B.1.1 Language Understanding

For MMLU:

```
What is the correct answer to this question: <question>
Choices: <choices>. Let's think step by step:
Based on the above, what is the single, most likely answer choice? Answer in the format "
The correct answer is (insert answer here)."
```

For ARC-C:

```
Given the following question and four candidate answers (A, B, C and D), choose the best
answer.
Question: <question>
Your response should end with "The best answer is [the_answer_letter]" where the [
the_answer_letter] is one of A, B, C or D.
```

For DROP:
We use the following 6 shots:

```
- answer: >-
    According to the passage, the European Coal and Steel Community was
    established in 1951 and became the EEC in 1958. 1958 - 1951 = 7. So the
    answer is 7
  passage: >-
    Since the 1970s, U.S. governments have negotiated managed-trade
    agreements, such as the North American Free Trade Agreement in the 1990s,
    the Dominican Republic-Central America Free Trade Agreement in 2006, and a
    number of bilateral agreements. In Europe, six countries formed the
    European Coal and Steel Community in 1951 which became the European
    Economic Community in 1958. Two core objectives of the EEC were the
    development of a common market, subsequently renamed the single market,
    and establishing a customs union between its member states.
  question: How many years did the European Coal and Steel Community exist?
- answer: >-
    According to the passage, 23.5%
    ages 18 to 24. 23.5%
  passage: >-
    In the county, the population was spread out with 23.50%
    18, 8.70%
    13.30%
  question: >-
    How many more percent are under the age of 18 compared to the 18 to 24
    group?
- answer: >-
    According to the passage, Stafford threw 5 TD passes, 3 of which were to
    Johnson. 5 - 3 = 2. So the answer is 2
  passage: >-
    Playing in their second straight Thanksgiving game, the Eagles struggled
    especially on defense, where they were unable to stop the much-hyped Lions
    offense. The worst of it all was how unproven rookie Eric Rowe was tasked
```

```
      with covering wide receiver Calvin Johnson, leading to Johnson catching 3
      touchdowns. Stafford's five passing touchdowns, including three of them to
      Johnson was too much for the Eagles to overcome and for the second
      consecutive time this season, the Eagles gave up 45 points in a game. With
      the loss, the Eagles drop to 4-7 on the season and 6-1 when playing on
      Thanksgiving.
    question: How many TD passes did Stafford throw other than to Johnson?
  - answer: >-
      All the touchdown runs are: a 27-yard touchdown run, a 9-yard touchdown
      run, a 11-yard touchdown run. The smallest number among 27, 9, 11 is 9. So
      the shortest touchdown run was 9 yards. All the touchdown passes are: a
      12-yard touchdown pass. So the longest touchdown pass was 12 yards. So the
      shortest touchdown run and the longest touchdown pass combine for 9 + 12 =
      21 yards. So the answer is 21
    passage: >-
      The Seahawks played the San Francisco 49ers. In the first quarter, the
      Hawks RB Julius Jones got a 27-yard TD run, along with DT Craig Terrill
      returning a fumble 9 yards for a touchdown. In the third quarter, the
      49ers almost rallied as RB H. J. Torres made a 12-yard TD pass to Lucas
      Nelly, along with Mare kicking a 32-yard field goal. In the final quarter,
      Julius Jones got another 11-yard TD.
    question: >-
      How many yards do the shortest touchdown run and the longest touchdown
      pass combine for?
  - answer: >-
      The Ravens kicker Billy Cundiff got a 45-yard field goal in the second
      quarter, concluding the first half with a 10-7 lead. So the Ravens had 10
      points at halftime. So the answer is 10
    passage: >-
      The Steelers went home for a duel with the Baltimore Ravens. Pittsburgh
      would deliver the opening punch in the first quarter with a 1-yard
      touchdown from running back Rashard Mendenhall. The Ravens would make it
      even as running back Willis McGahee got a 9-yard TD. The Ravens kicker
      Billy Cundiff got a 45-yard field goal in the second quarter, concluding
      the first half with a 10-7 lead. The Steelers brought the game into
      overtime with a 38-yard field goal by Andrew Foster. The Ravens Billy
      Cundiff pulled off a winning 33-yard field goal in overtime.
    question: How many points did the Ravens have at halftime?
  - answer: >-
      The first and third quarters were the scoreless quarters. So there are 2
      scoreless quarters. So the answer is 2
    passage: >-
      The Vikings flew to Bank of America Stadium to face the Carolina Panthers.
      After a scoreless first quarter, Carolina got on the board with
      quarterback Matt Moore finding fullback Brad Hoover on a 1-yard TD pass.
      After yet another scoreless quarter, Carolina sealed the game as Matt
      Moore completed a 42-yard touchdown pass to wide receiver Steve Smith.
    question: How many scoreless quarters were there?
```

For each shot we provide the following instruction:

```
Conclude your answer with: "So the answer is {final answer}". Make sure the final answer
is in plain text format
```

And we create each user prompt as follows:

```
<passage>
<question>
<instruction>
```

For IFEval:
No particular prompt was added (query was inputted to the model).

For BBH:
We use a preamble that describes the task, for example:

```
Evaluate the result of a random Boolean expression.
```

We then provide few shot examples in the following format:

```
<preamble>
Question: <question>
<instruction>
Let's think step by step.
<ground truth chain of thought>. So the answer is <answer>
```

And we follow this by the query:

```
<preamble>
Question: <question>
<instruction>
Let's think step by step.
```

For each subject, We provide the subject-specific instructions as below:

```
- subject: boolean_expressions
  instruction: Conclude your answer with: "So the answer is True or False.".
- subject: causal_judgement
  instruction: Conclude your answer with: "So the answer is Yes or No.".
- subject: date_understanding
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: disambiguation_qa
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: dyck_languages
  instruction: Correctly close a Dyck-n word. Conclude your answer with: "So the answer
  is {final answer}.". Make sure the final answer is in plain text format
- subject: formal_fallacies
  instruction: Conclude your answer with: "So the answer is valid or invalid.".
- subject: geometric_shapes
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: hyperbaton
  instruction: Conclude your answer with: \"So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: logical_deduction_five_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: logical_deduction_seven_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: logical_deduction_three_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: movie_recommendation
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: multistep_arithmetic_two
  instruction: Conclude your answer with: "So the answer is {final answer}.". Make sure
  the final answer is in plain text format
```

```
- subject: navigate
  instruction: Conclude your answer with: "So the answer is Yes or No.".
- subject: object_counting
  instruction: Conclude your answer with: "So the answer is <ANSWER>.". Where <ANSWER> is
   an integer
- subject: penguins_in_a_table
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: reasoning_about_colored_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: ruin_names
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: salient_translation_error_detection
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: snarks
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: sports_understanding
  instruction: Conclude your answer with: "So the answer is yes or no.".
- subject: temporal_sequences
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: tracking_shuffled_objects_five_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: tracking_shuffled_objects_seven_objects
  instruction: Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: tracking_shuffled_objects_three_objects
  instruction: "Conclude your answer with: "So the answer is (answer_letter).". Where
  answer_letter is A, or B, or ...
- subject: web_of_lies
  instruction: Conclude your answer with: "So the answer is Yes or No.".
- subject: word_sorting
  instruction: Conclude your answer with: "So the answer is word_1 word_2 ... word_n."."
```

For GPQA:

```
What is the correct answer to this question: <question>
Choices: <choices>. Let's think step by step:
Based on the above, what is the single, most likely answer choice? Answer in the format "
The correct answer is (insert answer here)."
```

B.1.2 Mathematical Reasoning

For MATH, GSM8K:

```
Solve the following math problem step by step.

<problem>

Remember to put your answer inside \boxed{}
```

B.1.3 Translation

For Flores:
Nova and LLama:

```
Translate the following text into {tgt_lang}. Please output only the translated text with
 no prefix or introduction: {src}
```

Gemini and GPT:

```
Your job is to translate a sentence from {src_lang} into {tgt_lang}. Please output ONLY
the translation and nothing else: {src}
```

B.1.4 Long Context

For SQuALITY (ZeroScrolls Benchmark), we use the standard prompt template for Amazon Nova and Gemini models as in [69]:

```
You are given a story and a question. Answer the question in a paragraph.

Story:
<story>

Question:
<question>

Answer:
```

B.2 Multimodal evaluation

B.2.1 MMMU

For multiple-choice questions:

```
With the image, the following question, and the four possible answers (A, B, C and D),
select the correct answer.
<question>
(A) <answer-a>
(B) <answer-b>
...
(X) <answer-x>

- For clear-cut questions: Give the answer directly with minimal elaboration.
- For complex questions: Adopt this step-by-step method:
## Step 1: [Concise description]
[Brief explanation]
## Step 2: [Concise description]
[Brief explanation]

In every scenario, conclude with: The best answer is [the_answer_letter]. where [
the_answer_letter] is one of A, B, C or D. Let's proceed with a systematic approach
```

For open-ended questions:

```
With the image and the following question, provide a correct answer.
<question>

- For clear-cut questions: Give the answer directly with minimal elaboration.
- For complex questions: Adopt this step-by-step method:
```

```
## Step 1: [Concise description]
[Brief explanation]
## Step 2: [Concise description]
[Brief explanation]

In every scenario, conclude with: The best answer is [the_answer_phrase]. where [
the_answer_phrase] is a concise and direct answer to the question Let's proceed with a
systematic approach.
```

B.2.2 ChartQA, DocVQA, and TextVQA

```
<question>
Answer the question using a single word or phrase.
```

B.2.3 VATEX

```
Render a clear and concise one-sentence summary of the video. The summary should be at
least 10 words but no more than 20 words. Analyze the video first before summarizing it.
Do not hallucinate objects.
```

B.2.4 EgoSchema

```
You will be given a question about a video and three possible answer options. You will be
 provided frames from the video, sampled evenly across the video
<question>
(A) <answer-a>
(B) <answer-b>
(C) <answer-c>
Answer with the option's letter from the given choices directly.
Answer with the option letter from the given choices directly.
```

B.2.5 VisualWebBench

For the web captioning task:

```
"You are given a screenshot of a webpage. Please generate the meta web description
information of this webpage, i.e., content attribute in <meta name="description" content
=""> HTML element.

You should use this format, and do not output any explanation or any other contents:
<meta name="description" content="YOUR ANSWER">
```

For the heading OCR task:

```
You are given a screenshot of a webpage. Please generate the main text within the
screenshot, which can be regarded as the heading of the webpage.

You should directly tell me the first sentence of the main content, and do not output any
 explanation or any other contents.
```

For the web QA task:

```
<question>
You should directly tell me your answer in the fewest words possible, and do not output
any explanation or any other contents.
```

For the element OCR task:

```
You are given a screenshot of a webpage with a red rectangle bounding box. The [x1, y1,
x2, y2] coordinates of the bounding box is <bbox_coords>.

Please perform OCR in the bounding box and recognize the text content within the red
bounding box.
```

For the action prediction task:

```
You are given a screenshot of a webpage with a red rectangle bounding box. The [x1, y1,
x2, y2] coordinates of the bounding box is <bbox_coords>.
Please select the best webpage description that matches the new webpage after clicking
the selected element in the bounding box:
<choices_text>

You should directly tell me your choice in a single uppercase letter, and do not output
any explanation or any other contents.
```

For the element grounding task:

```
In this website screenshot, I have labeled IDs for some HTML elements as candicates. Tell
 me which one best matches the description: <element_desc>

You should directly tell me your choice in a single uppercase letter, and do not output
any explanation or any other contents.
```

For the action grounding task:

```
In this website screenshot, I have labeled IDs for some HTML elements as candicates. Tell
 me which one I should click to complete the following task: <instruction>

You should directly tell me your choice in a single uppercase letter, and do not output
any explanation or any other contents.
```

B.2.6 MM-Mind2Web

```
Imagine that you are imitating humans doing web navigation for a task step by step. At
each stage, you can see the webpage like humans by a screenshot and know the previous
actions before the current step decided by yourself through recorded history. You need to
 decide on the first following action to take. You can click on an element with the mouse
, select an option, type text or press Enter with the keyboard. (For your understanding,
they are like the click(), select_option() type() functions in playwright respectively).
One next step means one operation within the three.

You are asked to complete the following task: <question>

Previous Actions:
<previous_actions>
The screenshot below shows the webpage you see.


Follow the following guidance to think step by step before outlining the next action step
 at the current stage:

(Current Webpage Identification)
Firstly, think about what the current webpage is.

(Previous Action Analysis)
```

```
Secondly, combined with the screenshot, analyze each step of the previous action history
and their intention one by one. Particularly, pay more attention to the last step, which
may be more related to what you should do now as the next step.

(Screenshot Details Analysis)
Closely examine the screenshot to check the status of every part of the webpage to
understand what you can operate with and what has been set or completed. You should
closely examine the screenshot details to see what steps have been completed by previous
actions even though you are given the textual previous actions. Because the textual
history may not clearly and sufficiently record some effects of previous actions, you
should closely evaluate the status of every part of the webpage to understand what you
have done.

(Next Action Based on Webpage and Analysis)
Then, based on your analysis, in conjunction with human web browsing habits and the logic
 of web design, decide on the following action. And clearly outline which element in the
webpage users will operate with as the first next target element, its detailed location,
and the corresponding operation.

To be successful, it is important to follow the following rules:
1. You should only issue a valid action given the current observation.
2. You should only issue one action at a time.

(Reiteration)
First, reiterate your next target element, its detailed location, and the corresponding
operation.

(Multichoice Question)
Below is a multi-choice question, where the choices are elements in the webpage. From the
 screenshot, find out where and what each one is on the webpage. Then, determine whether
one matches your target element. Please examine the choices one by one. Choose the
matching one. If multiple options match your answer, choose the most likely one by re-
examining the screenshot, the choices, and your further reasoning.

If none of these elements match your target element, please select, select <none_choice>.
 None of the other options match the correct element.
<choices><none_choice>. None of the other options match the correct element.

(Final Answer)Finally, conclude your answer using the format below. Ensure your answer is
 strictly adhering to the format provided below. Please do not leave any explanation in
your answers of the final standardized format part, and this final part should be clear
and certain. The element choice, action, and value should be in three separate lines.

Format:

ELEMENT: The uppercase letter of your choice.

ACTION: Choose an action from {CLICK, TYPE, SELECT, NONE}. Use NONE only if you choose
option F for the ELEMENT

VALUE: Provide additional input based on ACTION.

The VALUE means:
If ACTION == TYPE, specify the text to be typed.
If ACTION == SELECT, specify the option to be chosen.
If ACTION == CLICK, write "None".
```

B.2.7 GroundUI-1K

```
Which action should I do if I want to Click on <element> and where is the action? Express
 the location coordinates using the (x1, y1, x2, y2) format, scaled between 0 and 1000.
```

B.3 Functional Capabilities

B.3.1 FinQA

```
Given the following finance question, analyze the question in details step-by-step before
 giving the final answer. Your answer should begin with "Lets think step-by-step". Your
response should end with "The answer is [the_final_answer]", where [the_final_answer]
should be the most concise answer without any explanation.

### Input
Supporting Facts:
<pre-text>
<table>
<post-text>

Question:
<question>
```

We use regex “The answer is (.*)” to extract the answer. We convert answers with percent signs and magnitude terms to decimal numerical representation (e.g. convert “1.3%” to 0.013 and “5.2 millions” to 5,200,000). An answer is correct if it is identical to the ground truth when rounded to the same decimal places.

B.3.2 RAG

```
You are a teacher grading a quiz.
You are given a question, the student’s answer, and the true answer, and are asked to
score the student answer as either Correct or Incorrect.
Example Format:
QUESTION: question here
STUDENT ANSWER: student’s answer here
TRUE ANSWER: true answer here
GRADE: Correct or Incorrect here
Grade the student answers based ONLY on their factual accuracy. Ignore differences in
punctuation and phrasing between the student answer and true answer. It is OK if the
student answer contains more information than the true answer, as long as it does not
contain any conflicting statements. Begin!
QUESTION: {query}
STUDENT ANSWER: {answer}
TRUE ANSWER: {expected_answer}
GRADE:
Your response should be in json format as follows:
{{
 "justification": (Without mentioning the student/teacher framing of this prompt, explain
  why the STUDENT ANSWER is Correct or Incorrect. Use one or two sentences maximum. Keep
 the answer as concise as possible.),
 "grade": (correct or incorrect)
}}
```

C Qualitative examples of multimodal intelligence

User input

This looks like an amazing site. What is it and where is it located? Are there other fun things around this site to explore?

Response

This is the Space Needle, a landmark in Seattle, Washington, USA. It is a well-known observation tower and a symbol of Seattle. It was built for the 1962 World's Fair and has since become a popular tourist attraction. The Space Needle offers panoramic views of the city, the surrounding mountains, and the Puget Sound.
The Space Needle is located in the Seattle Center, which is a cultural and entertainment hub. The Seattle Center is home to many other attractions, including the Chihuly Garden and Glass, the Museum of Pop Culture, and the Pacific Science Center. The Seattle Center also hosts events like concerts, festivals, and art exhibitions.
The Seattle Center is also close to other popular attractions in Seattle, such as the Pike Place Market, the Seattle Aquarium, and the Seattle Art Museum. The city is known for its vibrant arts and culture scene, outdoor activities, and beautiful natural surroundings.

Figure 6: Created with Nova Pro. Photo taken by a team member.

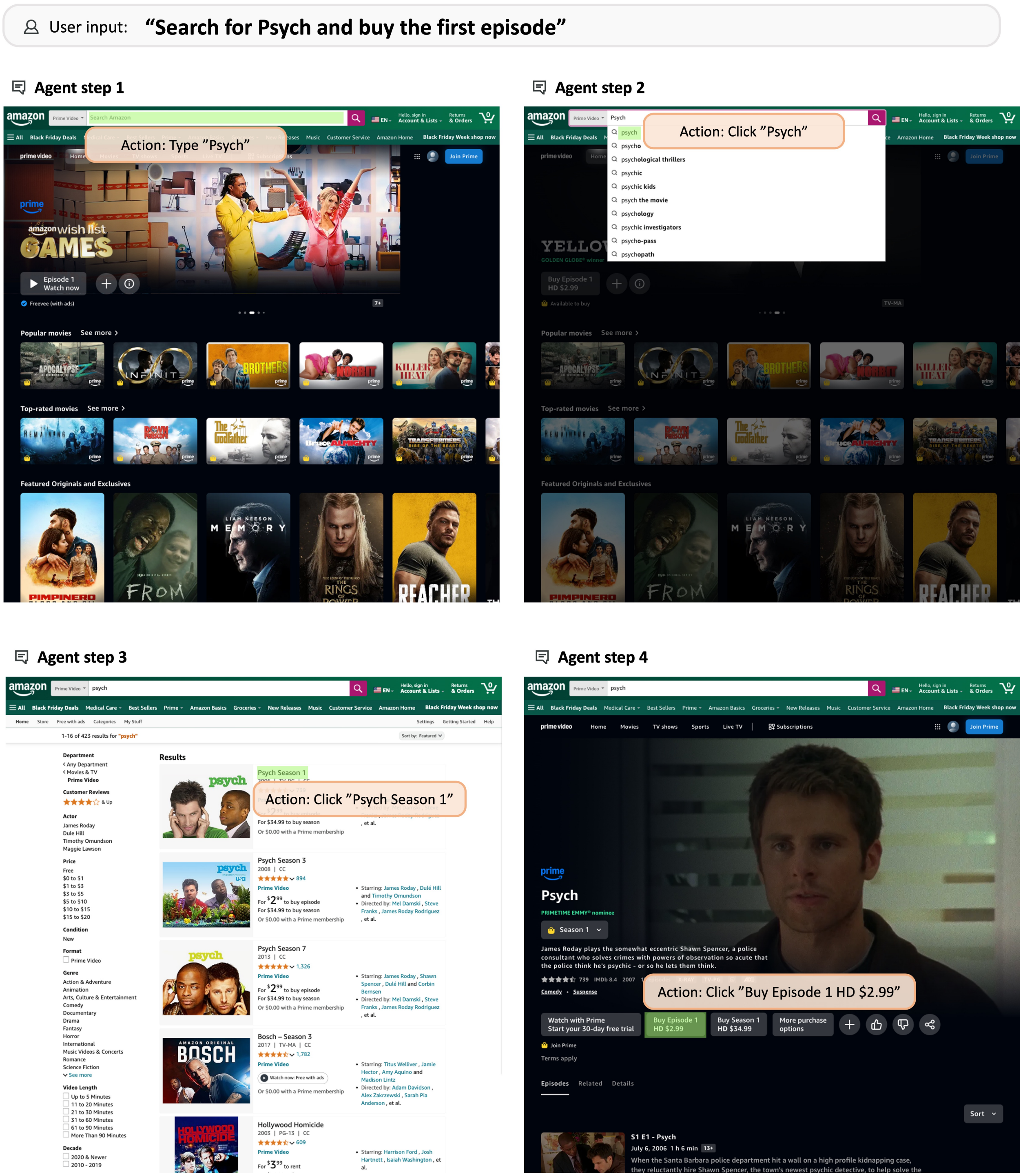
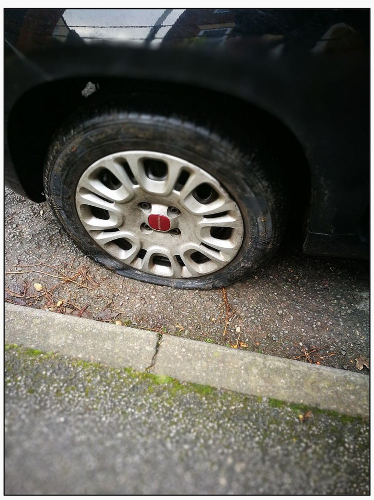


Figure 7: Example of a multimodal agent.

User input

What happened to my tire?
What should I do?



Response

It appears that your tire has a significant puncture, as evidenced by the deflated state and visible damage. Here's what you should do:

1. **Assess the Damage**: Confirm the puncture by checking for any visible holes or debris embedded in the tire.
2. **Check Tire Pressure**: Ensure the tire is completely deflated.
3. **Remove the Tire**: If you're comfortable, you can remove the wheel to inspect the puncture more closely.
4. **Temporary Fix**: Use a tire repair kit to patch the hole if it’s small. This is a temporary solution.
5. **Professional Repair**: Visit a tire shop for a proper repair or replacement. They can assess if the tire can be patched or if a new tire is needed.
6. **Inspect Other Tires**: Check the other tires for any signs of damage or wear.

Would you like more detailed instructions on any of these steps?

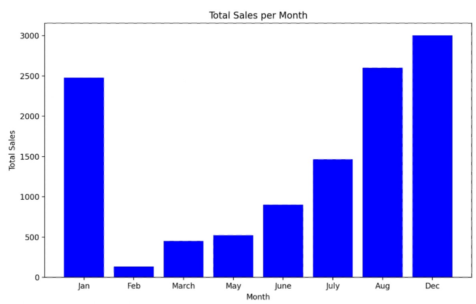
Figure 8: Created with Nova Pro. Image source: [88].

User input

Group this sales data by month using pandas and then create a bar chart of the sales per month.

Month	Sales
Jan	1523.13
Jan	957
Feb	133
March	452
May	521
June	901
July	1334
July	131
Aug	2601
Dec	3005

Generated plot:



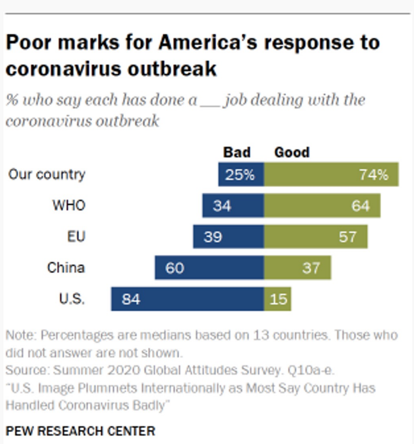
Response

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

# Data
data = {
    'Month': ['Jan', 'Jan', 'Feb', 'March', 'May', 'June', 'July',
              'July', 'Aug', 'Dec'],
    'Sales': [1523.13, 957, 133, 452, 521, 901, 1334, 131, 2601, 3005]
}

# Create DataFrame
df = pd.DataFrame(data)

# Group by month and sum sales
monthly_sales = df.groupby('Month')['Sales'].sum().reset_index()

# Sort months based on calendar
monthly_sales['Month'] = pd.Categorical(
    monthly_sales['Month'],
    categories=['Jan', 'Feb', 'March', 'April', 'May', 'June', 'July',
                'Aug', 'Sept', 'Oct', 'Nov', 'Dec'],
    ordered=True
)
monthly_sales = monthly_sales.sort_values('Month')

# Plot bar chart
plt.figure(figsize=(10, 6))
plt.bar(monthly_sales['Month'], monthly_sales['Sales'], color='blue')
plt.xlabel('Month')
plt.ylabel('Total Sales')
plt.title('Total Sales per Month')
plt.show()
```

Figure 9: Created with Nova Pro.

User input

How many people say the European Union responded well to the pandemic?



Response

The chart shows that 57% of people say the European Union responded well to the pandemic. This is indicated by the green bar labeled "Good" for the EU, which extends to a height of 57%. This suggests that a majority of the people surveyed had a positive view of the EU's response to the pandemic.

Figure 10: Created with Nova Lite. Image source: ChartQA dataset [50].

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The Nova family of models were built by the Amazon Artificial General Intelligence (AGI) organization and partner teams.

When citing this report, please use "Amazon AGI" as the sole author, as shown in the bibtex entry below.

```
@misc{novatechreport,
  author = {Amazon AGI},
  title = {The Amazon Nova Family of Models: Technical Report and Model Card},
  year = {2024},
  url = {https://www.amazon.science/publications/the-amazon-nova-family-of-models-
  technical-report-and-model-card}
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```

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