Jointly Training Large Autoregressive Multimodal Models

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Jointly Training Large Autoregressive Multimodal Models

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Abstract

In recent years, advances in the large-scale pretraining of language and text-to-image models have revolutionized the field of machine learning. Yet, integrating these two modalities into a single, robust model capable of generating seamless multimodal outputs remains a significant challenge. To address this gap, we present the Joint Autoregressive Mixture (JAM) framework, a modular approach that systematically fuses existing text and image generation models. We also introduce a specialized, data-efficient instruction-tuning strategy, tailored for mixed-modal generation tasks. Our final instruct-tuned model demonstrates unparalleled performance in generating high-quality multimodal outputs and represents the first model explicitly designed for this purpose.

1 Introduction

Autoregressive text-to-image models, as exemplified by works such as Yu et al. (2023; 2022), have made remarkable strides in generating highly detailed images, paralleling the achievements of Diffusion Models Nichol et al. (2022); Ramesh et al. (2022); Rombach et al. (2022). These models bear architectural resemblance to Large Language Models (LLMs), yet their training regimen is tailored for paired image-text data. LLMs on the other hand (Brown et al., 2020; Zhang et al., 2022; Touvron et al., 2023) are limited to text-based output, thus lacking multimodal generative capabilities despite their proficiency in textual tasks. The subfield of Multimodal Large Models has emerged in recent years Tsimpoukelli et al. (2021); Alayrac et al. (2022); Li et al. (2022a) in the quest to bring together the disparate strengths of vision and language models. Despite important advances in this direction, these models still predominantly generate one modality, thereby constraining their expressiveness. This study aspires to break this limitation by developing a multimodal model capable of generating integrated text and image outputs.

To achieve this objective, we conduct a comprehensive empirical investigation into the fusion of two specialized autoregressive, decoder-only, large transformer models, each designed for unique tasks (one for text-to-image and a text only model). We introduce a set of methods under the umbrella of the Joint Autoregressive Mixture (JAM) framework. In building this framework, we take advantage of the inherent architectural compatibility of autoregressive text-to-image models with LLMs, allowing us to do deep model fusion and joint training in ways which would otherwise not be possible. Our modular and data-efficient solution allows for deep, rapid and effective integration of continually evolving large models, using less than 1% of the original pretraining data for both parent models.

Our contributions to this study are twofold. First, we establish the feasibility of blending autoregressive text-to-image models with LLMs into a unified architecture that retains the core strengths of each while revealing new, emergent capabilities. Second, we present innovative strategies for multimodal instruction tuning, utilizing text-based instructions and a custom-curated dataset designed explicitly for image generation. The result is a first-of-its-kind large multimodal model which can coherently generate long-form content with interleaved text and images.

2 Methods

To tackle the challenge of creating a unified model that excels at vision-language generative tasks, we propose to combine two autoregressive decoder-only architectures. Our primary image-text model is

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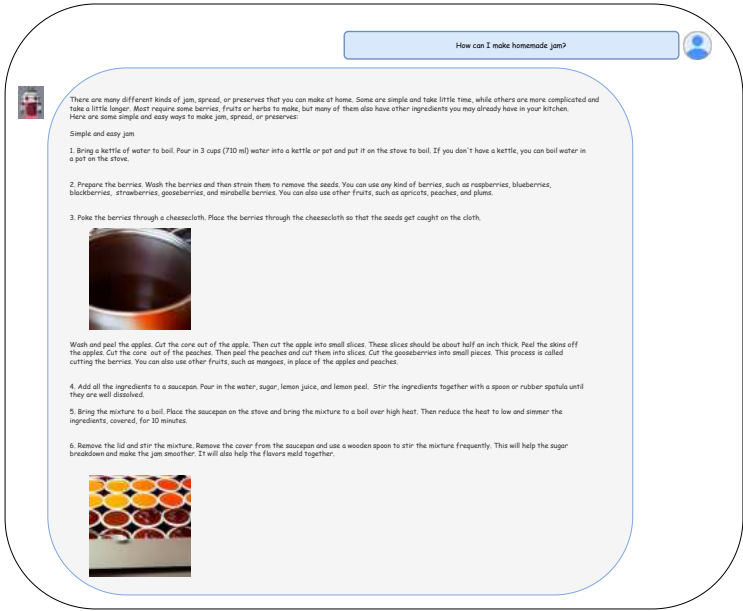
Figure 1: Selected sample generated by our instruction-tuned JAM-Cross model. The model can complex mixed-modal outputs with coherent alignment between generated text and images.

CM3leon (Yu et al., 2023), trained on 2.4T image-text caption tokens. In contrast, using the same architecture, our LLM (Molybog et al., 2023) has been trained on 1.4T text tokens. Both models have 7B parameters, we provide additional architectural details in Section 3.1. Our overall methodology develops in two stages. In the first stage (Sect. 2.1), we first combine and align the models. In the second stage (Sect. 2.2), we explore new directions for instruction tuning focused on interleaved image-text generation.

2.1 CONTINUED PRETRAINING

We combine the two pretrained models into a singular, cohesive structure in our proposed framework. This composite model is fine-tuned using a hybrid dataset comprising both text-only and image-text samples within our *continued pretraining* phase. The central motivation behind this approach is to seamlessly merge the capabilities of two pretrained models, capitalizing on the unique strengths of each. The training procedure is data-efficient since the original pretrained models are typically trained on trillions of tokens. In contrast, our procedure only uses 50 billion tokens, corresponding to 1.3% of the total data used during the pretraining.

2.1.1 MODEL MERGING

The concept of model merging has been previously utilized to combine models that share identical optimization trajectories (Kaddour et al., 2022), or models that are trained on identical datasets but have independent optimizations (for instance, Matena & Raffel (2022); Wortsman et al. (2022); Ainsworth et al. (2022)). A consistent approach across these studies is to combine models without any training. Our approach diverges from this convention; we view the merged model as a powerful initialization for subsequent training on mixed-modal data. The weights of the averaged model are defined as:

$$\boldsymbol{\theta}_{average} = \frac{1}{2}\boldsymbol{\theta}_{llm} + \frac{1}{2}\boldsymbol{\theta}_{img} \tag{1}$$

Where $\boldsymbol{\theta}_{llm}$ and $\boldsymbol{\theta}_{img}$ represent the weights of the LLM and the text-to-image model respectively. In this study, we explore weights merging specifically to multimodal decoder-only large transformer models, and notably, on an unprecedented scale, involving models trained on trillions of tokens from diverse datasets. In the following sections, we refer to our average model as JAM-Uniform.
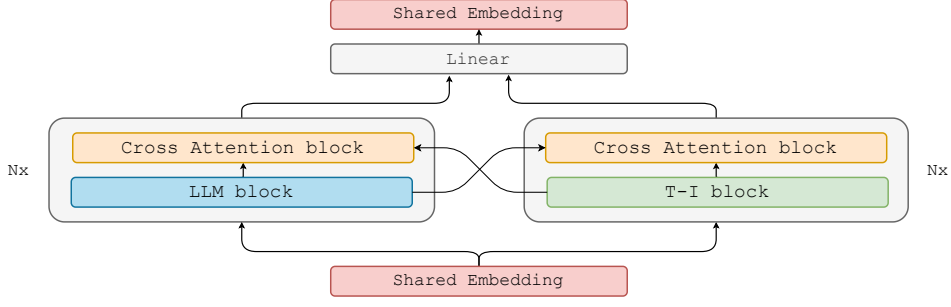
Figure 2: JAM-Cross, architecture overview. The cross-attention blocks are interleaved between the original LLM block and the Text-Image blocks, and the output embedding between the two branches are concatenated and then projected to the output embedding dimension.

2.1.2 WIDTH CONCATENATION

Our second approach employs the pretrained weights to initialize a wider architecture. Our new model has hidden dimensions $d_{joint} = 8192$, which is doubled with respect to one of the two original models $d_{llm} = d_{img} = 4096$. We keep the same number of layers of the original architectures. The resulting architecture has 26B parameters, initialized starting from the pretrained weights of our backbones. The token embedding input/output projections and the learned positional embeddings of the two initial models are concatenated on the hidden dimension. The attention weights (e.g query projection) $\boldsymbol{W}_{q,combined} \in \mathbb{R}^{d_{joint} \times d_{joint}}$ are initialized as:

$$\boldsymbol{W}_{q,combined} = \begin{pmatrix} \boldsymbol{W}_{q,llm} & \boldsymbol{W}_{q,llm} \\ \boldsymbol{W}_{q,img} & \boldsymbol{W}_{q,img} \end{pmatrix} \tag{2}$$

Where $\boldsymbol{W}_{q,llm}, \boldsymbol{W}_{q,img} \in \mathbb{R}^{d_{llm} \times d_{llm}}$ represent the weights for the query projection of a generic attention layer. All the other weights (FFNs and output projections) are initialized following the same logic. We also experiment with slight variations of the approach:

$$\boldsymbol{W}_{q,combined} = \begin{pmatrix} \boldsymbol{W}_{q,llm} & \boldsymbol{W}_{q,average} \\ \boldsymbol{W}_{q,img} & \boldsymbol{W}_{q,average} \end{pmatrix} \tag{3}$$

Instead of copying the two models' parameters, we use the average to initialize half of the new parameters. We name the resulting model JAM-Width.

2.1.3 CROSS MODEL FUSION

We propose to embed cross-attention layers between the foundational models to facilitate seamless information interchange while preserving the original models' knowledge. Given two decoder-only transformers models $\mathcal{T}_{llm}$ and $\mathcal{T}_{img}$, we introduce a bi-directional cross-attention mechanism that enables the layers of one model to attend to the corresponding layer's output of the other model. This approach allows for a progressive exchange of information at different representation levels. For a specific layer l, let the models produce sequences of hidden states $\boldsymbol{H}_{llm,l}$ for $\mathcal{T}_{llm}$ and $\boldsymbol{H}_{img,l}$ for $\mathcal{T}_{img}$ where these hidden states are outputs from layer l. The output of the cross-attention mechanism ($\boldsymbol{H}_{cross,l}$) from $\mathcal{T}_{img} \rightarrow \mathcal{T}_{llm}$ for a given layer is evaluated as:

$$\boldsymbol{Q}_{cross,l} = \boldsymbol{W}_{q,l}\boldsymbol{H}_{llm,l-1}, \quad \boldsymbol{K}_{cross,l} = \boldsymbol{W}_{k,l}\boldsymbol{H}_{img,l-1}, \quad \boldsymbol{V}_{cross,l} = \boldsymbol{W}_{v,l}\boldsymbol{H}_{img,l-1} \tag{4}$$

$$\boldsymbol{H}_{cross,l} = \text{Softmax}\left(\frac{\boldsymbol{Q}_{cross,l}\boldsymbol{K}_{cross,l}^T}{\sqrt{d_k}} \right) \boldsymbol{V}_{cross,l} \tag{5}$$

Where W_q, W_k, W_v represent the query, key, and value projection weights of the newly inserted cross-attention layers. A symmetric process is applied for the reverse direction $\mathcal{T}_{llm} \rightarrow \mathcal{T}_{img}$. We use a shared input-output projection layer, initializing the weights of the text tokens from the LLM input embedding and the weights of the image tokens from the image-text model. We insert a new linear projection layer that takes the concatenation of the two model's output embeddings as input.

Figure 2 illustrates a schematic of our model configuration. We refer to the model resulting from this approach as JAM-Cross. Additional architectural details and the underlying design choices can be found in Sect. 3.1. The ablation study for the optimal frequency of inserting new layers is presented in Sect. 3.3.

2.2 Multimodal Conversational Instruct Tuning

Supervised fine-tuning is a fundamental tool to leverage the abilities of large pretrained models. Recently, instruct tuning has been extended to a multimodal setting (Liu et al., 2023; Dai et al., 2023); however, all the existing approaches are focused on visual understanding abilities. In this work, we study instruction tuning tailored to interleaved image-text generation.

We collect a small and curated mixed-modal dataset to teach our JAM model to support textual explanations with coherent images. Since in the first stage, the model has been trained on image-text captions and text-only data; we train on interleaved image-text data during this phase. Our approach is inspired by the Superficial Alignment Hypothesis from LIMA (Zhou, 2023), which posits that a model's foundational knowledge and skills are entirely learnt during the pretraining. Instruction tuning is then used to guide the model in selecting the appropriate subdistribution of format used when interacting with users. Our results demonstrate that the model can quickly learn the style of images and text from a small curated dataset, suggesting that LIMA hypotesis holds not only for learning the text style but also for images. In our experiments, we consider two slightly different instruction tuning settings, we introduce a small portion of the image-text Shutterstock data with retrieval augmentation and we find this approach beneficial to preserve the generated image quality when generating with retrieval augmentation. Sect 3 presents a comparison between these two strategies. We train using a standard supervised procedure without leveraging any reinforcement learning or human preference strategy. In this instruction-tuning phase, we leverage interleaved image-text data in contrast to previous methods (Koh et al., 2023a) that rely only on image-text caption and no instruction tuning, our experimental results confirm the benefits of training with interleaved image-text data.

3 Experiments

3.1 Experimental Details

Tokenizers   For images, we use the VQ-VAE tokenizer from Gafni et al. (2022). The image resolution is set to 256×256, 1024 tokens represent each image, and the vocabulary has a size of 8192. Our text tokenizer is the same that have been used to train the two parent models, trained over the Zhang et al. (2022) data for text. We introduce the additional <break> token used by CM3leon to identify a modality break.

Image-Text Autoregressive Model   We adopt CM3leon as the image-text autoregressive backbone. The model has a standard decoder-only architecture with some peculiarities: no bias terms, dropout, and learnable parameters for layer norms. It has been trained on 2.4T image-text tokens and uses a sequence length 4096.

LLM   As an LLM backbone, we select a model with the same architecture as CM3leon, trained in Molybog et al. (2023) this allows us to experiment with a broader range of approaches, such as weight averaging and width concatenation. The model is trained on 1.4T text data with a 2048 context length, and we further fine-tuned it with a 4096 context length using only 30B text tokens.

Objective   In all our experiments, we employ the CM3 objective introduced in Aghajanyan et al. (2022); this objective accepts the original sequence as input or transforms it into an infilling instance by masking specific spans and relocating them to the end of the document. Then, the model is optimized for minimizing the standard autoregressive loss $-\log p(x_{input})$. This objective allows for optional bidirectionally and increases the versatility of the model that can be used for both infilling or standard autoregressive generation. We prevent the objective from masking across the modality <break> tokens.

Retrieval Augmentation   We employ multimodal retrieval augmentation introduced in Yasunaga et al. (2022) for our training procedure. The retrieval procedure employs a dense retriever r, a memory bank $\mathcal{M}$ and a specifically selected retrieval strategy. The retriever takes an input query
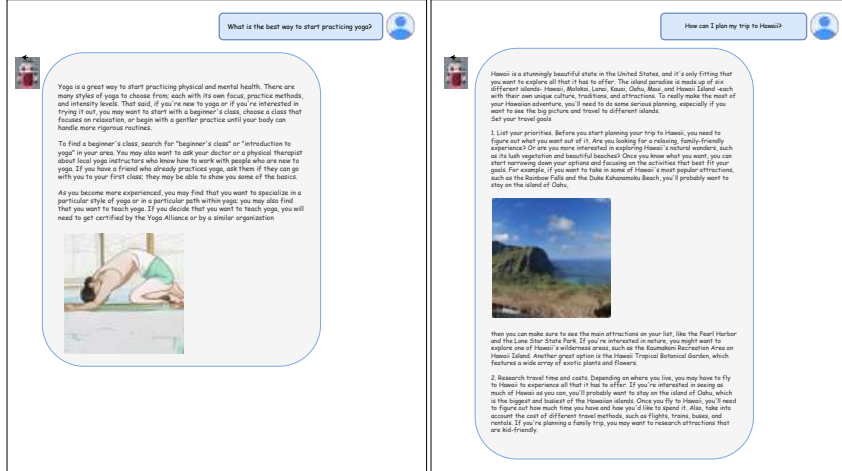
Figure 3: Samples generated by our JAM-Cross instruct tuned model. (Left - generated without retrieval augmentation; Right - generated with retrieval augmentation)

x and returns a relevance score $r(x, m)$ for each candidate document $m \in \mathcal{M}$. Each multimodal document is split between text and images and fed to the corresponding modality-specific VIT-B-32 CLIP encoder (Radford et al., 2021). The two embeddings are then averaged to form the documents' vector representation. We then use Maximum Inner Product Search (MIPS) over the memory bank to obtain a list of candidates. When sampling retrieved documents, we prioritize the diversity of the sampled documents by skipping candidates with a score $r(x, m) \geq 0.9$. We apply query dropout to regularize the training, dropping 20% of tokens from the input sequence x.

Training - Alignment Phase During the continued pretraining, we train for approximately 50B multimodal tokens. Our initial learning rate is $lr = 3 \times 10^{-5}$ we use 500 warm-up steps. We set our optimal batch size to 8M tokens, this hyperparameter is borrowed from the mixed-modal scaling laws introduced in Aghajanyan et al. (2023). The total number of training steps is 5960. This training procedure takes approximately one day on 256 80GB A100s for all models. We select the last checkpoint for all the different JAM models, which is always the one with the lowest average validation perplexity (PPL).

Training - Instruct Tuning Our instruct tuning training procedure is data efficient we train with our instruction tuning mixed corpora. The initial learning rate is set to 1×10^{-5}, and we use 300 warm-up steps and a batch size of 1M. The instruction tuning procedure takes less than 2 hours on 64 80GB A100s, we train for 15 epochs over our mixture of datasets and manually select the best checkpoint corresponding to the 9th epoch. Following Zhou et al. (2023), we notice that the validation PPL doesn't correlate with the quality of the responses.

Decoding Strategies We implement a mixed-modal decoding strategy for our interleaved generation. The model starts generating text tokens until a modality <break> token is detected, then an image is sampled. The generation process alternating the two modalities continues iteratively until a <eos> token is sampled. As a result our model is able to generate free-form multimodal documents. We employ temperature sampling, a common technique used in autoregressive model (e.g Ramesh et al. (2022)) to control the randomness of the prediction by modifying the softmax temperature τ. We pair this technique with TopP sampling introduced in Holtzman et al. (2019) consisting of sampling from the top-ranked tokens with a cumulative probability exceeding a predefined threshold τ_P. We also employ classifier-free guidance (CFG (Gafni et al., 2022)) for sampling images. This technique allows to condition the sampling procedure, blending the logits from an unconditional sample with the logits from a conditional sample. The procedure is mathematically described as

$$\text{logits}_{cf} = \text{logits}_{uncond} + \alpha_c(\text{logits}_{cond} - \text{logits}_{uncond}) \qquad (6)$$

where $\text{logits}_{cond} = \mathcal{T}(t_y|t_x)$ and $\text{logits}_{uncond} = \mathcal{T}(t_y| <mask>)$; $\mathcal{T}$ represent the transformer model, $<mask>$ represent the absence of the input text, t_x are the conditional input tokens, t_y are

the output tokens and α_c is the scaling factor for CFG. Thanks to the CM3 objective, our training procedure allows our models to sample with CFG without further fine-tuning. Inspired by Yu et al. (2023) we complement this technique to boost the generation quality. Our samples are generated using a temperature value $\tau = 1$, τ_P is set between 0.8 and 1, and we use classifier-free guidance with values 3.5 and 4. In contrast to other approaches, we don't make use of the computationally expensive clip-reranking (Ramesh et al., 2021; Yu et al., 2022; Gafni et al., 2022) or constrastive decoding (Li et al., 2022b; Yu et al., 2023).

3.1.1 DATASETS

Shutterstock   We randomly sample a subset of 30B tokens from CM3leon (Yu et al., 2023) pretraining data. The data consists of legally acquired image-caption pairs from Shutterstock, a commercial online platform offering images with ownership attribution and clear licensing terms.

Text corpora   We use 30B text tokens sampled from a mixture of several publicly available data, and we reuse the data used for training other common open-source LLM following the same preprocessing of (Touvron et al., 2023). The datasets are: English CommonCrawl (Touvron et al., 2023), C4 (Raffel et al., 2020), Wikipedia, Books3 from ThePile (Gao et al., 2020), and arXiv.

LIMA   We use the 1k dataset present in Zhou et al. (2023), which features various curated prompts and responses.

wikiHow   We collect an interleaved image-text dataset sampling 3000 articles from WikiHow, an online wiki publication that usually curates apposite images for each article. We sample balanced articles from each category to ensure diversity; moreover, we leverage the platform's community ratings to filter each article's quality, sampling only those with a score greater than $90/100$. For each article, we use the title (e.g., *'How to make ..?'*) as prompt, we modify the phrase *'This article...'* with *'The following answer..'*. Furthermore, we restrict the number of images as 3 per sample, to fit our 4096 context length.

3.2 CONTINUED PRETRAINING RESULTS

In the initial stage of continued pretraining, we evaluate the performance across various JAM models. Our primary objective is to ensure minimal performance degradation post-merging, relative to the parent models. Managing both image and text processing within a single model poses significant challenges. This evaluation seeks to quantify the retention of original performance in our different JAM models, benchmarked against the two parent models specialized in individual modalities.

3.2.1 TEXT MODALITY

For the text modality, we compare the zero-shot performance on some common sense reasoning tasks: PIQA (Bisk et al., 2020), ARC-Challenge, ARC-Easy (Clark et al., 2018), StoryCloze (Mostafazadeh et al., 2016), Winograd, and Winogrande (Sakaguchi et al., 2021). We also report some recent influential LLM (Brown et al., 2020; Touvron et al., 2023), and our LLM (Molybog et al., 2023) fine-tuned with 4k context as a reference. Results are presented in Table 1. The JAM-Uniform reaches slightly better text-only performance than JAM-Width however, it is crucial to remark that this approach consolidates the functionalities of both parent models within a constrained 7B parameter space. Our findings reveal that the intrinsic knowledge of the parent models can be recovered mainly from the parameter average utilizing only a minimal portion of the original pretraining data. The JAM-Cross model yields the best results, aligning with our primary LLM. This highlights the strength of our bidirectional cross-attention mechanism against other baselines.

3.2.2 IMAGE-TEXT MODALITY

To assess the performance of our different baselines over the image-text modality, we compare them using the validation perplexity (PPL) on MS-COCO dataset (Lin et al., 2014). We believe this metric robustly correlates with performance on subsequent tasks, such as image generation and captioning. Furthermore, it provides a reliable reference point for comparing different autoregressive models sharing an identical tokenizer. Results are reported in Table 2. Diverging from results

Table 1: Zero Shot Text Comparison on Common Sense Reasoning Tasks

Model	Size	PIQA	ARC-C	ARC-E	StoryCloze	Winograd	Winogrande
GPT-3	175B	81.0	51.4	68.8	-	-	70.1
LLaMa	7B	79.8	47.6	72.8	-	-	70.1
LLM-4k	7B	76.7	45.9	67.7	79.3	83.9	66.2
JAM-Uniform	7B	62.4	28.5	42.6	63.5	47.8	49.7
JAM-Width	26B	57.8	31.4	31.6	54.7	50.2	51.9
JAM-Cross	19B	75.4	41.6	67.2	79.8	81.0	66.0

Table 2: Image-Text Comparison

Model	Size	MS-COCO PPL
CM3	2.7B	200.1
RA-CM3	2.7B	193.1
CM3leon	760M	168.8
CM3leon	7B	149.0
JAM-Uniform	7B	177.5
JAM-Width	26B	159.5
JAM-Cross	19B	**147.6**

Table 4: Ablations - JAM-Cross Model

C-Attn	Size	Wikipedia PPL	MS-COCO PPL
✗	13B	7.86	153.2
1	26B	7.53	152.4
2	19B	**7.18**	**149.0**
4	16B	8.55	151.7

Table 3: Ablations - JAM-Width Model

Init.	Wikipedia PPL	MS-COCO PPL
Copy	**7.34**	**159.5**
Average	9.0	175.4

Table 5: Ablations - Instruction Tuning

Shutterstock	MS-COCO PPL
✗	190.2
✓	164.5

on the text-only modality, the JAM-Width model exhibits enhanced performance over the JAM-Uniform model in the image-text domain. Specifically, the JAM-Width model demonstrates superior efficacy in retaining image-text performance relative to text-only performance. Conversely, despite a decline in performance, the JAM-Uniform model remains a good parameters-performance trade-off. Interestingly, our JAM-Cross model not only reaches the best PPL between the JAM strategies but also surpasses our foundational image-text model, CM3leon. We hypothesize that such advancement can be attributed to integrating novel textual capabilities coupled with an augmented parameter count inherent to the combined architecture. Based on empirical evidence, the JAM-Cross emerges as the best strategy to combine two pretrained autoregressive models.

3.2.3 INTERLEAVED GENERATION

Our instruct-tuned JAM-Cross model reaches a high-quality level of image-text generated output. To demonstrate its ability to generate coherent modality interleaved responses, we show an extensive set of generated samples in Figure 3 and Section B. The samples generated with retrieval are obtained from the model instruct-tuned with a mixture of pretraining image-text Shutterstock data along with our corpora of instruct-tuning datasets, while the samples generated without retrieval are obtained from the model instruct tuned only on our instruct-tuning set. The generated samples show coherent image and text integration, demonstrating unprecedented abilities at this novel task. Overall we find our retrieval augmented solution to be more effective than standard image sampling, boosting image quality. We further report several qualitative comparisons with the most relevant previous work GILL (Koh et al., 2023a) that features mixed-modal generation. We use our retrieval-augmented JAM-Cross model and source generations for the GILL model from the original paper. From this comparison (Figure 4), it's immediate to notice how our model has a better overall quality of responses. The generated text is more complete and exhaustive, while the generated images are more relevant to the text context. We remark that our method is the first capable of such coherent and interleaved generation with a focus on instruction tuning and that our fine-tuning procedure is effective in
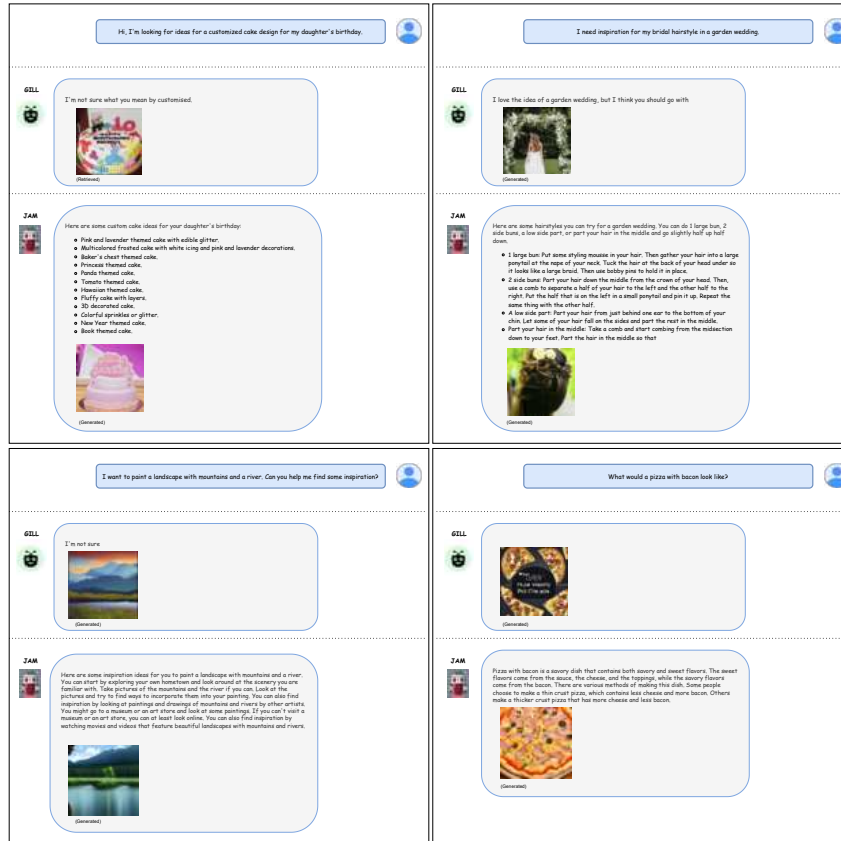
Figure 4: Qualitative comparison with previous interleaved generation models. Compared to GILL, our model is able to generate more complete and precise answers. Results for GILL are sourced from Koh et al. (2023a).

efficiently learning the style of the dataset, not only for text but even for images. Our model paves the way toward a larger adaption of mixed-modal generation in real-world use cases.

3.3 ABLATION STUDY

We compare the two approaches for the width concatenation model: copying the original models' weight or using the average to initialize the new parameters. Results (Table 3) show that copying the weights is more effective than averaging them to retain the original model capabilities. The ablation study for the Cross-attention model is presented in Table 4. We ablate the frequency of inserting cross-attention layers and the impact of not using any cross-attention layers. These experiments are performed training with 25B tokens, all the other parameters are the same as reported in Sect. 3.1. We remark that this is an even shorter training setting concerning our 50B tokens total training and that the difference in performance increases as the training progresses. We further ablate the contribution of image-text pretraining data in the instruction tuning procedure in Table 5. The results indicate the importance of using pretraining data mixed in the instruction tuning procedure to preserve the MS-COCO PPL. We do not report WikiHow PPL since analyzing the models shows that it doesn't correlate with generation quality similarly to Zhou et al. (2023).

4 RELATED WORKS

Generative Text-to-Image Models The field of generative text-to-image models has recently been dominated by diffusion models (Sohl-Dickstein et al., 2015; Ho et al., 2020). Recent enhancements have used pretrained text representations (Ramesh et al., 2022; Nichol et al., 2022) like CLIP (Radford et al., 2021) to improve the generation quality. Concurrently to developing diffusion-based generative models, significant steps have been made by autoregressive token models (Esser et al., 2021; Gafni et al., 2022). These models encode images into a discrete latent space (Van Den Oord et al., 2017)

and can be processed as a standard sequence-to-sequence modeling task, enabling the borrowing of techniques used from Large Language Models. A critical element that has been found beneficial in boosting text-to-image generative models is retrieval augmentation (Chen et al., 2022; Yasunaga et al., 2022). Yasunaga et al. (2022) propose to prefix decoder-only models, such as Aghajanyan et al. (2022), with retrieved images during training, resulting in a huge efficiency gain for the training procedure. Yu et al. (2023), scale this strategy to reach state-of-art performance in image generation using 5x less training compute. In this work, we borrow their model as our text-to-image autoregressive backbone.

Multimodal Language Models   The multimodal language model field has recently seen considerable development. Several prior works have focused on connecting language models to visual encoders. (Tsimpoukelli et al., 2021; Mokady et al., 2021; Najdenkoska et al., 2023; Li et al., 2023). These methods typically train a mapping network between a pretrained image encoder and a language model. Flamingo (Alayrac et al., 2022) introduces cross attention into a frozen LLM to inject visual features and trains a large corpus of image-text pairs. In this work, we similarly use cross attention to bridge the two models; however, our mechanism is bidirectional between the vision and language models, while for Flamingo, the visual knowledge is injected in the language model and not vice-versa. CM3 (Aghajanyan et al., 2022) is trained on a large corpus of structured HTML; it introduces the Casually Masked Language Modeling objective we adopt to train our models. Koh et al. (2023b) propose a multimodal language model capable of processing arbitrarily interleaved image and text inputs and generating interleaved output of text and retrieved image. Subsequently, on the same line of work, GILL Koh et al. (2023a) proposes to ground an LLM to a text-to-image model, using a mapping network and freezing the pretrained models, introducing the possibility of generating or retrieving images as output. Similarly to GILL, Sun et al. (2023b) propose to model different modalities in an autoregressive way with a single model they call Emu. Differently from our work, they employ EVA-CLIP (Sun et al., 2023a) encoder to generate visual embeddings and Stable Diffusion (Rombach et al., 2022) conditioned on the generated image tokens to decode images.

Instruction Tuning   Instruction tuning aims to teach language models to follow natural language instructions. Several methods have been proposed for instruction tuning, using existing NLP datasets converted in instruction formats Wei et al. (2021) Chung et al. (2022), or using LLMs like GPT-4 to generate instruction data with better diversity Wang et al. (2022) Honovich et al. (2022). Recently, LIMA Zhou et al. (2023) demonstrated that 1,000 carefully curated samples are enough to reach competitive results compared to bigger instruction-tuning datasets. The authors hypothesize that most of the knowledge is learned during the pretraining, and the instruction tuning teaches the style to interact with the users. In this work, we explore using a small set of multimodal instruction tuning data to fine-tune our model, verifying the effectiveness of a small dataset in this multimodal setting tailored to image generation. Several vision language works adopt instruction tuning for multimodal tasks-focused user interactions optimized for visual content understanding Liu et al. (2023) Dai et al. (2023) Ye et al. (2023) Zhu et al. (2023). Unlike previous works, we explore instruction tuning focused mixed-modal generation, paving the way for more significant adaptation of multimodal models that can generate interleaved image-text output.

5   CONCLUSIONS

In this work, we have presented novel methodologies for combining pretrained autoregressive models, demonstrating the viability of synthesizing the knowledge of two distinct models into a cohesive structure with extended capabilities. Our exploration validates that the integrated model can be adeptly fine-tuned using our tailored instruction-tuning procedure for interleaved image-text generation. To this end, we pioneered creating a specialized dataset centered on instruction tuning for this particular task. Nevertheless, the proposed study is limited to 7B parameter models with the same architecture. Future works may consider scaling the models' size and asymmetrically applying our cross-fusion method to bridge models of varying sizes. Increasing the context length and delving into multi-turn conversations could further represent an interesting exploration direction. In conclusion, our study sets the foundation for substantial advancements in the realm of multimodal autoregressive models. The fusion of text-to-image generation with large language models paves the way for sophisticated systems capable of interleaved image-text interactions, enriching the landscape of conversational AI.

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A LIMITATIONS

The generation quality of our proposed model presents some limitations. Our JAM frameworks rely on LLMs and text-to-image autoregressive models, inheriting their strengths and limitations, such as the potential for hallucinations and biases in image generation. These limitations may be addressed by improving and leveraging better autoregressive backbones.

Moreover, our instruct-tuning procedure focuses on a specific wiki-style single-turn question answering. Most of the time, the model generates a single or, at most, two images, while a longstanding goal could be to generate entire multimodal documents with >2 images. This is partially bottlenecked by the training data and the context length of 4k tokens; given that each image takes 1024 tokens, generate longer outputs it's still challenging.

Furthermore, our model is more effective in generating interleaved image text when the question style aligns with the dataset style and when the images refer to concrete objects. While the model usually struggles to represent more abstract concepts. We showcase some examples of this behavior in Figure 5. When the subject of the text dialogue are more abstract concepts such as "time travel", "music", or "research", the generated images fail to capture the textual context and enrich the model output faithfully.

B GENERATED EXAMPLES

This section shows several samples generated by our instruction-tuned models using both retrieval augmentation and standard image generation.

> You are a scientist who just invented a Time Machine. Where do you travel first?

> I would travel back in time to when I was a teenager. There are a few people I want to meet, and I have a lot of work to do!
> First, I would travel to about the year 2000, and spend some time getting to know my family. I think it would be really cool to talk to my parents when they were young, and see how their lives turned out. I'd also like to meet my grandparents, and see how they changed over the course of their lives.
> I would also travel to the past to try to influence history in ways that I think would be beneficial. I would travel to historical events and try to change the course of history for the better, or at least record what I do and let people see what I did. I would also travel to ancient times and try to make discoveries that have never been made before.
> I would also go to the future to see how society has changed and what kind of changes it has undergone. I would also like to see what kind of technological advances people have made in the future and what kind of impact those advances have had on society.

> How can I start playing guitar and become a better musician?

> There are several ways. Start with basic lessons. Many websites offer free lessons, including Google, YouTube, and Encyclopedia Britannica. Focus on learning the basics, playing songs, and becoming familiar with the guitar's neck and how the strings are positioned. Practice your chords and scales. When you have a basic foundation of knowledge, you can move on to more advanced techniques. Search for videos and lessons online. Check out popular websites such as YouTube, Vimeo, and Google Play. You can also find books at your local library that offer guidance.
> Create your own routine. When you first start learning how to play the guitar, you'll probably feel overwhelmed and not make any progress at all. This is normal; everyone was once a beginner. To help you overcome this, create a practice routine. Here are a few things to consider for your routine:
> - Set aside a set time and day to practice. This will help you establish a routine and stay motivated. Since you're a beginner, start with 15-20 minutes a day and 30-60 minutes a few times a week. As you progress, you can increase your practice time.
> - Review what you learned in your lesson and practice a few songs

> Why are you holding the guitar this way? What is the best technique you can find for this? Go slow and repeat until you get it right. Review and practice until you can do it without taking a break. This will help you build endurance and become a more efficient player.
> - Start with the basics and work your way up. Don't try to learn too much too fast. Focus on becoming a competent player who can play a few fun songs and review the basics along the way. You'll progress faster if you take your time and learn each aspect properly. There are plenty of resources that outline the basics of guitar playing. You can find them online or at your local music store.
> - Take your guitar with you. This way you can practice whenever you have free time. You'll also be able to take your practice further. For example, if you're in the middle of a movie, practice a few chords. If you're bored in between episodes of your favorite TV show, hit the practice pedal. Finally, if you're out on a walk or running an errand, riff away. Any time you have a few free moments, take out your guitar and practice a few chords. Your patience will pay off.

> How can I write a research paper?

> A research paper is an academic essay that researches and evaluates a topic and presents the results in the form of written content. Usually, a thesis statement (the main idea of the paper) will guide the research paper; the thesis statement will also be supported by the research and appear at the end of the paper. There are lots of different ways to write a research paper; the basic structure, however, stays essentially the same.
> Research paper introduction
>
> 1. Give a definition of the topic you are researching. A good research paper topic should be interesting, worthy of investigation, and have an aspect of immediacy. For example, you could research whether teenage   pregnancy rates have decreased over the past 15 years in your area. You might choose to research homelessness in your area, or early childhood education programs in your city. How does obesity in children affect   their growth and development? Do pregnant women in your area get screenings for gestational diabetes?
>
> 2. Describe why your topic is important. Your topic is important because people's lives are at stake. If you are researching homelessness in your area, people are living in unsanitary conditions, maybe they lack access   to basic necessities like food and shelter, they may be infected with diseases

> Read about the different styles and include what styles the professional uses in their work. You might want to research how different authors in your field have written their introductory chapters. Some research papers   even include a chapter titled "Acknowledgments" where the author acknowledges all of the people and resources that went into creating the work. Remember to cite all sources you use.
>
> 3. Provide context and weigh the severity of the issue. You want to tell your reader who or what will be affected by your topic, why that would be bad, and how your topic ties in to other issues and fields. How will your   research paper affect real people? If you are writing about homelessness, your research will either help homeless people get shelter and basic necessities or it will show that the current system of homelessness in your   area is unsustainable and needs to be altered. What will the outcomes of your research be? If you are researching obesity in children, you might find that children are not getting enough exercise, which can lead to health problems later in life, or you might find that parents are not doing a good enough job at watching their children's eating habits, which may lead to lifelong health problems and/or dependence on others.
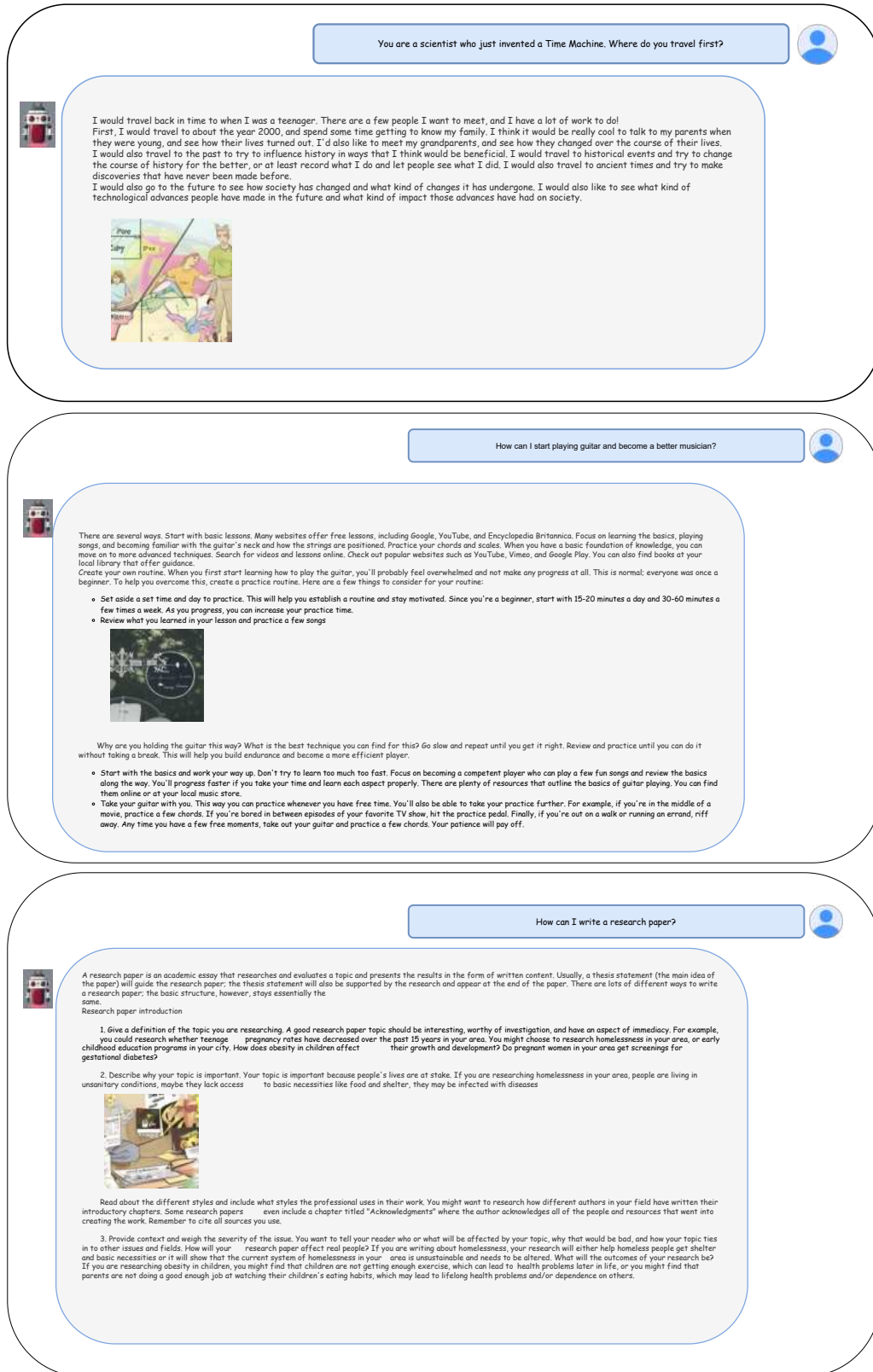
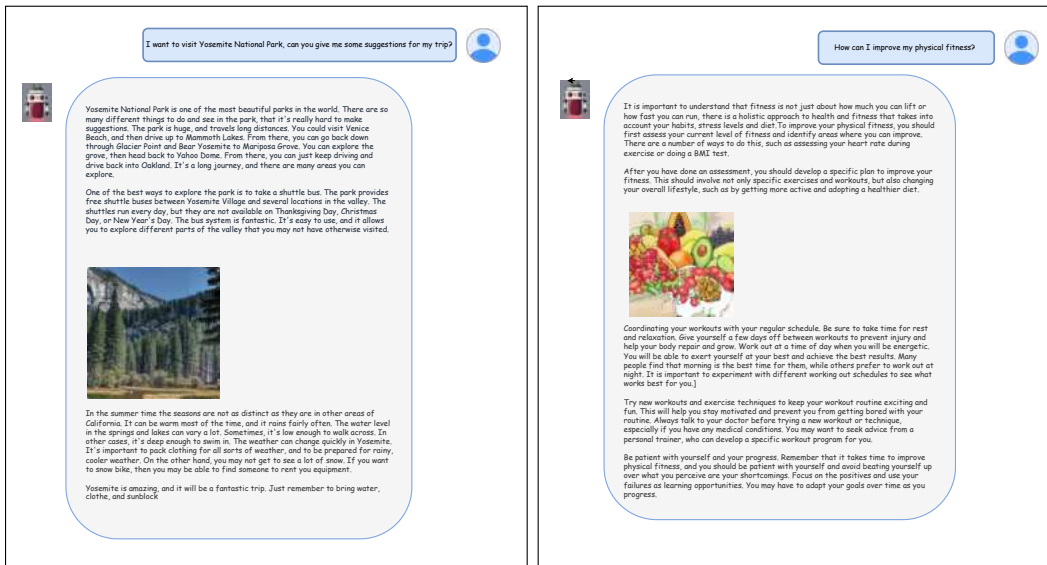Figure 5: Generated samples - Failure Cases

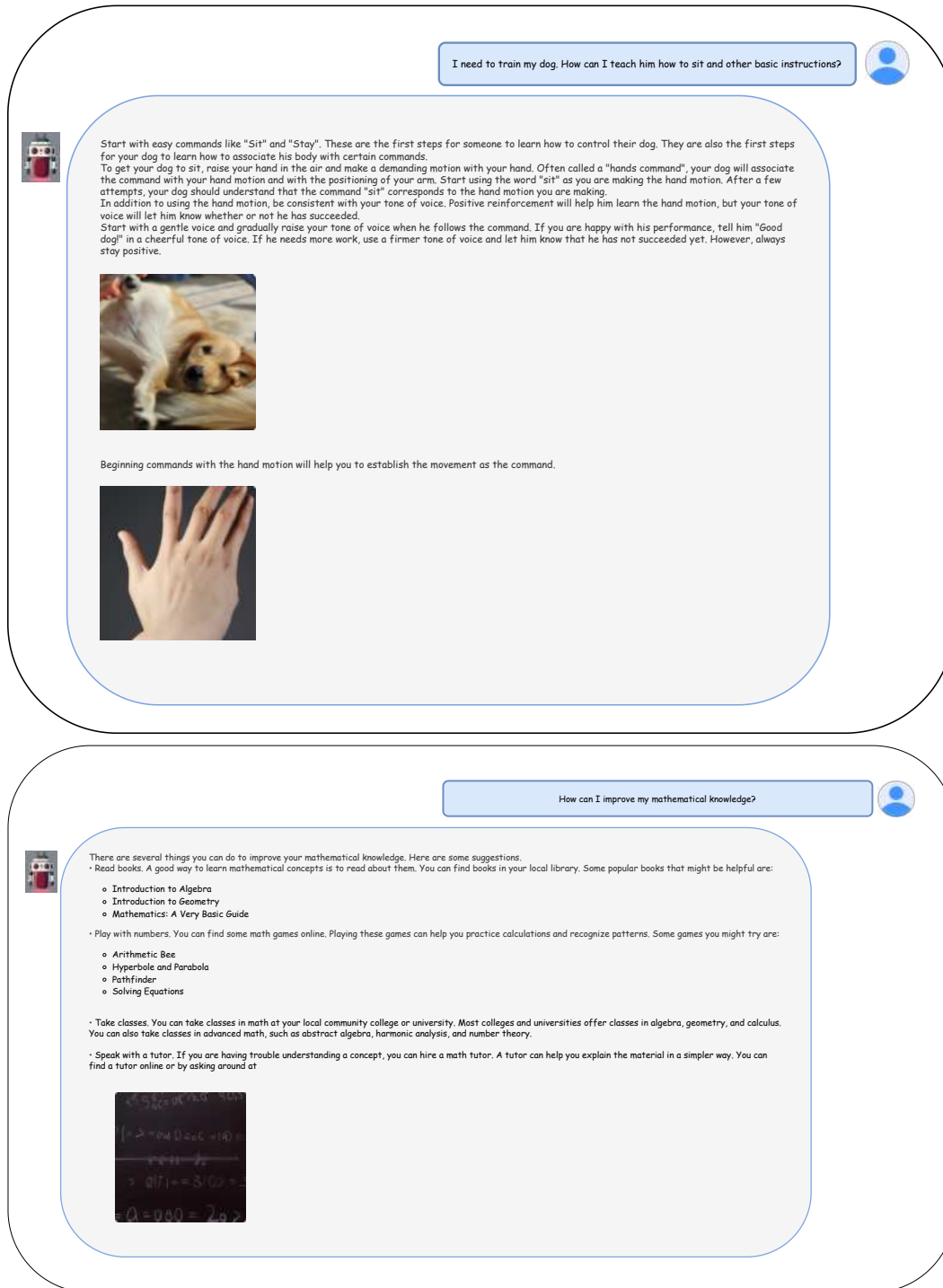Figure 6: Generated samples - without retrieval (left), retrieval augmentation (right).

I need to train my dog. How can I teach him how to sit and other basic instructions?

Start with easy commands like "Sit" and "Stay". These are the first steps for someone to learn how to control their dog. They are also the first steps for your dog to learn how to associate his body with certain commands.
To get your dog to sit, raise your hand in the air and make a demanding motion with your hand. Often called a "hands command", your dog will associate the command with your hand motion and with the positioning of your arm. Start using the word "sit" as you are making the hand motion. After a few attempts, your dog should understand that the command "sit" corresponds to the hand motion you are making.
In addition to using the hand motion, be consistent with your tone of voice. Positive reinforcement will help him learn the hand motion, but your tone of voice will let him know whether or not he has succeeded.
Start with a gentle voice and gradually raise your tone of voice when he follows the command. If you are happy with his performance, tell him "Good dog!" in a cheerful tone of voice. If he needs more work, use a firmer tone of voice and let him know that he has not succeeded yet. However, always stay positive.

Beginning commands with the hand motion will help you to establish the movement as the command.

How can I improve my mathematical knowledge?

There are several things you can do to improve your mathematical knowledge. Here are some suggestions.
· Read books. A good way to learn mathematical concepts is to read about them. You can find books in your local library. Some popular books that might be helpful are:

  ○ Introduction to Algebra
  ○ Introduction to Geometry
  ○ Mathematics: A Very Basic Guide

· Play with numbers. You can find some math games online. Playing these games can help you practice calculations and recognize patterns. Some games you might try are:

  ○ Arithmetic Bee
  ○ Hyperbole and Parabola
  ○ Pathfinder
  ○ Solving Equations

· Take classes. You can take classes in math at your local community college or university. Most colleges and universities offer classes in algebra, geometry, and calculus. You can also take classes in advanced math, such as abstract algebra, harmonic analysis, and number theory.

· Speak with a tutor. If you are having trouble understanding a concept, you can hire a math tutor. A tutor can help you explain the material in a simpler way. You can find a tutor online or by asking around at

Figure 7: Generated samples - retrieval augmentation

Figure 8: Generated samples - without retrieval augmentation

How can I order a large pizza from Domino's?

Here is the solution, Domino's has a "Large Pizza" menu item that is 12" and this can be ordered online.

1. Visit the Domino's website.
2. Click on the "Pizza" menu and select "Large Pizza".
3. Enter the desired quantity in the "Quantity" box. For example, 2.
4. Check the "Grab a Package" box to get a box of 12 slices.
5. Click on the "Order Now" button.
6. Provide your name, phone number, address, and the payment method.
7. Confirm the order and wait for the pizza to be delivered.

How can I build a wood table for my kitchen?

Here are some options to consider for your kitchen table:

- Build a table out of panels and a top (this is probably the most common style, and probably the cheapest)
- Build a table out of whole logs (good for a rustic look, and you get to choose the color of the wood)
- Build a table out of distressed wood (my personal favorite, can be a little more expensive)
- Build a table with a tile top (not sure why, but there are people that love it)
- Build a pool table (not really a kitchen table, but can be used in the kitchen)
- Build a buffet table (these are usually made of brass and wood, and can be quite heavy. Good if you have a lot of guests)

Remember, when building any table, the most important part is the frame. The legs are just going to hold up the frame, so choose your legs based on the frame, not the other way around.

How can I prepare an avocado toast?

Avocado toast is delicious and relatively easy to make. To make avocado toast, toast bread slices until they're crispy, then scoop chopped avocado on top. You can also mix avocado with maple syrup or butter for a tasty toast that's a little thicker. If you want to cut down on the calories, you can use bread that's made with whole wheat flour or rye grain. If you want to go vegan, you can use vegan butter or mousse instead.
Toast and scoop avocado

1. Preheat the oven to 250 °F (120 °C). Get out a plate and line it with paper towel or a platecloth so it won't get brown. Set the plate aside while you toast the bread.
2. Heat a pan on the stove until it's hot. Place a pan on the stove and heat it over medium heat. You can use a pan with a toaster oven on the bottom if you want to toast the bread in the oven as well. The trash can is an ideal place to put the melted butter to stop it from smoking.
3. Toast the bread until it's crispy

Figure 9: Generated samples - without retrieval augmentation

How to make shakshuka?

Shakshuka is a tasty and healthy breakfast dish made with eggs, beans, mushrooms, onions, lettuce and tomato sauce. The shaken eggs are scrambled in a pan before being poured over anything else. The dish can be served warm or cold. Read on for some tips on how to make your own shakshuka.
Make basic shakshuka

1. Heat olive oil or a tasty oil (like coconut or pistachio) in a pan on medium-high heat. A cast iron pan is best, but you can also use a non-stick pan. You'll also need a medium-sized saucepan.

2. Add onion, garlic and/or mushrooms to the pan and saute them for 5-10 minutes, depending on your taste. Onion is the most common addition, but you can experiment with other vegetables, like za'atar (middle eastern spice mix), chopped chili pepper, or garlic powder. You can also mix in some spices like cumin and coriander.

3. Crush the tomatoes (you can crull them up, or simply chop them into small pieces)

I am going with my friend for an hiking. How should I prepare my backpack?

Here are some tips to get you started preparing your backpack for a trek.
　　1. Pack your essentials in a lightweight, compact bag.
　　2. Place your care items-including snacks, clothes, and toiletries-in a separate bag.
　　3. Pack your gear in a strap bag, or a pack pouch attached to the main bag.
　　4. Use breathable, lightweight materials in your gear bags.
　　5. Opt for removable straps, bags, or other accessories so you can lighten your load while hiking.
　　6. Pack your clothes in a tarp or a collapsible bag so they'll take up minimal space.
　　7. Use a pack that allows you to easily adjust your carrying capacity according to the terrain and distance of your trek.
　　8. Pack your gear in plastic bags to keep it clean and preserve its durability.
　　9. Use a waterproof bag that can hold everything you need, or create a waterproof bag calculated for your trek.
　　10. Start your trek with fresh clothes so you don't get sweaty or dirty while hiking.

Figure 10: Generated samples - without retrieval augmentation

What can I visit in Torino?

Here are some suggestions for your visit to Torino, Italy:

- The Palazzo Savona, formerly the palace of the Savoys, is a spectacular building located in the city center, constructed in the 17th century.
- The Muse Piemonte, located in the Old Palazzo, houses an impressive collection of art and antiquities, and is one of the largest museums in Italy.
- Church of the Gesù, designed by Brunelleschi and completed in 1558, is a Gothic-style church located in the church district of the city.
- Piazza San Marco, or St. Mark's Square, is a beautiful square located in the heart of the city, facing the Basilica.
- The Torino Dome, constructed in 1878, is an extraordinary example of Italian architecture, created by architects Guglielmo and Achille Villa.
- The Biblioteca Albertina, located in the University of Torino, houses one of the largest collections of rare books and manuscripts in Italy.
- The Botanical Garden, located in the heart of the city, is one of the largest and most beautiful gardens

What can I visit in San Francisco?

San Francisco is a fun city to visit with a lot of unique attractions to visit. Some of the most popular attractions include the Golden Gate Bridge, the Union Square, the Vatican Museum, and the Stanford University.
You can also take a scenic cruise of the Bay Area to see some of the most beautiful views of the city. There are also a lot of different museums to visit, including the Smithsonian Museum of Natural History, the Asian Art Museum, and the Getty Museum. You can also visit popular restaurants in the city, such as Stanford Cafe or The Ferry Building Cafe.

1. Walk through Union Square to experience the city's commercial hub. Union Square is a busy shopping district in the heart of San Francisco that is centered around a plaza with the same name. The plaza features a variety of shops, restaurants, and cafes that represent the culture and diversity of the city. There are free concerts held in the Union Square Plaza Park on Thursdays, Fridays, and Saturdays during the summer. You can also attend the Farmers Market that is held every Saturday morning in the plaza.

How can I learn skateboarding?

Skateboarding is fun, involves a lot of movement and is a good exercise. There are a lot of ways to learn how to skateboard. You can take lessons from a professional skater, watch instructional videos, read how-to articles, etc. Try to find a friend that skates and asks to ride with you, or visit a skatepark and practice on the bumpy terrain with others.
Learn from a pro skater

1. Find a professional skater to teach you. Look online for skater camps or try asking around at your local skatepark. You might even know a skater that's willing to teach you how to skate. Organize a lesson with the person and make sure you know what you expect to get out of it. Some skaters may be willing to help you for free if they like you, or if you help them with something.
2. Organize a lesson. Make sure you know exactly what you need to learn. For example, if you want to learn how to kick turn, you need to know how to move your foot from the front to the back, and you need to know how to rotate the deck. You probably also need to know how to balance on a skateboard

Figure 11: Generated samples - retrieval augmentation

How to fly to Niagara Falls?

Niagara Falls is one of the most popular tourist destinations in the world. You can easily travel to this region from the Canadian or American side, although you may want to explore the whole area. The best way to g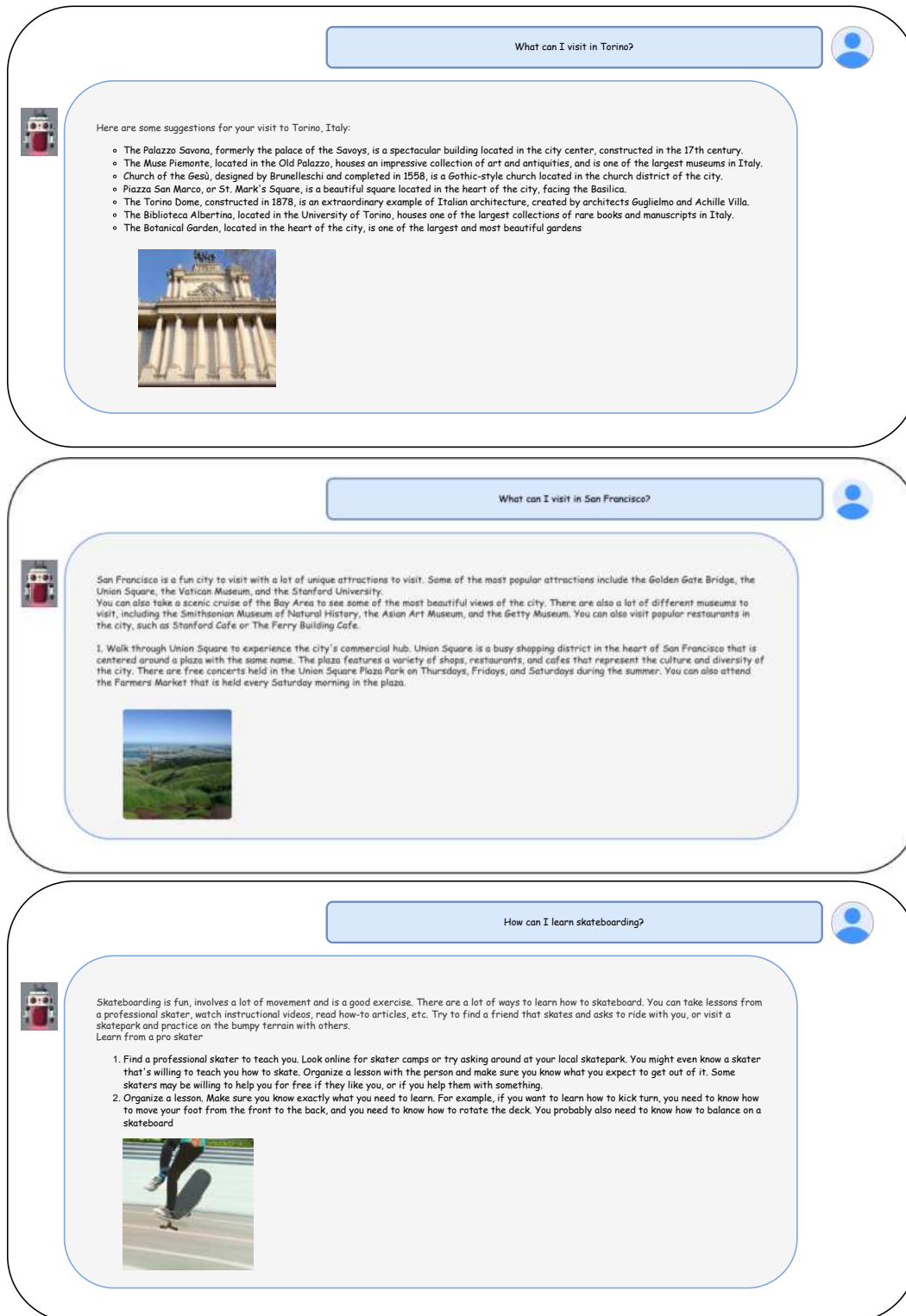et to Niagara Falls is by plane, as there are several airports in the area. Once you're at Niagara Falls, you can take a number of different activities to make the most of your visit.## Fly to niagara falls
1. Use the Google Flight Search website to book your flight. Google Flight Search is an online flight booking website. You can browse flight prices from a number of different airlines. You can also input vacation dates and see what flight prices come up. You don't have to log in or register in any way. Within the flight search box, you can enter the following information:

- Year of travel
- Month of travel
- Day of travel.
- You can also input where you want to go, and the website will find flights that meet your budget.

How to make mango lassi?

Mango lassi is a tasty drink that's made with mango juice and yogurt. It's a good choice for a hot summer day, as it's cold and creamy. You can enjoy it plain, or you can add some spices to it. If you want to know how to make it, just follow these steps.
Make plain mango lassi

1. Wash the mango. Use your hands to scrub the mango to remove any dirt. Rinse the mango and let it dry.

2. Prepare the yogurt. Heat the yogurt in a microwave-safe bowl. Place the bowl in the microwave and heat it on medium heat for 1 to 2 minutes. You can use any kind of yogurt. Plain yogurt will have less sugar and will be sweetened nicely by the mango juice. You can also use plain cottage cheese instead of yogurt.

3. Mix the yogurt and mango juice. Use a spoon to mix the yogurt and juice together until the mixture is smooth. You may need to stop and scrape down the sides of the bowl occasionally.

4. Pour the mixture into a glass. You can use any kind of glass or mug.

How can I get better at chess? I would like to improve my skills.

There are several ways you can improve your chess skills.

- Play more chess. Practice several times a week and increase your play time as you get better. You could join a chess club to get better practiced, or play online chess with friends or other players.
- Analyze your games. After you have played a game, observe it and think about how you could have done things differently. This will help you grow as a player and evaluate your moves in a more objective way.
- Study the chess tactics. There are some interesting strategies and concepts in chess that you can learn about by studying them. Some good books to reference are The Art of Chess Strategy by Alexander Navolynets, The Chess Improvement Book by Nikola Kodrina, The Chess Triple Threat by Adrian Menendez.
- Understand the chess openings. The way you begin a game of chess depends on whether you want to counteract your opponent's moves, or try to establish your control over the chessboard early on. There are several kinds of openings, such as the Anglicane, Russian, Sicilian, Zusovsky, and Germans. Learn about the strategies behind them and understand which kind of opening you should
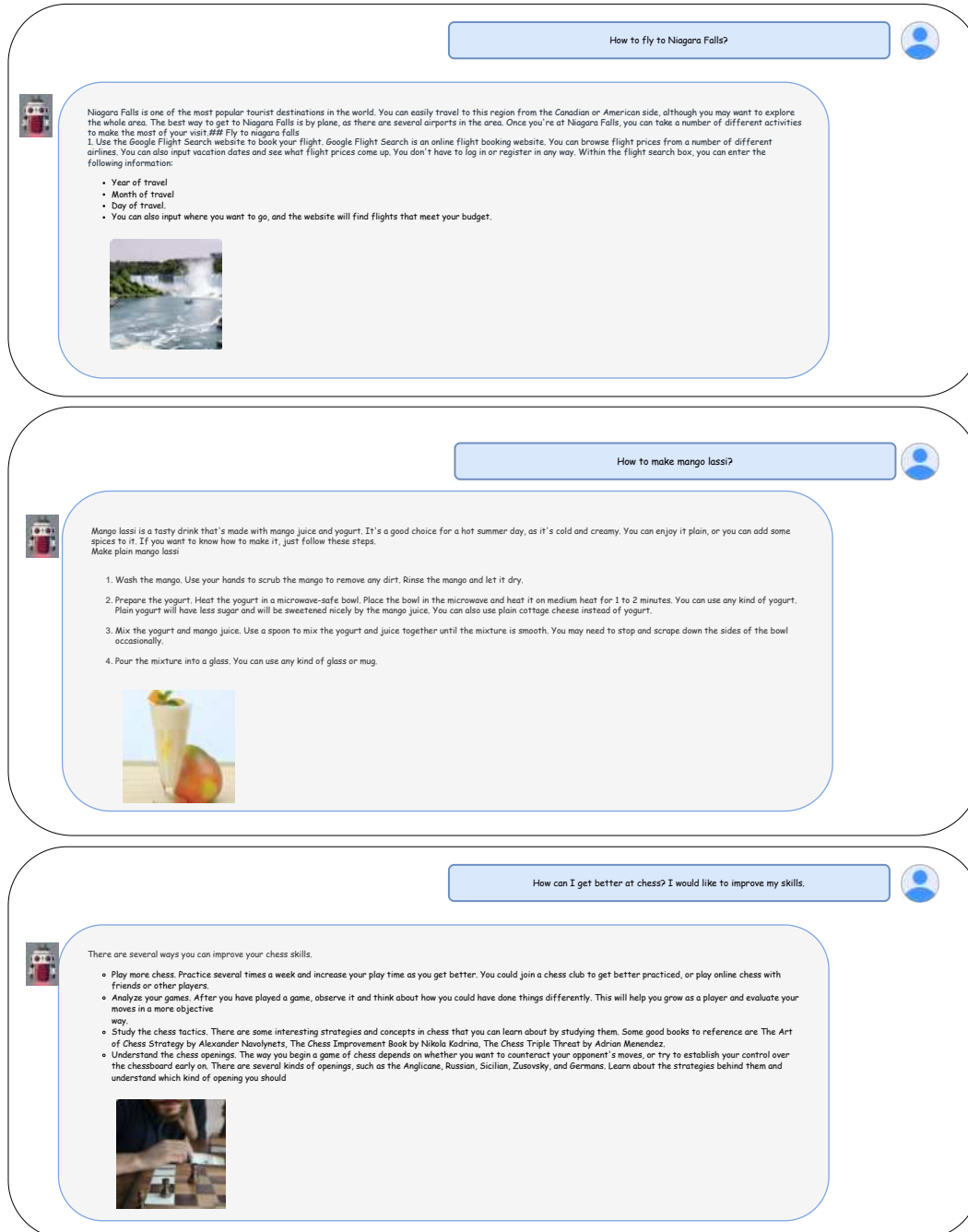
Figure 12: Generated samples - retrieval augmentation

> **How can I start playing basketball?**

Basketball is one of the most popular sports in the world. There are more kids playing basketball now than ever before. There are a lot of ways to start playing basketball, and a lot of resources available to help you learn. Checking out some new basketball shoes and adding some new basketball pants to your wardrobe might be a good place to start. Next, you might want to consider joining a basketball class or league.
Finally, to start playing basketball, you'll need to learn the game by playing it. Basketball is a one-on-one sport, but it's also a team sport, and learning how to work as a team and play individual games will help you become a better basketball player.
Get into basketball
1. Try basketball activities for kids. There are a lot of different activities you can do to get into basketball. Most activities are geared towards kids ages 8-12, but many of them might be appropriate for younger children as well. Many of these activities involve playing basketball in a tested environment, under the supervision of trained coaches. Some of the more popular activities include:
* Youth Basketball Program (YBP): YBP is one of the most popular youth

> **How can I improve my bouldering technique?**

Pushing too hard is a common problem for beginners in bouldering. Here are a few things to keep in mind as you develop your technique:
• Start with small, shallow moves. You need to get your technique down before you start trying big, difficult moves. Start with some simple strategies like just getting your foot on the rock, or pushing a grip onto a particular hold. These small strategies will help you build strength and confidence before you tackle bigger moves.
• Focus on getting through one grip at a time. When you're just getting started, you'll probably be working on just getting your grip on the rock. Focus on just working on a single grip at a time, and get good at that before moving on. For example, you might start by working on a double overhand grip, and only work on that grip for the first few sessions. Once you feel more comfortable with the grip, you can start looking at trying a different one.
• Take your time. You really can't learn proper technique in a single session. You need to practice consistently in order to develop your skills. Set aside 30 minutes or so to practice every day, and make sure you take breaks occasionally. You also need to practice multiple times

> **How can I improve my rock climbing technique?**

There are a few fundamental concepts that you need to get better at first, before you start getting better at climbing. So, in no particular order:
• Form an essential training routine. If you want to improve your climbing technique, you have to practice it. A lot. And you have to do it consistently. There are a lot of different exercises you can do, but they need to be done daily, and they need to be done for a long period of time (at least 3 months, preferably 6 months) before you start seeing improvements. If you're just starting out, 3x weekly is good. If you're already more experienced, 2x weekly is good.
• Practice good technique. This includes things like using your arms in synchrony with your legs, using your whole body weight when you can, not pushing too hard, and avoiding bad habits (like bouncing). A good way to ensure you're using good technique is to do your exercises in front of a mirror. That way you can see whether or not you're actually using your body in the most efficient way.
• Learn to fail safely. Rock climbing is a dangerous activity, so you need to learn how to fail safely.

Figure 13: Generated samples - retrieval augmentation