

# On Vision-Language Models

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## Abstract

In this article <sup>1</sup> we investigate vision-language models (VLM) design on two axes: 1. VLM architectures as reasoners; 2. Text-aware image encoding in VLMs. Going deeper with transformers-like layers as well as proper hyperparameter and other training choices, as well as stronger visual grounding from fused frozen pretrained backbones, led to strong improvements (up to 48% gain in accuracy) over baselines on the SMART task, further underscoring the power of deep multimodal learning. Eight different algorithmic reasoning skills are evaluated-math, counting, path, measure, logic, spatial and pattern-and the smarterVLM which includes a novel QF layer improves upon best previous baselines in every skill. Code at <https://github.com/droberts308/DL7643-project-vlms>.

## 1. Introduction/Background/Motivation

Opportunities for improvement of VLM were mentioned across several recent articles: problem-solving and algorithmic reasoning ability of transformers including VLMs is limited; there are still challenges on the vision modality; architectures for encoding, decoding and aligning are still to be explored. In the [17] several VLM design choices are explored. We take inspiration from their comprehensive approach to conduct two parallel and complementary investigations of our own in the VLM design space: reasoning ability and text-conditioned visual features. How we define intelligence (artificial or not) is still an open question. In “On the Measure of Intelligence” [10] the author conducts an in depth discussion and formulates a formal definition of intelligence based on algorithmic information theory, introducing the concept of algorithmic reasoning. Intelligence is also related to multimodal reasoning, as we humans use all our senses to get input for our higher abstractions to be built from. Better abstractions are akin to better mental representations. Deep neural networks excel at learning (artificial) representations [6]. **Why is this an**

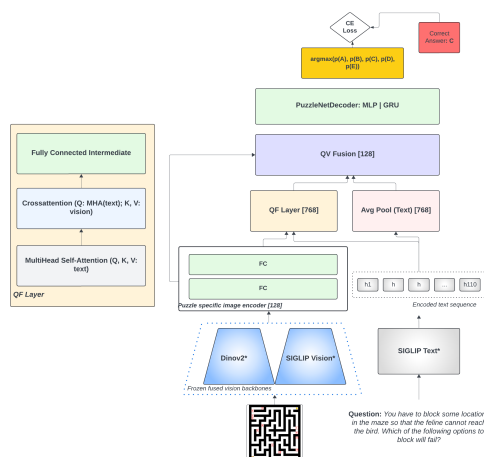
<sup>1</sup>Overleaf project draft

Figure 1. The smarterVLM reasoner architecture (right) and the novel QF layer (left). Vision (DinoV2+SigLIP) and language (SigLIP) backbones are frozen. All other layers are trained from scratch.

**important problem?** If we make neural networks better at algorithmic reasoning (I include here a few types of reasoning such as creative problem solving in math, physics, logic and coding algorithms, puzzles and IQ tests, learning, planning and decision making), this skill may be transferable to science, strategy, medical, law and commonsense, with far reaching real world impact. In the reasoning realm, many recent works focused on evaluating vision-language models on more general multimodal tasks [25, 34] or applying a chain of thought approach for in context learning [36, 37]. In [4] large language models are pretrained to solve text only questions bringing on the full power of heavy-weight LLM, but without taking the visual signal into account. Then a separate line of work builds very large VLM akin to LLM. In [19] a vision-language architecture, the Query Transformer, adds transformer layers to frozen image and text encoders and learns in a contrastive pretraining paradigm on massive datasets. Llava [20, 21] versions [20] emerge as a multimodal instruction tuned large model finetuned on a science dataset. In [14] authors use an LLM and parameter-

efficient visual instruction tuning, focusing on learning efficiently only the adapters, with early fusion of visual tokens in LLM layers. In [30] the deficiencies in visual grounding of large multimodal models is investigated and mixture of visual features are proposed to improve the vision modality. In [18], another pretrained and visual instruction tuned framework is proposed, employing Clip [?], Llama [31] and Perceiver adapters (from Flamingo) [1] as well as a dataset, MIMIC-IT. The pretrained vision encoder in DinoV2 [28] aims to leverage different techniques and diversity of images to pretrain backbones exactly for the purpose of using them as general-purpose features, as aimed in this investigation. However, it is not necessarily true that even this general purpose encoder will encode all the visual signal, so fusing with representations from a backbone pretrained in a different fashion, for instance the SigLIP [35] representation, may provide additional visual signal boost. Specifically, SigLIP improves on CLIP [?] for language-image pretraining by employing a sigmoid loss instead of the contrastive learning with softmax normalization and performs better across tasks.

## 2. Denisa R: The VLM Reasoning Problem

So how can we help (deep) artificial neural networks reason better? We can get inspired from the current works on the very large VLM and build upon them. In [9] experiments show that the visual signal is very important in solving complex multi-reasoning skill puzzles and that language only really large models lag behind. In the article “Are Deep Neural Networks SMARTer than Second Graders?” [9] another task, a Simple Multimodal Algorithmic Reasoning Task (SMART), is introduced with visuo-linguistic puzzles designed for children in the 6-8 age group (from the US Kangaroo Olympiad), which align with intelligence desiderata in [10]. The puzzles measure intelligence across 8 different skill classes: counting, math, logic, path, measure, logic, pattern. Problems include an image and a text question and are formulated as multiple choice. We can see a few examples in Figure 2 and more problems with full text in Appendix A, Figure 6. Vision-language models trained in [9] struggle to solve this task, especially transformers. In this Section I investigate how we can craft and train deep neural networks which employ transformer-like blocks and multimodal inputs from deep frozen transformers to reason better.

### 2.1. VLM Reasoners: Approach

In [2,3,27] the authors demonstrated how a **deep learning module** including transformers, which encode a sequence of image-and-text items using diverse representations composed on several axes-across modalities, across time steps, and across pooling methods, obtained massive results in sponsored search and recommendations. Building upon the

ADPM in [2, 3, 27] and using tricks for properly training vision transformers in [13], a smarterVLM is built. In this article I make the following **contributions** on the vlm reasoning axis: 1. Architectural and deep learning training innovation: go deeper and make architectures work better with the multimodal input. 2. Introduce a novel QF-layer to learn a composite representation. 3. Improve the MLP decoders through gelu activations, residual connections and layer normalization. 4. Improve the sequence decoder by replacing the LSTM with a GRU. 5. Strengthen vision encoder by fusing two vision backbone: SigLIP [35] and DinoV2 [28] similarly to [17]. 6. Strengthen the text-vision alignment by using a frozen SigLIP language encoder together with the fused vision backbone, which does not overpower the visual signal. The improvements lead to up to 48% accuracy improvement in some skills on test set over best performing baseline from the SMART task.

#### 2.1.1 Benchmark, Dataset and Challenges

A set of vision-language models are trained as benchmarks in [9] and **SMART-101 with 202K text-image pairs for train, validation and test dataset** is released. There are 101 origin puzzles and additional problems are generated programmatically in each puzzle group for a total of 202,000 question-image pairs. Figure 6 clearly describes a training example problem. All the trained VLMs struggle on the SMART task, with transformers underperforming ResNet50 [15] based models. The learning tasks depend on the type of puzzle and are in the classification, regression and sequence generation category. Several image and text encoder backbones are considered. A puzzle specific set of image features are learned via an MLP and the text embeddings are aggregated using an LSTM layer. The decoder for the sequence generation is another LSTM layer. All image encoders are finetuned. Based on these characteristics, there are a few research opportunities worth exploring, especially since transformer based VLM reasoners are doing so poorly on the challenging SMART task in [9].

#### 2.1.2 Methodology

I scope the problem to focus on the supervised learning formulation with a **classification loss**. For each image-question instance, **we predict the probability of one of five answer** options. When the options are a sequence, the GRU decoder decodes the sequence but the answer is still translated to one of  $\{A, B, C, D, E\}$  options. Furthermore, I focus on training deep learning architectures from scratch for the SMART task with inputs from diverse pretrained **frozen** backbones. I focus the investigation on the eight skill classes counting, (**math, logic, algebra, path, pattern, measure, spatial**) rather than individual puzzle

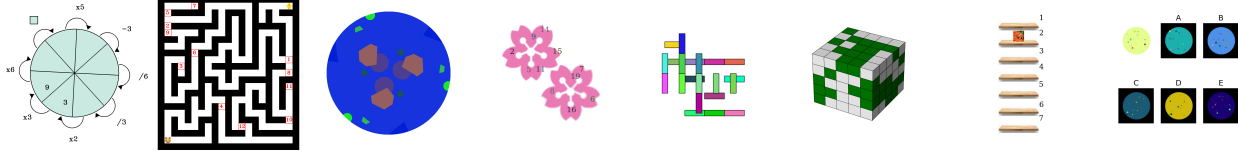


Figure 2. **Math Question:** What do we need to put in the square to get a correct diagram? **Answer Options:** A: -3; B: /9; C: x6; D: x2; E: 2; **Path Question with Sequence Answer:** You have to block some locations in the maze so that the feline cannot reach the bird. Which of the following options to block will fail? **Answer Options:** A: 1, 2, and 3; B: 4; C: 5, 6, and 7; D: 8 and 9 ; E: 10, 11, and 12. **Counting; Algebra; Measure; Spatial; Logic; Pattern.**

groups since these are of more general interest across domains and trademarks of intelligence. In [8] authors demonstrate that strong pretrained backbones can perform without meta-learning so I do not employ it, as they do in [9]. Since it is a classification loss, the **accuracy metric** calculated on validation set is used to tune the models and evaluate **method success**, and the accuracy for the five class classification is evaluated on the test set. The accuracy is calculated overall, and more interestingly, on skill class (counting, math etc.). Detailed information on development, training, evaluation and artifacts is in Appendix A. **Architectural Innovation.** I derive a composite representation via a novel layer, the QF layer, inspired from the ADPM in adsFormers [2, 3, 27] and the QFormer in [19, 39]. More recently, [17] and [30] combine multiple image representations to leverage diversity of signal in vision-language models, in a similar vein to the ADPM. The choice of the SigLIP text encoder is two-fold: first, due to the alignment with the SigLIP vision encoder; second, to tame the language power by not employing a large language model. In [30] we see that visual grounding is lacking in large multimodal models. Furthermore, in [9] the visual signal is quite important, the accuracy loss is more when removing the image rather than the text question, so the visual signal needs to be protected as it is critical. Details for the VLM reasoner architecture in Figure [?] are in Appendix A, including equations. The QF layer representation for the image-question input is concatenated to the average pooled text representation and the puzzle-specific image representation from the image encoder. The composite representation  $compositeR$  takes as input three component representations,  $r_1$ ,  $r_2$ , and  $r_3$ , defined as follows, with equations in the Appendix A.3. Text representation  $r_3$  is an average pooled encoding of the question sequence of max length 110 tokens. Each token is first encoded using the frozen SigLIP text model into a representation of size 768. An image representation  $r_1$  from the puzzle-specific image encoder block of dimension 128. The dimension is a hyperparameter selected via optimization. The image encoder consists of two feed forward layers with a gelu unit, with separate weights for each puzzle head, for the 101 separate puzzle groups. Each encoder takes as input the image representation from the two fused

pretrained vision backbone, Dinov2 [28] and SigLIP [35], each of dimension 768. A QF representation,  $r_2$ , is produced by the optional QF layer which takes as input the encoded image representation  $r_1$  and the SigLIP-encoded sequence of text tokens. The QF layer, passes the text sequence through a multi-head self-attention block, as in [32]. The resulting hidden representation is then fed to a cross attention layer as query, with key and values being the image encoder representation inspired from the q-former and ViLBERT [24]. Finally, an intermediate stack of fully connected with residual connections [15] and layer normalisation [5] produces the QF text-and-vision representation. The the QVfusion layer as input the composite representation  $CompositeR \in \mathbb{R}^{2*768+128}$  and passes through a three layer feed forward module with Gaussian error linear units in between [16], before being read by the puzzle specific decoder as seen in Figure 1. Finally the decoder, which is either a stack of three fully connected layers separated by gelu activations, or a gated recurrent neural network for sequence type answer puzzles, produces predictions fed to a cross-entropy loss. Each puzzle group calculates its own loss. The introduction of gelu units, layer normalisation, boost performance, as they do in most recent attention-based neural networks and not only allowing for a smoother loss landscape than relus and batchnorms.

## 2.2. VLM Reasoners: Experiments and Results

Several baselines from [9] are trained have results in 4 in Appendix A. I chose to move forward with the frozen BERT+Resnet50 as **baseline** for two reasons: 1. Note that the numbers are extremely close between the frozen and unfrozen variants but the frozen variant does better on Math, a skill of interest for this investigation; 2. This investigation focuses on a frozen backbones scope for efficiency reasons. Furthermore, keeping the backbone frozen afford a better comparison between models and the ability to reuse some hyperparameter settings such as batch size, number of epochs, optimizer, because if we choose to finetune the transformer based backbones as well, it does not make sense to employ the same techniques as for convnets. **Results on a subset of the SMART101 training set** are discussed next. The biggest **challenges and limitations** for getting better

models are as always in terms of **compute requirements**: to tune deep neural networks you need to run many experiments; transformers are data hungry as well so the GPUs for training large models with large memories and disk are needed for a long time. So I sampled and raised the bar on the model architectures rather than data and compute. A different split of *train : val : test* = 60 : 20 : 20 and only **1000 out of the total 2000 question-image pairs per puzzle group** are utilized for fast training and insight, with a total budget of three epochs of training. This results in **474 training batches, 158 validation and 158 test batches of size 128**. Since both the vision and text pre-trained backbones are frozen, the additional model layers result in **29,623,375 trainable parameters** (unless dismissing the qf layer or experimenting with additional residual blocks, which some of the runs contained). Experiments are tracked in CometML [11], the **multimodalai** public project. The Table 5 in Appendix A shows results from intermediary experiments ran in the process of model development to make architecture, optimization, and hyperparameter decisions toward to final model; watching curves is what deep learning is all about.

As we can see in Table 1 of **best results**, some of the new models **display massive gains in accuracy (eg. +48% gain over the baseline** in the counting skill). Recall that the baseline was chosen amid the original paper’s choices as the strongest in math; and truly so, it was hardest to beat in math vs other skills. **The smartest VLM reasoner** was trained employing the following deep learning implementations, building upon results obtained in [3, 27], [13], [29] and [26]: 1. Adam optimizer with decoupled weight decay from [23] with weight decay of 0.2,  $eps = 1e - 8$ , and  $beta2 = 0.98$ . 2. Cosine learning rate scheduler [22] with ten warmup steps, with the implementation in the Hugging-Face repository [33]. 3. Clipping the gradient norm to no more than one. 4. Layer normalization throughout the architecture modules with  $eps = 1e - 6$ . 5. A SigLIP frozen language backbone and fused DinoV2 and SigLIP vision backbone. 6. A composite hidden representation with a QF layer with two attention heads. 7. Dropout probability of 0.2 anywhere it is used. 8. Gaussian error linear units; the MLP decoder is akin to SigLIP’s MLP block. 9. Representation sizes of 128 and 256 within the various layers. 10. GRU decoder for problems with sequence answer, as they are easier to train than LSTMs. **A vital insight** arose through the **training process**. In Figure 3 and 4, notice how the eight skill sets have different training dynamics and respond differently to learning rate choices, as well as to the cosine scheduler’s learning rate decision throughout the training steps. This is something commonly seen in multitask learning [7, 13]. All experiments are run with seed 0 for the sake of **reproducibility** but I also evaluated the test accuracy standard deviation across a few seeds (0, 42,

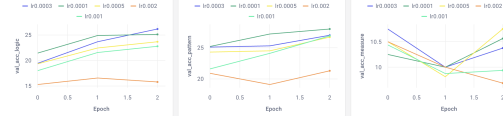


Figure 3. Validation accuracy curves per skill class -counting, math, spatial- for five different learning rates.

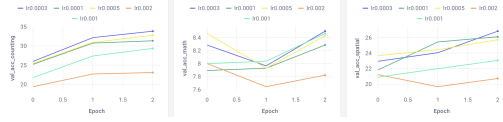


Figure 4. Validation accuracy curves per skill class -logic, pattern, measure- for five different learning rates.

7): mean overall test accuracy 20.8 ( $\sigma = 0.16$ ), math skill mean accuracy of 9.73 ( $\sigma = 0.38$ ), pattern mean accuracy 25.2 ( $\sigma = 0.53$ ). As expected, we see more variability on smaller individual skill class sets. **Future direction**. Considering the different learning dynamics for the eight skill classes, a multitask learning approach with eight tasks may afford modulating the impact of eight weighted losses to account for the different dynamics. A mixture-of-experts approach [38] within the multitask learning framework could further help. Furthermore, we see that the qf learning helps, for some skills especially more so, and further deepening transformer-like specialized reasoning architectures, which read from frozen per-modality or multimodal encoders, can further help. Experimenting with further general purpose backbones, deeper or wider, is another potential avenue, since we see improvements from the fused Dinov2+siglip.

### 3. Ahmad’s: Don’t take vision features for granted : An Efficient Text Aware Image Encoding

Recent VLM Research can be divided into two different but yet very similar axes. Vision language alignment and Instruction following capabilities.

Alignment Approaches can be ordered as follows in terms of their complexity:

1. Simple linear projection or MLP projection such as LLava series which project the vision encoder features into the same space of language model embedding, so that the image features can be passed as a soft prompt input for the language model.
2. Extra complex modules such as Q-Former in BLIP series.
3. Integration of vision features through cross-attention with language model such as Flamingo and Otter Series.



Neural Net	Counting	Math	Logic	Path	Algebra	Measure	Spatial	Pattern	Overall
BERT+Resnet50	23.4(-)	9.6(-)	17.9(-)	17.5(-)	10.5(-)	9.9(-)	25.8(-)	20.3(-)	17.1(-)
SmarterVLM lr0.001	29.0(+24%)	9.9(+3%)	21.2(+18%)	17.9(+2%)	10.8(+3%)	11.1(+12%)	23.2(-10%)	25.7(+27%)	19.12(+12%)
SmarterVLM lr0.0005	32.9(+41%)	10.0(+4%)	22.8(+27%)	<b>19.5(+11%)</b>	11.2(+7%)	<b>11.6(+17%)</b>	26.3(+2%)	25.8(+27%)	20.86(+22%)
<b>SmarterVLM lr0.0003</b>	<b>34.7(+48%)</b>	9.5(-1%)	<b>25.7(+44%)</b>	<b>19.5(+11%)</b>	<b>11.3(+8%)</b>	11.1(+12%)	<b>26.7(+3%)</b>	<b>27.4(+35%)</b>	<b>21.59(+26%)</b>
SmarterVLM (no QF)	32.3(+38%)	<b>10.3(+7%)</b>	23.3(+30%)	18.8(+7%)	10.0(-5%)	10.1(+2%)	25.8(+0%)	23.6(+16%)	20.14(+18%)

Table 1. Test set skill class accuracy for a few top models and comparison to the baseline in first row (percentage change). From CometML [multimodalai](#).

4. A complete unified approach such as Fuyu-8B which a transformer decoder which accepts both text and images as inputs.

After alignment, the instruction tuning process doesn't differ among most of the previous works. The only difference might be in the dataset collection procedure, the prompting strategy and the sampling process.

All of the following approaches use a frozen vision encoder except for Fuyu which relies on a vision-encoder free pipeline. Some of the approaches fine-tune full parameters of the language model. While others use some parameter efficient methods such as LoRa and complicated variant of prefix tuning such as Llama Adapter v2.

After surveying the literature, it became obvious that relying on a frozen vision encoder is one of the weaknesses of current VLM design aspects. On the other hand, fine-tuning the visual encoder while training the whole system might not be the best case as shown in Prismatic. This can be attributed to the fact that the vision encoder doesn't interact directly with the textual input. Only two approaches got close to that conclusion, Fuyu8B which removed the whole visual encoder. And BLIP2 which condition the visual encoder output on the instruction text but inside the Q-former. I argue that the textual context should be fused in the visual encoder from the start, not after the feature extraction process. Because the feature that LLM might be looking for, might not be present in the visual encoder features itself.

### 3.0.1 Planned Contributions

My proposed architecture is shown in Figure 11.

I plan to follow the dataset recipe from LLaVa 1.5 combined with LLaVaR for the tuning and alignment part. And transform the dataset from LLaVaRLHF to DPO format and do DPO alignment after training. I don't plan to follow the two stage pretraining like it has been done in all previous work, instead, as the authors of Prismatic showed that combining the two stages might be more beneficial. For the alignment components in the figures I plan to start from the simple possible and increase complexity as needed :

1. MLP Projection
2. Zero-Gated Prefix Tuning (LLama Adapter V2)

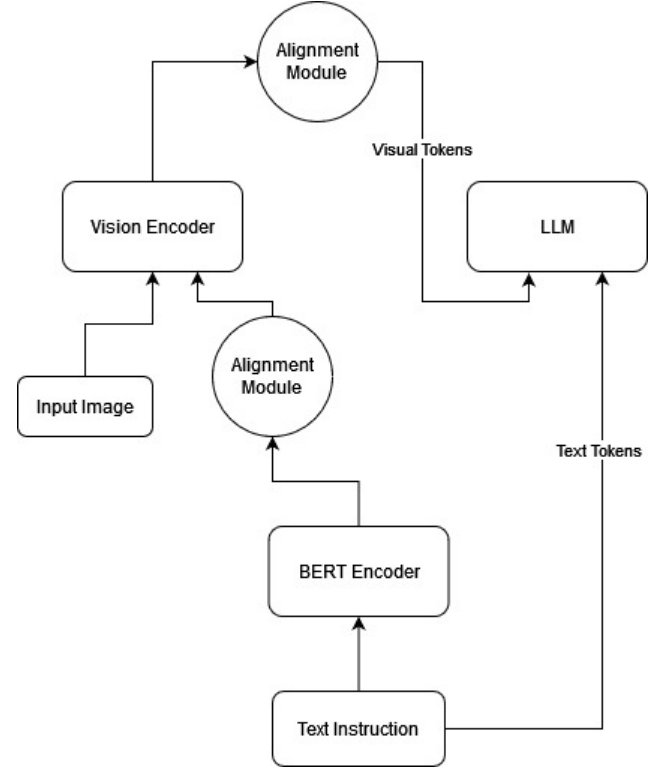


Figure 5. Proposed Architecture

3. DoRa or LoRa variants.

BERT and LLM can be replaced with Flan T5 encoder and decoder respectively to ensure that the text representation passed to both the vision encoder and language decoder come from the same distribution. I plan if I had time to try both approaches, using bert and off the shelf decoder based LLM and use T5 or any encoder decoder based LLM.

For the Visual Encoder part, adapting it efficiently to a task won't be that complex because I'm planning to use ViT based visual encoders such as CLIP or DINOv2 or an ensemble of both.

In addition to the benchmarks in LLaVa Series, and Prismatic Models. I plan to benchmark my results also on :

1. MMVP Benchmark "Eyes Wide Shut" which address multiple visual preception tasks

2. MagnifierBench From OtterHD which address smaller tress on minute details and spatial relationships of small objects.

## 4. Conclusion

Going deeper with transformer-like architectures, deep learning representations, and visual grounding lead to improvements across reasoning and general ability of VLMs and the path is open for further improvements.

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Student Name	Contributed Aspects	Details
Denisa Roberts	Initial Phase	Weekly research meetings (Feb1-Mar1)
Denisa Roberts	Initial Phase	Literature review and summaries
Denisa Roberts	Initial Phase	Initial list of ideas generation and proposal
Denisa Roberts	VLM Reasoners End-to-End Development	Preprocessing, Neural Net architecture development, Hyperparameters, Loss, Training, Eval, Metrics (Details in Appendix A.2)
Ahmad Shapiro	Initial Phase	Weekly research meetings (Feb1-Mar1)
Ahmad Shapiro	Initial Phase	Literature review and summaries
Ahmad Shapiro	Initial Phase	Initial list of ideas generation and proposal

Table 2. Contributions of team members.

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## A. Additional Information on VLM Reasoners

### A.1. Example of Puzzles Problems and Image-Question Pairs For Each of the Eight Skills

In Figure 2 I showed a few examples of problems across skill sets but omitted text question for most skill classes. In Figure 6 I include all the questions for a full understanding of train/val/test examples in the SMART 101 dataset.

### A.2. Denisa’s Project and Code Development Log and Contributions

The step-by-step development (341 commits) starting from the SMART project fork can be found at [github.com/D-Roberts/smarter](https://github.com/D-Roberts/smarter), with details documented via commits and PRs and included in Appendix A, Table ?? . All models were trained in PyTorch (see all required library versions in supplementary materials code requirements), on the PACE cluster, on one V100 GPU with 40Gb of memory, and model artifacts as well as development logs can be found in droberts308 user directory. Model training and ablation experiments were tracked via CometML [11] in the public projects [droberts308/multimodalai](https://github.com/D-Roberts/multimodalai) (for final models) and [droberts308/vlm-reasoners](https://github.com/D-Roberts/vlm-reasoners) (for development runs).

In the initial phase before proposal (February 1, March 1), there were weekly project research meetings and literature reading and reviews. I contributed literature review summaries and initial general pool of ideas in the project proposal, which is included as another appendix to the final project report, beyond the vlm reasoners path which I then developed.

In Table 3 I list git repositories and PRs used to develop the smarter VLM reasoners. More details can be seen from the code changes and commit messages (for a total of 341 commits to the current state of the smarter git repository). There are references in code files. Additional report development for vlm reasoners is at [overleaf-vm-reasoners](https://github.com/D-Roberts/vlm-reasoners).

Here is a screen shot for training smarter VLMs on Georgia Tech’s PACE GPU, in Figure 7.

### A.3. Architectural Innovation Equations

The QF layer representation for the image-question input is concatenated to the average pooled text representation and the puzzle-specific image representation from the image encoder. The composite representation  $compositeR$  takes as input three component representations,  $r_1$ ,  $r_2$ , and  $r_3$ , defined as follows.

- Text representation  $r_3$  is an average pooled encoding of the question sequence of max length 110 tokens. Each token is first encoded using the frozen SigLIP text model into a representation of size 768. Then

$$r_3 = AveragePooling([h_1, h_2, \dots, h_{110}]).$$

- An image representation  $r_1$  from the puzzle-specific image encoder block of dimension 128 seen in 1. The dimension is a hyperparameter selected via optimization. The image encoder consists of two feed forward layers with a gelu unit, with separate weights for each puzzle head, for the 101 separate puzzle groups. Each encoder takes as input the image representation from the two fused pretrained vision backbone, Dinov2 [28] and SigLIP [35], each of dimension 768. Specifically, for an image  $X$ ,  $r_1$  is

$$r_1 = FC_{1i}(Gelu(FC_{2i}(y))),$$

$$y = Concat([Dino(x), SigLIP(x)])$$

for  $i \in \{1, \dots, 101\}$ , a distinct puzzle group.

- A QF representation,  $r_2$ , is produced by the optional QF layer which takes as input the encoded image representation  $r_1$  and the SigLIP-encoded sequence of text tokens. The QF layer, passes the text sequence through a multi-head self-attention block, as in [32]. The resulting hidden representation is then fed to a cross attention layer as query, with key and values being the image encoder representation inspired from the q-former and ViBERT [24]. Finally an intermediate stack of fully connected with residual connections [15] and layer normalisation [5] produces the QF text-and-vision representation. Specifically,

$$r_2 = LayerNorm(x + Drop(FC(Gelu(FC(x)))))$$

$$X = MHCrossA(MHA([h_1, h_2, \dots, h_{110}], r_1))$$

Finally, the composite representation is

$$CompositeR = CLayer([r_1, r_2, r_3])$$

$$= LayerNorm(Concat([r_1, r_2, r_3])).$$

The the QVFusion layer as input the composite representation  $CompositeR \in \mathbb{R}^{2 \times 768 + 128}$  and passes through a three layer feed forward module with Gaussian error linear units in between [16], before being read by the puzzle specific decoder. Specifically, the QVFusion layer in 1 is

$$QVFusion(y) = LayerNorm(GELU(y))$$

$$y = FC(GELU(FC(compositeR))).$$

### A.4. Additional Experiments for VLM Reasoners

In Figure 8 we can see training loss nicely descending over the training steps in the three epochs modulated by five different learning rates with a cosine scheduler which



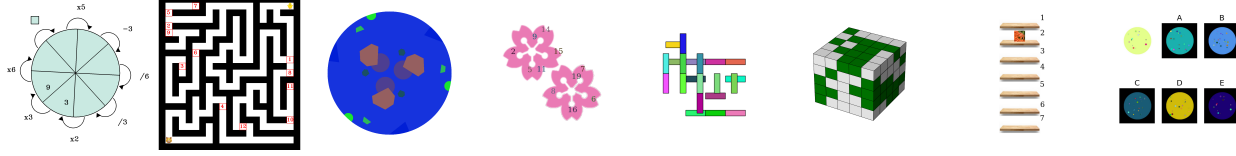


Figure 6. **Math Question:** What do we need to put in the square to get a correct diagram? **Answer Options:** A: -3; B: /9; C: x6; D: x2; E: 2; **Path Question with Sequence Answer:** You have to block some locations in the maze so that the feline cannot reach the bird. Which of the following options to block will fail? **Answer Options:** A: 1, 2, and 3; B: 4; C: 5, 6, and 7; D: 8 and 9 ; E: 10, 11, and 12. **Counting Question:** The entire pie is divided among several children. Each child receives a piece of pie, and each piece of pie looks identical. The maximum possible number of children there is: **Answer Options:** A: 7; B: 2; C: 1; D: 4; E: 3. **Algebra Question:** The entire pie is divided among several children. Each child receives a piece of pie, and each piece of pie looks identical. The maximum possible number of children there is: **Answer Options:** A: 5; B: 4; C: 2; D: 0; E: 6. **Measure Question:** A student had a few canes with a height of 1 cm and a length of 5cms. Using the canes, she built the arrangement illustrated. What is the width of the arrangement? **Answer Options:** A: 20; B: 30; C: 15; D: 5; E: 35. **Spatial Question:** Cristina made a setup using some green blocks and 94 white blocks. How many of these white blocks are not visible in the figure? **Answer Options:** A: 28; B: 61; C: 64; D: 90; E: 79. **Logic Question:** Emily has 7 toy items: a remote, a hair brush, a truck, an eraser, a rubber duck, carrots, and a toe ring. She keeps each toy at a different row of the shelf. The carrots lower to toe ring. Remote lower to truck and toe ring higher to truck. Toe ring higher to rubber duck. She keeps carrots as shown. On which row can the rubber duck not be placed? **Answer Options:** A: 4; B: 3; C: 7; D: 5; E: 6. **Pattern Question:** Which picture on the right matches with the left, if we invert the colors? **Answer Options:** A; B; C; D; E

Final VLM Reasoners code for the project supplementary material	<a href="https://github.com/droberts308/DL7643-project-vlms/tree/main/modules/denisa_vlm_reasoners">https://github.com/droberts308/DL7643-project-vlms/tree/main/modules/denisa_vlm_reasoners</a>
Original SMART repo fork for running baselines	<a href="https://github.com/D-Roberts/SMART">https://github.com/D-Roberts/SMART</a>
Step-by-step development repo with timestamped PRs and commits	<a href="https://github.com/D-Roberts/smarter">https://github.com/D-Roberts/smarter</a>
PR to add the Dinov2 vision backbone and update requirements to allow	<a href="https://github.com/D-Roberts/smarter/pull/1">https://github.com/D-Roberts/smarter/pull/1</a>
PR to add metric and CometML logging	<a href="https://github.com/D-Roberts/smarter/pull/3">https://github.com/D-Roberts/smarter/pull/3</a>
PR to update torch and transformers; refactor Dino processing	<a href="https://github.com/D-Roberts/smarter/pull/4">https://github.com/D-Roberts/smarter/pull/4</a>
PR to improve deep learning training	<a href="https://github.com/D-Roberts/smarter/pull/5">https://github.com/D-Roberts/smarter/pull/5</a>
PR to refactor code to remove extraneous code (meta-learn, regression, etc)	<a href="https://github.com/D-Roberts/smarter/pull/6">https://github.com/D-Roberts/smarter/pull/6</a>
PR to fix rnn code in new torch; test siglip	<a href="https://github.com/D-Roberts/smarter/pull/7">https://github.com/D-Roberts/smarter/pull/7</a>
PR to add the siglip vision encoder and associated processing and requirement updates	<a href="https://github.com/D-Roberts/smarter/pull/8">https://github.com/D-Roberts/smarter/pull/8</a>
PR to fuse dinov2 and siglip vision; add siglip language	<a href="https://github.com/D-Roberts/smarter/pull/9">https://github.com/D-Roberts/smarter/pull/9</a>
PR to add the QF Layer, CLayer and QV Fusion layer;	<a href="https://github.com/D-Roberts/smarter/pull/10">https://github.com/D-Roberts/smarter/pull/10</a>
PR to further make architectural changes (add layernorms, extra residuals etc)	<a href="https://github.com/D-Roberts/smarter/pull/11">https://github.com/D-Roberts/smarter/pull/11</a>
PR to make necessary code changes to be able to run the bertresnet50 baseline as was	<a href="https://github.com/D-Roberts/smarter/pull/12">https://github.com/D-Roberts/smarter/pull/12</a>
PR to remove grad clip from baseline (wasn't done in original repo)	<a href="https://github.com/D-Roberts/smarter/pull/13">https://github.com/D-Roberts/smarter/pull/13</a>
Some refactor, debug and temporary changes to run experiments PRs(14-18)	<a href="https://github.com/D-Roberts/smarter/pull/14">https://github.com/D-Roberts/smarter/pull/14</a>
PR to finalize code (19 and 20)	<a href="https://github.com/D-Roberts/smarter/pull/19">https://github.com/D-Roberts/smarter/pull/19</a>

Table 3. VLM Reasoners Code Development

adapts the learning rate based on the step number. Note how the large 0.002 learning rate (orange) impacts learning negatively in the strongest way. Noticeable bumps in curves depend on the scheduler’s change points.

For thoroughness of comparison in the developmental phase I proceeded with training and evaluation on a very

small subset of data for quick insight and iteration: only 20 questions per puzzle, with a batch size of 16, a split ration of  $train : val : test = 40 : 20 : 40$ . Complete experiment results are available were tracked with CometML [11] and publicly accessible at [vlm-reasoners](https://github.com/droberts308/DL7643-project-vlms/tree/main/modules/denisa_vlm_reasoners). Results are included in Table 6 in the Appendix A. In

SMART Baseline	Counting	Math	Logic	Path	Algebra	Measure	Spatial	Pattern	Overall
BERT+Resnet50	35.6	<b>26.4</b>	36.8	21.5	18.1	26.0	32.2	27.0	28.0
BERT+Resnet50(unfrozen)	35.7	20.8	39.6	22.2	18.4	28.2	33.7	30.6	28.2
BERT+MAE [?]	29.8	19.7	29.4	20.5	16.1	18.9	26.6	27.8	23.1
CLIP VL	35.5	8.6	27.1	17.9	11.8	16.0	26.8	26.3	22

Table 4. Skill class accuracy for original baselines with a 10hr budget training. All backbones are frozen unless noted otherwise.

	counting	math	logic	path	algebra	measure	spatial	pattern	vision	language
final_lr0.0006	23.6	8.4	19	18.6	9.5	10.6	23.9	22.4	dinov2siglip	siglip
baseline_mbert	23.4	8.1	18.9	17.9	10.3	10.2	23.8	20.8	resnet50	mbert
baseline_bertresnet50	23.4	8.1	19.2	17.8	10.7	10.3	24.8	20.5	resnet50	bert
lstm_decoder_siglipvision	24.6	7.9	17.9	17.9	10	9.1	22.6	21.4	siglip	siglip
lstm_decoder	27.7	8.4	21.3	18.6	11.2	9.2	23.3	25.1	dinov2siglip	siglip
qf_fusion_extra_residualinmlpdec	21.5	7.4	17.5	17.8	9.3	10.4	21.6	20.3	dinov2siglip	siglip
single_image_head	27.2	8.4	20.2	18.5	10.3	10.2	23.4	22.1	dinov2siglip	siglip
warmup0	29.8	7.4	21.3	20.3	10.1	10.8	22.8	26.6	dinov2siglip	siglip
warmup0.06	30	7.8	22.3	19	9.6	9.8	22.9	25.1	dinov2siglip	siglip
warmup0.01_no_extra_residuals	29.6	8.5	22.9	19.3	9.8	9.8	21.1	26.5	dinov2siglip	siglip
hardcode <sub>n</sub> um <sub>s</sub> teps <sub>1</sub> 0	29.9	8.1	17.8	18.8	9.5	9.7	23.2	19.8	dinov2siglip	siglip
final_lr0.001	29.3	8.5	22.8	19.1	10.3	9.9	23.1	26.9	dinov2siglip	siglip
noqf	32.8	8.5	23.8	19.7	11.5	10.3	25.6	25.4	dinov2siglip	siglip
batch64	26.1	8.2	21.4	18.8	10.1	10.8	22.3	26	dinov2siglip	siglip
reprsize256	25.3	8	21.5	18.5	10.3	10.6	23.8	26.3	dinov2siglip	siglip
hidddense128	28.4	8.4	22.4	18.8	10.6	10.2	25.9	23.3	dinov2siglip	siglip
lneps1e-5	30	8.3	22.3	19.6	9.9	9.8	22.8	26.1	dinov2siglip	siglip
pdrop0.1	29.7	8.2	20.9	19.8	10	9.6	23.1	26.2	dinov2siglip	siglip
adamweps_beta2_defaults	29.5	8	21.1	19.1	10.7	9.7	23.2	26.8	dinov2siglip	siglip
final_lr0.002	23.1	7.8	15.8	18.8	10.2	9.7	20.7	21.3	dinov2siglip	siglip
l_mha_head_qf	29.7	8.2	23.1	19.4	10.5	10.8	23.2	22.7	dinov2siglip	siglip
final_lr0.0005_seed0	32.8	8.4	23.7	20.1	10.4	10.8	25.7	26.7	dinov2siglip	siglip
final_lr0.0001	31.3	8.3	25.1	19.4	10.4	10.6	26.1	28	dinov2siglip	siglip
final_lr0.0003	33.8	8.5	26.2	20.1	11.2	10.4	26.8	27	dinov2siglip	siglip

Table 5. Validation Accuracy per Skill Class for Architectural, Optimization and Hyperparameter Choices. From CometML [multimodalai](#).

Description	counting	math	logic	path	algebra	measure	spatial	pattern	num.qf.heads	pdrop	wd	word.embed	model.name
run21_lr0.005	13.5	8.9	5.6	16.7	8.3	3.1	27.8	30	2	0.2	0.2	siglip	fused_dinov2_siglip
run20_lr0.0001	18.3	10.7	5.6	14.6	8.3	15.6	27.8	10	2	0.2	0.2	siglip	fused_dinov2_siglip
run19_pdrop0.1	13.5	10.7	2.8	18.8	15	3.1	30.6	30	2	0.1	0.2	siglip	fused_dinov2_siglip
extra_resid_run18	14.4	7.1	5.6	16.7	8.3	9.4	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
siglip_vision_run17	12.5	7.1	5.6	16.7	10	15.6	33.3	15	2	0.2	0.2	siglip	siglip
run16_feat64	13.5	7.1	5.6	16.7	11.7	6.3	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
repr_256_run15	18.3	8.9	5.6	16.7	10	9.4	30.6	20	2	0.2	0.2	siglip	fused_dinov2_siglip
run14_noqf	12.5	5.4	5.6	18.8	6.7	12.5	27.8	30	2	0.2	0.2	siglip	fused_dinov2_siglip
composite_back_run13	15.4	10.7	5.6	18.8	11.7	3.1	30.6	30	2	0.2	0.2	siglip	fused_dinov2_siglip
run12_rm_text_incomposite	16.3	7.1	5.6	14.6	6.7	12.5	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
run11_noim_repr_in_composite	10.6	5.4	5.6	16.7	3.3	9.4	30.6	20	2	0.2	0.2	siglip	fused_dinov2_siglip
run_full_single_image_w_qf and extra_resid	17.3	3.6	5.6	14.6	6.7	9.4	30.6	20	2	0.2	0.2	siglip	fused_dinov2_siglip
rm_a_gelu_in_mlp_decoder	13.5	10.7	5.6	16.7	6.7	3.1	30.6	30	2	0.2	0.2	siglip	fused_dinov2_siglip
residual_back_in	16.3	8.9	11.1	14.6	10	12.5	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
no_residual_in_qf	12.5	7.1	5.6	18.8	11.7	12.5	30.6	25	2	0.2	0.2	siglip	fused_dinov2_siglip
ivory_cliff_394									2	0.2	0.2	siglip	fused_dinov2_siglip
qf_128	17.3	5.4	5.6	16.7	6.7	12.5	25	25	2	0.2	0.2	siglip	fused_dinov2_siglip
768_dim_in_qf	15.4	5.4	8.3	16.7	6.7	9.4	30.6	20	2	0.2	0.2	siglip	fused_dinov2_siglip
scheduler_back_in	16.3	8.9	11.1	14.6	10	12.5	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
no_scheduler	8.7	3.6	8.3	6.3	1.7	3.1	16.7	15	2	0.2	0.2	siglip	fused_dinov2_siglip
relu_not_getu	14.4	8.9	11.1	14.6	8.3	12.5	30.6	15	2	0.2	0.2	siglip	fused_dinov2_siglip
qf3heads	15.4	5.4	5.6	16.7	6.7	9.4	27.8	20	3	0.2	0.2	siglip	fused_dinov2_siglip
lqf_head	17.3	5.4	8.3	16.7	6.7	12.5	30.6	25	1	0.2	0.2	siglip	fused_dinov2_siglip
lstm_decoder	14.4	8.9	5.6	16.7	6.7	12.5	27.8	25	2	0.2	0.2	siglip	fused_dinov2_siglip
wd0	14.4	7.1	11.1	14.6	8.3	9.4	27.8	20	2	0.2	0	siglip	fused_dinov2_siglip
wd0.05	14.4	7.1	11.1	14.6	8.3	9.4	27.8	20	2	0.2	0.05	siglip	fused_dinov2_siglip
wd0.1	15.4	7.1	11.1	14.6	8.3	9.4	27.8	20	2	0.2	0.1	siglip	fused_dinov2_siglip
wd0.2	15.4	7.1	11.1	14.6	8.3	9.4	25	25	2	0.2	0.2	siglip	fused_dinov2_siglip

Table 6. Small Experimental Runs: Architecture and Hyperparameter Choices Impact on Skill Class Accuracy. From [vlm-reasoners](#).

## B. Appendix 2: Project Proposal From Graded Submission for Reference

During the literature review, brainstorming and project timelines/planning meetings during the months of February 2024 and early March 2024, we came up with a longer pool of potential ideas related to vlms, from which we se-

lected based on personal preferences. This section of the appendix includes the initial list included in the Project Proposal. Based on feedback from the professor, the final implementations on each path are a further smaller subset of each path to keep it manageable within time and space toward submission deadline of April 29, 2024.

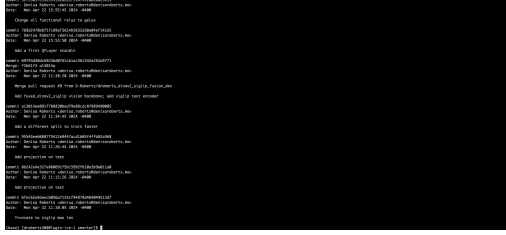


Figure 7. Dev on PACE

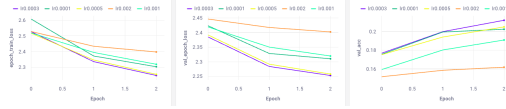


Figure 8. Epoch Train Loss, Validation Loss, and Validation Accuracy for five different learning rates. From CometML [multimodalai](#).

## B.1. Denisa: On the Algorithmic Reasoning Abilities of Vision-Language Multimodal Transformers

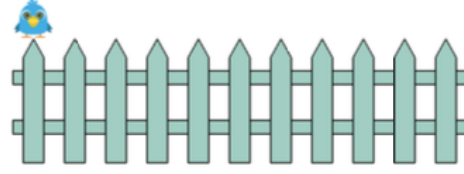
### B.1.1 Problem

How we define intelligence (artificial or not) is still an open question. In “On the Measure of Intelligence” [10] the author conducts an in depth discussion on this open question. They formulate a new formal definition of intelligence (and dataset) based on algorithmic information theory and introduce the concept of algorithmic reasoning, a topic of current interest with a dedicated workshop at CVPR 2024. Specifically, scope, generalization difficulty, priors and experience are listed as desiderata for intelligent systems. In a related work in the multimodal domain, the article “Are Deep Neural Networks SMARTer than Second Graders?” [9] another task, a Simple Multimodal Algorithmic Reasoning Task (SMART), is introduced with visuo-linguistic puzzles designed for children in the 6-8 age group (the US Kangaroo Olympiad style), which comes close to testing for of the listed intelligence desiderata. The starting challenge consists of 101 unique puzzles with a picture and a question, as seen in Figure ??

To solve such a puzzle one needs a mix of several skills including arithmetic, algebra and spatial reasoning among others.

### B.1.2 Benchmarks and Challenges

A set of vision-language models are trained as benchmarks and a dataset created pragmatically is released (SMART-101 with 200K puzzles for train and test). All the trained VLMs struggle on the SMART task, with transformers underperforming ResNet50-based models. In Figure ?? we can see how the VLM does as compared to a second grade



**Question:** Bird Bobbie jumps on a fence from the post on the left end to the other end. Each jump takes him 4 seconds. He makes 4 jumps ahead and then 1 jump back. Then he again makes 4 jumps ahead and 1 jump back, and so on. In how many seconds can Bobbie get from one end to the other end?

**Answer Options:** A: 64 B: 48 C: 56 D: 68 E: 72

human kangaroo olympic (not well):

Puzzle Category →	Count	Arithmetic	Logic	Path Trace	Algebra	Measure	Spatial	Pattern Finding	Average
Puzzle Split (PS) – Extreme Generalization Experiments									
Avg. 2 <sup>nd</sup> Grader Performance	72.8	81.3	82.2	81.1	64.5	90.4	74.8	88.6	77.1
Greedy (baseline)	19.1/21.4	14.0/21.4	18.5/21.1	21.8/21.1	13.5/21.5	23.1/20.9	18.2/21.2	21.4/21.4	17.7/21.3
Uniform (baseline)	7.9/20.0	8.0/20.0	7.6/20.0	18.9/20.0	6.9/20.0	5.6/20.0	14.2/20.0	20.0/20.0	11.2/20.0
MAE + BERT	7.2/12.0	3.3/23.1	10.4/34.1	9.6/22.0	7.3/14.7	3.7/15.2	8.5/16.5	2.6/16.4	7.2/19.1
SimSiam + BERT	6.4/18.4	4.8/20.9	7.7/41.4	2.5/22.2	4.2/25.3	7.9/20.5	11.8/22.2	0.2/17.2	6.4/23.9
Swin.T + BERT	810.5/17.3	4.7/24.7	5.6/29.3	11.4/21.5	6.5/16.8	10.3/23.3	11.9/16.3	17.3/19.1	9.25/20.1
VIT-16 + BERT	9.4/22.7	5.7/26.8	6.95/25.1	4.72/18.7	5.57/15.1	8.68/21.3	11.6/21.5	18.9/19.7	8.51/21.6
CLIP	9.1/15.7	1.4/18.5	7.4/30.6	14.2/21.4	7.5/18.6	8.9/22.2	12.4/18.4	19.0/19.6	11.9/24.1
FLAVA	8.3/20.2	4.0/22.2	8.1/31.3	9.5/20.3	3.1/22.2	19.0/32.0	9.7/18.1	20.9/21.2	7.21/19.0

Interestingly in Figure ?? is an ablation of a ResNet50, which points to the fact that the vision modality is quite important in this task (take it out, the drop in performance is larger than when removing text).

Method	$S_{acc} \uparrow$	$O_{acc} \uparrow$
Instance split		
R50 + BERT	<b>42.8</b>	<b>50.2</b>
No meta learning/MTL	29.7	37.3
Image only (no question)	28.3	36.3
Question only (no image)	15.1	23.2
Single image head	25.0	34.3

Table 5. Ablation studies using the R50 + BERT model.

The reasoning VLM architecture proposed in the article is displayed in Figure ??.

The learning tasks depend on the type of puzzle and are in the classification, regression and sequence generation category. Several image and text encoder backbones are considered. A puzzle specific set of image features are learned via an MLP and the text embeddings are aggregated using a GRU layer. The decoder for the sequence generation is another GRU layer. All image encoders are fine-tuned. Based on these characteristics, there are a few research opportunities worth exploring, especially since transformer based VLM reasoners are doing so poorly on the challenging SMART task.

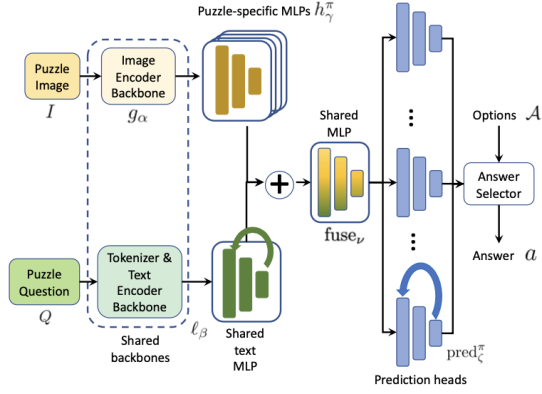


Figure 3. An illustration of our learning and reasoning model.

### B.1.3 Planned Investigations for the VLM reasoner

Specifically, proposed research investigations on the VLM reasoning path are as follows:

- Train at least one of the baseline VLM reasoners in the article and aim to replicate their results (ResNet50+BERT seems to do the best).
- Strengthen vision encoder. In [17] good results are obtained with frozen/non-finetuned vision encoder with two fused vision backbone: SigLip [35] and DinoV2 [28]. Experiment with this technique for the vlm reasoner.
- In recent VLMs a series of alignment modules such as the Q-Former [39] as seen in Figure ?? and the Perceiver Resampler [1] in Figure ?? led to improved results on question answering and other multimodal tasks. Experiment with enhancing/replacing the MLP and the GRU modules in the VLM reasoner.
- Consider a flamingo like decoder for the sequence generation learning task (certain puzzles require a sequence answer) [1].
- Train and evaluate on SMART101.

Other stretch goals that I may consider in next steps:

- Consider strengthening the vision encoder with a Llama2 [31] and instruction tuned VLM text encoder.
- Reformulate problem in Chollet’s article on intelligence [10] to develop, train and evaluate a multi-modal model on the Abstraction and Reasoning Corpus (ARC) task.

A number of other ideas already listed in the general idea section are also to be considered in future steps toward improving algorithmic reasoning of vlm/multimodal

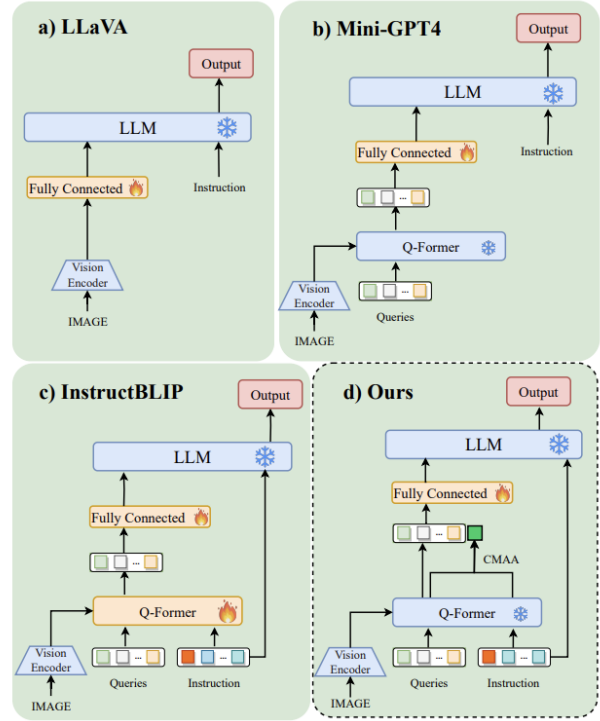


Figure 1: The structural comparison among the alignment modules of different MMLMs. The orange modules in the figure represent open weights, while the blue modules indicate frozen weights.

Figure 9. Example Q-former usage from VisLingInstruct article.

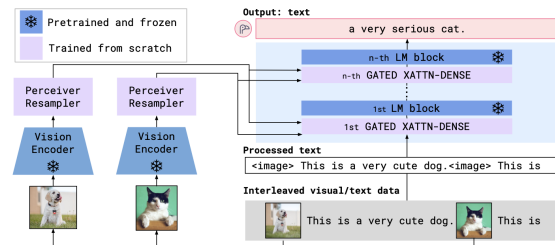


Figure 3: **Flamingo architecture overview.** Flamingo is a family of visual language models (VLMs) that take as input visual data interleaved with text and produce free-form text as output.

Figure 10. The Perceiver Resample based VLM architecture.

models. Other limitations beyond timeboxing are compute resources, which the new VLM in the Llava1.5 [20] and Prismatic [17] style and new architectures such as including FlashAttention2 [12] require (Ampere family NVIDIA GPUs with large memories). I intend to use Colab and school resources (PACE) and limit to what is possible in



terms of architectures.

### B.1.4 Motivations - Why VLM reasoners?

In my motivation for pursuing algorithmic reasoning line of multimodal deep learning architectures research I rely on a few conjectures:

- Intelligence is related to multimodal reasoning. If a person is deaf and cannot hear more than 50% of what is being said the speech modality input is supplemented with reading faces and other visual aids (vision modalities), captions(text) as well as other modalities (all the other senses as well as enhanced reasoning and computation abilities). So it is worth striving to improve multimodal deep learning architectures and their reasoning abilities. As a reviewer for MathAI Workshop at NeurIPS'23, I noticed that the work was almost exclusively with language models, with other modalities being almost nonexistent. I consider mathematical reasoning a subset of algorithmic reasoning.
- Training leads to learning and enhanced reasoning. As a former math and physics olympic I know that math and physics olympiad expert competitors practice more than non-experts in environments that value the pursuit. Polgar sisters chess players grandmasters were brought up to perform at chess. Mozart and Beethoven were brought up to perform at music. More generally, a partially deaf person learns to make sense of the world especially if deafness occurred at the pre-verbal stage, through years of world training. In fact evolution is training and learning; we learned to grow better brains (because we needed to). So training transformers to enhance reasoning makes evolutionary sense.
- Intelligence is related to better abstractions and those are related to better representations. Expert chess players, thespians, martial artists, mathematicians, coders have fine grained relevant representations they can reason with to create/imagine new plays rapidly. Improving the representations derived with deep learning architectures is worth pursuing (better image, text etc. representations as well as their cross-play).
- If we make neural networks better at algorithmic reasoning (I include here a few types of reasoning such as creative problem solving in math, physics, logic and coding algorithms, puzzles and IQ tests, learning, planning and decision making) they will be better at science QA, medical and law QA and some other types of reasoning such as commonsense reasoning.

### B.2. [Ahmad's Path] : Don't take vision features for granted : An Efficient Text Aware Image Encoding

Recent VLM Research can be divided into two different but yet very similar axes. Vision language alignment and Instruction following capabilities.

Alignment Approaches can be ordered as follows in terms of their complexity:

1. Simple linear projection or MLP projection such as Llava series which project the vision encoder features into the same space of language model embedding, so that the image features can be passed as a soft prompt input for the language model.
2. Extra complex modules such as Q-Former in BLIP series.
3. Integration of vision features through cross-attention with language model such as Flamingo and Otter Series.
4. A complete unified approach such as Fuyu-8B which a transformer decoder which accepts both text and images as inputs.

After alignment, the instruction tuning process doesn't differ among most of the previous works. The only difference might be in the dataset collection procedure, the prompting strategy and the sampling process.

All of the following approaches use a frozen vision encoder except for Fuyu which relies on a vision-encoder free pipeline. Some of the approaches fine-tune full parameters of the language model. While others use some parameter efficient methods such as LoRa and complicated variant of prefix tuning such as Llama Adapter v2.

After surveying the literature, it became obvious that relying on a frozen vision encoder is one of the weaknesses of current VLM design aspects. On the other hand, fine-tuning the visual encoder while training the whole system might not be the best case as shown in Prismatic. This can be attributed to the fact that the vision encoder doesn't interact directly with the textual input. Only two approaches got close to that conclusion, Fuyu8B which removed the whole visual encoder. And BLIP2 which condition the visual encoder output on the instruction text but inside the Q-former. I argue that the textual context should be fused in the visual encoder from the start, not after the feature extraction process. Because the feature that LLM might be looking for, might not be present in the visual encoder features itself.

#### B.2.1 Planned Contributions

My proposed architecture is shown in Figure 11.

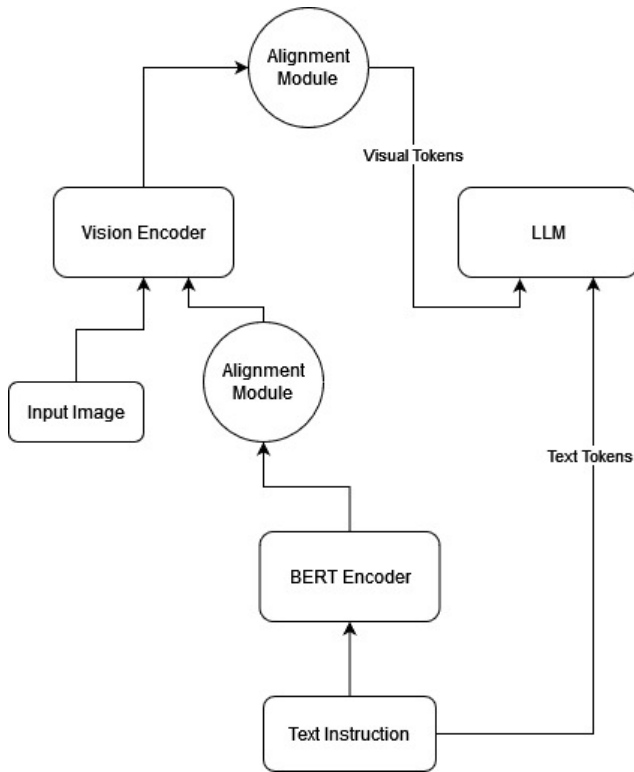


Figure 11. Proposed Architecture

I plan to follow the dataset recipe from LLaVa 1.5 combined with LLaVaR for the tuning and alignment part. And transform the dataset from LLaVaRLHF to DPO format and do DPO alignment after training. I don't plan to follow the two stage pretraining like it has been done in all previous work, instead, as the authors of Prismatic showed that combining the two stages might be more beneficial. For the alignment components in the figures i plan to start from the simple possible and increase complexity as needed :

1. MLP Projection
2. Zero-Gated Prefix Tuning (LLama Adapter V2)
3. DoRa or LoRa variants.

BERT and LLM can be replaced with Flan T5 encoder and decoder respectively to ensure that the text representation passed to both the vision encoder and language decoder come from the same distribution. I plan if i had time to try both approaches, using bert and off the shelf decoder based LLM and use T5 or any encoder decoder based LLM.

For the Visual Encoder part, adapting it effeciently to a task won't be that complex because I'm planning to use ViT based visual encoders such as CLIP or DINOv2 or an ensemble of both.

In additions to the benchmarks in LLaVa Series, and

Prismatic Models. I plan to benchmark my results also on :

1. MMVP Benchmark "Eyes Wide Shut" which address multiple visual preception tasks
2. MagnifierBench From OtterHD which address smaller tress on minute details and spatial relationships of small objects.

### B.3. Rough Initial Pool of Considered Ideas on Improving Multimodal Models

We can start from Prism codebase [17] (and Llava 1.5 codebase [20]) or another codebase and baseline model, each of the two contributions can use something different. A list of research questions/hypotheses to possibly pick and choose from:

- Maybe adapt Dora for efficient finetuning
- Maybe improve the connnecting architecture in Prism and Llava1.5 (MLP) (consider a Q-former adaptation from Blip-2 or Perceiver variation).
- Maybe improve the vision feature module. Consider technique in Eyes Wide Shut. Consider encoder from SigLip and a vision model like DINOv2 for vision feature combination as in Prism (possibly other vision encoders). Possibly consider finetuning some of the vision encoder too or just some of its layers (Fuyu inspiration).
- Consider the bias tuning mechanism from Llama-Adapter v2.
- Consider continuing pretraining of one of the base models on Pile2dataset from Llama for improved mathematical reasoning ability which can possibly improve the overall reasoning ability.
- Can we use two images for input? I am not sure of a dataset. The issue would also be the context. We could use the patch mix technique from the World Model LMM paper (for videos and long context). The two images can be two-shot from the video.
- consider the technique in MM-CoT to reduce hallucinations.
- If necessary, we can augment at inference time with another module from a pretrained open source off the shelf model for the input augmentation, the way Llama-adapter V2 does. They call them "experts" to overcome the shortcoming of the visual abilities of their models.

- Mix the image and text patches - adapt early instead of late (to include the textual prompt early). Look at the big world model how they do with the video and at Fuyu. (dataset to train?)
- Mix in multilingual for improved ability in multilingual reasoning? Dataset to train on? TO mix with the image-caption pairs and visual instruction datasets from Llava1.5 and blip2?
- What does the Perceiver do that we could improve the architecture of token mixing with?
- Can evaluate on ARB dataset with images that were not used for problem solving, ScienceQA and the new MMMU dataset with diverse images and hard problems.
- Can evaluate the COCOt style with contrastive chain of thought with multiple images as in a visual story.

A few candidate datasets for training (pretraining and/or finetuning) are made available in Llava, Llama for math, world model (LWM), Blip, Aya from Cohere for multilingual.

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