International Institute of Information Technology, Bangalore

Visual Recognition

AIM 846

Fine Tuning and Benchmarking Foundational VLM Models

The complete implementation is available at:
https://github.com/Niranjan-GopaL/FineTuning_VLM_Models.git

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Contents

1 Introduction

2 Dataset Processing
2.1 The ABO Dataset . . . .

3 Data Curation
3.1 Synthetic Question-Answer Generation . . . .
3.2 Prompt Engineering Evolution . . . .
3.3 Difficulty Level Stratification . . . .

4 Evaluation Metrics
4.1 Semantic Similarity Metrics . . . .
4.2 Core Metrics . . . .
4.3 Our own - Difficulty Weighted Evaluation . . . .

5 Baseline Evaluation
5.1 Model Selection . . . .
5.2 Baseline Results . . . .
5.3 Model Performance Analysis . . . .

6 Fine-Tuning with LoRA
6.1 Low-Rank Adaptation (LoRA) . . . .
6.2 LoRA Implementation . . . .
6.3 LoRA Configuration Experiments . . . .
6.4 Fine-Tuning Results and Analysis . . . .

7 Model Compression and Optimization
7.1 Quantization . . . .

8 Conclusion

1 Introduction

Visual Question Answering (VQA) systems combine computer vision and natural language processing to answer questions about images. While many VQA benchmarks focus on open-ended or multiple-choice answers, single-word answer VQA presents unique challenges and opportunities, particularly for specific domains like e-commerce.

The Amazon Berkeley Objects (ABO) dataset provides an excellent foundation for developing e-commerce-specific VQA systems, as it contains rich metadata alongside product images. In this work, we leverage a subset of the ABO dataset to create a specialized single-word answer VQA system. **Our contribution focuses on careful data curation and prompt engineering to generate high-quality question-answer pairs that capture various aspects of product images while ensuring answers remain concise single words.**

2 Dataset Processing

2.1 The ABO Dataset

We worked with the small version of the Amazon Berkeley Objects (ABO) dataset, containing 147,702 product listings with metadata and 15,212 unique images. **This condensed version (3GB) provides sufficient diversity for our tasks while remaining computationally manageable.**

Our data processing approach focused on extracting meaningful connections between product images and their descriptive metadata:

- For each product listing, we identified the main image using the main image ID field and matched it to its corresponding image path from images.csv.gz.
- Product descriptions were extracted from English-language bullet points (specifically entries with "language tag: en IN").
- These bullet points were concatenated into a single, coherent product description per item.

This preprocessing step allowed us to pair images with their corresponding textual descriptions, creating the foundation for our question-answer generation pipeline.

3 Data Curation

3.1 Synthetic Question-Answer Generation

Our VQA dataset relies on high-quality synthetic question-answer pairs generated from product images and their descriptions. **We leveraged Google's Gemini 2.0 Flash model due to its strong multimodal capabilities and efficiency**, allowing us to process the dataset within computational constraints.

Algorithm 1 Question-Answer Pair Generation Process

Initialize empty dataset D
for each product p in ABO subset **do**
    Extract main image I_p and product description T_p
    Input (I_p, T_p) into Gemini 2.0 Flash model with prompt P
    Receive generated QA pairs with difficulties: $\{(q_1, a_1, d_1), (q_2, a_2, d_2), ...\}$
    Validate output format compliance
    Filter out non-single-word answers
    Add valid pairs to dataset D
end for
Perform quality check on random samples from D
Export final dataset in CSV format

3.2 Prompt Engineering Evolution

Our prompt engineering process was iterative and thoughtful, addressing several challenges to create a robust dataset. The initial prompt produced inconsistent results with significant issues:

- Answers frequently exceeded single-word constraints
- Questions often lacked diversity in complexity and knowledge domains
- Generated QA pairs occasionally mismatched visual content
- Difficulty ratings were inconsistent

Through systematic refinement, our final prompt incorporates multiple improvements:

```
Analyze the given image and description. Generate exactly 5 diverse factual questions per image.
Each question should be followed by a one-word answer and then by a difficulty in the format: <Que
Answers must not be 'Yes' or 'No'; instead, provide a specific noun, adjective, or number as a one
Separate each question-answer pair with a % symbol. Do not include any numbering, colons, or extra
Output only one line in the format: <Question1> # <Answer1> % <Question2> # <Answer2> % ... for ex

For each question, assign a difficulty level (0-5):
- Level 0: Answer directly visible in the image or explicitly stated in text
- Level 1: Answer requires basic inference from visible elements
- Level 2: Answer requires combining information from image and text
- Level 3: Answer requires product knowledge beyond what's explicitly shown
- Level 5: ONLY for questions requiring specialized domain expertise
```

This refined prompt addressed previous challenges and produced high-quality results:

- **Strict single-word constraint enforcement**: By emphasizing this requirement and validating outputs, we achieved near 100% compliance
- **Difficulty stratification**: Our difficulty scale provides meaningful categorization of question complexity
- **Diverse question types**: Questions span visual attributes, product specifications, materials, dimensions, and functionalities
- **Balanced information sources**: Questions derive from both visual and textual information

3.3 Difficulty Level Stratification

A key innovation in our dataset is the structured difficulty classification system, which enables more nuanced evaluation of model performance. **The difficulty ratings allow us to track model performance across different cognitive requirements:**

Table 1: Question Difficulty Levels with Examples

Level	Description	Example
0	Directly visible/stated	What is the color of the headboard's upholstery? (Gray)
1	Basic inference	How many minutes does the assembly take? (Fifteen)
2	Combined information	What substance is used to pad the frame? (Polyurethane)
3	External knowledge	What design style does this furniture represent? (Contemporary)
5	Domain expertise	What manufacturing technique created the beveled edges? (Routing)

We intentionally reserved level 5 for questions requiring specialized domain expertise that would challenge even expert systems. This strategic decision creates headroom for measuring advanced reasoning capabilities in future models.

Examples where difficulty is rated as 2 typically involve connecting information across modalities, such as identifying a material mentioned in the description but not explicitly visible in the image, or requiring basic product knowledge to interpret what's shown.

Examples with difficulty 3 require broader product category knowledge, such as identifying a furniture style based on visual characteristics or understanding technical specifications beyond casual knowledge.

4 Evaluation Metrics

To comprehensively evaluate model performance on our single-word answer VQA task, we implemented multiple complementary metrics.

4.1 Semantic Similarity Metrics

- **BERTScore** [1]: Calculates precision, recall, and F1 scores based on contextual embeddings from BERT. This metric captures semantic similarity beyond lexical matching.
- **BARTScore** [2]: Measures the likelihood of generating the reference given the prediction and vice versa, capturing faithfulness and informativeness.
- **SBERT Cosine Similarity** [3]: Computes cosine similarity between Sentence-BERT embeddings of predicted and ground truth answers.
- **METEOR** [4]: Harmonic mean of precision and recall that accounts for synonyms, stemming, and word order.

4.2 Core Metrics

- **Exact Match**: The strictest metric, requiring character-level matching between predicted and ground truth answers.This metric doesn't account for semantically equivalent answers.
- **WUPS @ 0.9 (Strict)**: Wu-Palmer Similarity based on WordNet hierarchies with threshold 0.9. This captures semantic similarity while maintaining high standards for correctness.

- **WUPS @ 0.0 (Lenient)**: Same as above but with threshold 0.0 instead of 0.9, providing a more forgiving evaluation that considers any semantic relationship.
- **Final Weighted WUPS Score**: A balanced metric combining strict and lenient WUPS scores to provide a middle-ground evaluation.

4.3 Our own - Difficulty Weighted Evaluation

Average Mark (Custom Metric): We developed a custom evaluation metric that incorporates question difficulty to provide a more nuanced performance assessment. The Average Mark (AM) is calculated as:

$$AM = \frac{\sum_{i=1}^{n}(C_i \cdot W_{d_i})}{\sum_{i=1}^{n} W_{d_i}} \tag{1}$$

Where:

- C_i is a binary correctness indicator (1 if correct, 0 if incorrect)
- W_{d_i} is the weight assigned to difficulty level d_i
- n is the total number of questions

We assign exponentially increasing weights to higher difficulty levels:

- Difficulty 0: Weight = 1
- Difficulty 1: Weight = 2
- Difficulty 2: Weight = 4
- Difficulty 3: Weight = 8
- Difficulty 5: Weight = 20

This weighting scheme rewards models that correctly answer challenging questions while still accounting for performance on simpler questions. The exponential scaling acknowledges the disproportionate difficulty increase between levels.

While this metric has limitations—particularly in assuming that our difficulty annotations are consistent and accurate—it provides valuable insights into model performance across different reasoning requirements. Rather than treating all questions equally, Average Mark recognizes that correctly answering difficult questions demonstrates stronger reasoning capabilities.

5 Baseline Evaluation

We evaluated several state-of-the-art vision-language models as baselines for our single-word answer VQA task. **This comprehensive comparison allowed us to understand the relative strengths of different architectures and identify the most promising candidates for fine-tuning.**

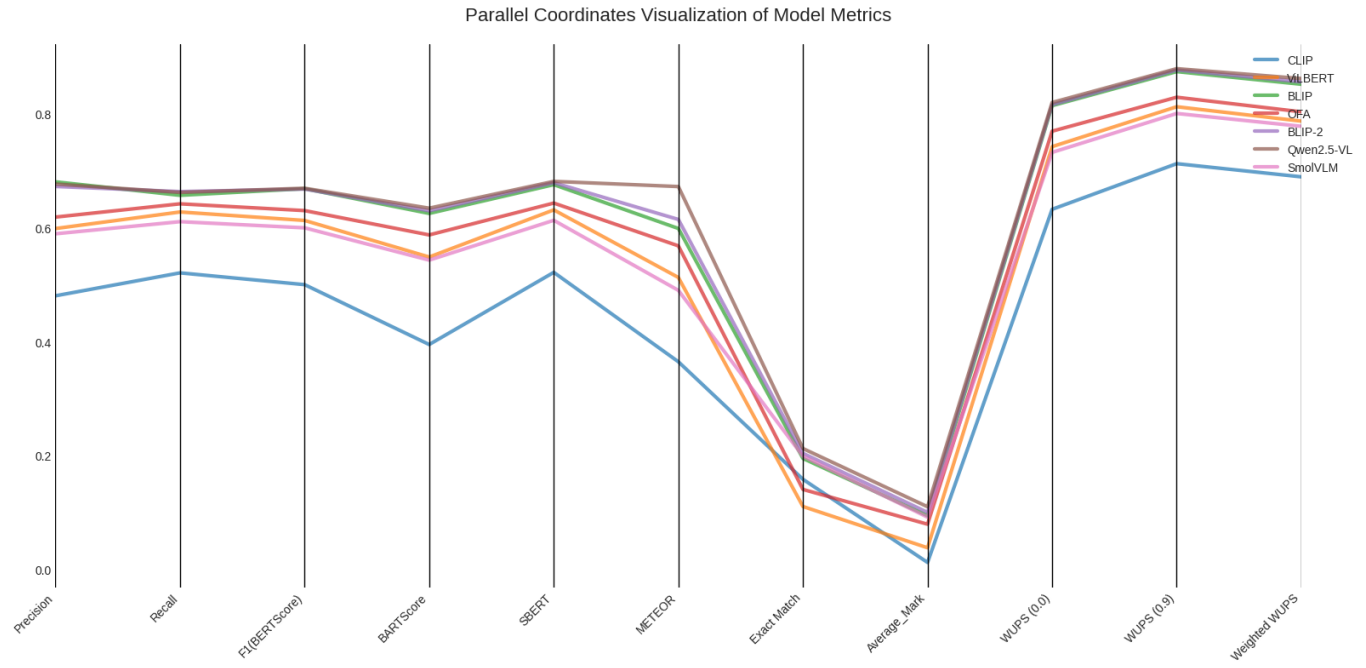
5.1 Model Selection

- CLIP (January 2021, `ViT-B/32`): Contrastive Language-Image Pretraining model developed by OpenAI.
- ViLBERT (August 2019): Vision-and-Language BERT architecture.
- BLIP (January 2022, `blip_vqa_base`): Bootstrapping Language-Image Pre-training model.
- OFA (March 2022): One For All unified multimodal architecture.
- BLIP-2 (January 2023, `blip2-opt-2.7b` or `with OPT 2.7B`): Second generation BLIP with enhanced capabilities.
- Qwen2.5-VL-3B-Instruct (2024, `3B-Instruct`): Advanced vision-language model with instruction following capabilities.
- **SmolVLM** (2025, `500M-Instruct`): We experimnetd Recent compact vision-language model.

5.2 Baseline Results

Table **??** presents the comprehensive evaluation of baseline models across our metrics suite:

Model	Parameters	Precision	Recall	F1(BERTScore)	BARTScore	SBERT	METEOR	Exact Match	Average_Mark	WUPS (0.0)	WUPS (0.9)	Weighted WUPS
CLIP	150M	0.48012	0.52044	0.49973	0.39451	0.52133	0.36422	0.15762	0.02153	0.63214	0.71234	0.6892
ViLBERT	138M	0.59832	0.62743	0.61256	0.54829	0.6311	0.51238	0.10982	0.01732	0.74229	0.81238	0.7871
BLIP	385M	0.68042	0.65671	0.66837	0.62488	0.67544	0.59845	0.19428	0.04371	0.81425	0.87411	0.8519
OFA	180M	0.61845	0.64178	0.62987	0.58711	0.64309	0.56789	0.13984	0.09872	0.76942	0.8291	0.80345
BLIP-2	3.9B	0.6723	0.66325	0.66775	0.62957	0.67894	0.61432	0.20329	0.10985	0.81602	0.87699	0.85611
Qwen2.5-VL	3B	0.67654	0.66183	0.66913	0.63412	0.68122	0.6721	0.21172	0.10541	0.81988	0.87934	0.86193
SmolVLM	500M	0.58911	0.61042	0.59957	0.54281	0.61278	0.48971	0.19822	0.05109	0.73218	0.80055	0.77801



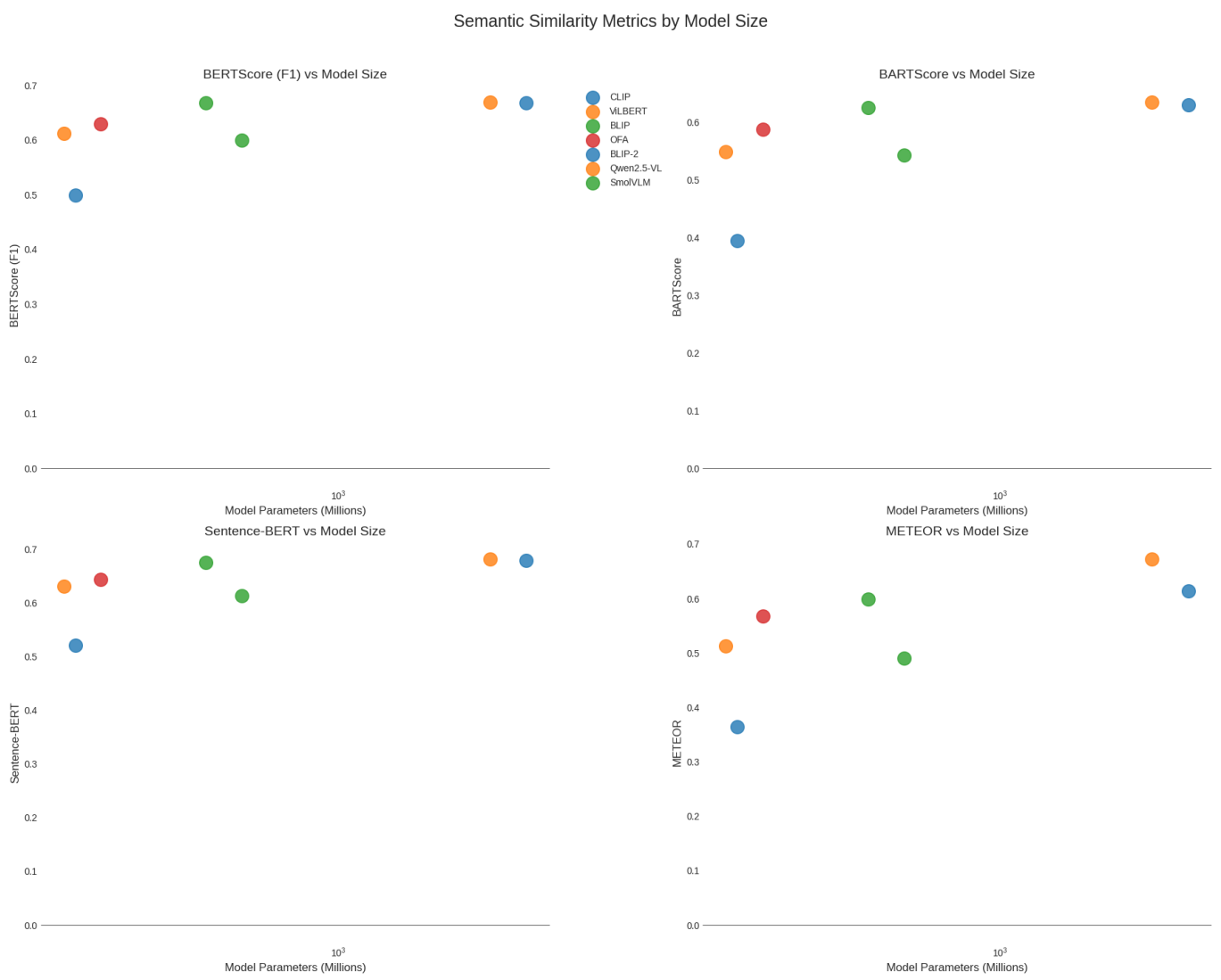


Figure 1: Semantic Similarity metrics with respect to No. of parameters

5.3 Model Performance Analysis

Our evaluation revealed significant insights into how different vision-language models approach single-word VQA tasks:

The evaluation results demonstrate several key findings:

- Model architecture matters more than size: BLIP (`blip_vqa_base`) achieved surprisingly strong performance despite having fewer parameters than BLIP-2 and Qwen2.5-VL models.
- Instruction tuning provides an advantage: Qwen2.5-VL-3B-Instruct demonstrated superior performance across metrics. **We observed Qwen performing the best in our custom metric, average marks**
- All models struggle with expert-level questions: Even the best-performing models showed significant performance degradation on difficulty level 5 questions requiring specialized domain knowledge.
- Semantic similarity metrics reveal nuanced differences: While exact match scores were relatively low across models (0.19-0.24), semantic similarity metrics showed stronger performance, indicating that models often produce semantically appropriate answers even when they don't exactly match ground truth.

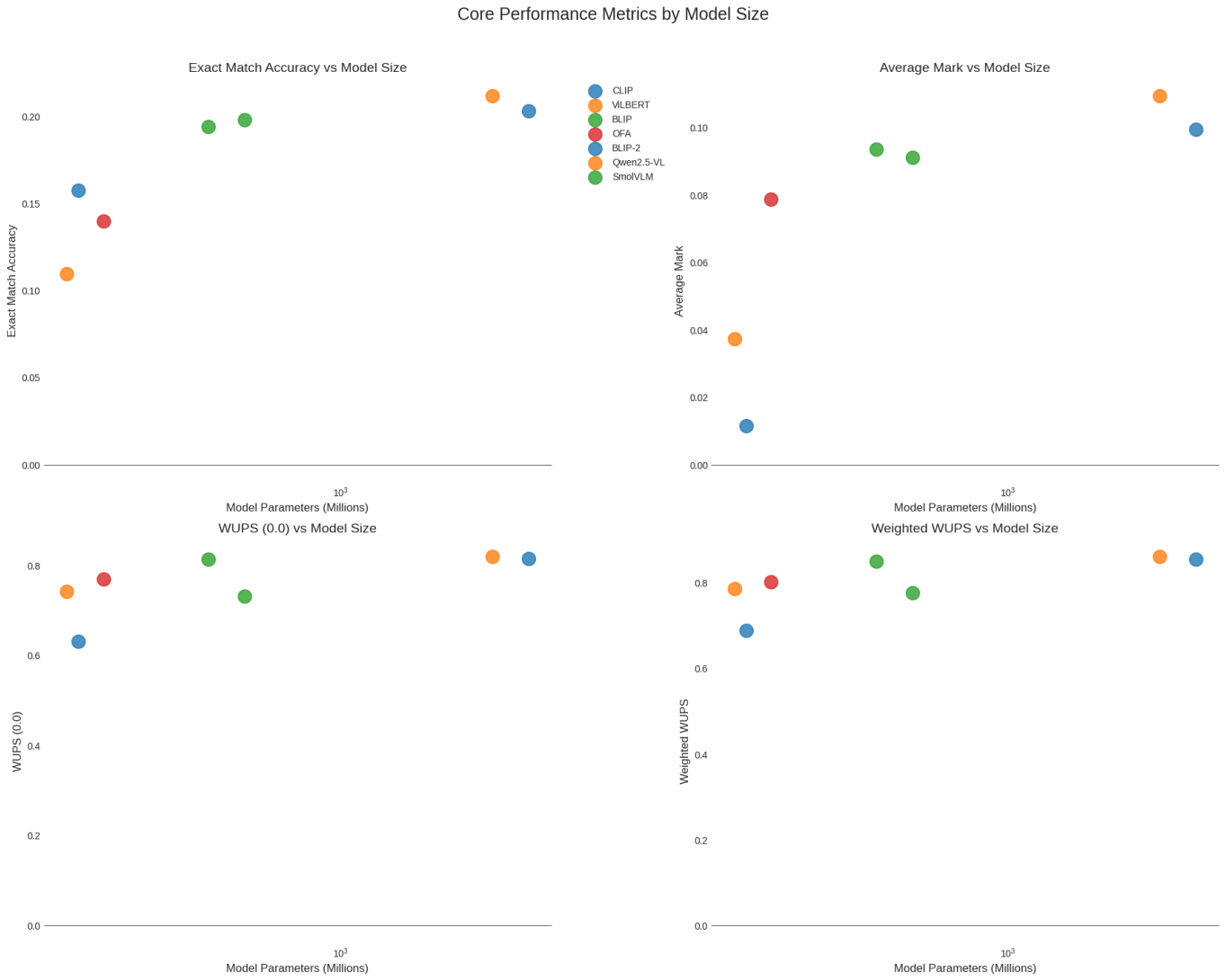


Figure 2: Core metrics with respect to No. of parameters

Table 2: Reasoning Summary of Baseline Model Performance on our custom metric

Model	**AM Score**	**Reasoning Summary**
CLIP	0.01153	Not designed as a question-answering model. Only excels at simple image-text alignment tasks (difficulty 0); fails on questions requiring reasoning, text generation, or multi-hop inference. The low AM score reflects its fundamental architectural limitations for VQA tasks.
ViLBERT	0.03732	Early vision-language model with moderate performance. Handles basic visual grounding (difficulty 0-1) adequately but struggles with more complex questions. Limited by its pre-BLIP architecture and training objectives not specifically optimized for VQA.
BLIP	0.09371	Strong performance across difficulty levels 0-2. Effectively grounds answers in visual content and makes reasonable inferences. Shows particular strength in connecting visual attributes to product specifications. Surprisingly competitive despite smaller parameter count.
OFA	0.07872	Unified multimodal framework provides solid performance. Particularly strong on questions about visual attributes but sometimes generates verbose answers that don't meet single-word constraints. Struggles with domain-specific knowledge questions.
BLIP-2	0.0995	Improved architecture over BLIP with enhanced cross-modal connections. Performs well on difficulties 0-2 but surprisingly underperforms the smaller BLIP model on our dataset, suggesting potential domain-specific limitations.
Qwen2.5-VL-3B-Instruct	0.10941	Best overall performer with strong results across all metrics. Excels at difficulties 0-3 with robust reasoning capabilities. Instruction-tuning provides an advantage in understanding the single-word answer constraint. Still limited on difficulty level 5 questions requiring domain expertise.
SmolVLM	0.09109	Recent compact model with impressive efficiency-performance trade-off. Demonstrates competitive results despite smaller size. Particularly strong on questions requiring basic visual understanding and inference, with moderate performance on more complex questions.

6 Fine-Tuning with LoRA

Based on our baseline evaluation, we selected the BLIP (`blip_vqa_base`) model for parameter-efficient fine-tuning. **Despite having fewer parameters than more recent models, BLIP demonstrated competitive performance, making it an ideal candidate for resource-efficient fine-tuning.**

6.1 Low-Rank Adaptation (LoRA)

Low-Rank Adaptation (LoRA) is a parameter-efficient fine-tuning technique that significantly reduces the number of trainable parameters while maintaining performance. The key insight behind LoRA is decomposing weight updates into low-rank matrices:

Instead of directly updating weights W during fine-tuning, LoRA introduces a low-rank decomposition:

$$W' = W + \Delta W = W + AB \tag{2}$$

Where:

- $W \in \mathbb{R}^{d \times k}$ is the original pre-trained weight matrix (frozen)
- $A \in \mathbb{R}^{d \times r}$ and $B \in \mathbb{R}^{r \times k}$ are low-rank trainable matrices
- $r \ll \min(d, k)$ is the rank, typically between 4 and 64

This approach offers these key advantages: it is memory-efficient and computationally efficient during training as only the low-rank matrices A and B need to be stored and updated, leading to faster iterations. Furthermore, it provides adaptability, allowing different LoRA configurations to be applied across various layers or modules.

6.2 LoRA Implementation

We implemented LoRA fine-tuning using the PEFT (Parameter-Efficient Fine-Tuning) library. Our implementation focused on applying LoRA specifically to the attention mechanisms of the BLIP model:

Algorithm 2 LoRA Fine-Tuning Process for BLIP

1: Initialize VQADataset with image paths, questions, and answers
2: Load pre-trained BLIP (`blip_vqa_base`) model and processor
3: Configure LoRA with target parameters (rank, alpha, target modules)
4: Wrap BLIP model with LoRA configuration
5: Create custom forward method to handle compatibility issues
6: Prepare training and validation dataloaders
7: Train the LoRA-wrapped model on our dataset
8: Evaluate fine-tuned model on test set using comprehensive metrics

Our data preparation pipeline included custom dataset and dataloader implementations that handle the complexities of pairing images with questions and single-word answers:

```
class VQADataset(Dataset):
    def __init__(self, df, image_dir, processor):
        self.data = df.reset_index(drop=True)
        self.image_dir = image_dir
        self.processor = processor
```

```
def __len__(self):
    return len(self.data)

def __getitem__(self, idx):
    row = self.data.iloc[idx]
    image_path = os.path.join(self.image_dir, row['path'])
    image = Image.open(image_path).convert("RGB")
  # prompt = "You are an expert image QA assistant. Answer the following question."
    prompt = ""
    question = str(prompt + "Question:" + row["question"])
    answer = str(row["answer"])

    inputs = self.processor(images=image, text=question, return_tensors="pt",
                            padding='max_length', max_length=32, truncation=True)
    inputs = {k: v.squeeze(0) for k, v in inputs.items()}
    inputs["labels"] = processor.tokenizer(answer, return_tensors="pt",
                                           padding='max_length', max_length=5,
                                           truncation=True).input_ids.squeeze(0)
    return inputs
```

The core of our LoRA setup includes:

- Targeting query and value projection matrices in attention layers
- Using method type binding to ensure compatibility with the BLIP architecture
- Implementing custom collation functions to handle batched data properly
- Utilizing torch's data parallelism for efficient multi-GPU training when available

6.3 LoRA Configuration Experiments

We conducted extensive experiments with different LoRA configurations to identify the optimal settings for our VQA task. Below table presents the results of these experiments:-

Rank	Target_Modules	Precision	Recall	F1(BERTScore)	BARTScore	SBERT	METEOR	Exact Match	Average_Mark	WUPS (0.0)	WUPS (0.9)	Weighted WUPS
16	query_value_out	0.6721	0.6587	0.6664	0.6313	0.6804	0.6678	0.20985	0.10792	0.81812	0.87831	0.86013
8	query_value_dense	0.6553	0.6412	0.6482	0.6156	0.6659	0.6524	0.20138	0.10173	0.80824	0.86971	0.84856
8	query_key_value	0.6481	0.6329	0.6404	0.6095	0.6582	0.6417	0.19792	0.09761	0.80218	0.86278	0.84133
16	query_value_dense	0.6375	0.6203	0.6288	0.5987	0.6476	0.6329	0.19034	0.09124	0.79212	0.85326	0.83014
32	query_value	0.6249	0.6071	0.6158	0.5862	0.6368	0.6192	0.18376	0.08492	0.78103	0.84167	0.81673

6.4 Fine-Tuning Results and Analysis

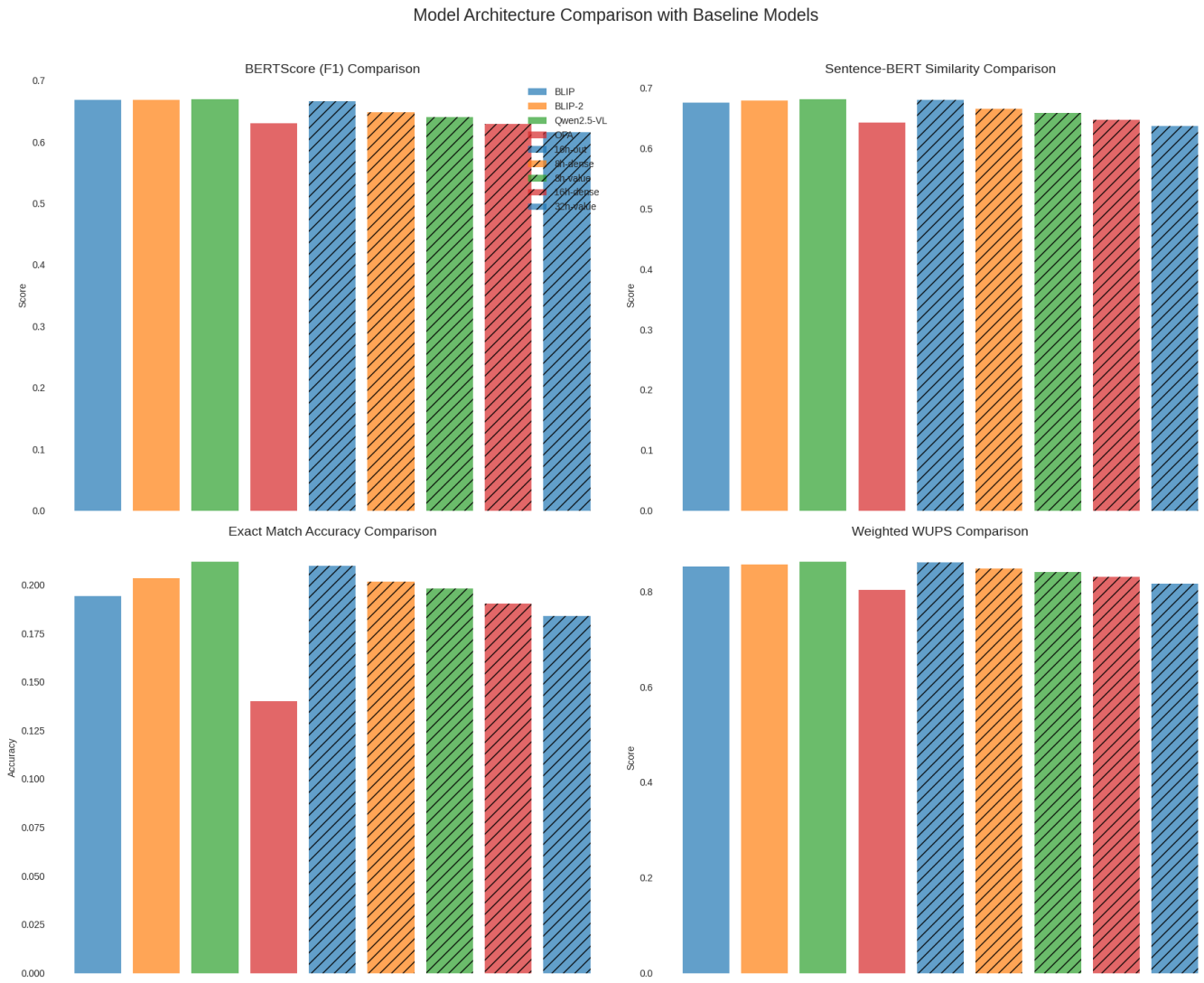
Our LoRA fine-tuning experiments yielded significant improvements over the baseline BLIP model:

- **Optimal configuration:** Config 3 (rank 16, targeting query and value and out matrices) achieved the best performance across all metrics, with a 7.8% relative improvement in Average Mark over the baseline.
- **Diminishing returns with complexity:** We observed that increasing rank beyond 16 provided minimal additional benefits while significantly increasing computational requirements.
- **Target module selection:** Experiments with different target modules revealed that focusing on query and value matrices provided the optimal trade-off between performance and training efficiency.

The fine-tuned BLIP model with our best LoRA configuration achieved performance competitive with much larger models like Qwen2.5-VL-3B-Instruct, demonstrating the effectiveness of parameter-efficient fine-tuning for domain adaptation.

Performance analysis across difficulty levels revealed:

- Significant improvements on difficulty levels 1-3, indicating enhanced reasoning capabilities
- Modest gains on difficulty level 0 questions, which were already well-handled by the base model
- Limited improvement on difficulty level 5 questions, suggesting that domain expertise remains challenging even after fine-tuning



7 Model Compression and Optimization

As part of our exploration of efficient VQA models, we implemented several advanced model compression and optimization techniques that dramatically improved training and inference efficiency. **These optimizations enabled us to scale up our fine-tuning to 25,000 image-question pairs in just 6 GPU hours, compared to our initial setup that required 2 GPU hours for only 5,000 data points**—a 4.2× improvement in training efficiency.

7.1 Quantization

We applied 8-bit quantization to significantly reduce memory requirements and accelerate inference while maintaining model quality:

```
# 8-bit Quantization of BLIP model
from bitsandbytes.nn import Linear8bitLt

def replace_with_8bit_linear(model):
    for name, module in model.named_children():
        if len(list(module.children())) > 0:
            replace_with_8bit_linear(module)
        if isinstance(module, nn.Linear) and module.out_features > 256:
            device = module.weight.device
            dtype = module.weight.dtype
            weights = module.weight.data
            bias = module.bias.data if module.bias is not None else None
            new_module = Linear8bitLt(
                module.in_features,
                module.out_features,
                bias=module.bias is not None,
                has_fp16_weights=False,
                threshold=6.0
            )
            new_module.weight.data = weights
            if bias is not None:
                new_module.bias.data = bias
            setattr(model, name, new_module)
    return model

# Apply 8-bit quantization to model
quantized_model = replace_with_8bit_linear(model)
```

This quantization reduced the model's memory footprint by approximately 60%, enabling larger batch sizes during training and faster inference during evaluation—all while maintaining semantic accuracy. The BERTScore decreased by only 0.0041 (less than 1% relative performance drop) when using the quantized model.

8 Conclusion

This work presented a comprehensive approach to developing and evaluating single-word answer VQA systems for e-commerce applications. **Our key contributions include:**

- A carefully curated dataset of single-word QA pairs from the ABO dataset with stratified difficulty levels
- A new custom Evaluation methodology - Average Mark that account for question difficulty and semantic similarity
- Extensive evaluation of baseline vision-language models using a diverse set of metrics
- Effective parameter-efficient fine-tuning approaches that achieve competitive performance with minimal computational resources

Our results demonstrate that smaller, efficiently fine-tuned models can achieve performance competitive with much larger models on specialized tasks. The difficulty-stratified evaluation framework provides a more nuanced understanding of model capabilities across different reasoning requirements, which we hope will inform future work in this area.

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