Multimodal Recognition Project

Final Session: Project Presentation

Group 6

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***Module**: C5 - Visual Recognition*
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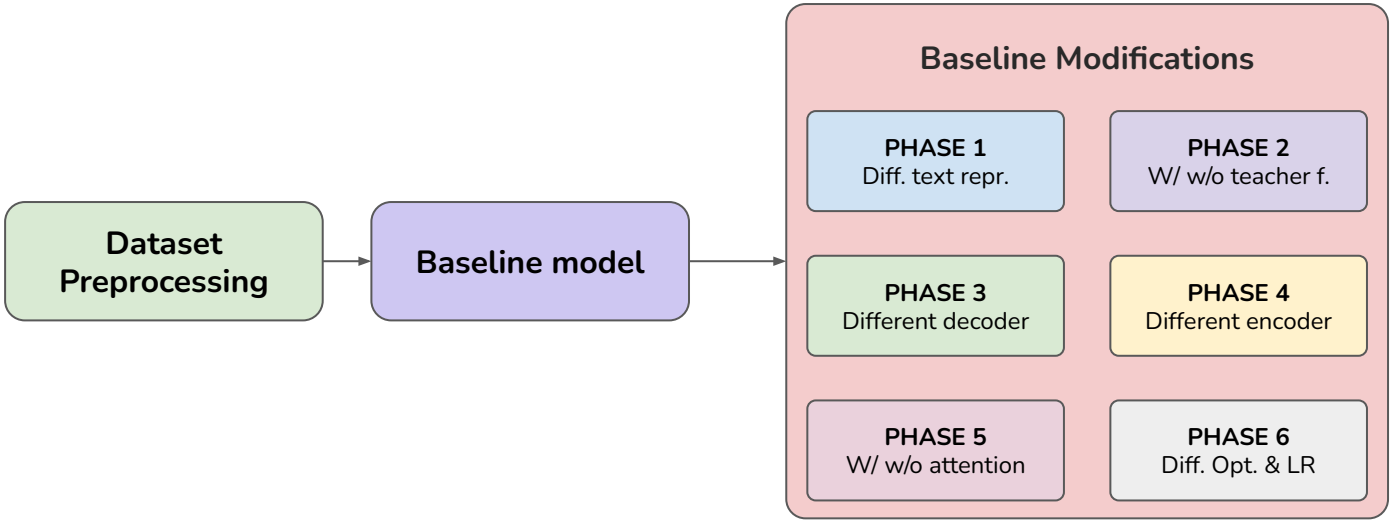
Contents

1 **Session 3**: Image Captioning (1)

Workflow overview for this session:



Data analysis

NaNs

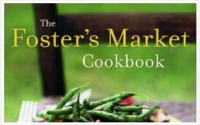
Duplicates

Non-overlap

Rare char.

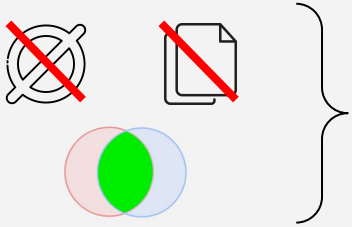
Min: 3
Max: 112

Different lengths



Strange images

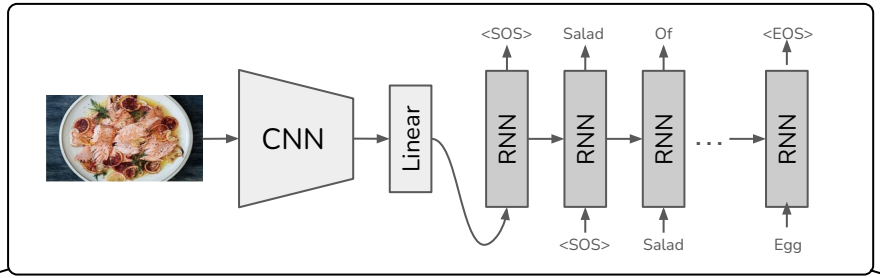
Preprocessing



13,466
Valid
(img, cap.)

Data split

Baseline model modifications



CNN-RNN architecture

Generalization of the architecture

ENCODER	DECODER	TEXT REPR.	TEACHER F.	ATTENTION
ResNet-18	GRU	Character-level	Without teacher forcing	Without attention
ResNet-34	LSTM	Wordpiece-level	With teacher forcing	With attention
ResNet-50	xLSTM	Word-level		
VGG-16				
VGG-19				

Baseline

Baseline model modifications (details)

ENCODER

- **Projection** before passing features to decoder (always 512 dim.).
- **Pooling** before extracting final VGG features to reduce dim.

DECODER

- **In xLSTM:** introduction of third state, extended memory gate, and layer normalization to the hidden, cell, and memory states.

TEXT REPRESENTATION

- **Characters:** list of common characters.
- **Words**: top N most common words.
- **Wordpiece**: autotokenizer.

TEACHER FORCING

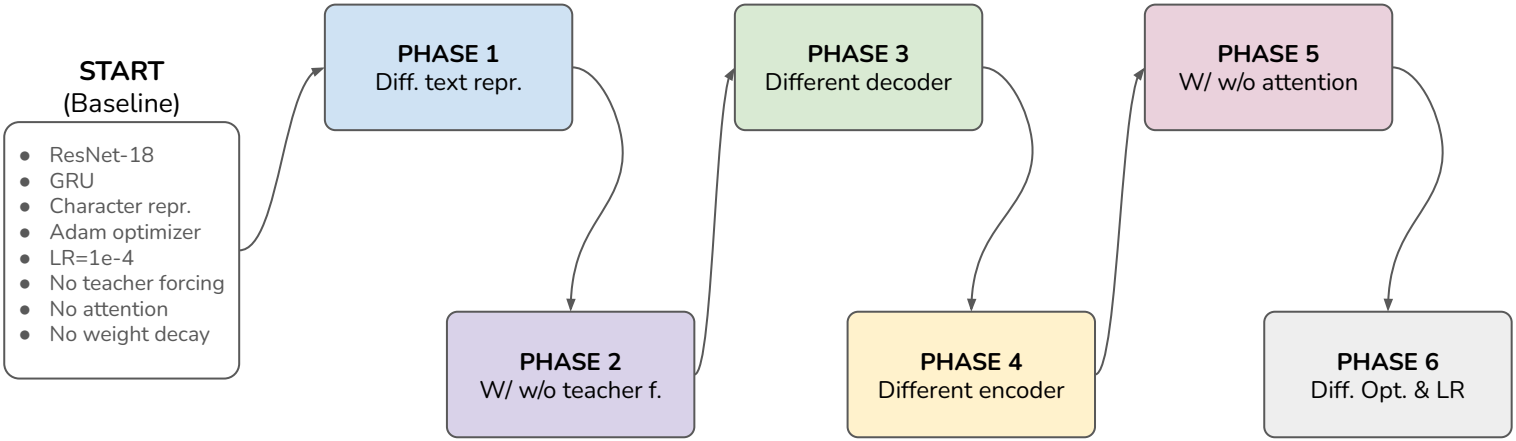
- Modifications to **forward function** & **decoding loop** to add GT tokens.
- Can choose **teacher forcing ratio** (0.8) and **teacher forcing decay** (0.95).

ATTENTION

- **Bahdanau attention** (additive attention).
- Keep **feature maps unflattened** so decoder can attend over them.

Experiments overview

Progressively accumulate good-performing configurations executing experiments in decreasing order of expected importance.



Results

Text representation: by far the most impactful in the results.

Text repr.	BLEU-1	BLEU-2	ROUGE-L	METEOR
Character	0	0	0	0
Wordpiece	8.23	0	8.97	4.30
Word	**10.35**	0	**12.78**	**6.03**

Teacher forcing: marginal improvements.

Decoders: minimal differences between them.

Encoders: ResNets outperform VGGs. Depth not important.

Attention: slight decrease in performance.

Other hyperparam.: no improvements after optimization.

Best: ResNet-18 · LSTM · Word-Lvl · Teacher F. · No Att.

Model	BLEU-1	BLEU-2	ROUGE-L	METEOR
Best	**10.37**	0	**13.07**	**6.26**

Character

Original caption: Big-Batch Pancake and Waffle Mix
Predicted caption: Caaeee

Wordpiece

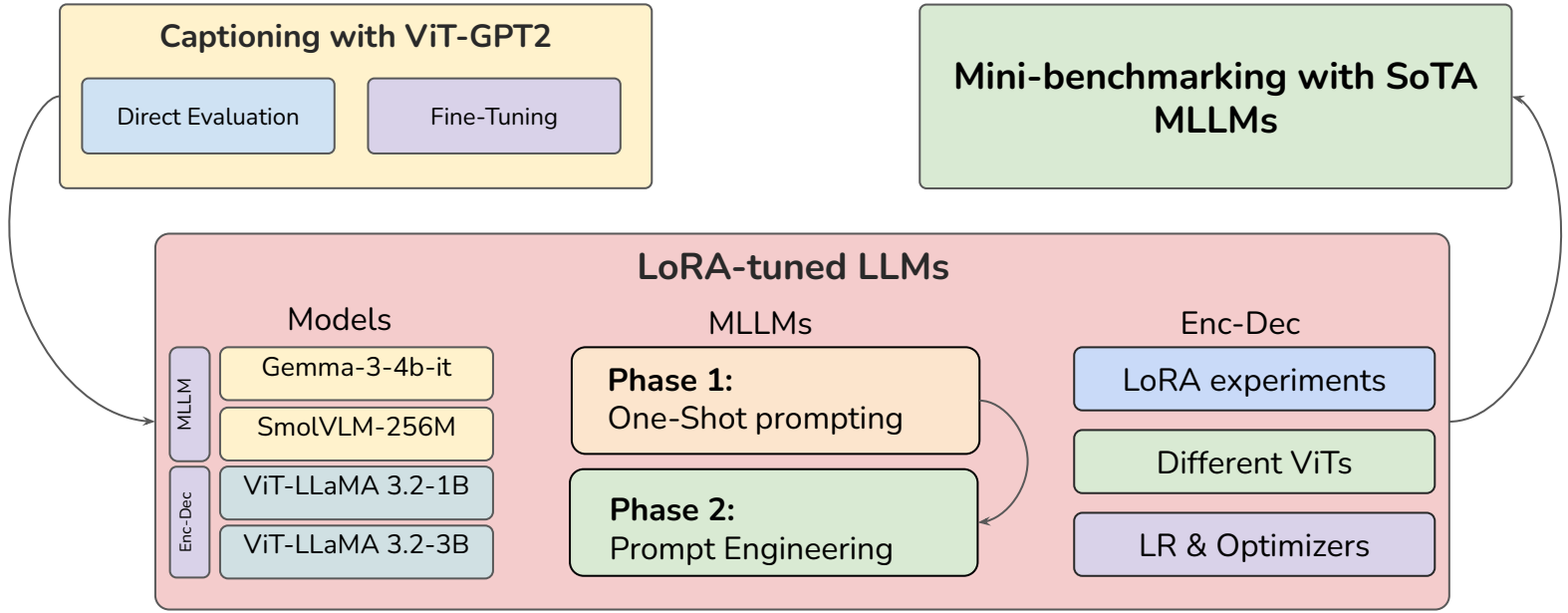
Original caption: Grilled Radicchio Salad with Sherry-Mustard Dressing
Predicted caption: grilled with with with with with and and and

Word

Original caption: Carrot-Coconut Soup
Predicted caption: creamy soup soup soup

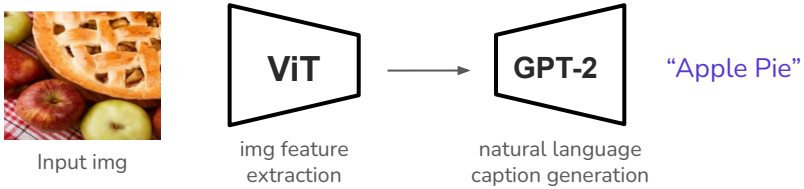
2 **Session 4**: Image Captioning (2)

Workflow overview for this session:



Captioning with ViT-GPT2

Architecture



Fine-Tuning

Set-up

Epochs: 25
Batch size: 16
Learning rate: 5e-5
Loss: Cross-entropy
Evaluation metrics: BLEU-1, BLEU-2, ROUGE-L, METEOR
Optimiser: AdamW with linear learning rate scheduler

Strategies

- **ViT (🔥) & GPT-2 (🔥)**
- **ViT (🔥) & GPT-2 (🧊)**
- **ViT (🧊) & GPT-2 (🔥)**

Approach (best config.)	BLEU-1	BLEU-2	ROUGE-L	METEOR
Pre-trained Weights	3.44	0.23	5.80	4.06
ViT (🔥) GPT-2 (🧊)	7.37	1.27	8.58	10.74
ViT (🧊) **GPT-2 (🔥)**	14.80	6.22	8.96	13.22
ViT (🔥) GPT-2 (🔥)	**16.21**	**6.54**	**9.98**	**14.44**

Qualitative results of ViT-GPT2

Image	Original caption	Pre-trained Weights	ViT (🔥) GPT-2 (🧊)	ViT (🧊) GPT-2 (🔥)	**ViT (🔥) GPT-2 (🔥)**
	Chocolate Panna Cotta Layer Cake	A piece of chocolate cake sitting on top of a plate	A chocolate cake topped with whipped cream cheese frosting	Chocolate Cake with Chocolate Frosting	Chocolate-Hazelnut Cheesecake

More specific captions

More relevant words

Preparations and dishes

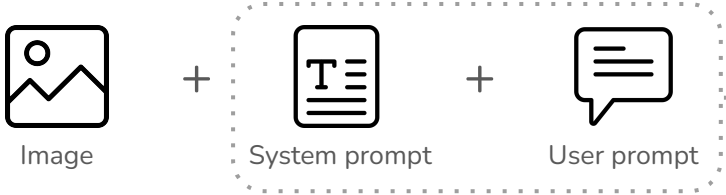
Best results in full Fine-tuning

Easy to implement and Fine-tune

Direct evaluation using gemma-3-4b-it and SmolVLM-256M-Instruct

Experiments performed

3 inputs used:



Multiple experiments carried to assess how **different prompts** affected the models' performance.

Phase 1 - Simple prompts

8 experiments:

2 with "generic" prompts

EXAMPLE:

"You are a visual description assistant."

"Give the caption for this image. Do not include any other information."

6 with "specific" prompts

EXAMPLE:

"You are a food recognition system trained on thousands of recipes."

"State the specific recipe title for this food preparation. Do not include any other information."

Phase 2 - More complex prompts (prompt engineering)

8 experiments:

EXAMPLE:

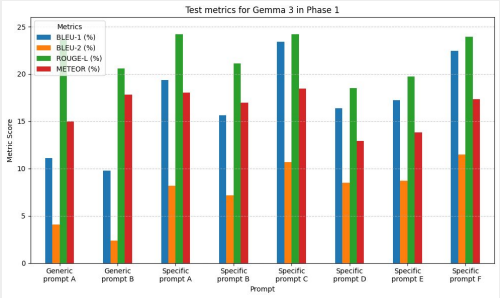
"You are a culinary historian specializing in recipe identification. Begin by analyzing the dish's composition—consider individual ingredients, their proportions, and how they interact. Compare this structure to historical and modern recipes to determine the most precise culinary title. Ensure that the final answer follows the structured naming conventions of dishes like 'Braised Beef Short Ribs' or 'Lemon Whipped Cream."

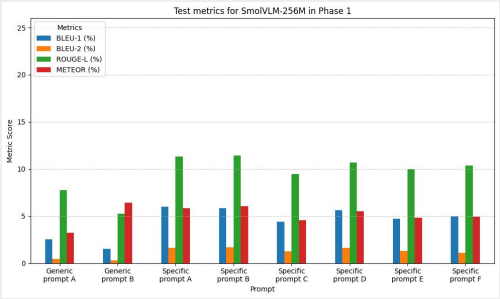
"Name this dish with its most accurate culinary title. Output only the exact name of the dish, nothing else."

Direct evaluation using gemma-3-4b-it and SmolVLM-256M-Instruct

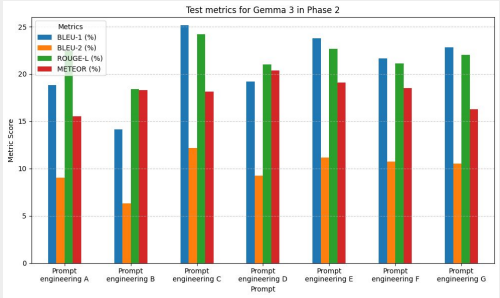
Results

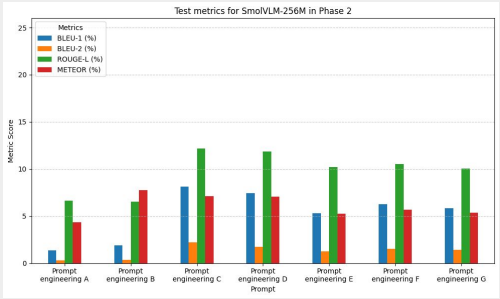
Phase 1 - Simple prompts





Phase 2 - More complex prompts (prompt engineering)





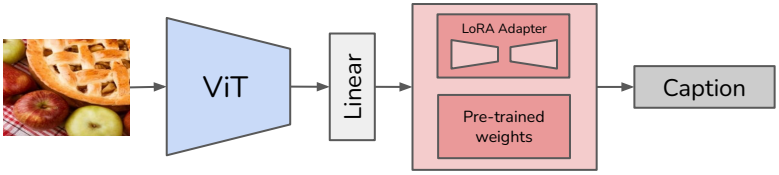
Best-performing caption (in both models): ‘Prompt engineering C’

"You are a highly trained food recognition assistant that identifies recipes with clarity and conciseness. First, you analyze the dish by recognizing its core ingredients. Then, you reconstruct its likely recipe based on ingredient combinations and common culinary techniques. Using this structured reasoning, you can determine the most appropriate recipe name."

"Give the recipe name for this food dish in one concise sentence. Output only the name of the dish, nothing else."

Fine-tuning with LoRA

ARCHITECTURE OVERVIEW



IMPLEMENTATION DETAILS

- Trainable **projection** to map ViT and LLaMA hidden sizes.
- **Concatenate** image and text embeddings in the forward pass.
- While training, **teacher-forced** validation.

EXPERIMENTS OVERVIEW

Different combinations of LoRA rank and alpha for the 1B and 3B models

Different dropout values

Different modules to apply LoRA to

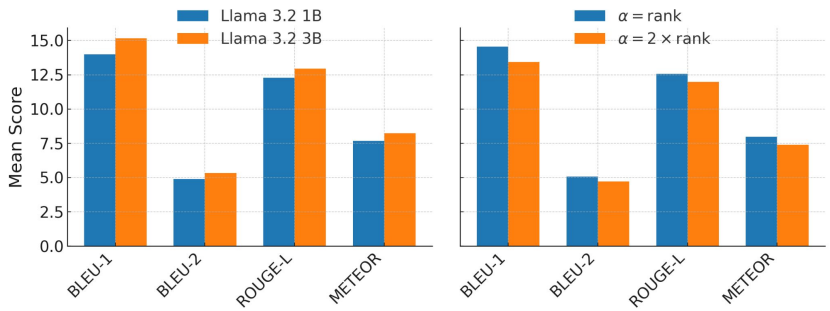
Different ViTs

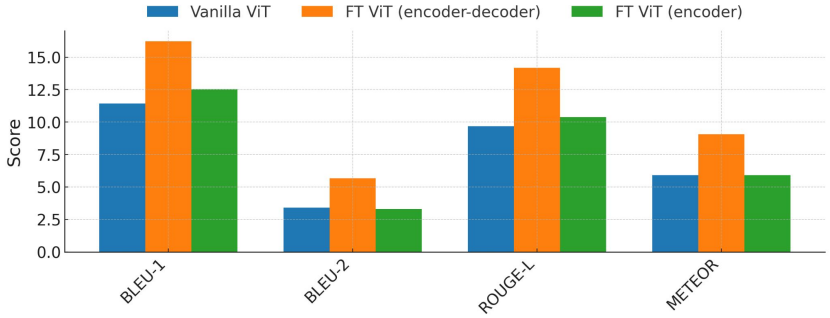
Different LR values

Different optimizer

Fine-tuning with LoRA

KEY RESULTS





Insights from the plots:

- **LLaMA 3B** generally outperforms LLaMA 1B.
- Setting **alpha=rank** works better than following the rule of thumb alpha=2*rank
- **Fine-tuning the ViT** increases performance.
- **FT ViT using enc-dec** outperforms the one FT only enc in ViT-GPT2 architecture.

Other insights:

- **Ranks** 8/16 and **alpha** 8/16 seem to provide consistently high results.
- The rest of the parameters marginally change the final performance.

Best configuration:

Approach	BLEU-1	BLEU-2	ROUGE-L	METEOR
ViT-LLaMA (3B)	15.69	5.13	13.21	8.25

Mini benchmarking SoTA MLLMs

- Small additional study to grasp how good available SoTA MLLMs are.
- Evaluation of two popular MLLMs: **ChatGPT** 4o (April) & **Claude** 3.7 Sonnet (April)
- **Prompt**: *"Provide the precise culinary name of this dish in under 10 words. Do not include any other information."*
- Manually introducing **10 randomly selected images**.

RESULTS SUMMARY

Metrics	ChatGPT 4o	Claude 3.7 Sonnet
BLEU-1	**16.92**	12.07
BLEU-2	**7.84**	0
ROUGE-L	**31.35**	21.66
METEOR	**27.42**	18.24

Original: Chinese Egg Noodles with Smoked Duck and Snow Peas
ChatGPT: Asian-style stir-fried noodles with vegetables and ham
Claude: Lo Mein with vegetables

- Competitive results with our fine-tuned models.
- Grammatically perfect sentences but fail to capture fine-grained details.
- Sometimes captions not in the same "style".

Model comparison

Approach	BLEU-1	BLEU-2	ROUGE-L	METEOR
Worst CNN-RNN (baseline)	0	0	0	0
Best CNN-RNN	10.37	0	13.07	6.26
Best ViT-GPT2 (Enc-Dec FT)	16.21	6.54	9.98	14.44
Best MLLM (Gemma-3-4b)	**25.15**	**12.17**	**24.19**	**18.12**
Best ViT-LLaMA (3B)	15.69	5.13	13.21	8.25
ChatGPT 4o (n=10)	16.92	7.84	31.35	27.42
Claude Sonnet 3.7 (n=10)	12.07	0	21.66	18.24

Worst RNN-CNN-based (ResNet18-GRU)

Original: Big-Batch Pancake and Waffle Mix
Pred: Caaeee

Best RNN-CNN-based (ResNet18 + LSTM)

Original: Carrot-Coconut Soup
Pred: creamy soup soup soup

Best Advanced MLLM (ChatGPT 4o)

Original: Chinese Egg Noodles with Smoked Duck and Snow Peas
Pred: Asian-style stir-fried noodles with vegetables and ham

Worst LLM-based (Pre-trained ViT-GPT2)

Original: Rice with Parsley, Almonds, and Apricots
Pred: A plate of food on a table

Intermediate LLM-based (LLaMA 3.2 1B)

Original: Chocolate Panna Cotta Layer Cake
Pred: Chocolate Cake with Chocolate Ganache and [...]

Best LLM-based (Gemma-3-4b)

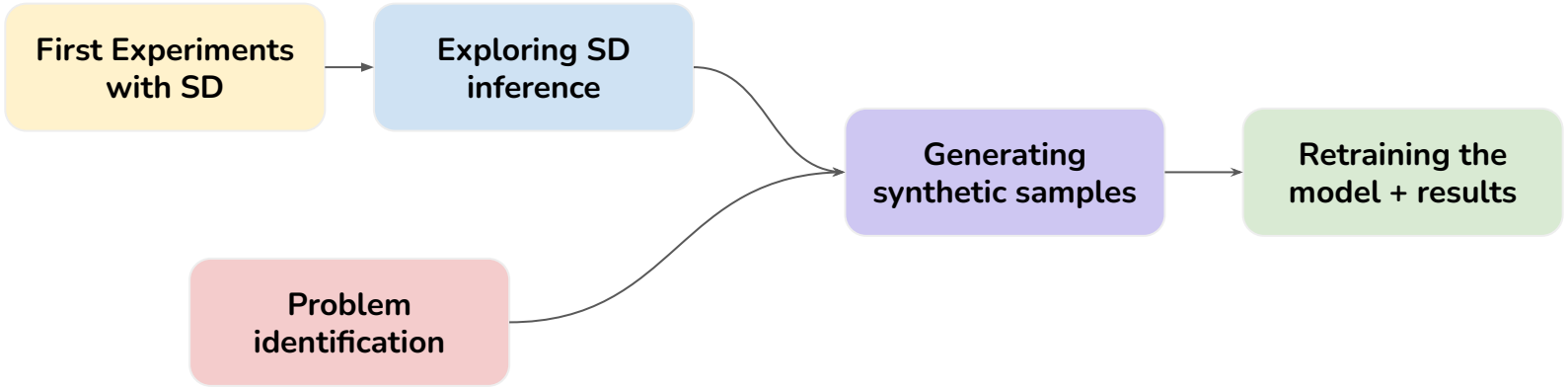
Original: BBQ Pork Chops with Herb-Butter Corn and Sweet Potatoes
Pred: Smoked Ribs with Sweet Potatoes and Corn on the Cob

- LLM-based approaches far superior to classic CNN-RNN ones.
- Directly prompting MLLMs provided better results than fine-tuning.
- Advanced online SoTA MLLMs like ChatGPT and Claude can compete with our models.

- CNN-RNNs show rudimentary understanding of image content but lack caption structure, mostly repeating common tokens.
- LLM-based show better caption structure and understanding but struggle with details.

3 **Session 5**: Diffusion Models

Workflow overview for this session:



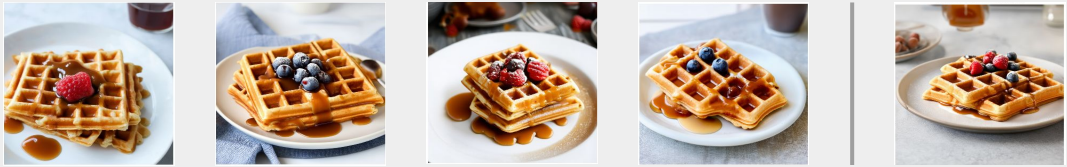
Exploring SD - Comparison Setup

For each of these models:

- SD 2.1
- SDXL Base
- SDXL Turbo
- SDXL w/ Refiner
- SD 3.5 Medium

We generate:

- **4 img** w/ **rand.** seed
- **1 img** w/ **fixed** seed
  → *seed 42*



We do it for:

- **20 different prompts** from **FIRD** captions

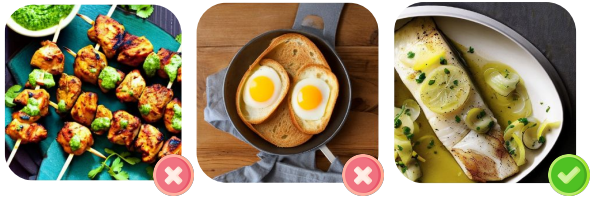
"Apple pie"

"Aperol spritz"

"Halibut confit with leeks coriander and lemon"

Exploring SD - Analysis

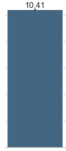
SD 2.1



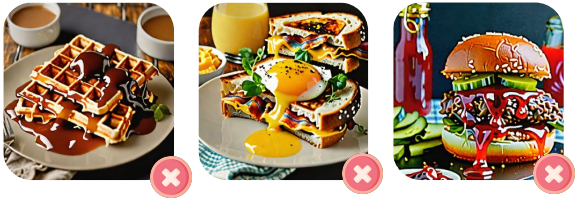
Gen. time:
1.85s

SDXL Base

Gen. time:
10.41s



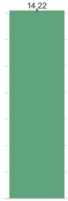
SDXL Turbo



Gen. time:
4.41s

SD 3.5 Medium

Gen. time:
14.22s



SDXL w/ Refiner

No significant difference with SDXL Base & high gen. time of **14.00s**

Exploring SD - Final models chosen

Parameter optimization based on **quality not metrics**

Classifier Free Guidance Scale

Denoising steps

Neg. prompt

Extra experiments

Playing w/ prompt

Apple Pie

Apple Pie, food photography

prompt + **“, food photography”**

Generation size

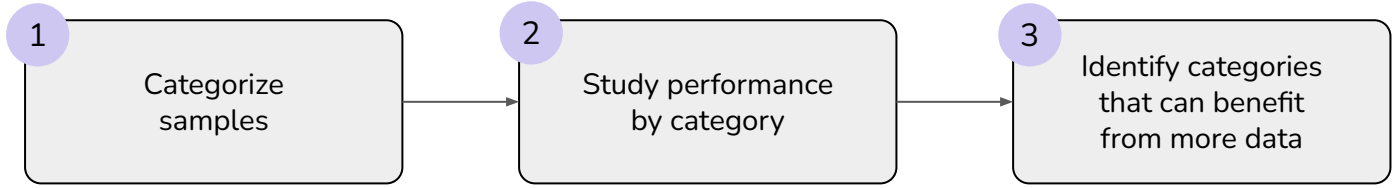
Best models

Best config.

SDXL BASE	CFG **5**	Denoising Steps **50**	Sampler **DDIM**	Negative Prompt **None**
SD 3.5 Medium	CFG **5**	Denoising Steps **50**	Sampler **DDIM**	Negative Prompt **None**

Problem identification

GENERAL STRATEGY



- Helps us **better target our limited** time and compute **resources**.
- **Easier to evaluate** whether our efforts succeeded by focusing on specific categories.

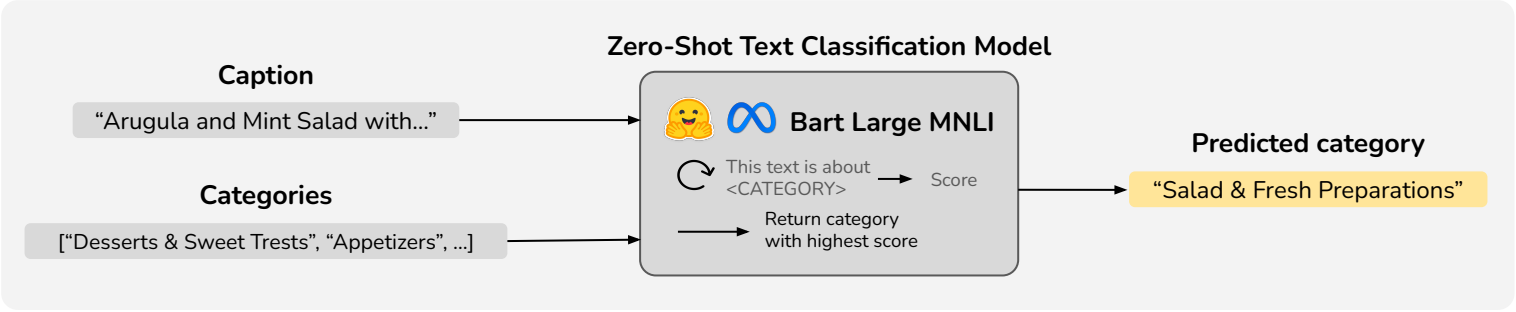
Problem identification

CREATING THE CATEGORIES

- Feeding **1000 random samples to Claude**. Ask to suggest categories.
- Posterior **manual refinement** of the suggestions

} **11** different dish categories

CATEGORIZING THE SAMPLES (THROUGH THEIR CAPTIONS)

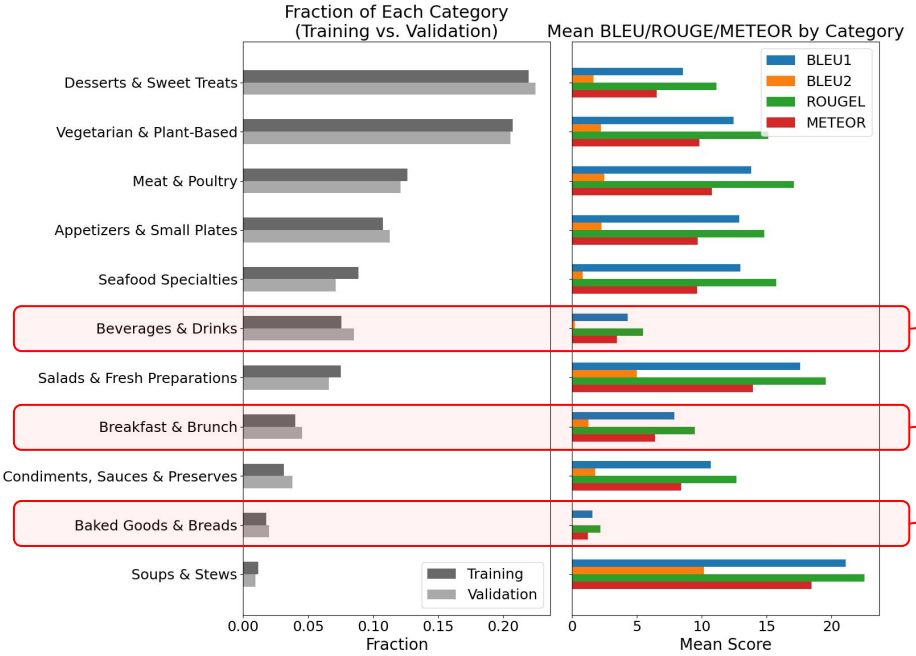


CREATING NEW CAPTIONS

- Feeding **1000 random samples to Claude**. Ask to **summarize caption style** in a prompt.
- Repeatedly **prompt ChatGPT** for new captions. **Check uniqueness** with Python script.

Problem identification IDENTIFYING CATEGORIES THAT CAN BENEFIT FROM MORE DATA

Model that we use: **ViT-LLaMA 3.2 1B with opt. params**



These categories are both underrepresented and are hard for the model

↓

Good candidates for data augmentation

Generating synthetic samples to mitigate our problem

For these 3 selected categories:

Beverages & Drinks | Breakfast & Brunch | Baked goods & Breads

We generate **955 different captions**

We generate **3 images for each caption**

getting **2864 (image, caption)** pairs

For each model

SDXL BASE



SD 3.5 Medium



Prompt: "Almond-Stuffed Brioche Twists"

Generating synthetic samples to mitigate our problem

DIFFUSION MODELS USED

Stable Diffusion 3.5 Medium

Optimized for our case of food generation

Stable Diffusion XL Base 1.0

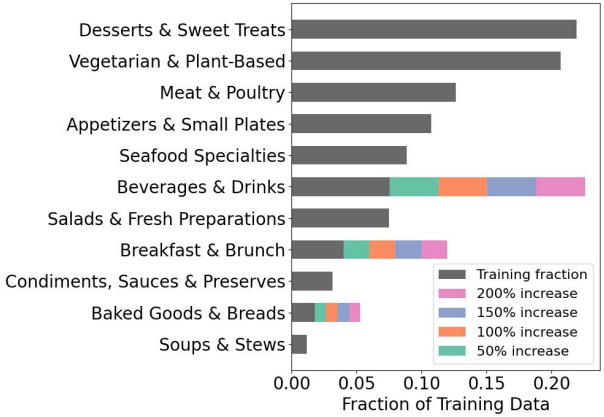
Less good than 3.5 Medium, for comparison

EXPERIMENTS OVERVIEW (FOR EACH CATEGORY)

Amount of extra data with respect to training data

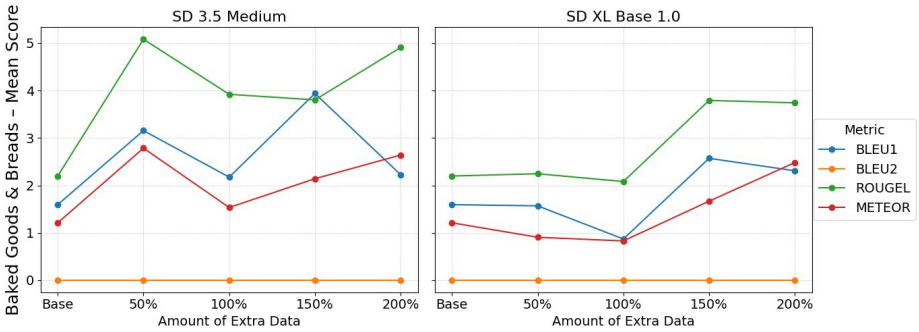
Stable Diffusion model used	+50%	+100%	+150%	+200%
3.5 Medium	*Exp. 1*	*Exp. 2*	*Exp. 3*	*Exp. 4*
XL Base 1.0	*Exp. 5*	*Exp. 6*	*Exp. 7*	*Exp. 8*

AMOUNT OF DATA GENERATED



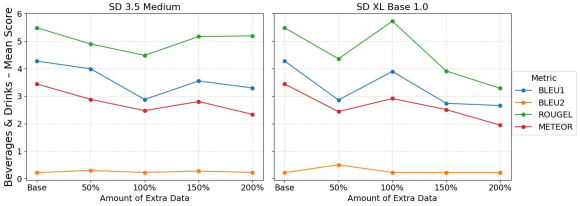
Retraining our model with augmented data

RESULTS FOR "BAKED GOODS & BREADS"

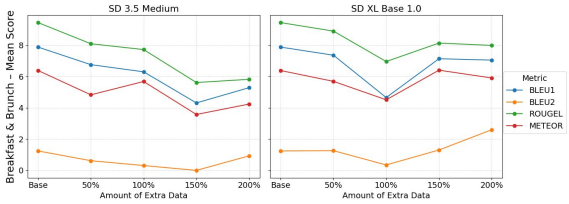


- Only improvements in category "Baked Goods & Breads".
- More data seems to be better.
- SD 3.5 better than SD XL.
- Other categories are negatively affected.

RESULTS FOR "BEVERAGES & DRINKS"



RESULTS FOR "BREAKFAST & BRUNCH"



Why did we get mixed results?

Model architecture

The model itself might have architectural limitations. Other designs might be more effective.

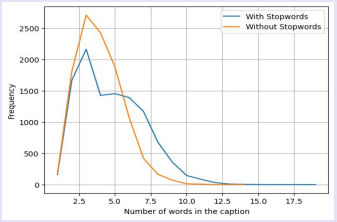
Data quality

The generated captions and images might not be high quality enough, or across all necessary categories.

Difficulty metrics

They require very precise word matches and can't capture quality as easily as humans.

Caption distribution



Long tails of rare and unique words.

4 Conclusions & Insights

Limitations of **CNN + RNN**

Best **LLM-based** models often identify core ingredients

Challenging **dataset**. Many terminology

Good prompts in **MLLMs** can outperform fine-tuned models

More data ≠ better results

Challenges in quantitative evaluation for **generative models**

Multimodal Recognition Project

Final Session: Project Presentation

Group 6

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***Module**: C5 - Visual Recognition*
***Coordinators**: Ernest Valveny, Carlos Boned, Lei Kang*