

Poster Presentation Tips

Administrative

- Grades for Assignment 3, 4 out
- Grades for Quiz 4 out
- Grades for Milestone out
- A5 due 2 days ago

The rest of the course:

- Quiz 5 today!
- Poster Session on Thursday
- Grade reports posted to gradescope friday/saturday
 - Time to check over your late days/ any extensions etc

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Logistics

1. Arrive in lobby of allen building
2. Pick up poster from us (send by tomorrow at noon) or bring your printed poster
3. Set up poster board and poster stand
4. We will come around and assign you group 1 or group 2
 - a. Group 1 presents poster in first half and looks at other poster second
 - b. Group 2 looks at posters in first half and presents second
5. In either the first or second half of the session, you will stand by your poster and explain your project to us/ other students

How to make a good poster/presentation

Start with a good presentation, make the poster to match

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How to make a good presentation?

30 - 60 second overview

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1. **High level intro** (10 seconds)
 1. What is the motivation for your work? What is not done yet that you are solving? Make sure you set it up for why your project is necessary.
 2. Explain your approach at a high level

How to make a good presentation?

30 - 60 second overview

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 2. Explain your approach at a high level
2. **Details of your method** (15 - 25 seconds)
 1. What are you actually doing specifically?

How to make a good presentation?

30 - 60 second overview

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2. **Details of your method** (15 - 25 seconds)
 1. What are you actually doing specifically?
3. **Results** (15 - 25 seconds)
 1. What experiments did you run? What did you find?
 2. How does this show that you solved the problem that you set up?

How to make a good poster/presentation

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How to make a good poster?

Your poster is a tool to help you with your presentation

You don't want just all the text of everything you are planning on saying aloud

Go through your presentation script and see which of the points could use a visual component

- A diagram of your model to reference as you are explaining it?
- The graph of your results?

How to make a good poster?

Flow of visual elements
in poster matches flow
of presentation

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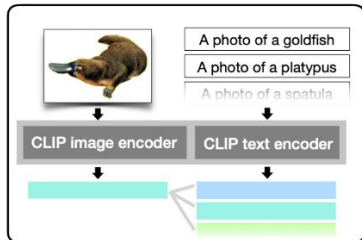
WHAT DOES A PLATYPUS LOOK LIKE?

Generating **customized prompts** for **zero-shot image classification**

Sarah Pratt¹ Ian Covert¹ Rosanne Liu^{2,3} Ali Farhadi¹

"A platypus looks like a beaver with a ducks bill"

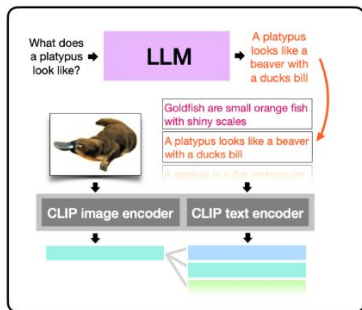
LLM



Standard CLIP Prompts :

Handwrite custom templates ("a photo of a ____") for each dataset and fill them in with each category.

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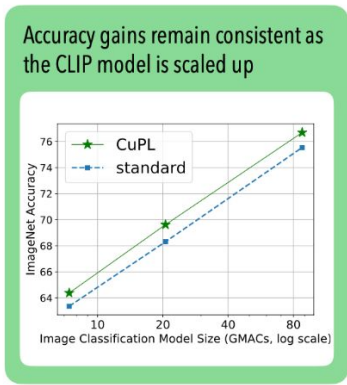
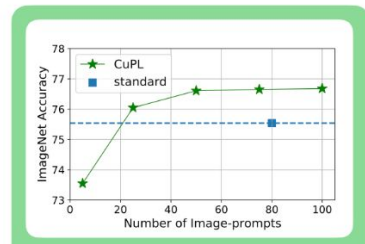
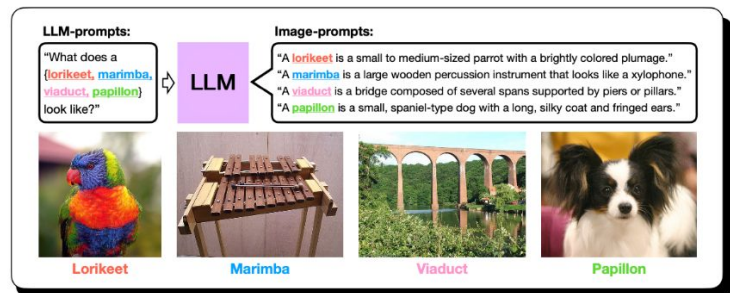
CuPL Prompts (ours):

Customized Prompts via Language models

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More descriptions lead to higher accuracy and LLMs can generate many descriptions without additional human effort

ImageNet				Average across 15 benchmarks			
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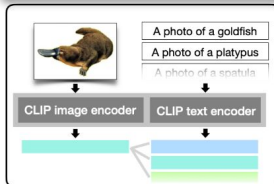
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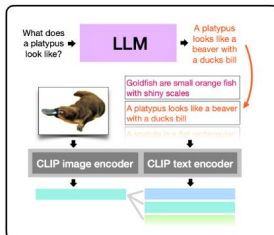
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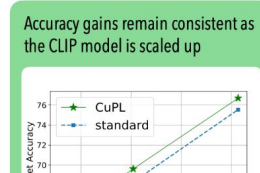
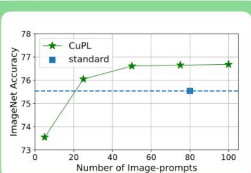
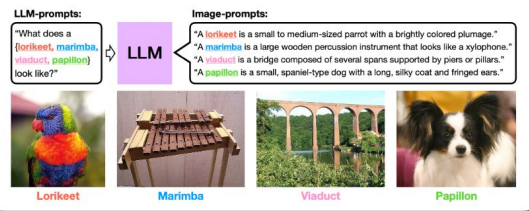
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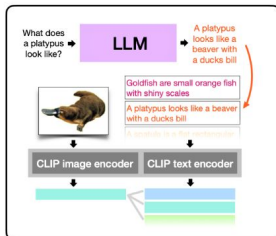
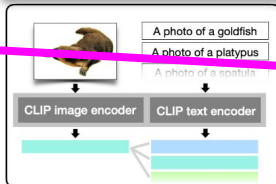
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Motivation + method



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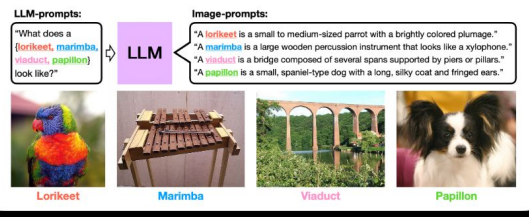
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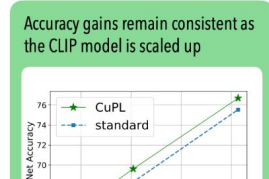
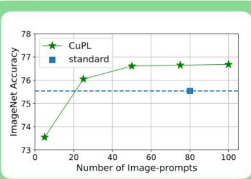
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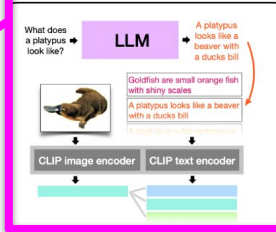
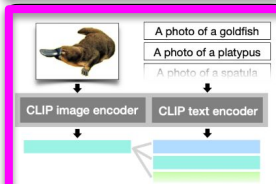
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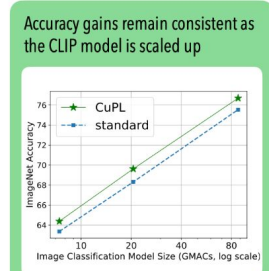
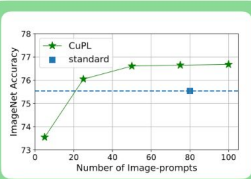
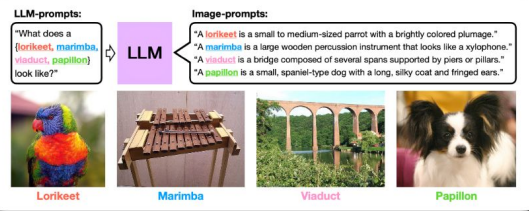
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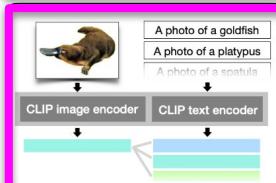
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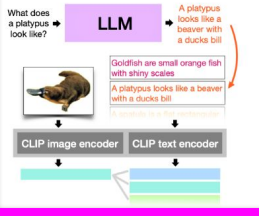
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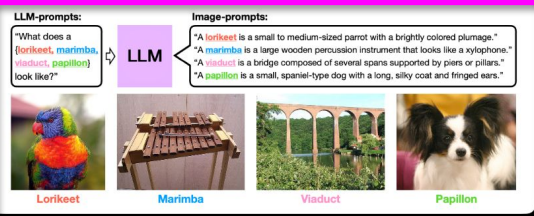
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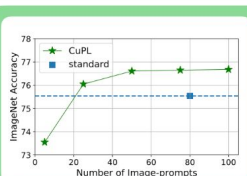
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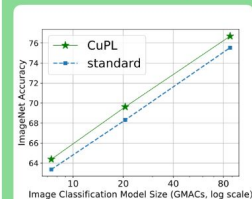
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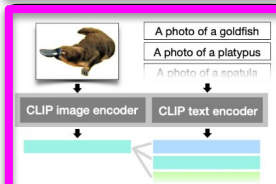
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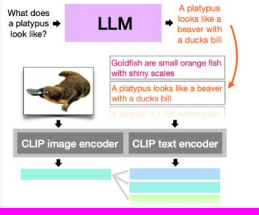
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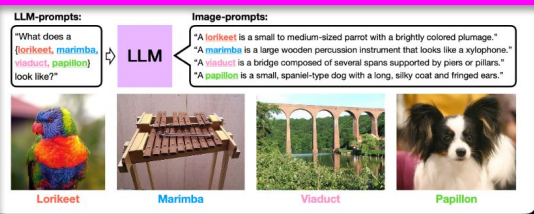
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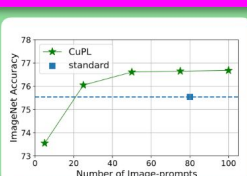
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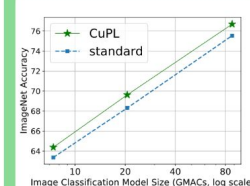
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