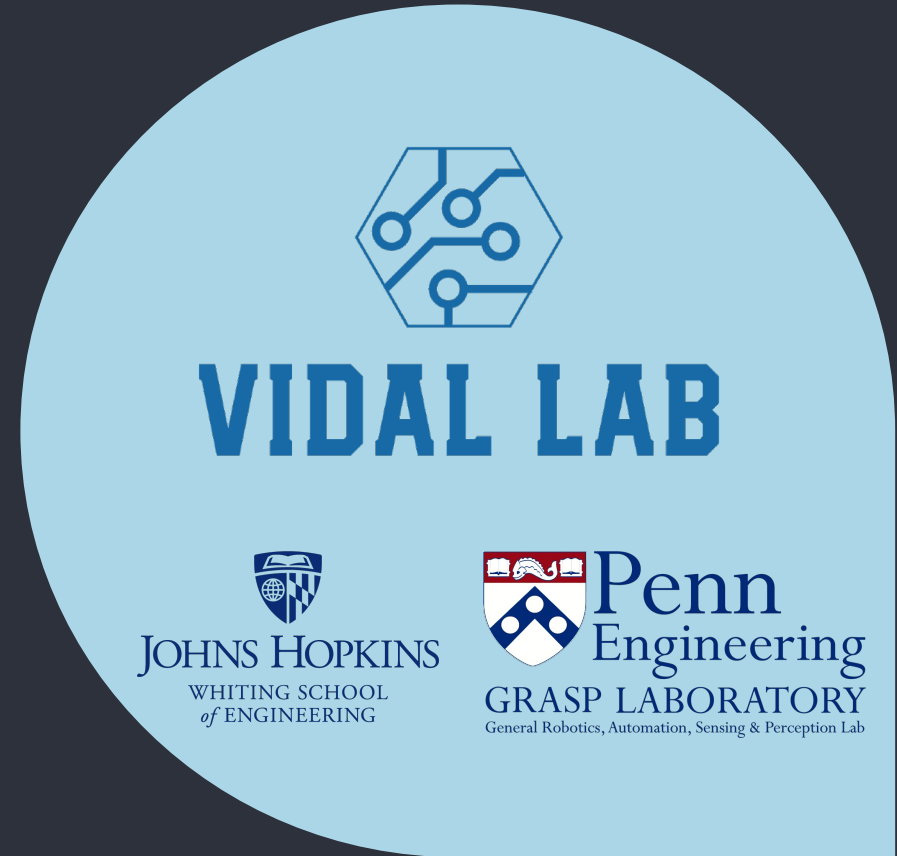


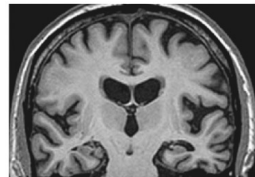
Bootstrapping Variational Information Pursuit with Large Language and Vision Models for Interpretable Image Classification

Aditya Chattopadhyay, Kwan Ho
Ryan Chan, René Vidal

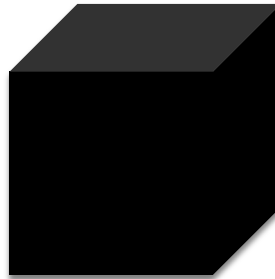


Background: Need for interpretable models

Current models



MRI Scan

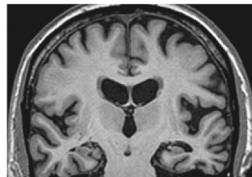


Black-Box

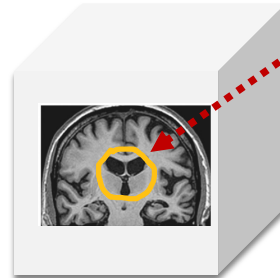


Patient has Alzheimer's disease with 98.6% probability

Desired models



MRI Scan



Black-Box



Patient has Alzheimer's disease with 98.6% probability



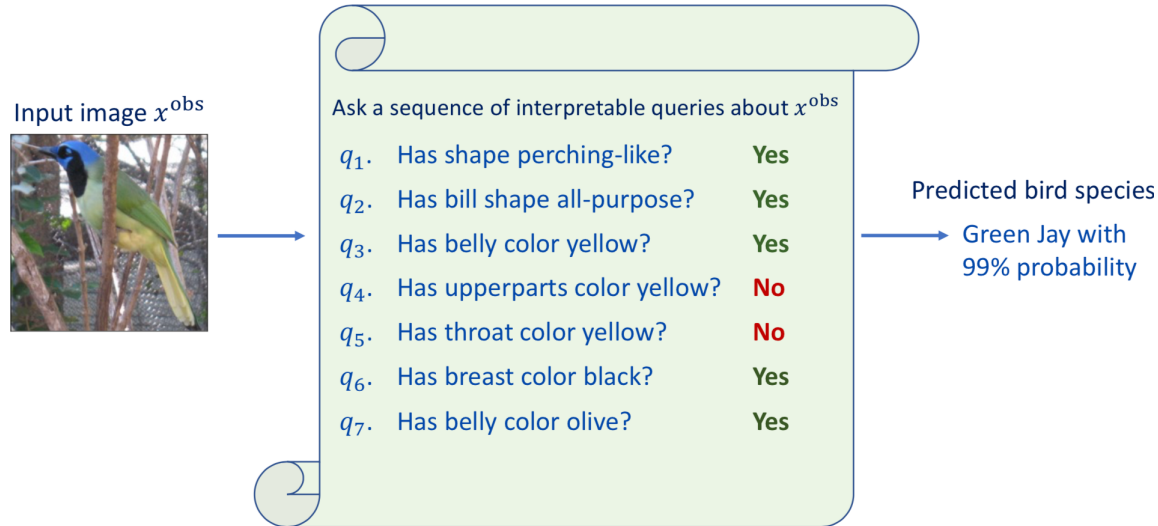
Background: Post-hoc explainability vs interpretable-by-design



- Most current methods to explaining model decisions are post-hoc.
 - No need to retrain model, accuracy maintained.
- **Post-hoc methods don't provide faithful explanations.**¹
- Need for models that are **interpretable-by-design** → provides **explanations** for decisions that are **interpretable to the user**.

1. Adebayo, J., Gilmer, J., Muelly, M., Goodfellow, I., Hardt, M., & Kim, B. (2018). Sanity checks for saliency maps. Advances in neural information processing systems, 31.

Prior Work: Interpretable decisions via 20 Questions (20Q)



- An **interpretable-by-design** approach based on the 20-Question game.¹
 1. Specify a large **set of interpretable queries**, Q , about the input.
 2. Given Q , **ask informative queries one at a time**. Each query choice depends on the query answers obtained so far.
 3. Once confident, make a **prediction based only** on the **obtained query-answers**.

1. Chattopadhyay, A., Slocum, S., Haeffele, B. D., Vidal, R., & Geman, D. (2022). Interpretable by design: Learning predictors by composing interpretable queries. IEEE Transactions on Pattern Analysis and Machine Intelligence.

Motivation: How to apply 20Q for interpretable ML?



- Applying the framework to any ML task requires:

1. **Specification of query set:** In prior work, queries were user-defined. Progress in LLMs make it possible to **automatically specify task-relevant query sets**.¹ ✓
2. **Mechanism for what to ask next:** Use **Variational Information Pursuit (V-IP)**² a greedy algorithm, to select the **next most informative query** from Q . ✓
3. **Mechanism to answer the queries:** A major bottleneck → often requires **manually annotated data** for training classifiers to answer queries at test time. ✗

1. Oikarinen, T., Das, S., Nguyen, L. M., & Weng, T. W. (2023). Label-free Concept Bottleneck Models. In The Eleventh International Conference on Learning Representations.

2. Chattopadhyay, A., Chan, K. H. R., Haeffele, B. D., Geman, D., & Vidal, R. (2023). Variational Information Pursuit for Interpretable Predictions. In The Eleventh International Conference on Learning Representations.

Challenge: How to answer queries?



- Most datasets **don't come with manually annotated query answers.** 😞
- **This work:** Interpretable predictions via V-IP + visual question-answering system trained to answer queries without any manual annotations.
 - Use pseudo-labels provided by pretrained Vision Language Models (VLMs) instead!

Our Contribution: Concept-QA



- Given, an image classification dataset, say Imagenet.
- A set of of task-relevant queries/concepts obtained from an LLM (say GPT4).
- Use pseudo-labels generated by a pretrained VLM to train Concept-QA
 - Can then use Concept-QA this to answer queries at test time

Our Proposal: Concept-QA

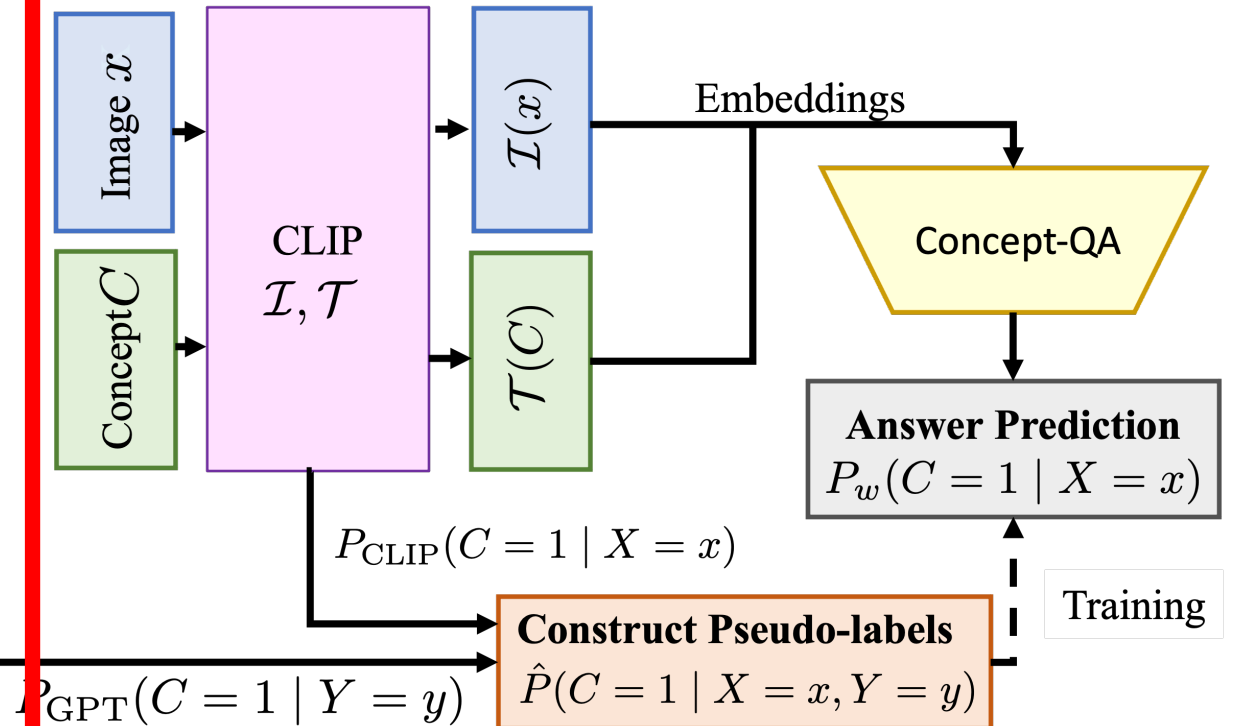
For every {class}:

PROMPT to GPT:

Answer yes/no/depends for whether the following concepts are salient for recognizing a '{class=bear}': a predator, a prey, a pride, ...

RESPONSE:

Description: A bear is a large mammal characterized by its robust...
 a predator: Yes: Bears, with their sharp teeth..
 a prey: Yes: Despite being a top predator..
 a pride: No: Bears are typically solitary animals...
 ...



Our Proposal: Concept-QA

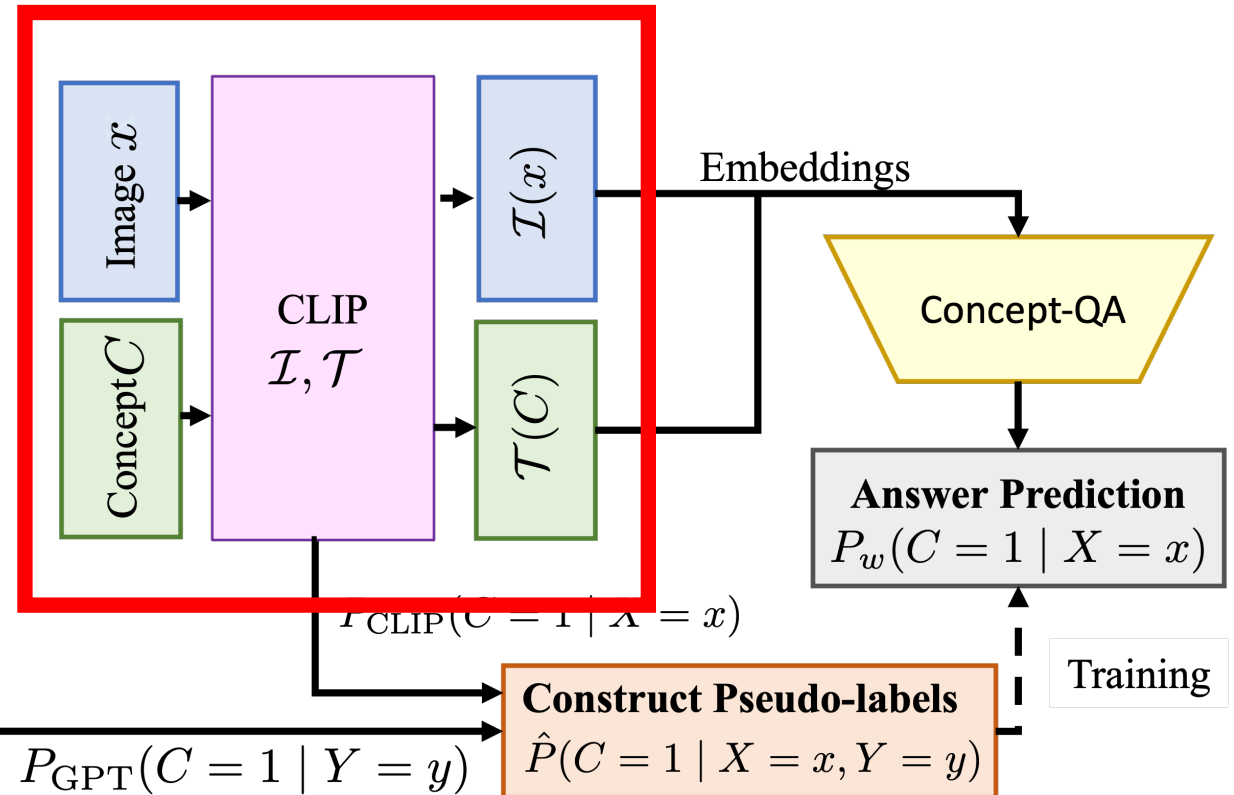
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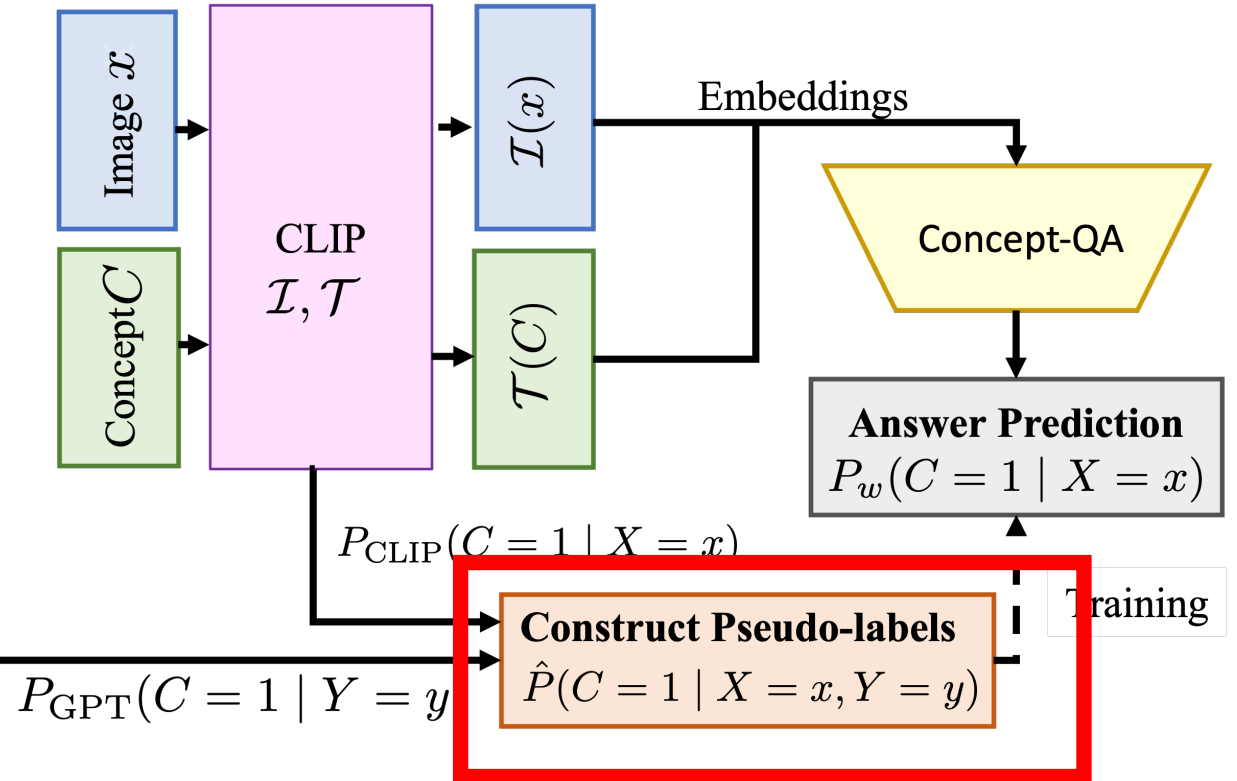
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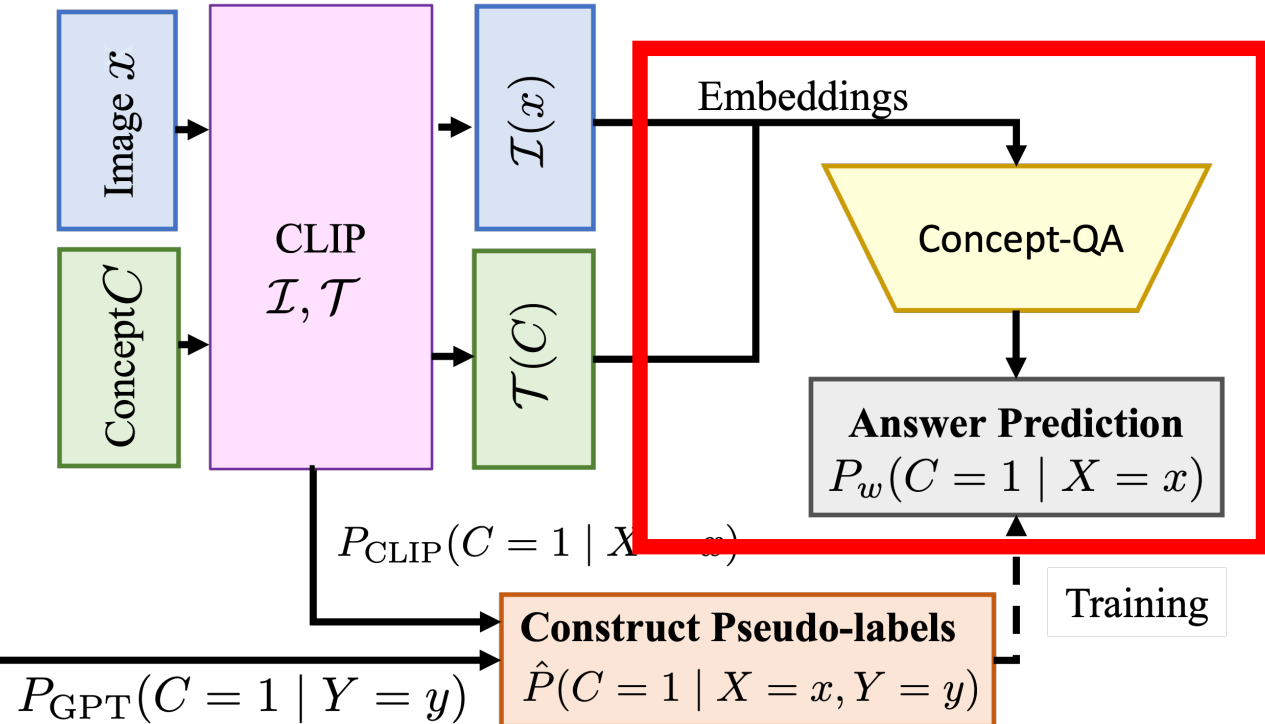
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What not directly use pretrained VLMs?



- Current **state-of-the-art VLMs** like Llava-1.5 and BLIP-2 are **too slow** to be used in an online sequential manner.
 - In contrast, **Concept-QA** is lightweight, **much faster** and **competitive**.
- **Concept-QA outperforms CLIP** in its ability to accurately answer queries.
 - Evaluated by manually annotating a subset of the dataset with query-answers.

Interpretable Predictions with VIP and Concept-QA

- **Task:** Image Classification (ImageNet)
- **Query set:** Queries about presence of different semantic concepts.



More Information,



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Thank You!



https://github.com/adityac94/conceptqa_vip