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CLiMB
A Continual Learning Benchmark for Vision-and-Language Tasks

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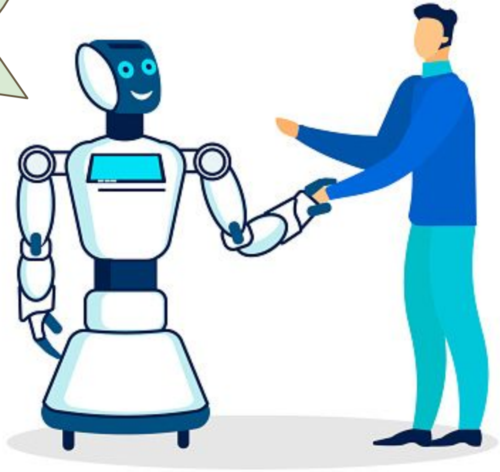
Multimodal Agents that can be Deployed

Responses/actions by reasoning over inputs from multiple modalities

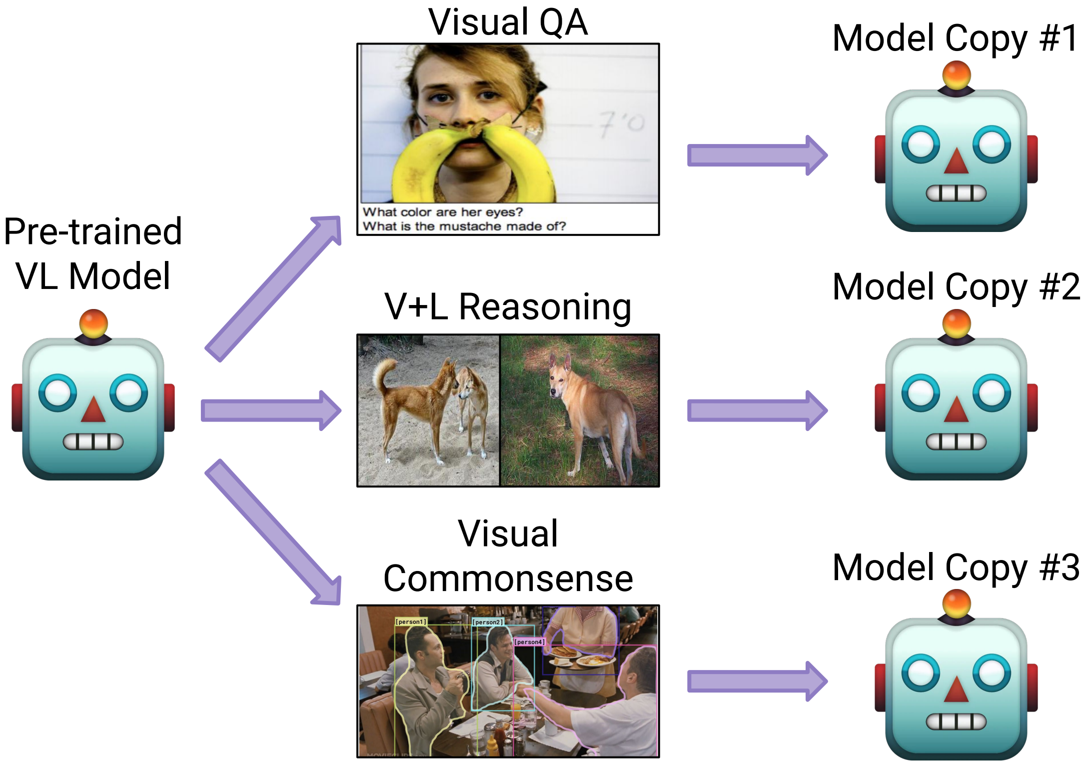
Visual QA + Dialog



Image/Scene Classification

Knowledge-based QA

Paradigms of VL Deployment: Single-Task Finetuning



Need to store a copy of the model for each task!

Paradigms of VL Deployment: Multi-Task Learning

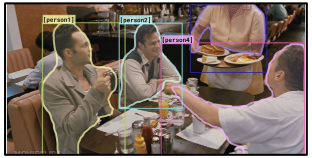
Pre-trained
VL Model

Visual QA

What color are her eyes?
What is the mustache made of?

V+L Reasoning

Visual
Commonsense



Deployed
Multi-task
VL Model

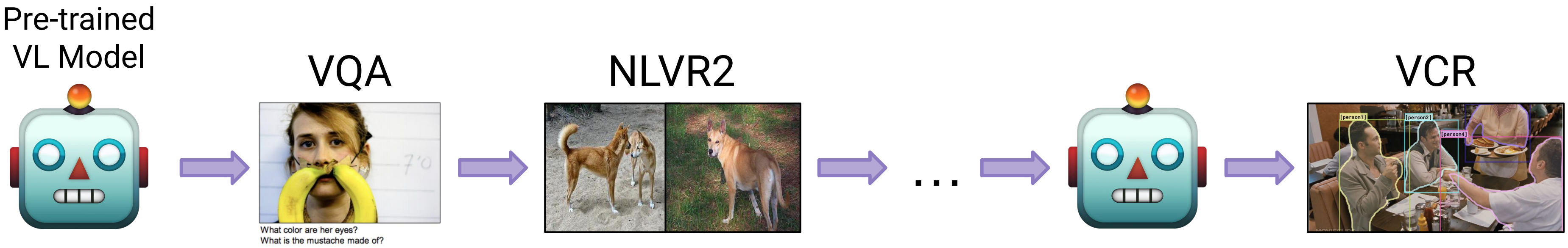
New Task
Visual Entailment

A man shoots a basketball
Contradiction

???

Static; cannot learn new tasks that it encounters!

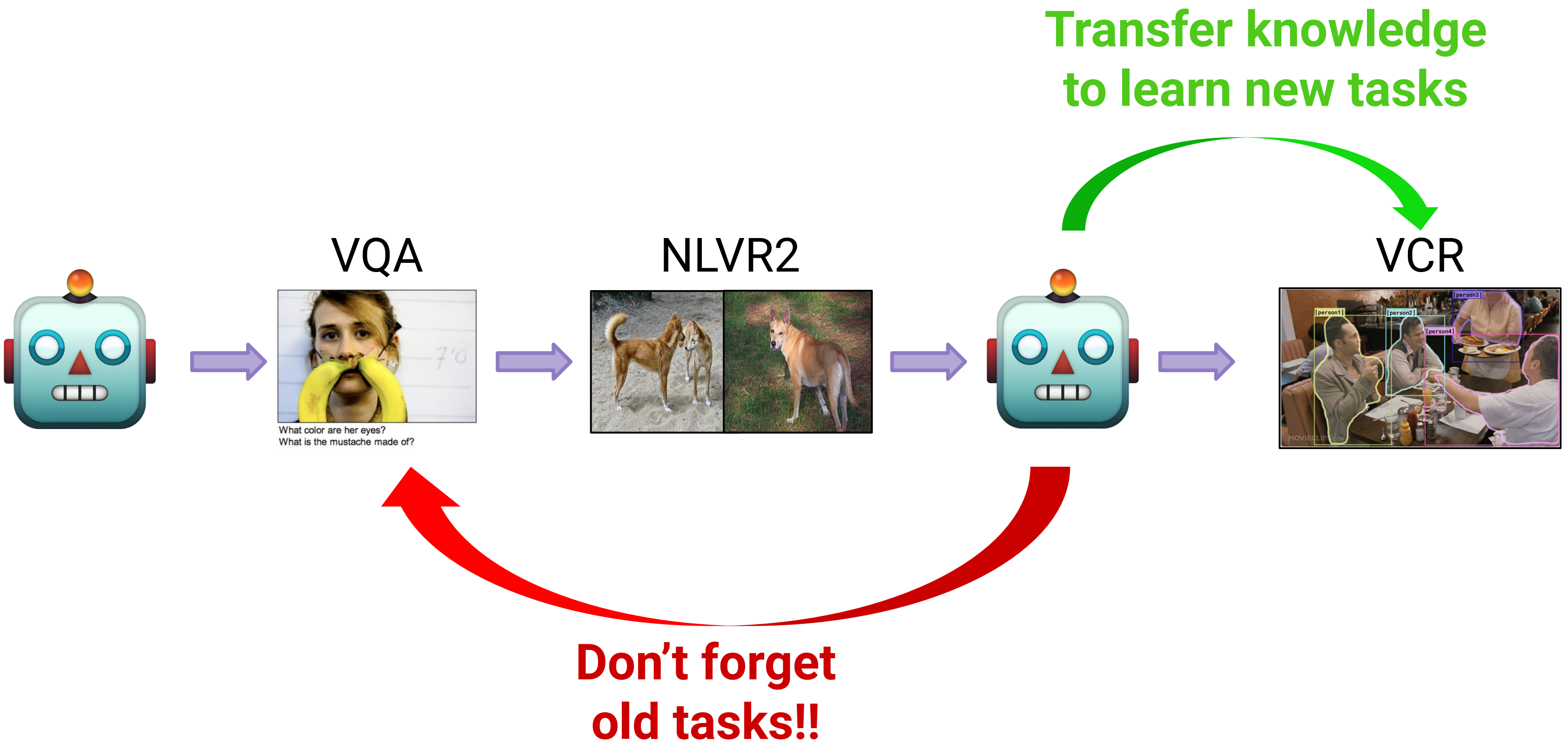
Paradigms of VL Deployment: Continual Learning



Dynamic, continually evolving paradigm

Unexplored in multimodal domain!

Challenges of Multimodal Continual Learning Deployment



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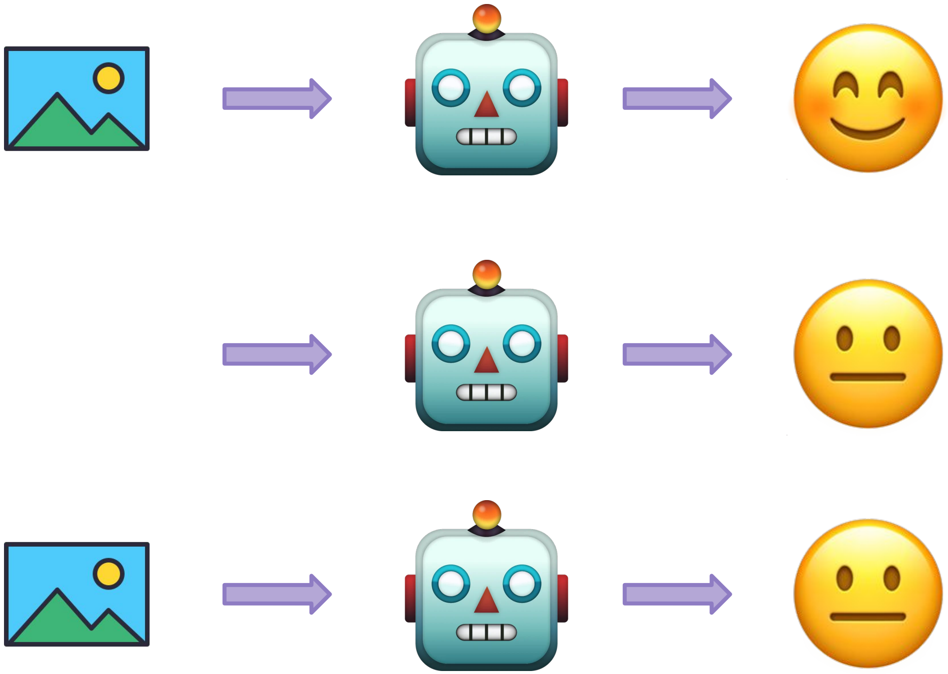
Challenges of Multimodal Continual Learning Deployment

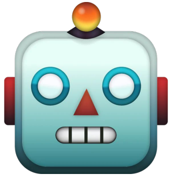
Not guaranteed to have all modalities when encountering new tasks!



CLiMB: The Continual Learning in Multimodality Benchmark

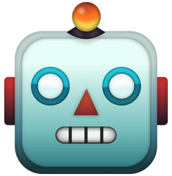
Phase I. Upstream Continual Learning

Pre-trained
VL Model

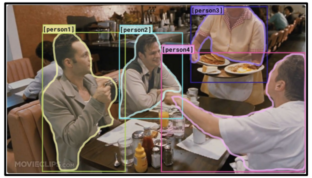


VQA

NLVR2

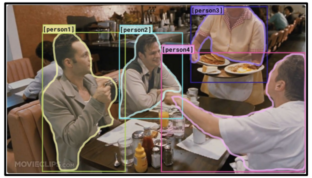


VCR



Phase II. Downstream Low-Shot Transfer

Unseen V+L Tasks



Language Tasks

GLUE

Vision Tasks

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COCO
Common Objects in Context

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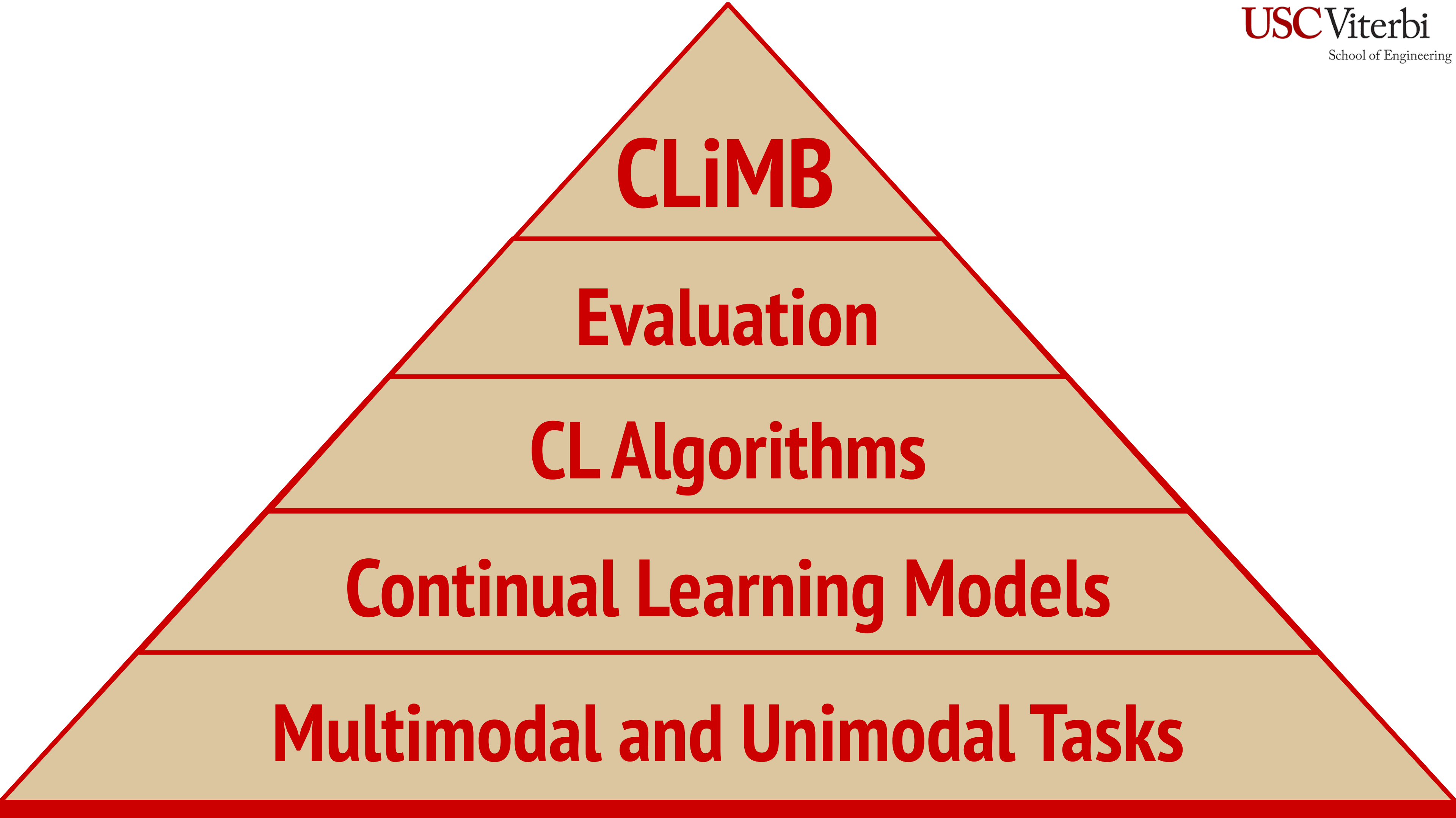
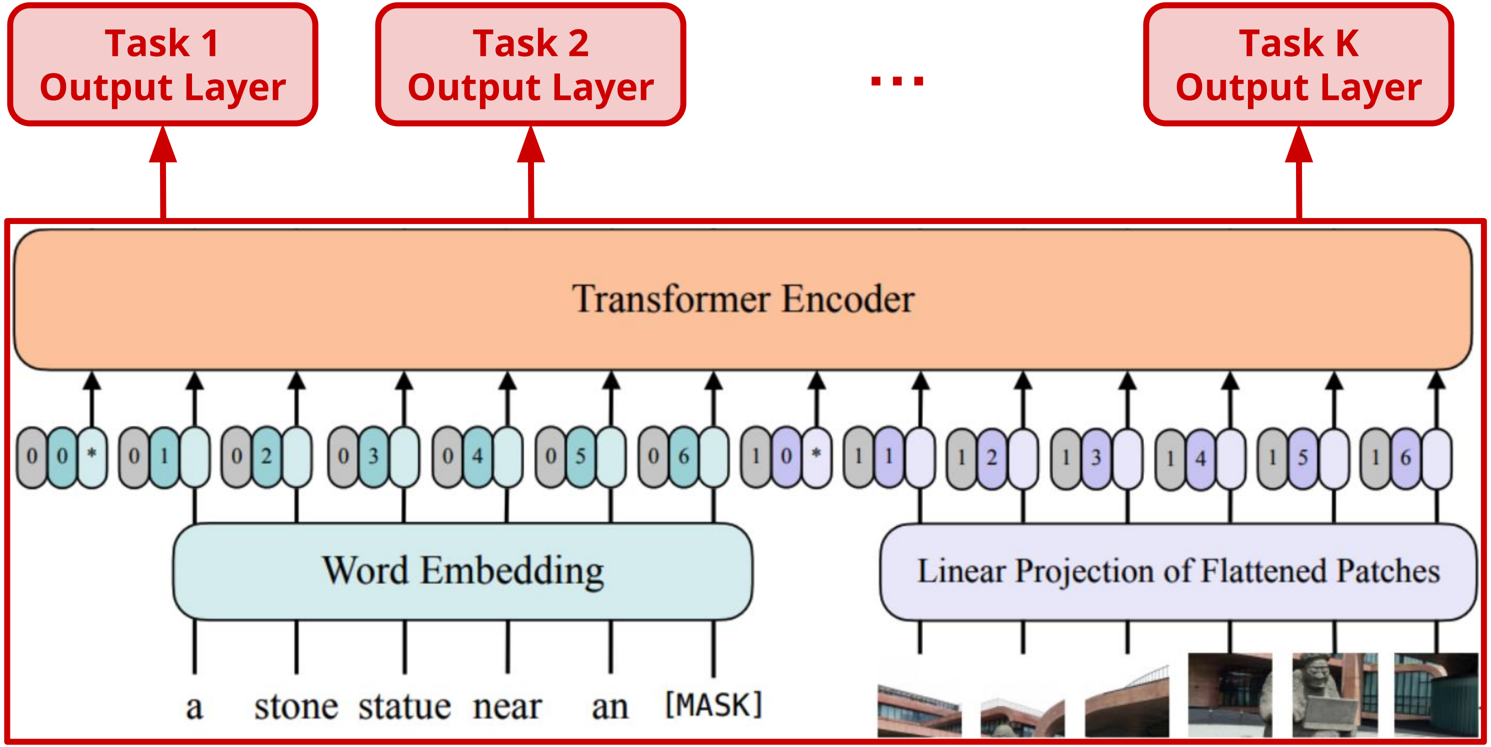


I. Multimodal and Unimodal Tasks

Vision-and-Language Tasks	• Visual Question Answering (VQAv2) • Natural Language Visual Reasoning (NLVR2) • Visual Entailment (SNLI-VE) • Visual Commonsense Reasoning (VCR)
Language-Only Tasks	• IMDb, SST-2 Sentiment Classification • HellaSwag • CommonsenseQA • Physical Interaction QA (PIQA)
Vision-Only Tasks	• ImageNet-1K Image Classification • iNaturalist2019 Image Classification • Places365 Image Classification • MS-COCO Object Detection

CLiMB can be easily extended to include new multimodal and unimodal tasks!

II. Continual Learning Models

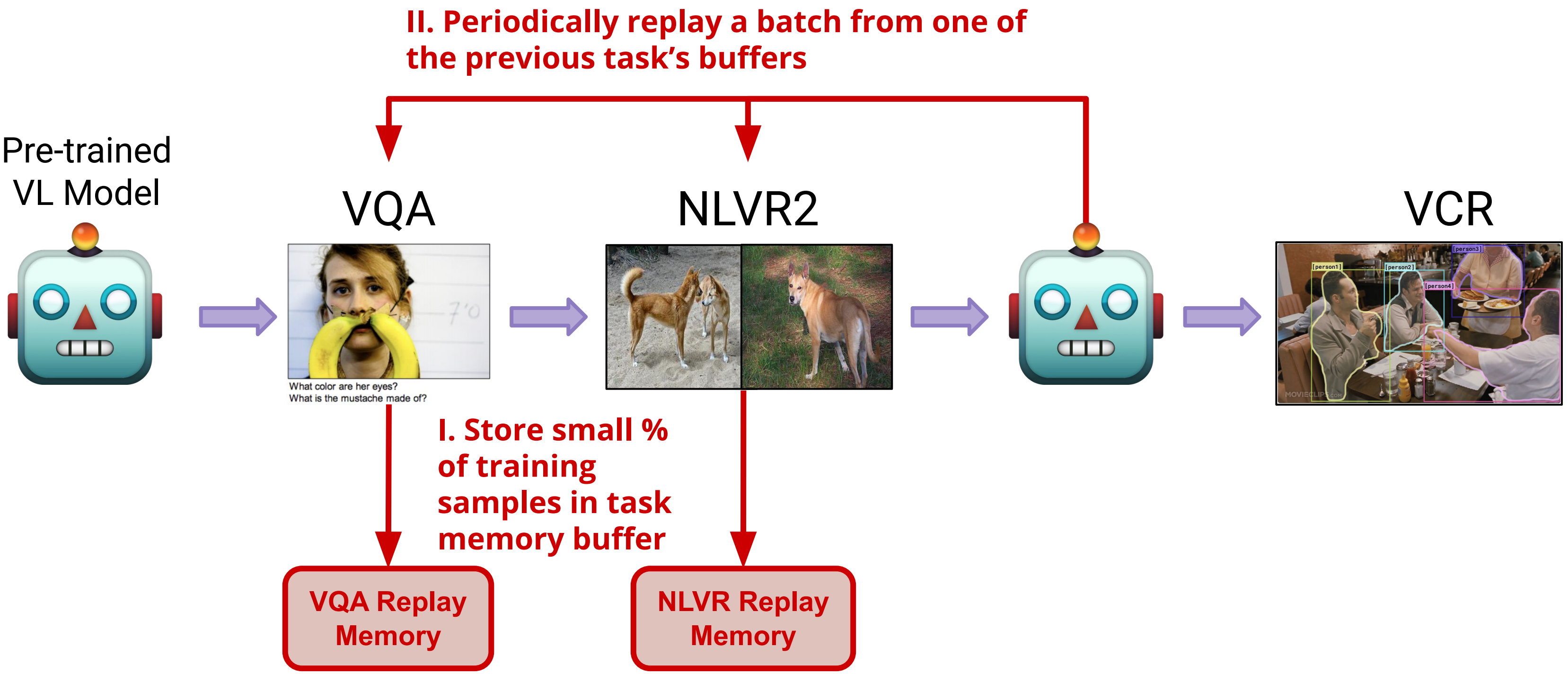


III. Continual Learning Algorithms

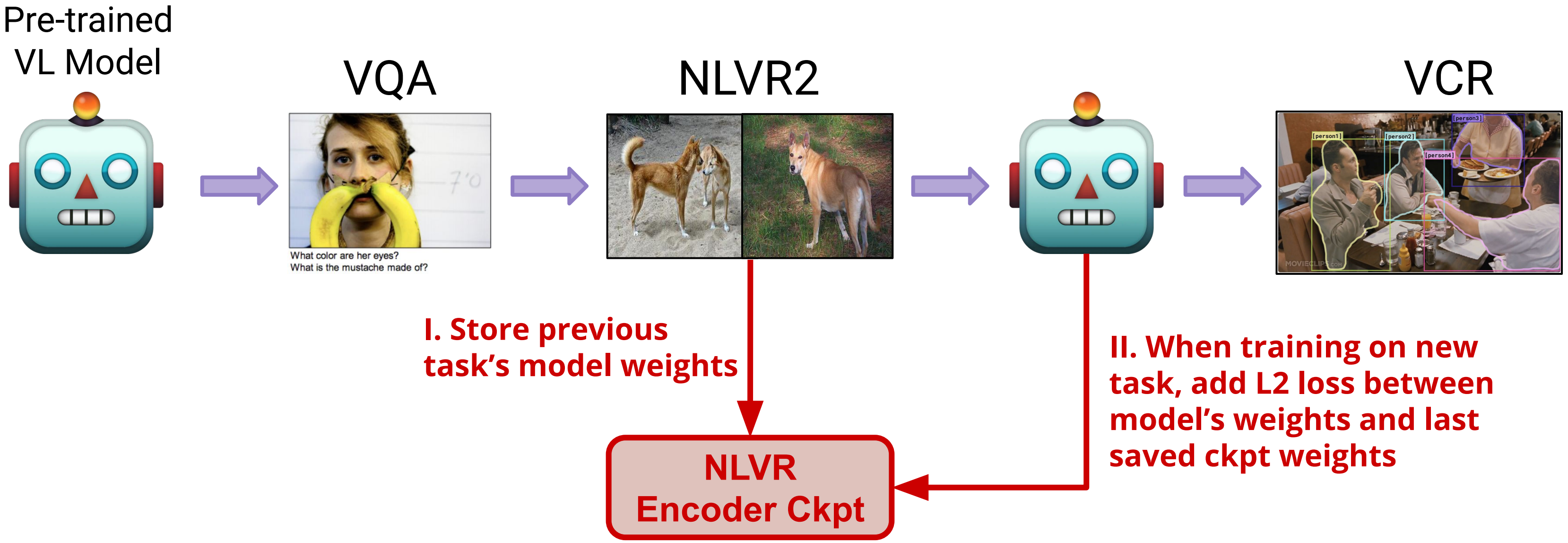
Currently, CLiMB supports 6 different Continual Learning algorithms:

- **Sequential Fine-tuning:** Fine-tune full encoder and task-specific layers
- **Frozen Encoder:** Train only task-specific layers
- **Frozen Bottom-K:** Fine-tune only top encoder layers and task layers
    - We set K=9
- **Experience Replay (ER)**
- **Elastic Weight Consolidation (EWC)**
- **Adapters**

Experience Replay



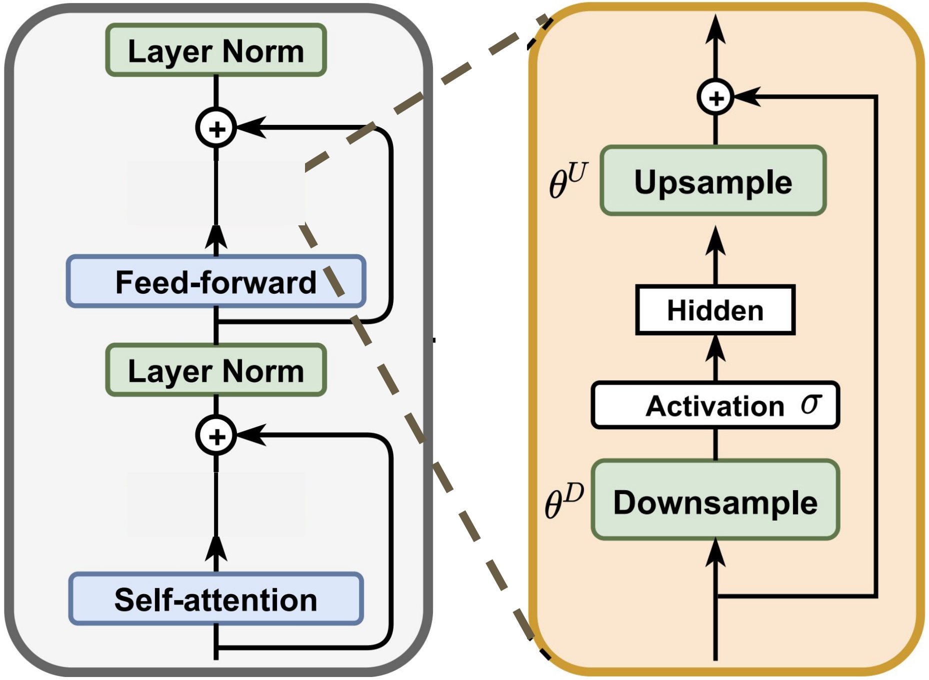
Elastic Weight Consolidation



Adapters

Insert new task-specific parameters into Transformer layers

- Transformer parameters kept frozen - **no forgetting!**
- **Fewer learnable parameters, faster to train**
- **Comparable performance as full model fine-tuning**
- **No cross-task knowledge transfer**



Transformer Layer

Adapter Module

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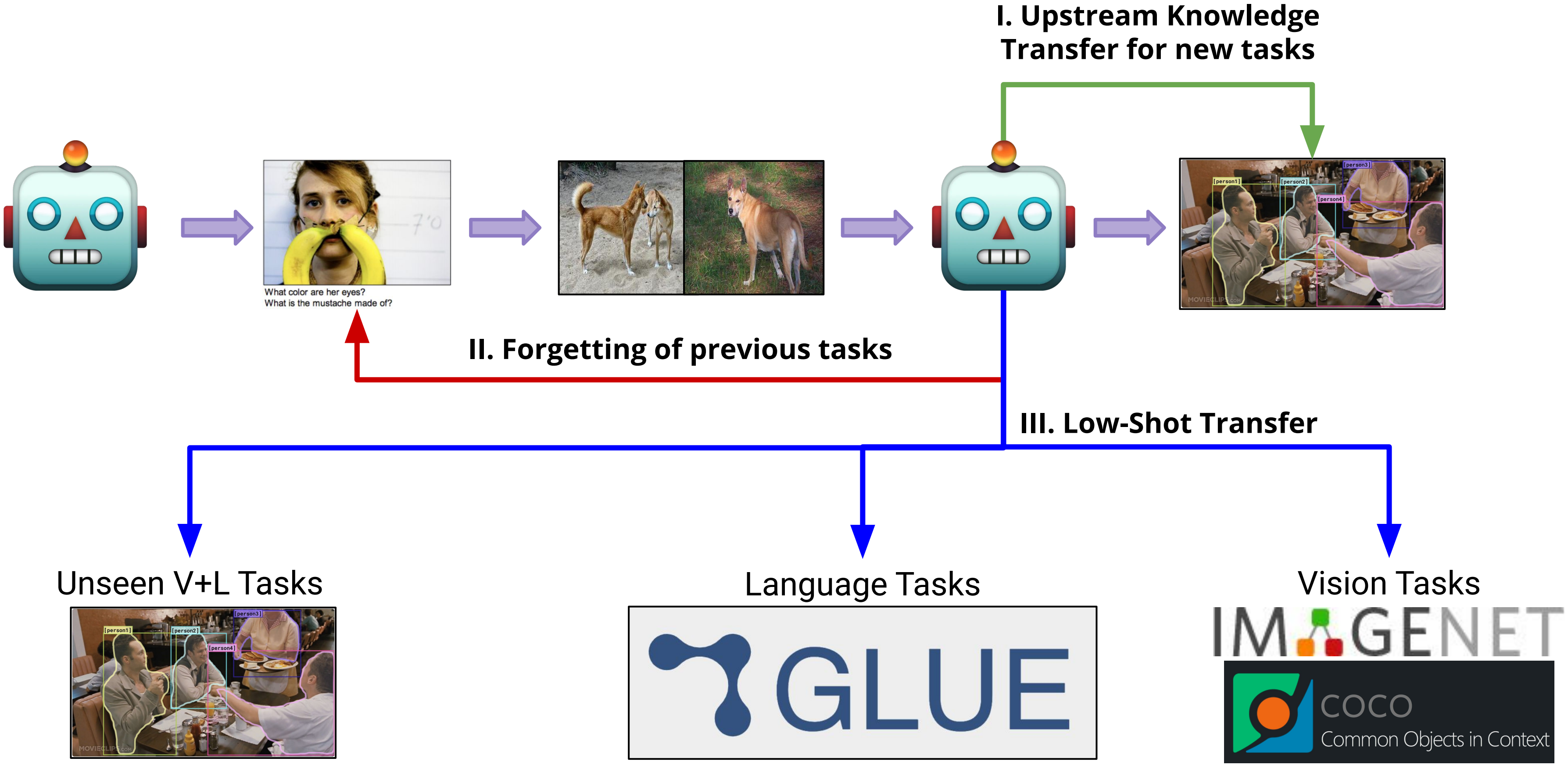
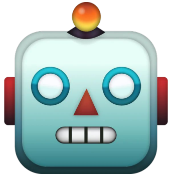
IV. Evaluation



Upstream Evaluation I: Upstream Knowledge Transfer

With Continual Learning Algorithm A:

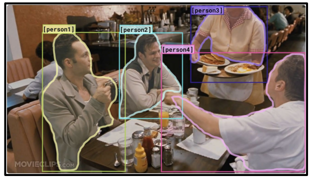


VQA

NLVR2

...

VCR

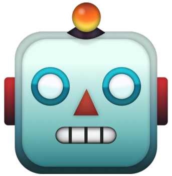


Score S^i_A

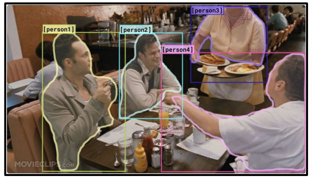
Tasks {1,...,i-1}

Task i

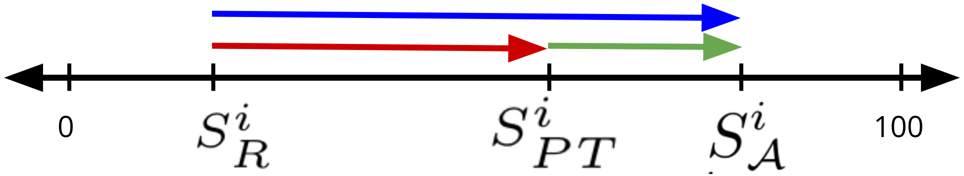
Without Continual Learning:



VCR



Score S^i_{PT}



$$\mathbb{T}_{UK}(i) = \frac{S^i_A - S^i_{PT}}{S^i_{PT} - S^i_R}$$

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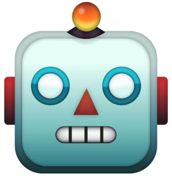
Upstream Evaluation II: Forgetting Transfer

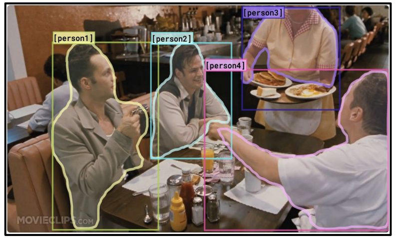
Directly evaluate on previously learned task j

Score $S_{\mathcal{A}}^{j \leftarrow i}$



...

Task j: VCR

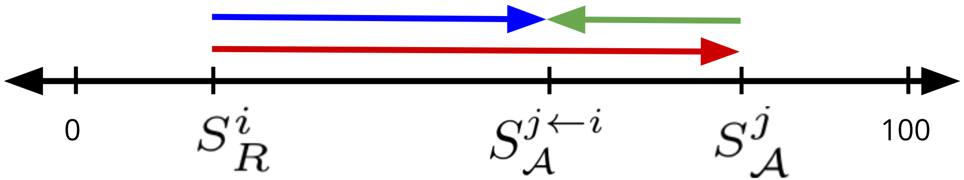


Score $S_{\mathcal{A}}^{j}$

...

Task i: SNLI-VE

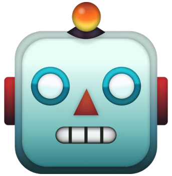
A man shoots a basketball
Contradiction



$$\mathbb{T}_F(j \leftarrow i) = \frac{S_{\mathcal{A}}^{j} - S_{\mathcal{A}}^{j \leftarrow i}}{S_{\mathcal{A}}^{j} - S_R^{j}}$$

Downstream Evaluation: Low-Shot Transfer

With Continual Learning Algorithm $\mathcal{A}$:

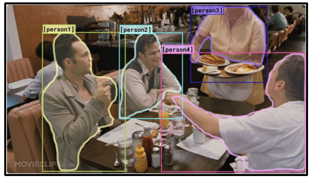


VQA

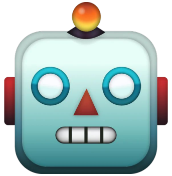
What color are her eyes?
What is the mustache made of?

...

VCR



Task i



Low-Shot V+L/V/L Task

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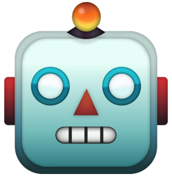
Score $S_{\mathcal{A}}^{LS(i)}$

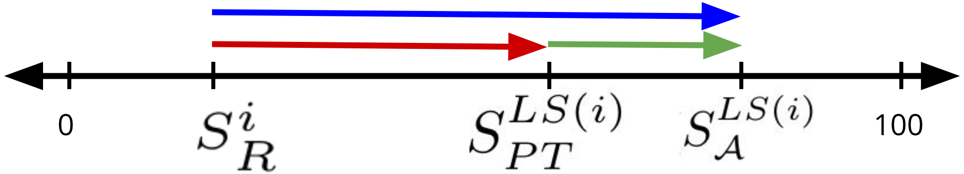
Without Continual Learning:



Low-Shot V+L/V/L Task

IMAGENET

Score $S_{PT}^{LS(i)}$



$$\mathrm{T}_{LS}^{M}(i) = \frac{S_{\mathcal{A}}^{LS(i)} - S_{PT}^{LS(i)}}{S_{PT}^{LS(i)} - S_R^i}$$

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Experiments I: Upstream Continual Learning

- 4 V+L Tasks, ordered **VQA → NLVR2 → SNLI-VE → VCR**
- **ViLT**-based continual learning model
- **6** different Continual Learning algorithms

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Results I: Upstream Continual Learning

Upstream Knowledge Transfer: How does Continual Learning affect model's ability to learn newly arriving tasks?

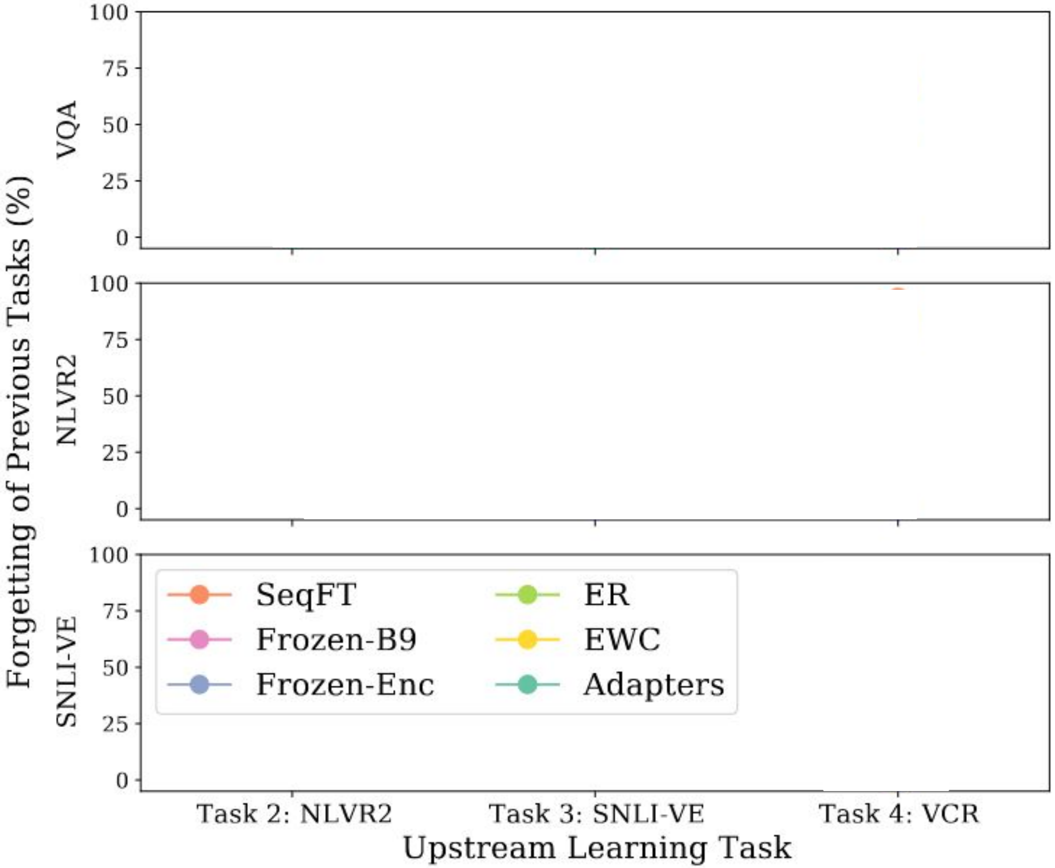
Alg $\mathcal{A}$	Params Trained	Task 1 VQAv2	Task 2 NLVR2	Task 3 SNLI-VE	Task 4 VCR
Direct FT	100%	[67.70]	[73.07]	[76.31]	[61.31]

- **More continual learning hurts ability to learn new tasks**
- **Adapters do not show negative transfer**, comparable to full model fine-tuning

Results I: Upstream Continual Learning

Forgetting: How does learning new tasks affect model's performance on already-learned tasks?

- **More fine-tuned params == more forgetting**
- **ER > EWC**
- **Adapters >>>>**
- **Forgetting more severe after VCR**

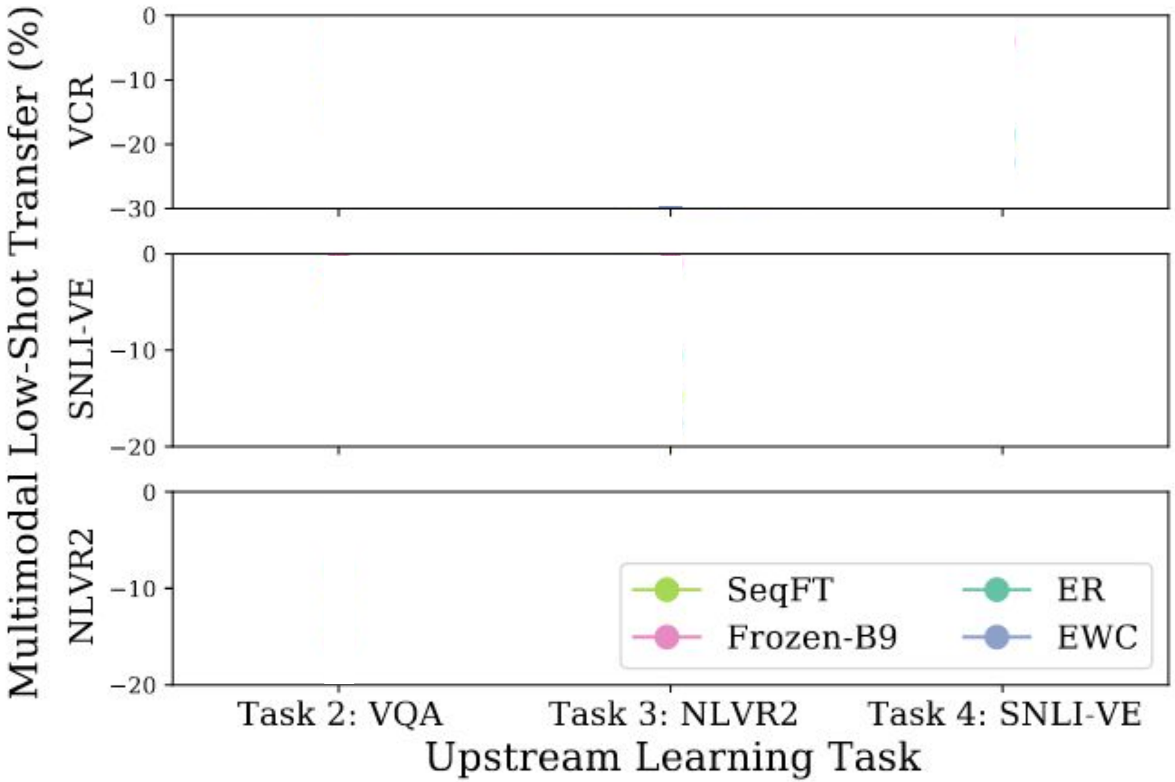


Effect of Continual Learning Task Order

Experiments and Results II: Downstream Low-Shot Transfer

Low-Shot Transfer to Unseen V+L Tasks

- **Low-Shot transfer is always negative**
- **Unsurprising — CL also hurts model transfer with full training data**

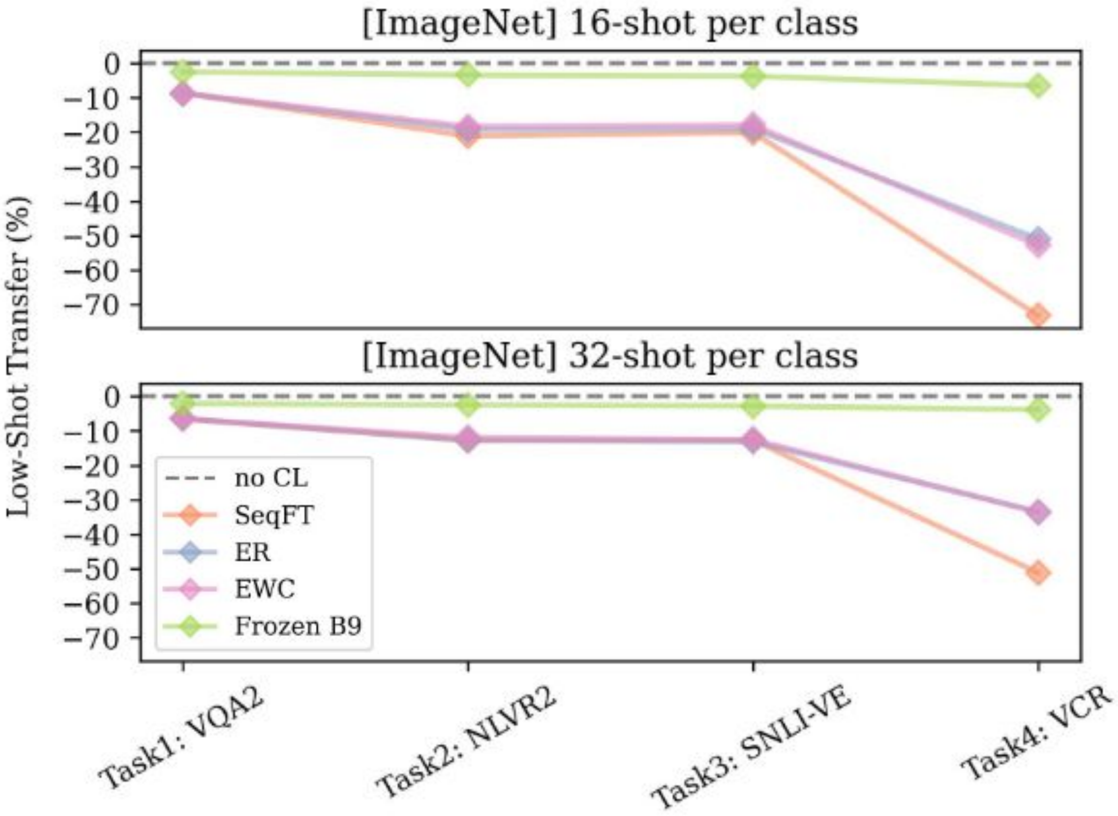


Experiments and Results II: Downstream Low-Shot Transfer

Low-Shot Transfer to Vision-Only Tasks

Language prompt: "This is an image."

- **ViLT achieves good low-shot performance on vision tasks**
- **CL hurts low-shot transfer**
- **NLVR2 and VCR have more negative effect**

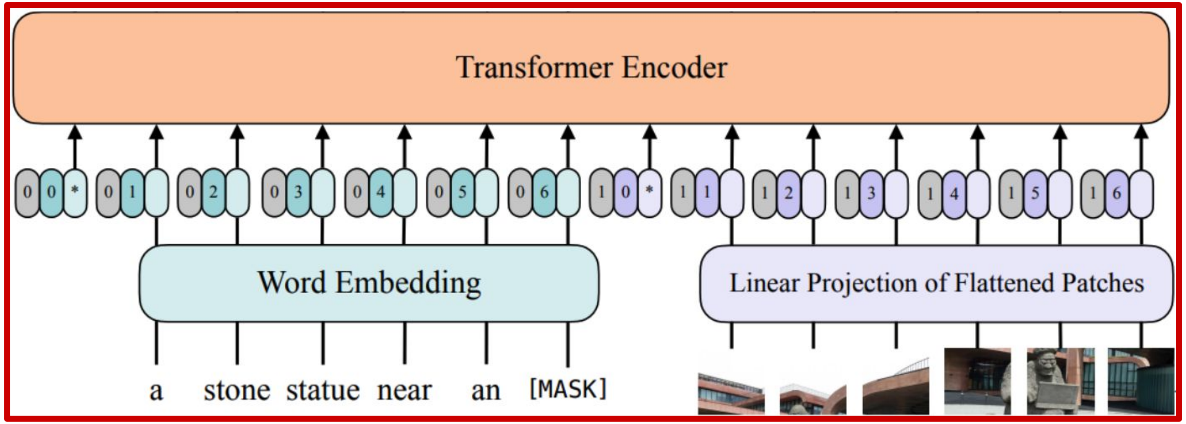


Experiments and Results II: Downstream Low-Shot Transfer

Low-Shot Transfer to Language-Only Tasks

Adapting ViLT for NLP tasks:

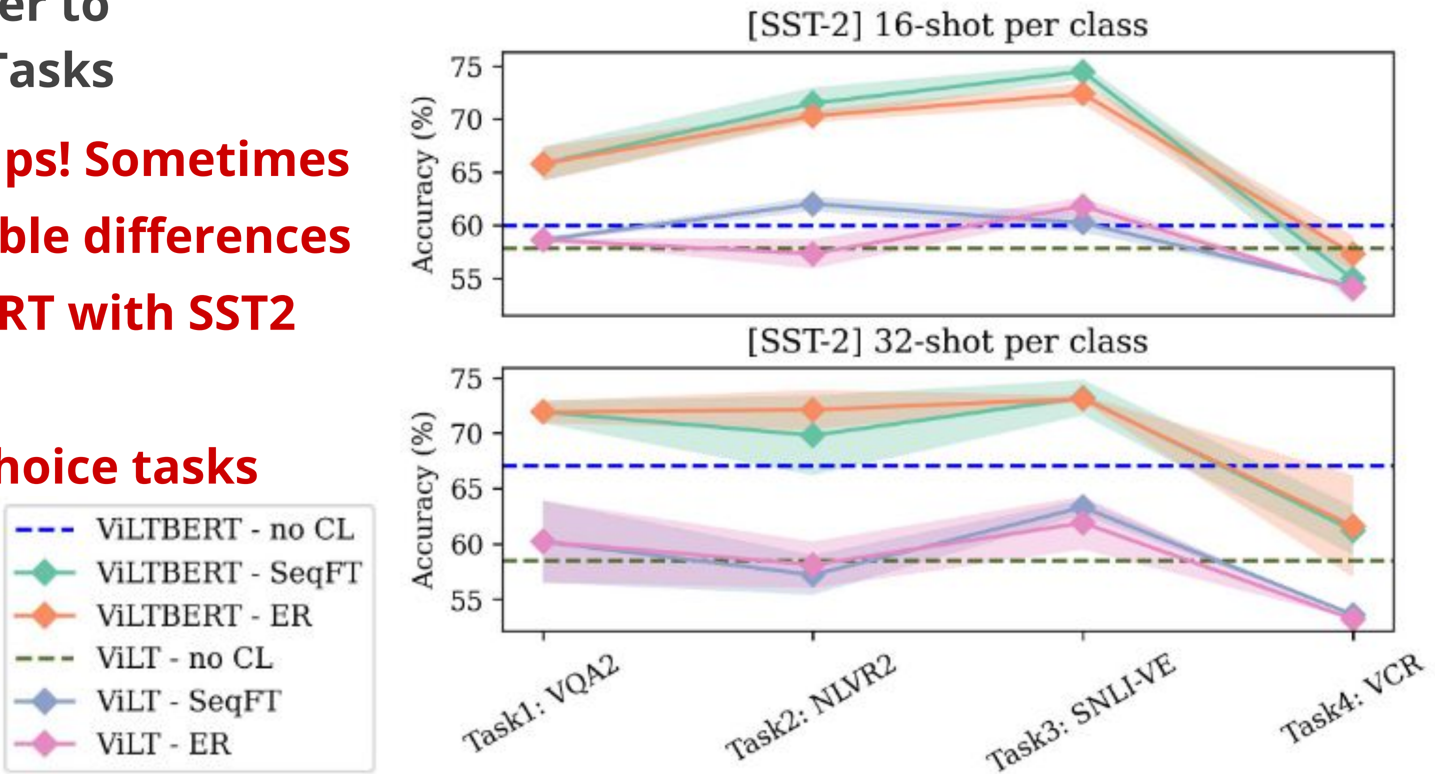
- Use **“average” MS-COCO image** for in-distribution visual input
- **Extend** language position embeddings
- **ViLT-BERT:** Replace language input embeddings with BERT representations



Experiments and Results II: Downstream Low-Shot Transfer

Low-Shot Transfer to Language-Only Tasks

- Upstream CL helps! Sometimes
- ViLT sees negligible differences
- CL helps ViLT-BERT with SST2
- VCR hurts SST2
- CL hurts multi-choice tasks



Conclusions

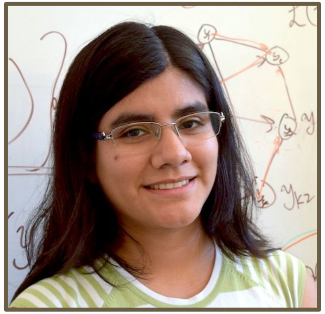
- We propose **CLiMB**, a benchmark to study CL in multimodal settings
- CLiMB is an **extensible community tool** for studying tasks, model architectures, and CL algorithms.
- **Existing Continual Learning methods fail** at:
  - generalizing well to sequences of multimodal tasks
  - Enabling low-shot adaptation to multi/unimodal tasks
- **Adapters are most effective** at preserving pre-trained model knowledge and forgetting mitigating
- There is **a need for new research** into Continual Learning strategies for this challenging multimodal setting.

Future Directions

- **Adapters that share knowledge across tasks**
- **Multimodal Adapters**
- Studying **multimodal distribution shifts**
- Building a **task-agnostic** modeling framework:
  - Sequence-to-sequence task formulations
  - Integrating **generalist models** into CLiMB
  - **Embodied** navigation, task completion

Acknowledgements

Ting-Yun Chang✨



Leticia Pinto Alva✨

Georgios Chochlakis

Mohammad Rostami

Jesse Thomason ✨

Thank You!!

https://github.com/GLAMOR-USC/CLiMB