



THU-PM-274



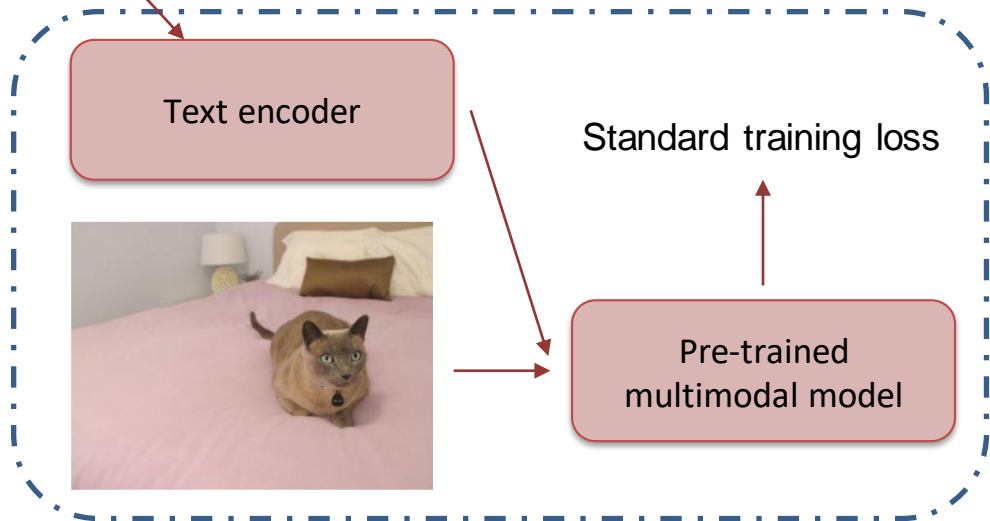
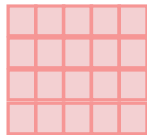
Learning to Name Classes for Vision and Language Models

Sarah Parisot, Yongxin Yang, Steven McDonagh

Huawei Noah's Ark Lab

Adapt vision-language models to new dataset by **learning class names**

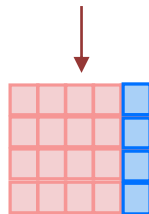
[prompt context] + [class name]



Adapt vision-language models to new dataset by **learning class names**

- Removes class name ambiguities
- Increases robustness to prompt context
- Language agnostic: adapt to model's observed language
- Directly applicable to both classification and object detection tasks

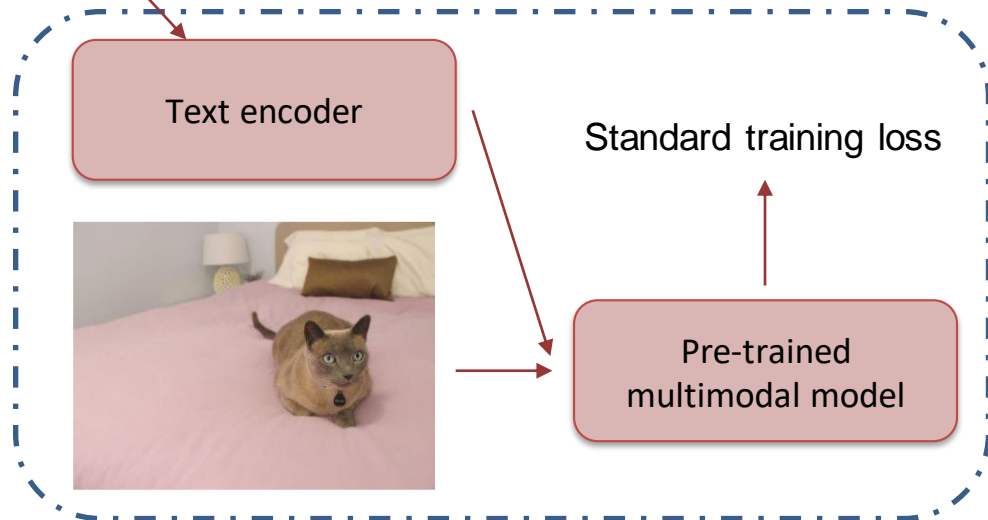
[prompt context] + [Placeholder]



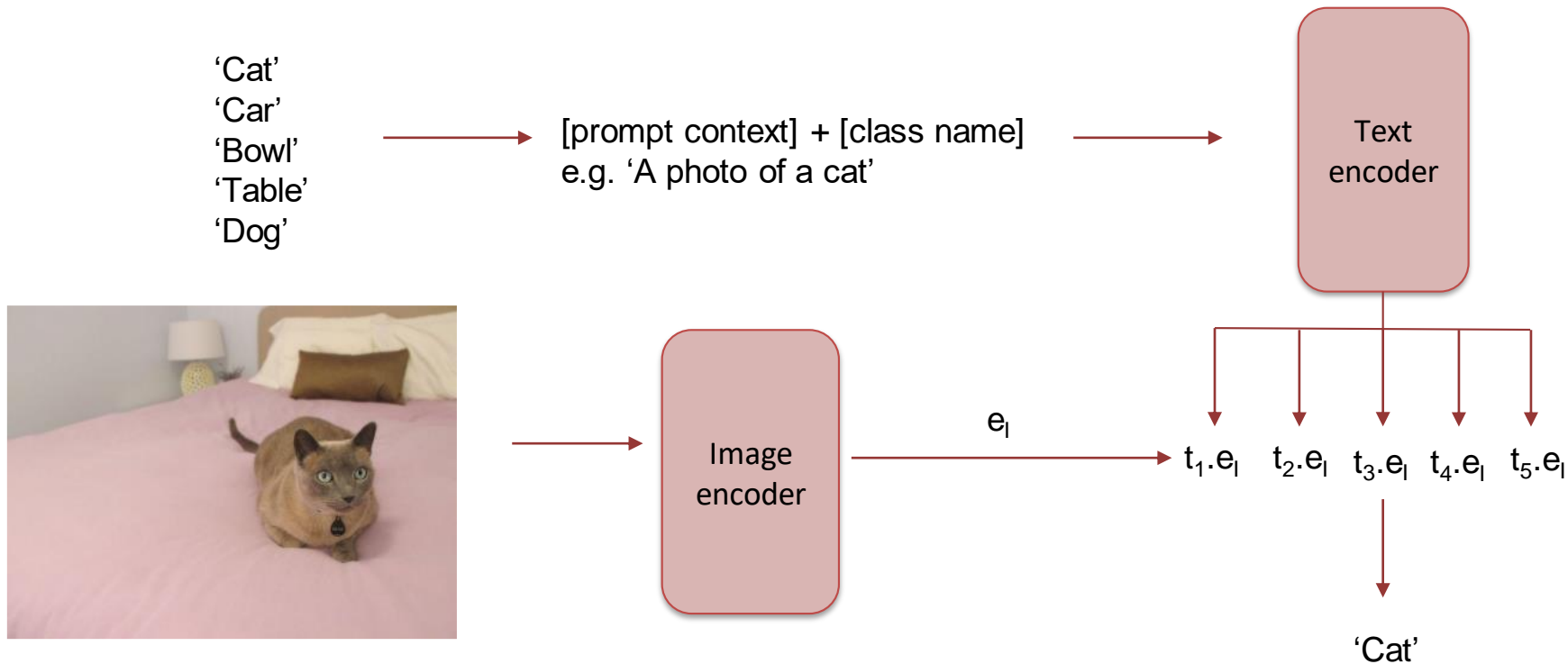
Learnable word embeddings



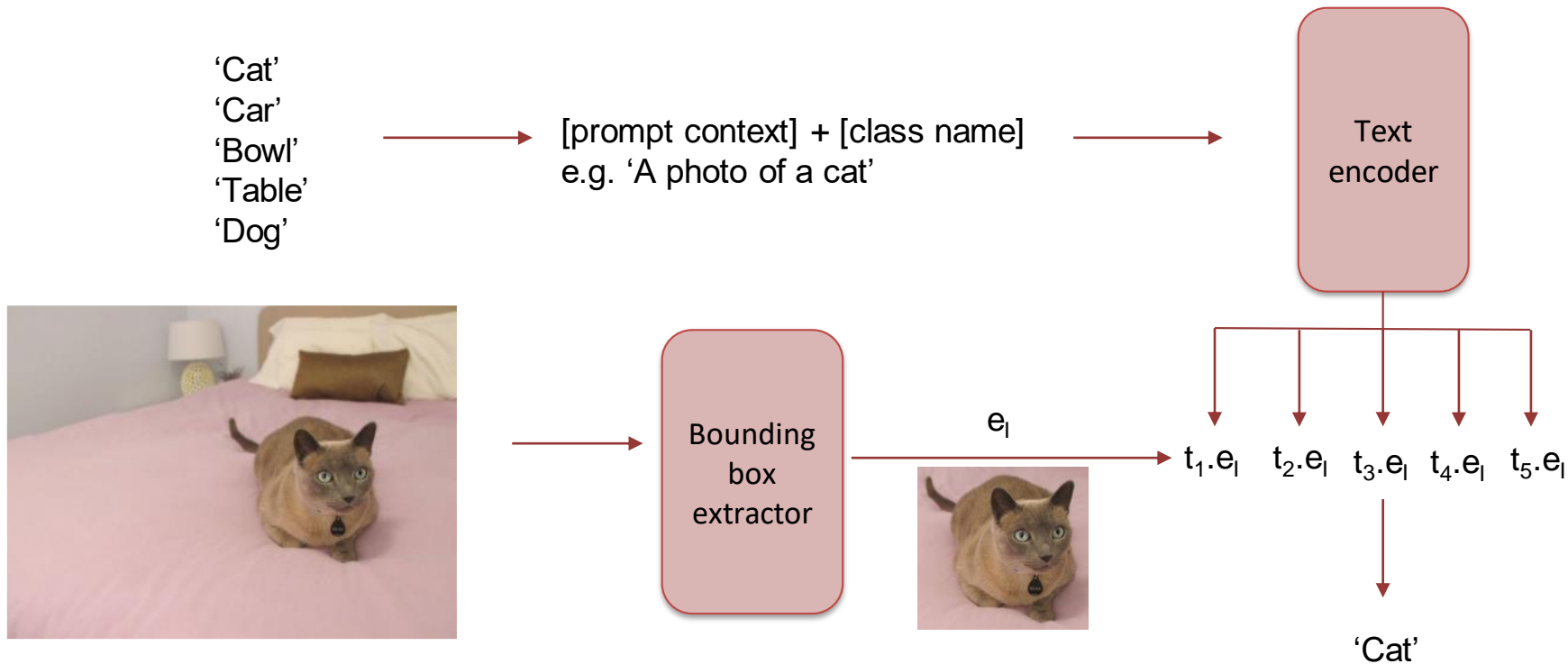
Cat
Car
Table
Bed



Vision-language classification models



Vision-language detection models

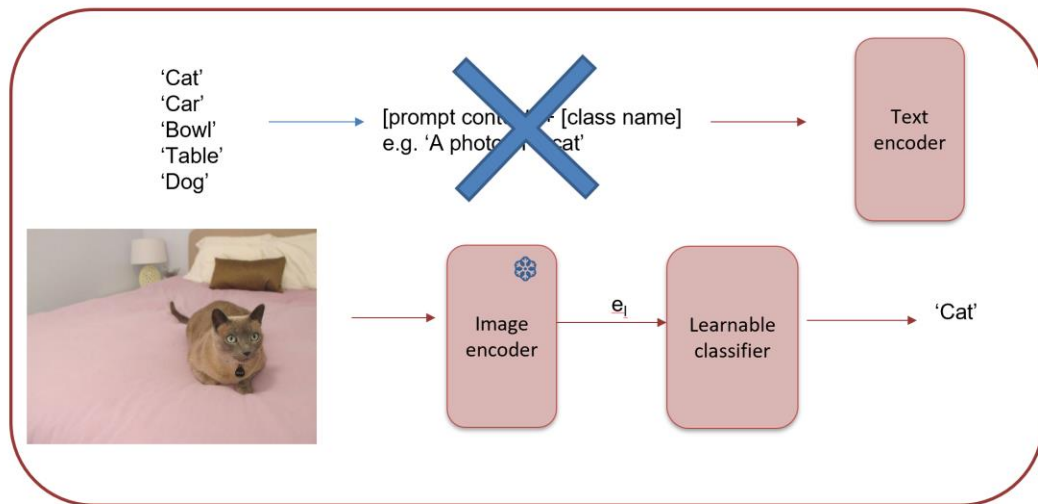
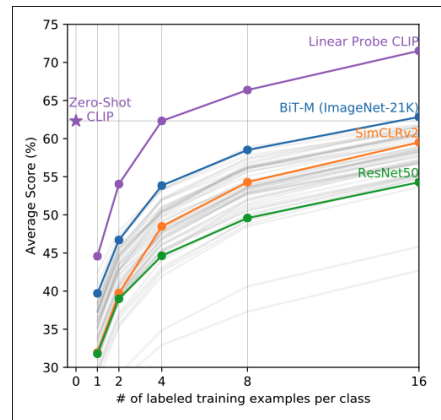


Fine-tuning

- Adapting vision-language models to new data: **challenging!**
 - Small dataset overfitting
 - Losing generalisation ability
- Linear probing
 - Train a standard linear classification layer using frozen image encoder

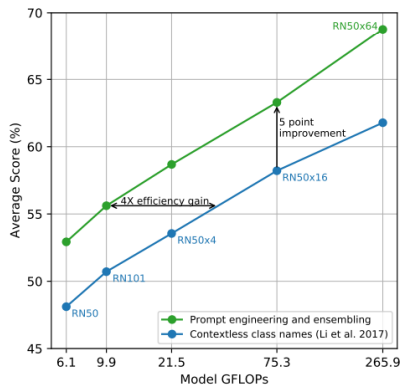
- ✓ Data efficient
- ✓ improves over zero-shot performance
- ✓ no hand-crafted text components

- ✗ Loses open-set and zero-shot properties



Sensitivity to prompt input

- Model performance is sensitive to text input



- Existing methods rely on *handcrafted* class names. Potentially:
 - Ambiguous
 - Too technical
 - Unrepresentative of image content

Ambiguous class names



Both named 'bow'



Both named 'bat'

Technical class names



Class name:
2007 Cadillac Escalade EXT Crew Cab



Class name:
A340-200

Prompt context learning

- Learn prompt context word embeddings (frozen vision-language)

Data efficient

- ✓ Improves over zero-shot performance
- ✓ Address prompt sensitivity limitations
- ✓ Maintain open-set properties
- ✗ Relies on handcrafted class names
- ✗ Difficult continual adaptation
- ✗ Weak object detection performance

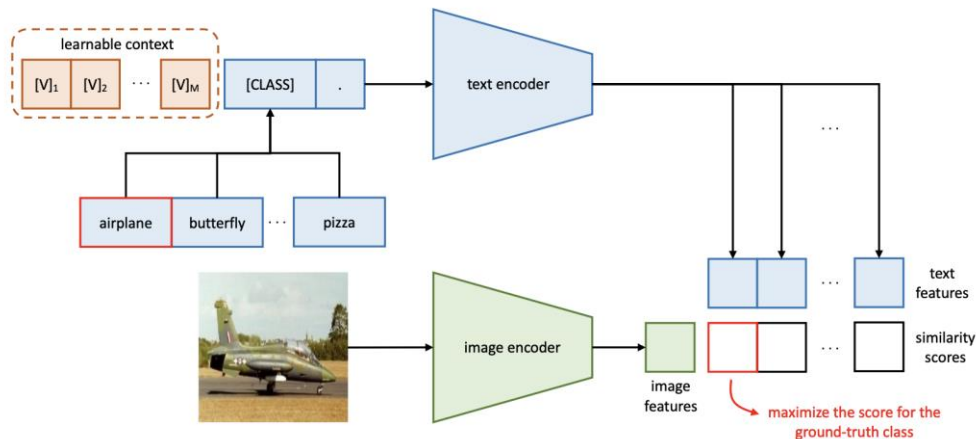
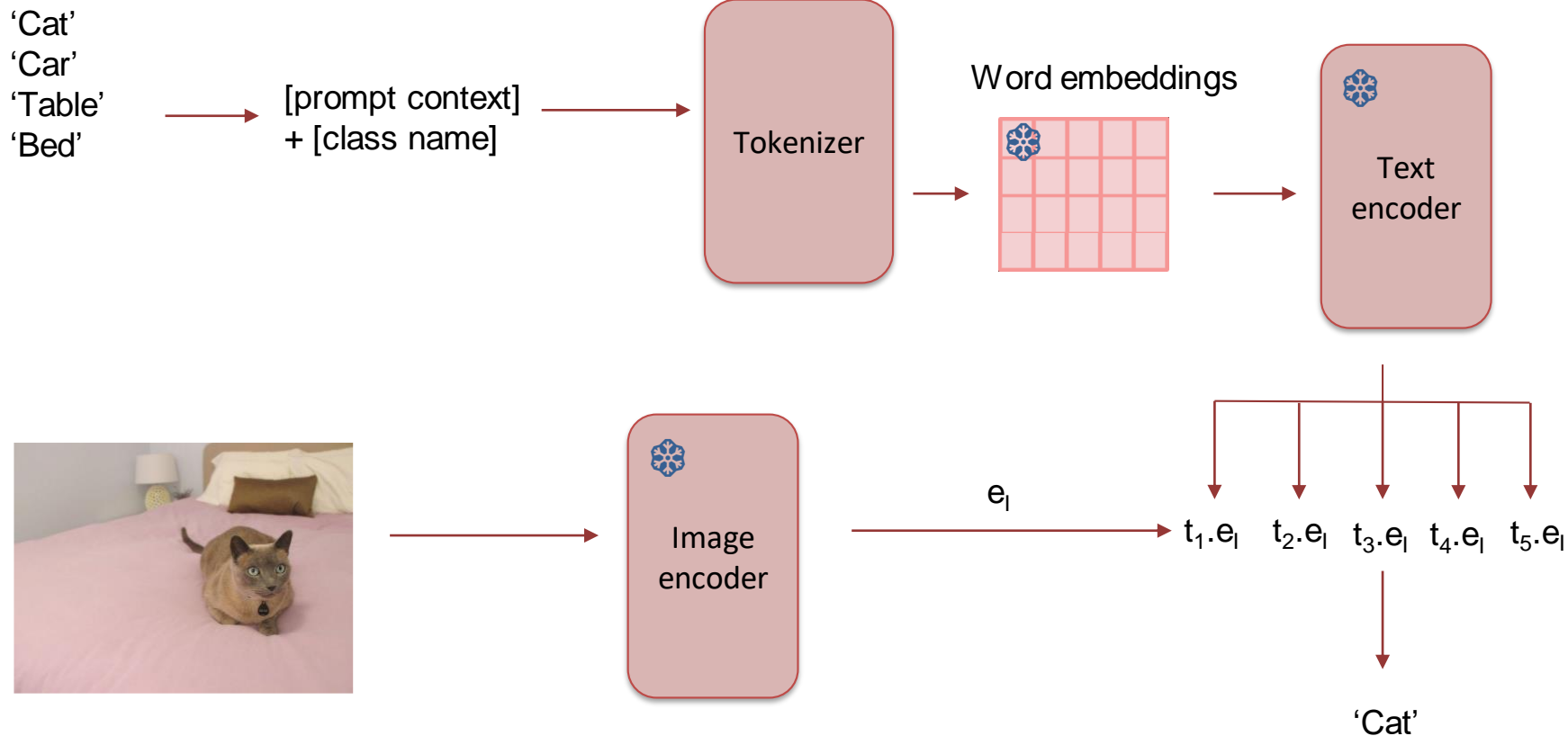
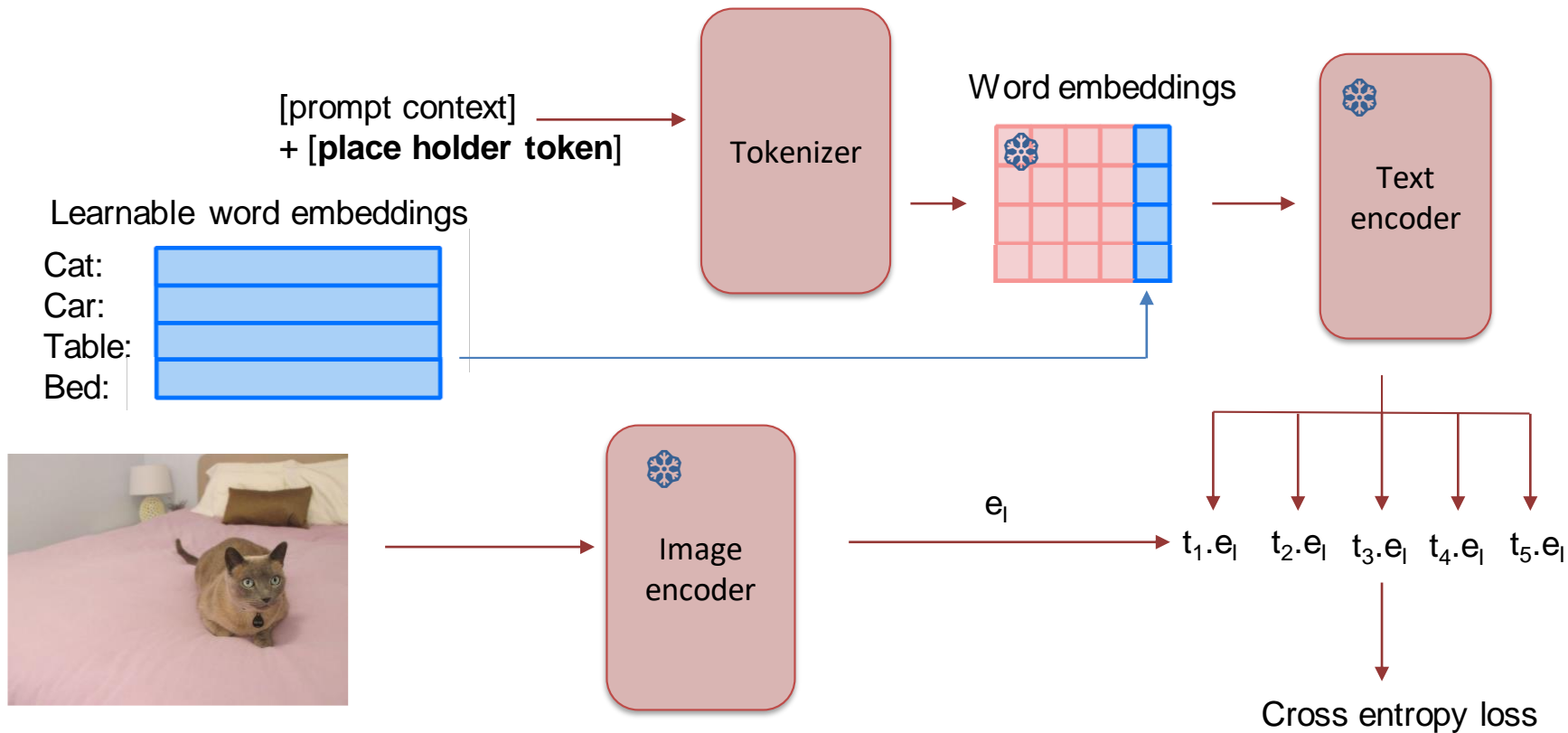


Figure 2: Overview of context optimization (CoOp).

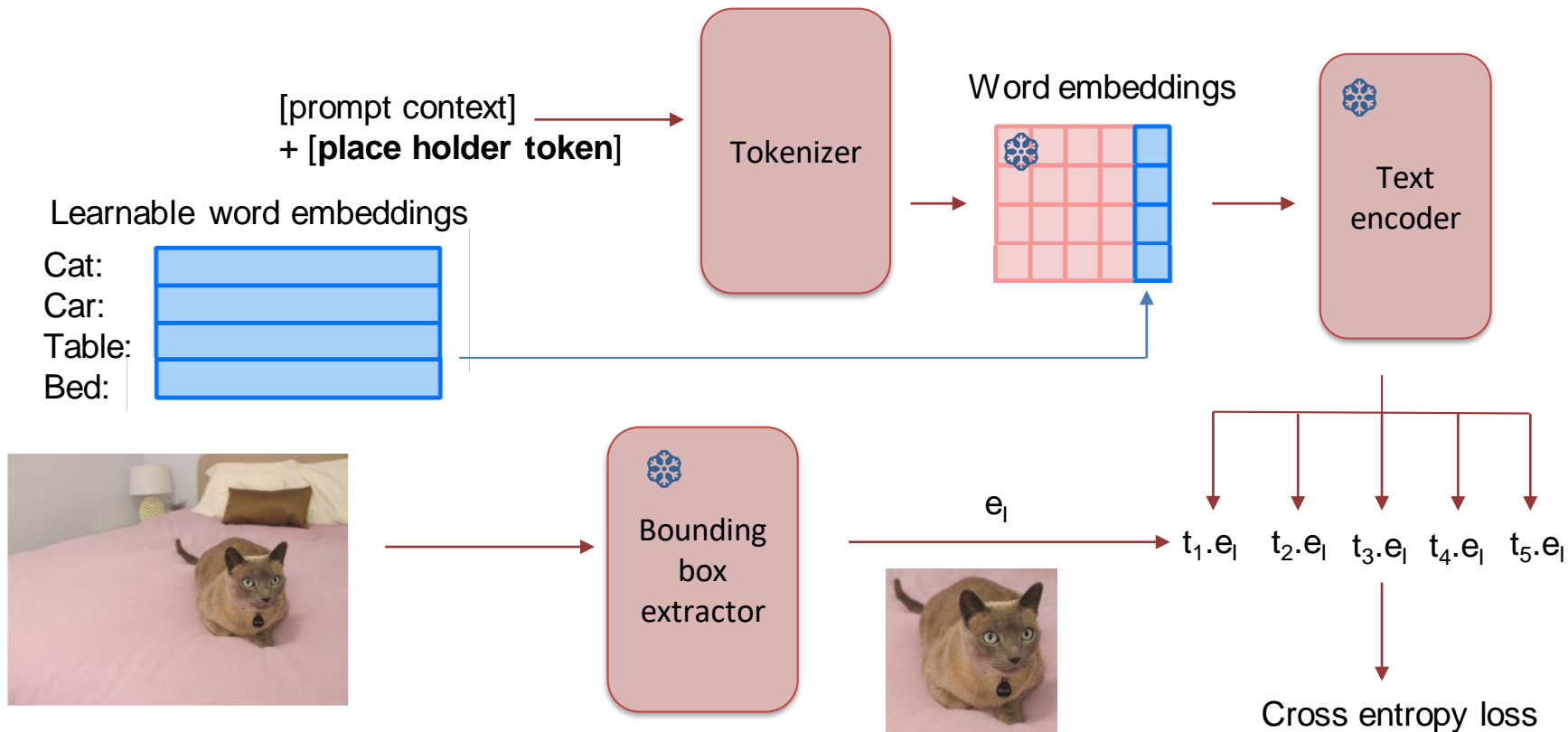
Proposed solution



Proposed solution



Proposed solution



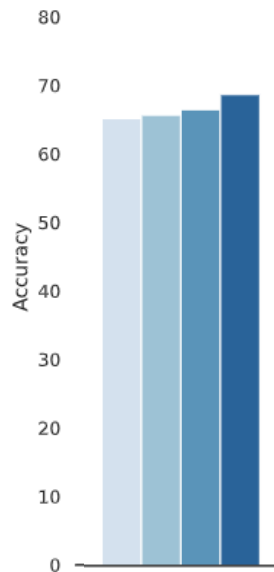
Experiments: classification with CLIP

- Outperforms SOTA in open-vocabulary and sequential training settings
- Learning all class names strongly reduces dependency on prompt context

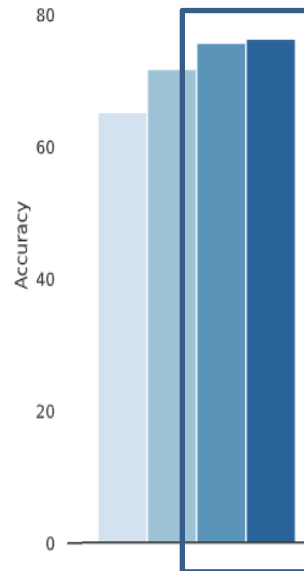
Method - * with engineered context



Open-vocabulary setting:
learning half of the dataset
class names

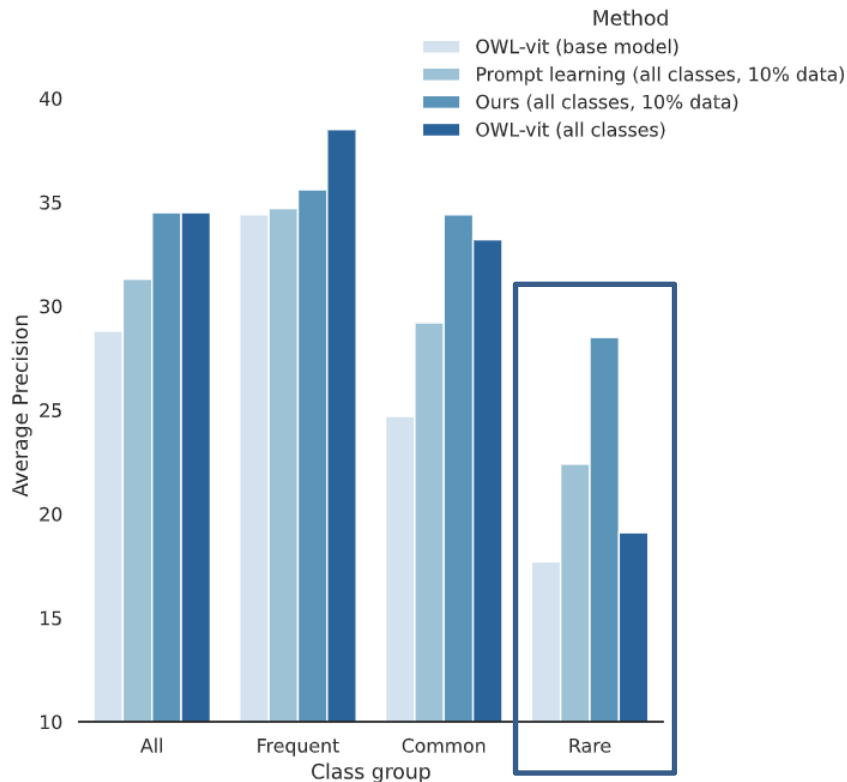


Sequential training setting:
learning two sets of class
names sequentially

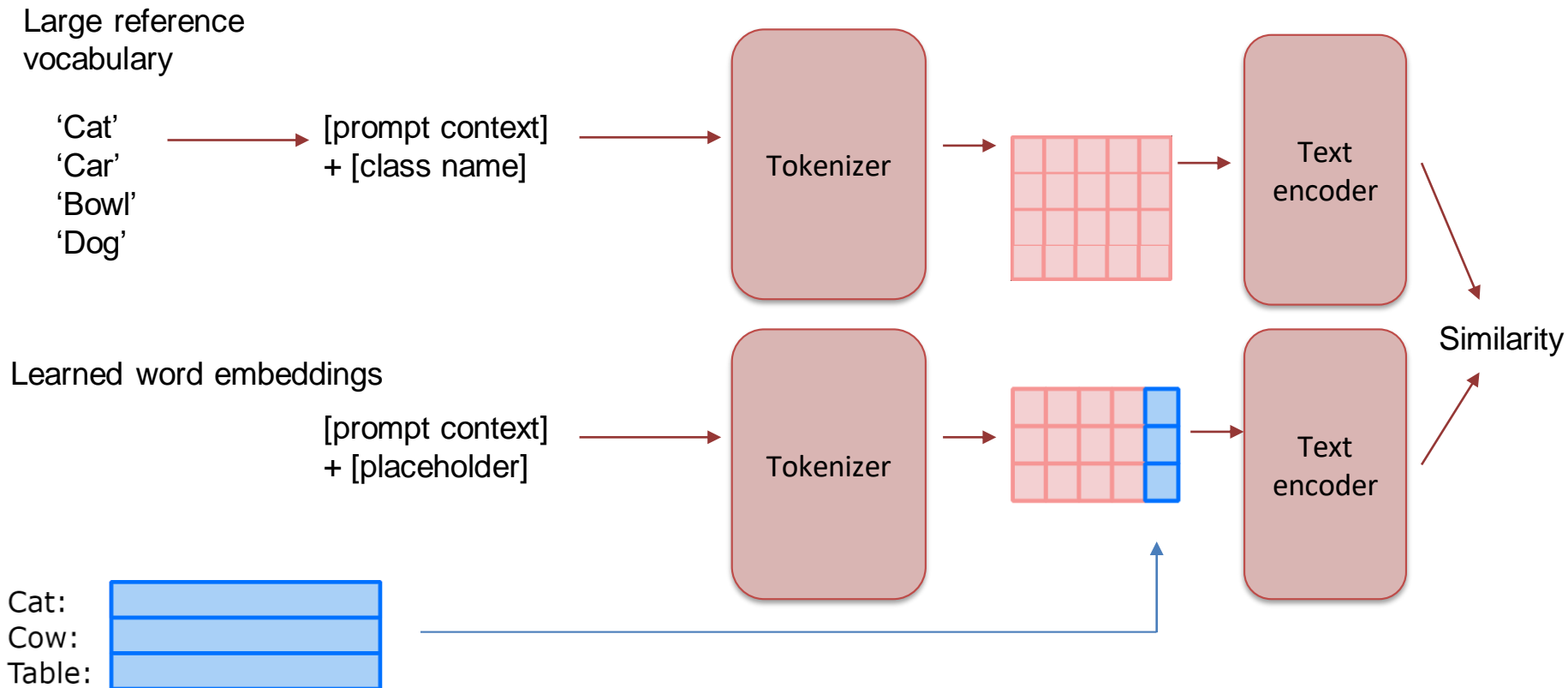


Experiments: Object detection with OWL-vit

- Learning class names (10% of data) – match performance of fully fine-tuned model
- Significant performance improvement for rare classes
- Significant gains compared to prompt context learning



Interpretability



Interpretability



Original name:
Arctic



Boot, ski boot



Original name:
Tricycle



Cart, rickshaw



Original name:
Miscellaneous



wheel, waterwheel



Interpretability

Identifying model biases: American English over British English

Original name:

Clothes hamper



Laundry basket

Original name:

Wall socket



Power outlet

Original name:

Postbox



Mailbox

Original name:

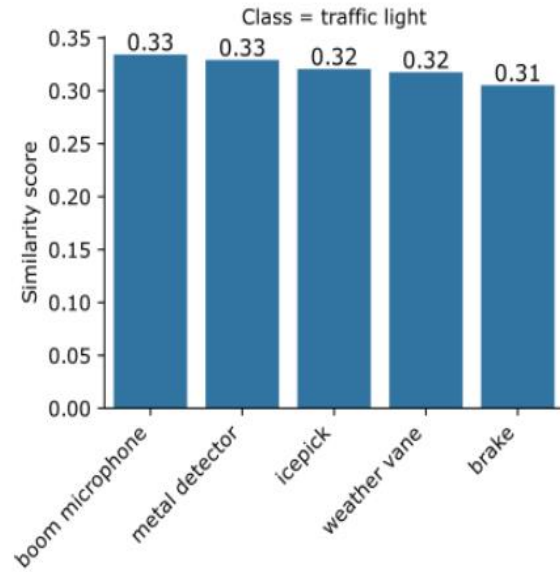
Trousers



Clothes, Pants

Interpretability

Potential to identify mislabelled data and failures modes of our method



class examples



Conclusion

- Novel data efficient adaptation for vision-language models
 - Removes dependency on hand-crafted class names
 - Learn optimal class word embeddings from visual content
- Out of the box usage on classification, detection models
- Complementary to prompt context learning methods
- High interpretability



THU-PM-274

JUNE 18-22, 2023

CVPR



VANCOUVER, CANADA

Learning to Name classes for Vision and Language Models

Sarah Parisot, Yongxin Yang, Steven McDonagh

Huawei Noah's Ark Lab

Paper:

