



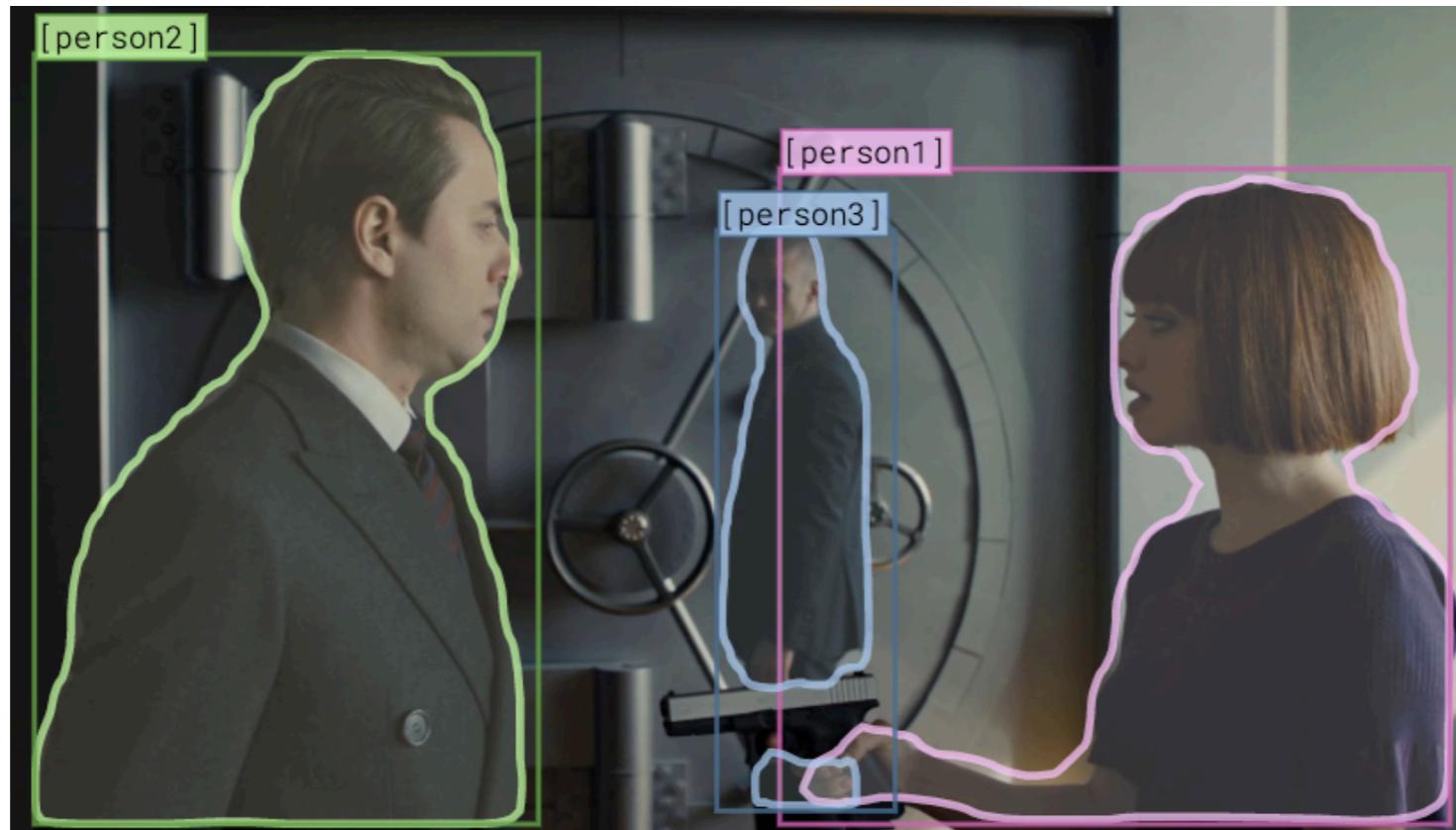
# VL-BERT: Pre-training of Generic Visual-Linguistic Representations

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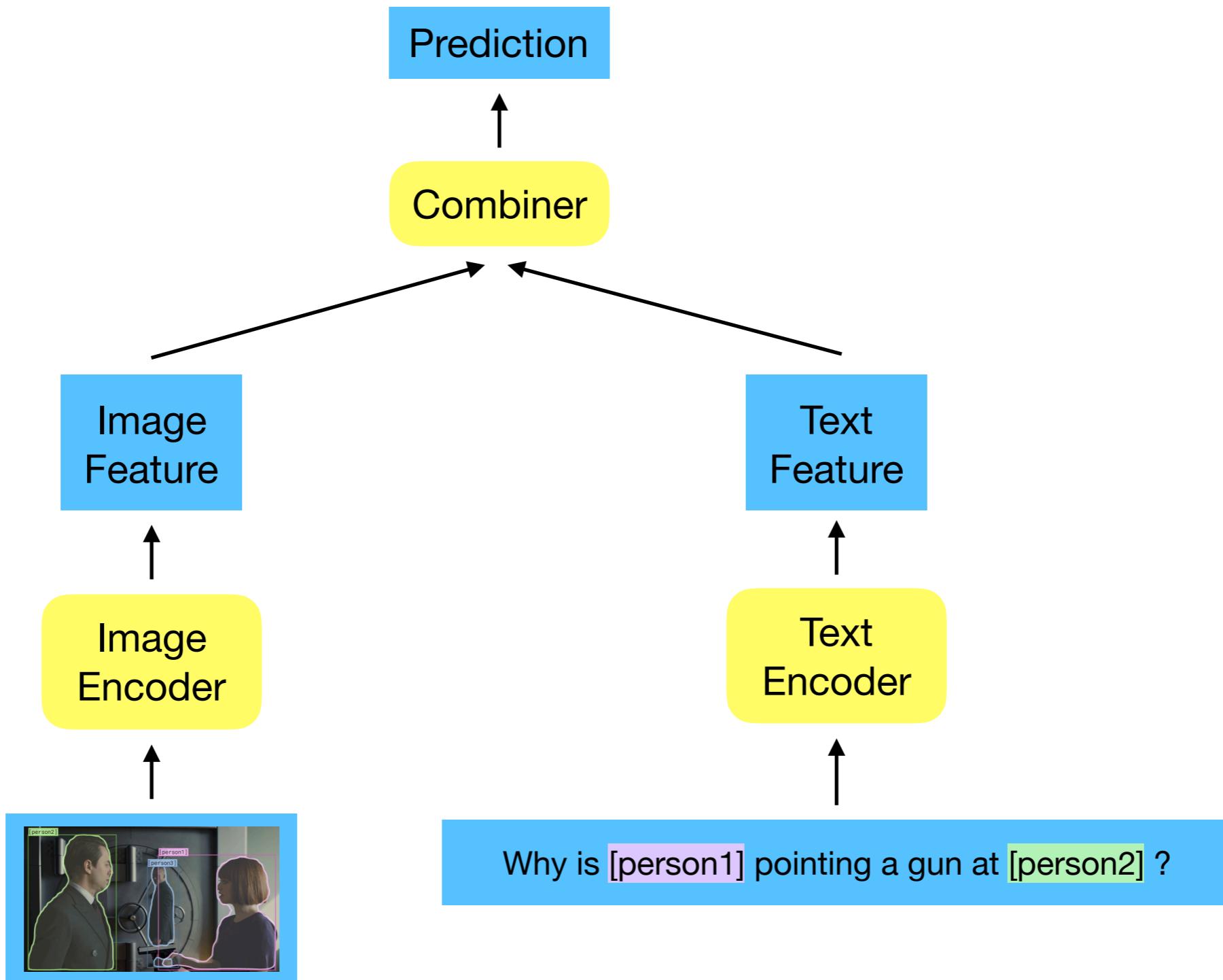
# An Example of Visual-Linguistic Tasks



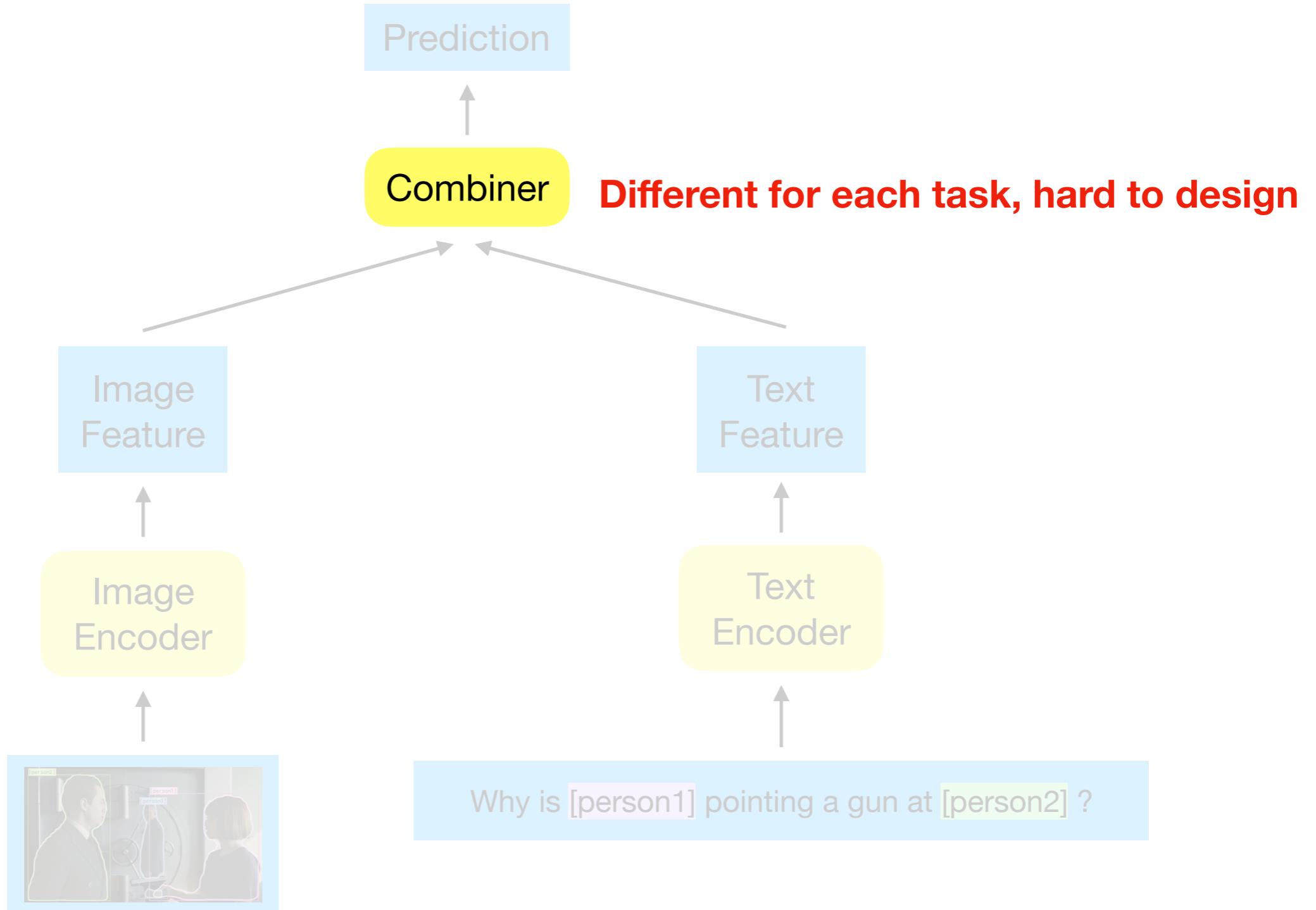
*Question* Why is [person1] pointing a gun at [person2] ?

*Answer* [person1] and [person3] are robbing the bank and [person2] is the bank manager

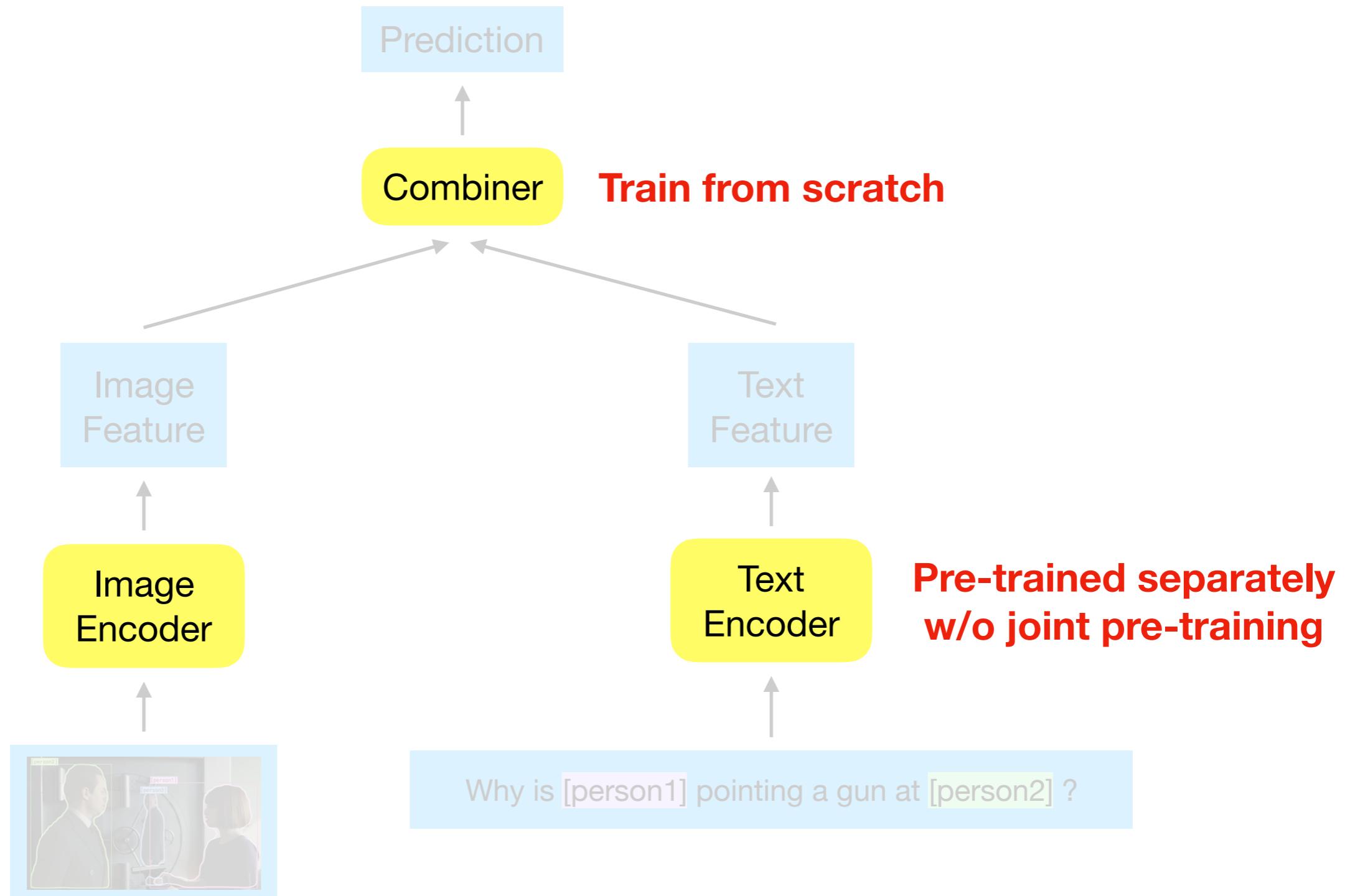
# Previous Paradigm



# Problem (I) High Design Cost



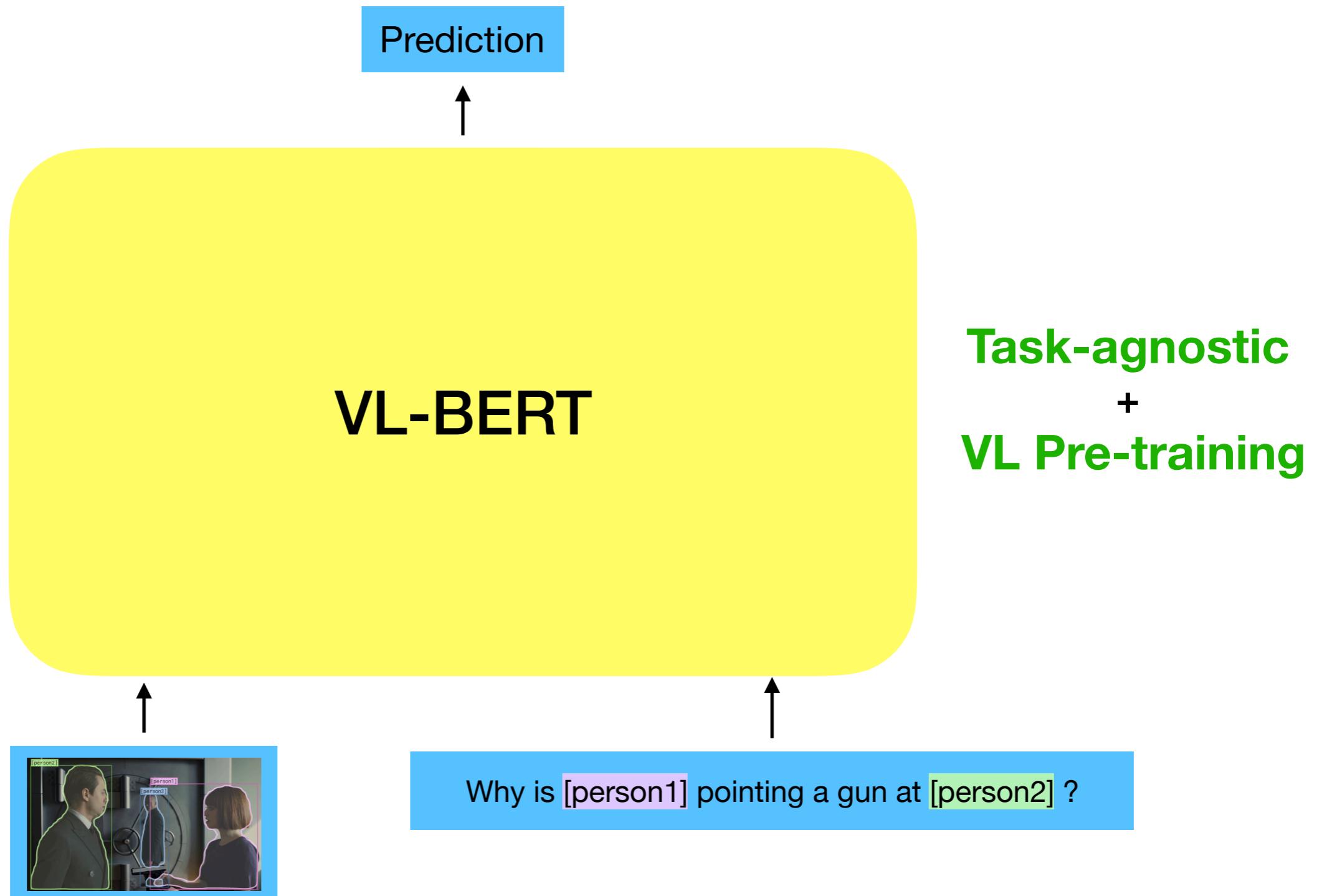
# Problem (II) Overfitting



# Inspiration

- Transformer is a unified and powerful architecture in NLP
- It can aggregate and align word embedded features
- MLM based pre-training in BERT enhances the capability

# Solution



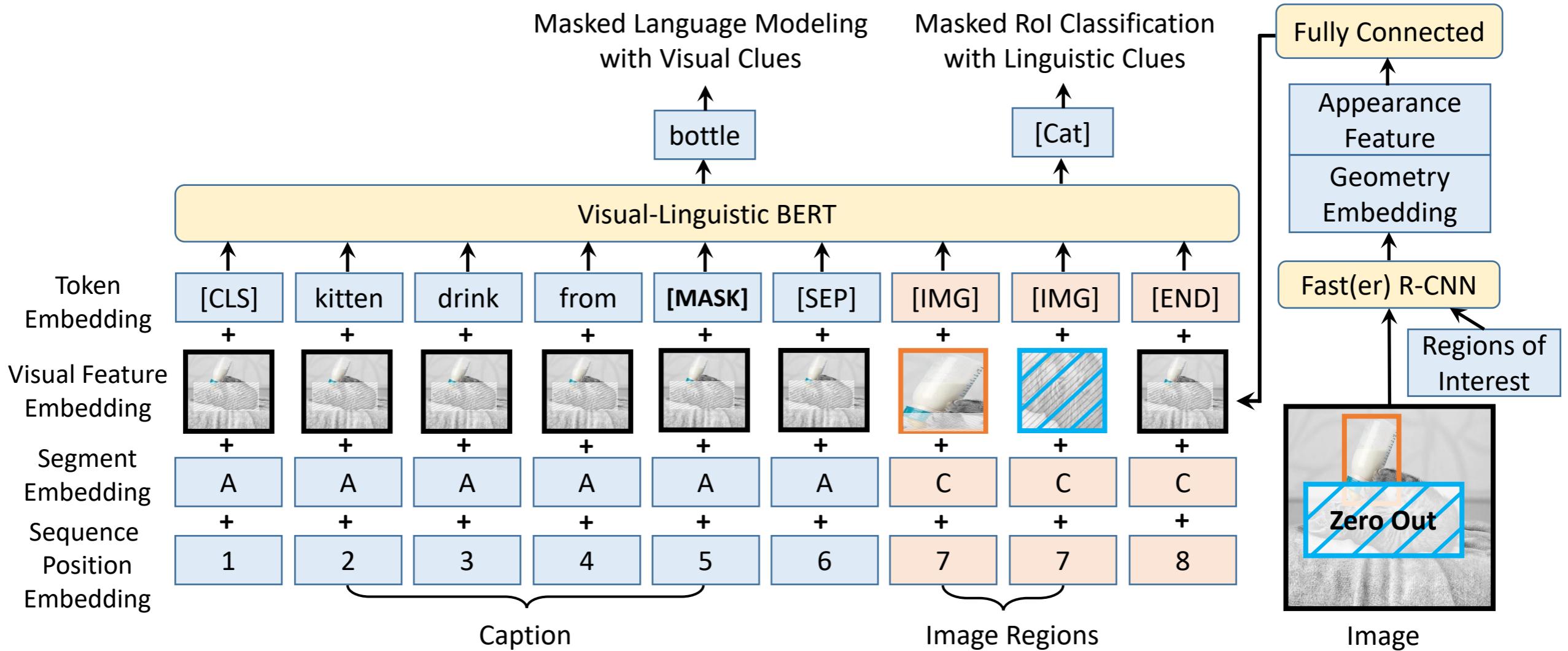
# Lots of concurrent works in just 3 weeks!

	Method	Architecture	Visual Token	Pre-train Datasets	Pre-train Tasks	Downstream Tasks
Published Works	VideoBERT <a href="#">(Sun et al., 2019b)</a>	single cross-modal Transformer	video frame	Cooking312K <a href="#">(Sun et al., 2019b)</a>	1) sentence-image alignment 2) masked language modeling 3) masked visual-words prediction	1) zero-shot action classification 2) video captioning
	CBT <a href="#">(Sun et al., 2019a)</a>	two single-modal Transformer (vision & language respectively) + one cross-modal Transformer	video frame	Cooking312K <a href="#">(Sun et al., 2019b)</a>	1) sentence-image alignment 2) masked language modeling 3) masked visual-feature regression	1) action anticipation 2) video captioning
	ViLBERT <a href="#">(Lu et al., 2019)</a>	one single-modal Transformer (language) + one cross-modal Transformer (with restricted attention pattern)	image ROI	Conceptual Captions <a href="#">(Sharma et al., 2018)</a>	1) sentence-image alignment 2) masked language modeling 3) masked visual-feature classification	1) visual question answering 2) visual commonsense reasoning 3) grounding referring expressions 4) image retrieval 5) zero-shot image retrieval
	B2T2 <a href="#">(Alberti et al., 2019)</a>	single cross-modal Transformer	image ROI	Conceptual Captions <a href="#">(Sharma et al., 2018)</a>	1) sentence-image alignment 2) masked language modeling	1) visual commonsense reasoning
Works Under Review / Just Got Accepted	LXMERT <a href="#">(Tan &amp; Bansal, 2019)</a>	two single-modal Transformer (vision & language respectively) + one cross-modal Transformer	image ROI	‡ COCO Caption + VG Caption + VG QA + VQA + GQA	1) sentence-image alignment 2) masked language modeling 3) masked visual-feature classification 4) masked visual-feature regression 5) visual question answering	1) visual question answering 2) natural language visual reasoning
	VisualBERT <a href="#">(Li et al., 2019b)</a>	single cross-modal Transformer	image ROI	COCO Caption <a href="#">(Chen et al., 2015)</a>	1) sentence-image alignment 2) masked language modeling	1) visual question answering 2) visual commonsense reasoning 3) natural language visual reasoning 4) grounding phrases
	Unicoder-VL <a href="#">(Li et al., 2019a)</a>	single cross-modal Transformer	image ROI	Conceptual Captions <a href="#">(Sharma et al., 2018)</a>	1) sentence-image alignment 2) masked language modeling 3) masked visual-feature classification	1) image-text retrieval 2) zero-shot image-text retrieval
	Our VL-BERT	single cross-modal Transformer	image ROI	Conceptual Captions <a href="#">(Sharma et al., 2018)</a> + BooksCorpus <a href="#">(Zhu et al., 2015)</a> + English Wikipedia	1) masked language modeling 2) masked visual-feature classification	1) visual question answering 2) visual commonsense reasoning 3) grounding referring expressions

‡ LXMERT is pre-trained on COCO Caption [\(Chen et al., 2015\)](#), VG Caption [\(Krishna et al., 2017\)](#), VG QA [\(Zhu et al., 2016\)](#), VQA [\(Antol et al., 2015\)](#) and GQA [\(Hudson & Manning, 2019\)](#).

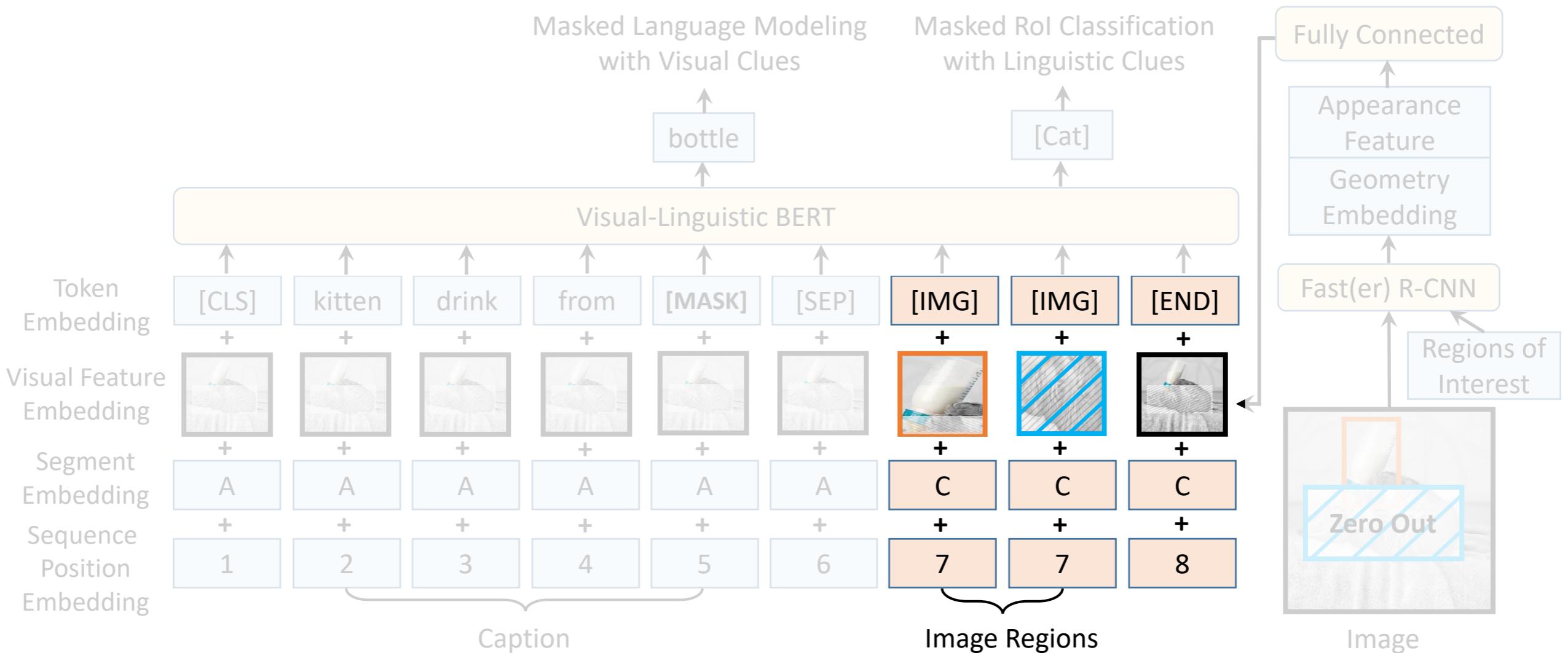
Comparison among our VL-BERT and other concurrent works for pre-training generic visual-linguistic representations

# Model Architecture



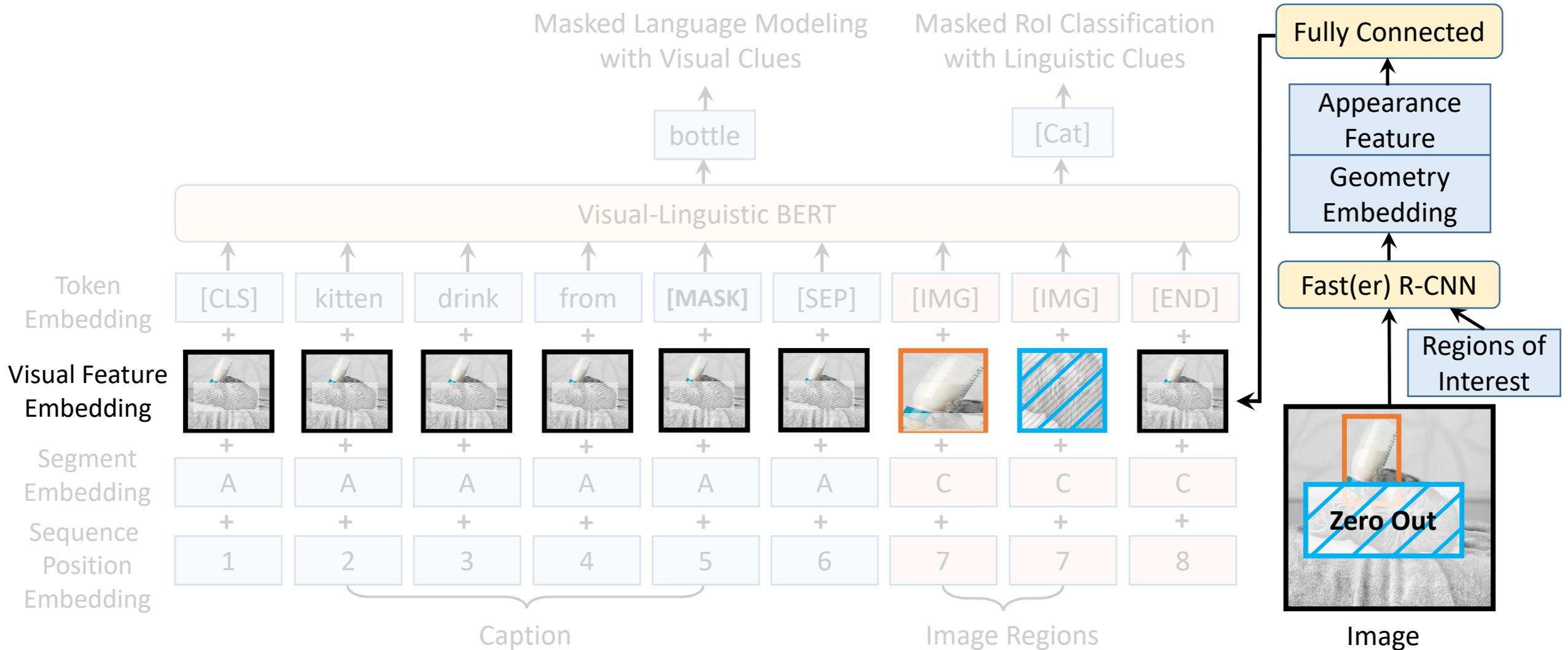
# Modification (I)

## Add Image Regions in Input Sequence



# Modification (II)

## Add Visual Feature Embedding

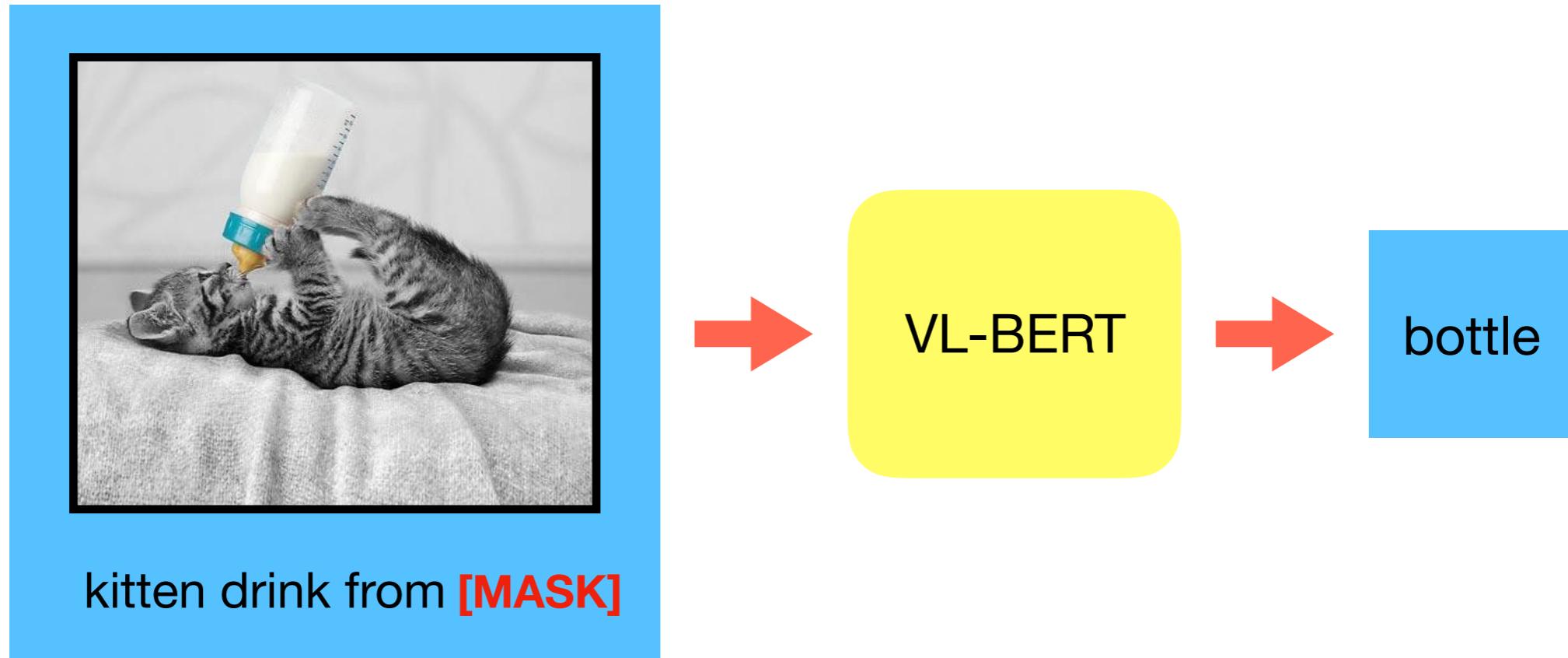


# Pre-training Datasets

- Visual-Linguistic Corpus: Conceptual Captions
  - Harvested from the Internet
  - ~3M **image-text** pairs
- Text-only Corpus: English Wikipedia & BooksCorpus
  - Improve generalization over **long and complex sentences**

# Pre-training Tasks #1

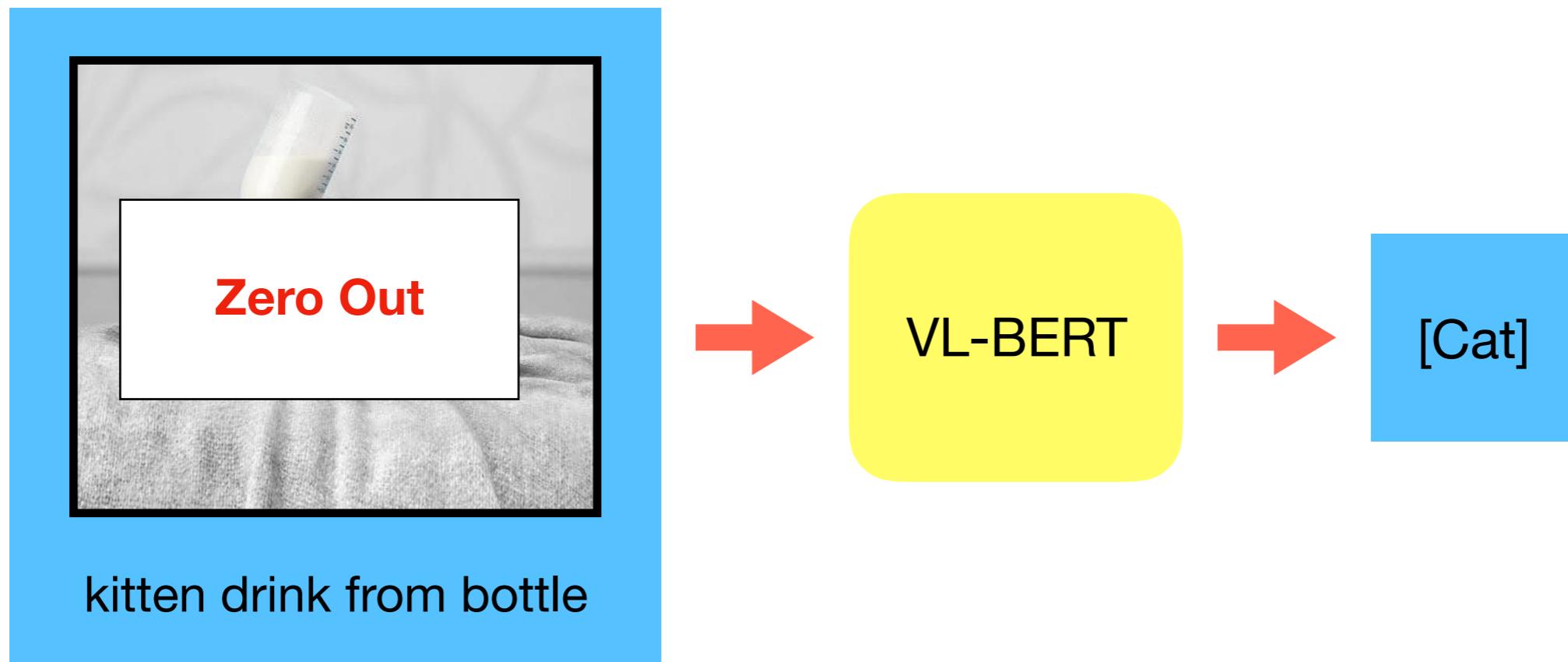
## Masked Language Modeling with Visual Clues



P.S. For samples from text-only corpus, it degenerate to original MLM in BERT.

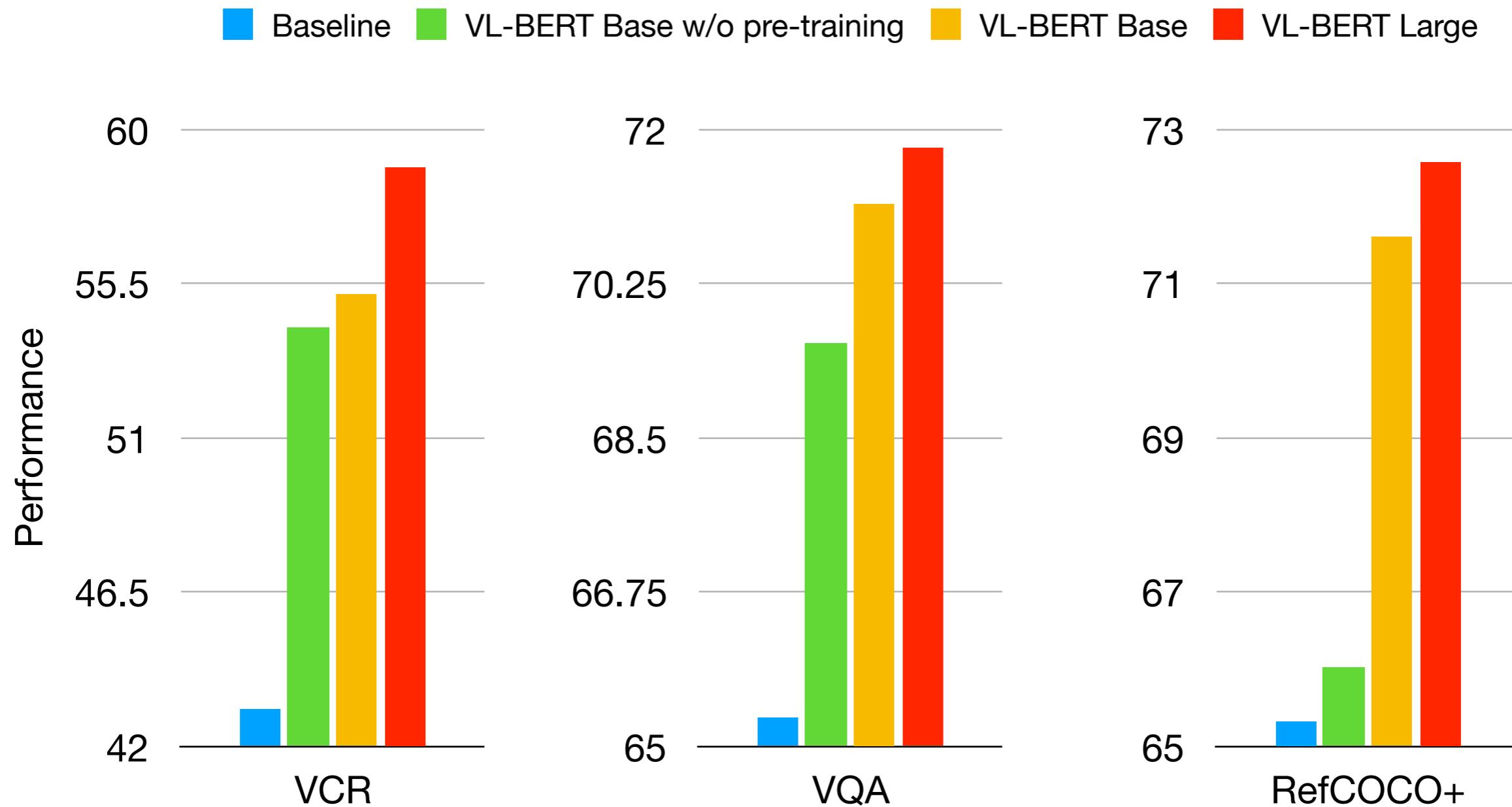
# Pre-training Tasks #2

## Masked RoI Classification with Linguistic Clues

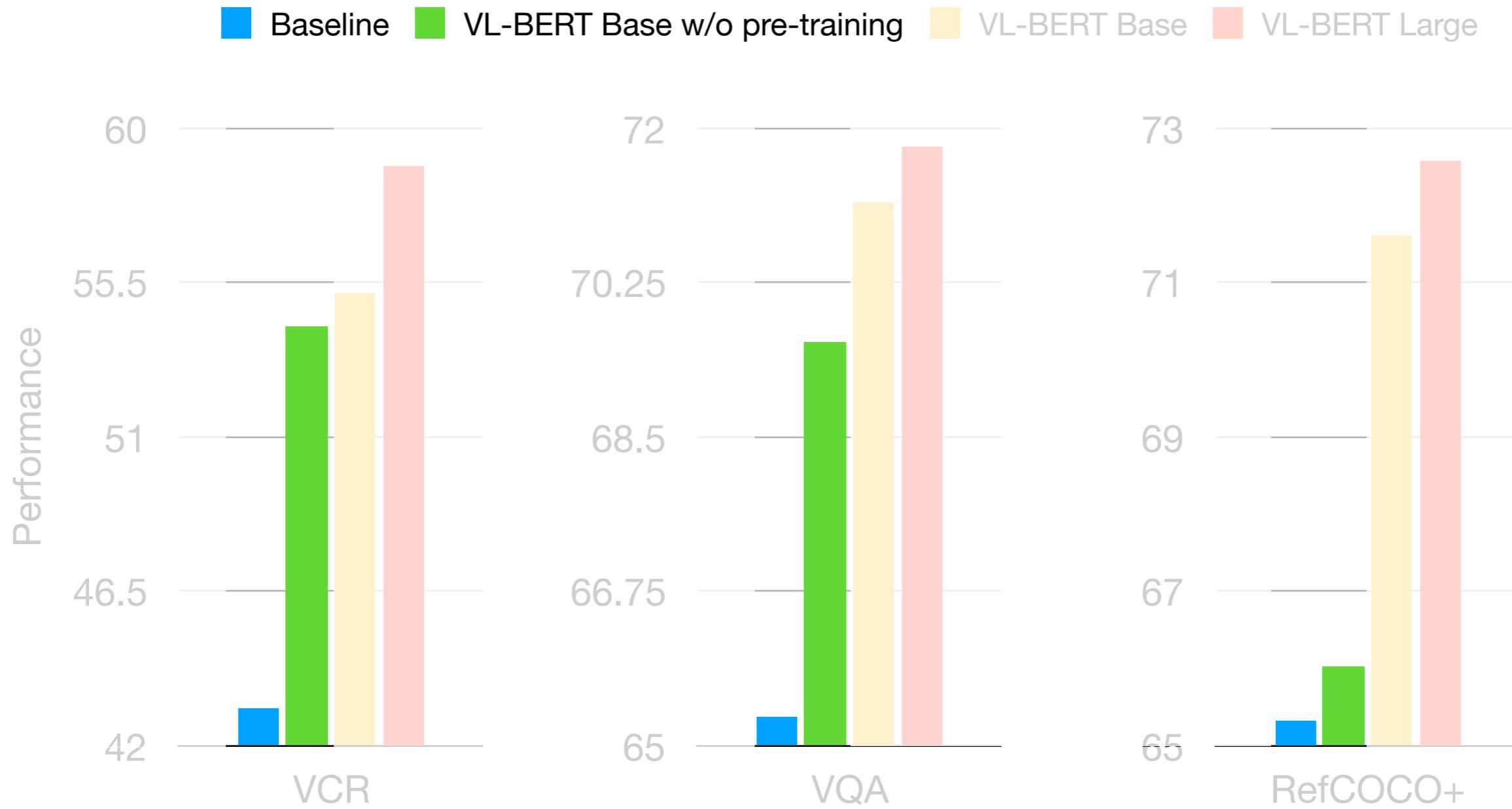


P.S. This task is not used in text-only corpus.

# Results on Downstream Tasks

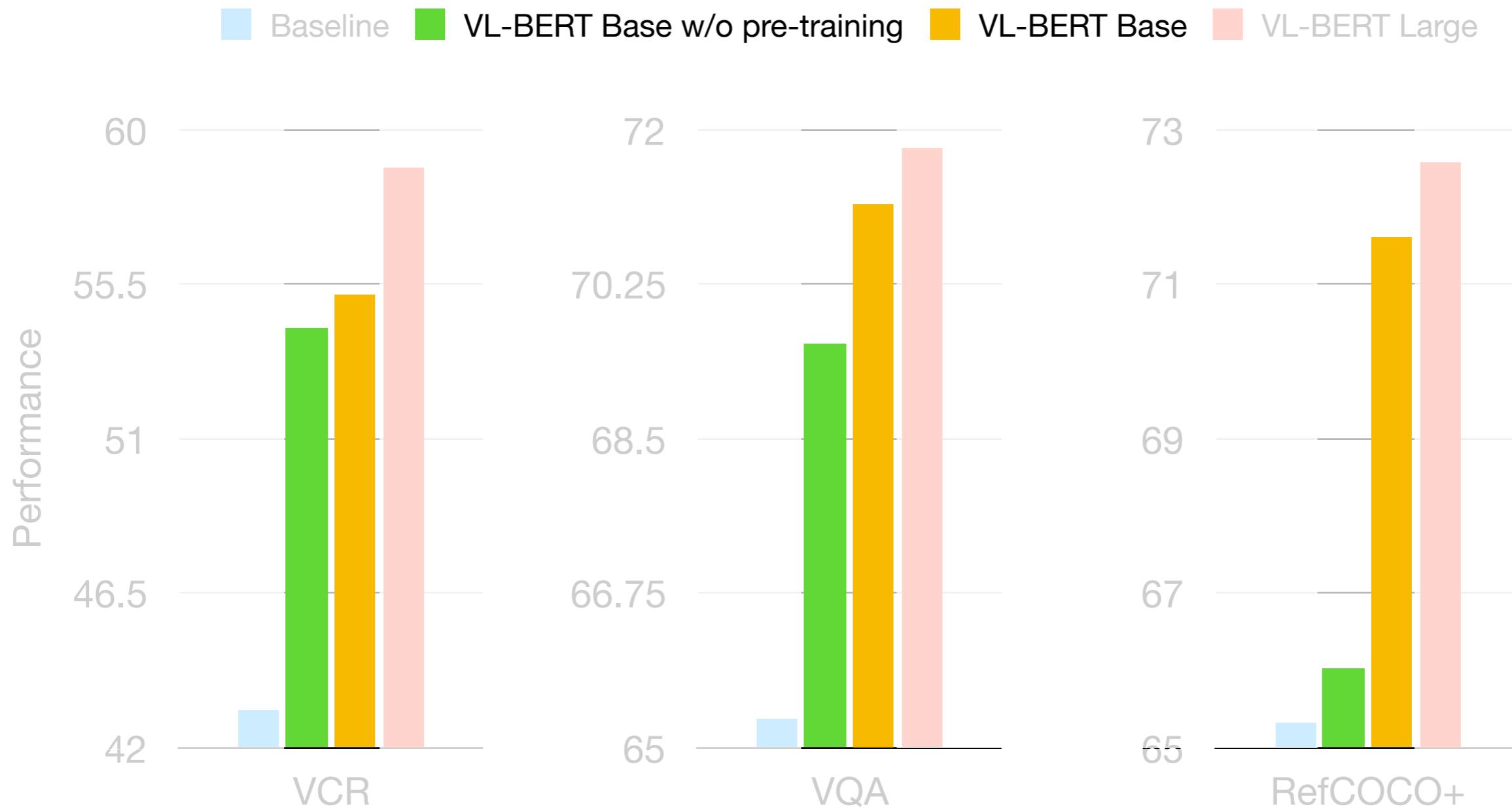


# Results on Downstream Tasks



Our generic representation surpasses task-specific baseline by a large margin

# Results on Downstream Tasks



Pre-training further enhances the capability

# Conclusion

- A new pre-trainable generic representation for VL tasks
- Pre-training procedure can better align VL clues
- Future work: seek better pre-training tasks, benefit more downstream tasks (e.g., Image Caption Generation)

**VL-BERT: Pre-training of Generic Visual-Linguistic Representations**

