

Visual-Linguistic Pre-training for Visual Question Answering

2020 VQA Challenge Runner-up

Team: Renaissance@DamoNLP

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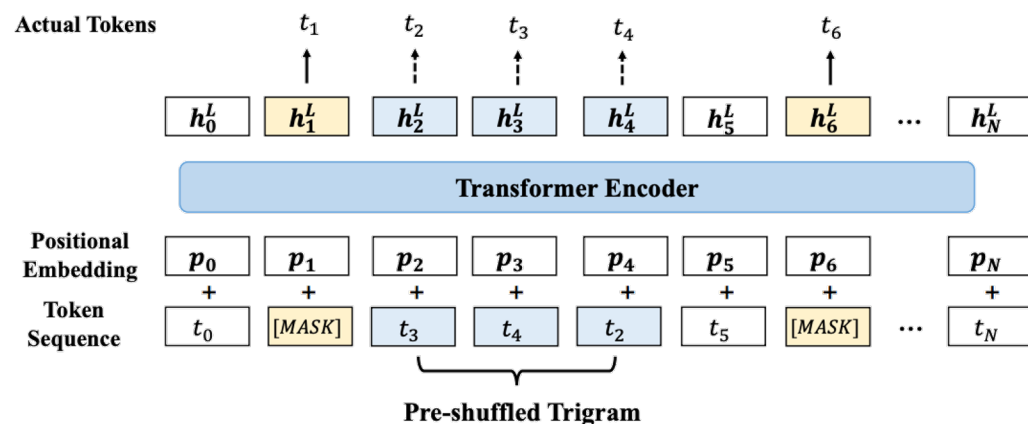
2020 VQA Leaderboard (Test-Standard)

Rank	Participant team	yes/no	number	other	overall	Last submission at
1	Renaissance (StructVBERT-base Ensemble)	90.71	59.80	66.92	76.01	19 days ago
2	DL-61 (BGN, ensemble)	90.89	61.13	66.28	75.92	19 days ago
3	MS D365 AI (UNITER + AVALON Ensemble)	91.30	59.23	66.20	75.85	18 days ago
4	hsslab	89.85	60.68	65.59	75.11	19 days ago
5	MoVie+GridFeat (Single, w/o VLP)	89.18	58.01	64.77	74.16	20 days ago

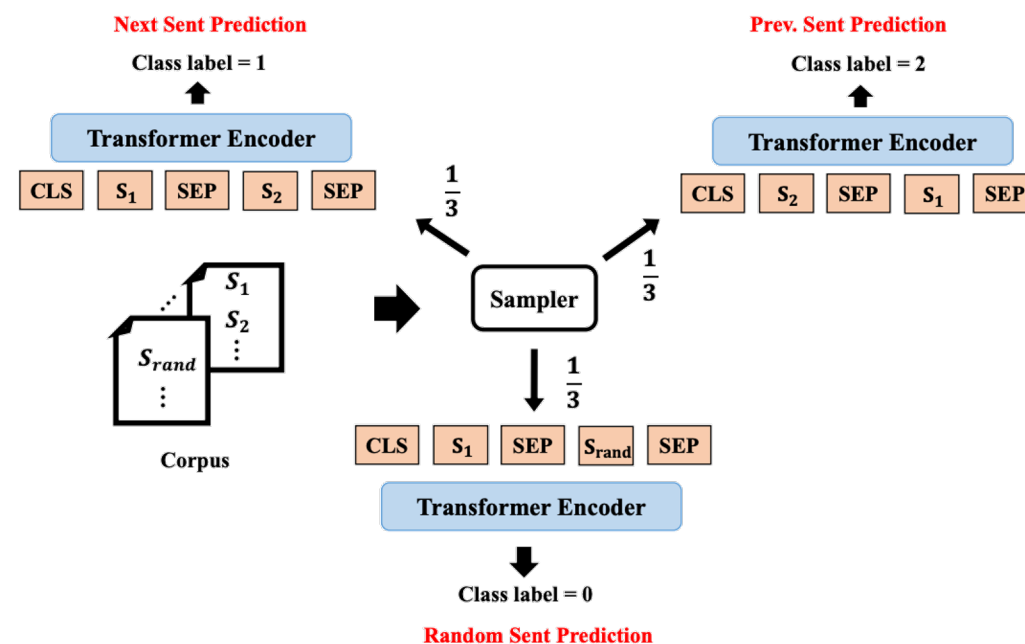


Language Model Pre-training

StructBERT



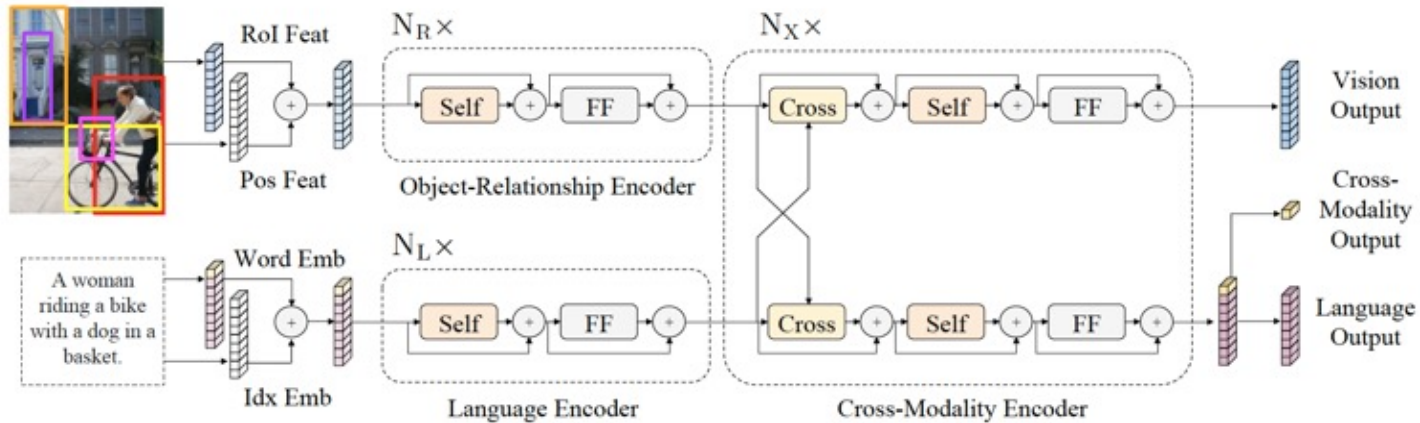
(a) Word Structural Objective



(b) Sentence Structural Objective



Visual-Linguistic Pre-training



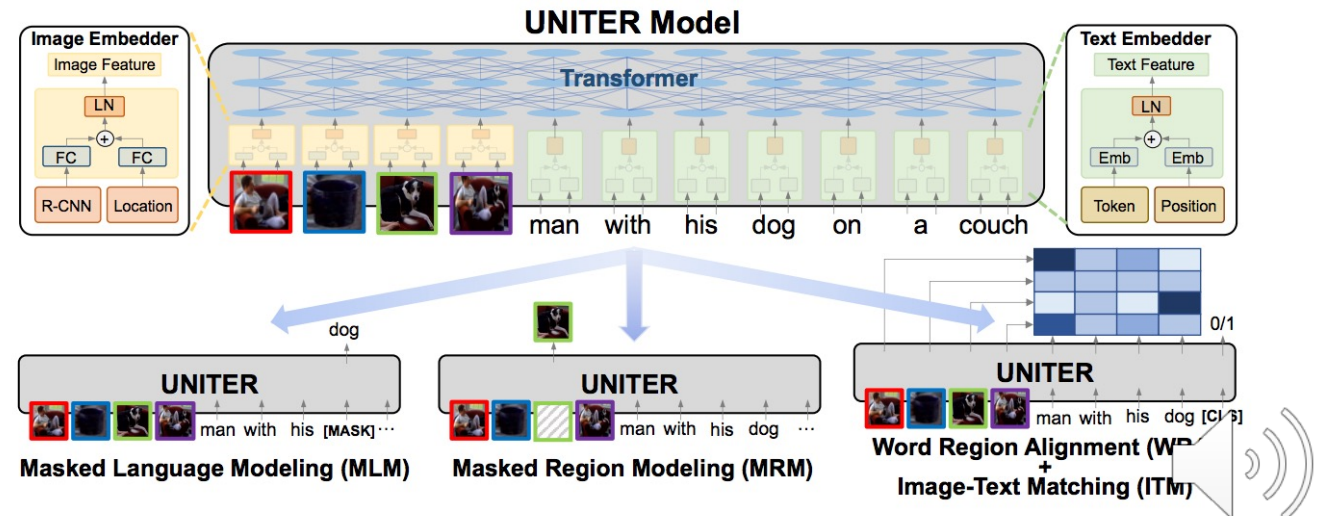
LXMERT

Two-stream Architecture

LXMERT: Learning Cross-Modality Encoder Representations from Transformers, EMNLP 2019

UNITER

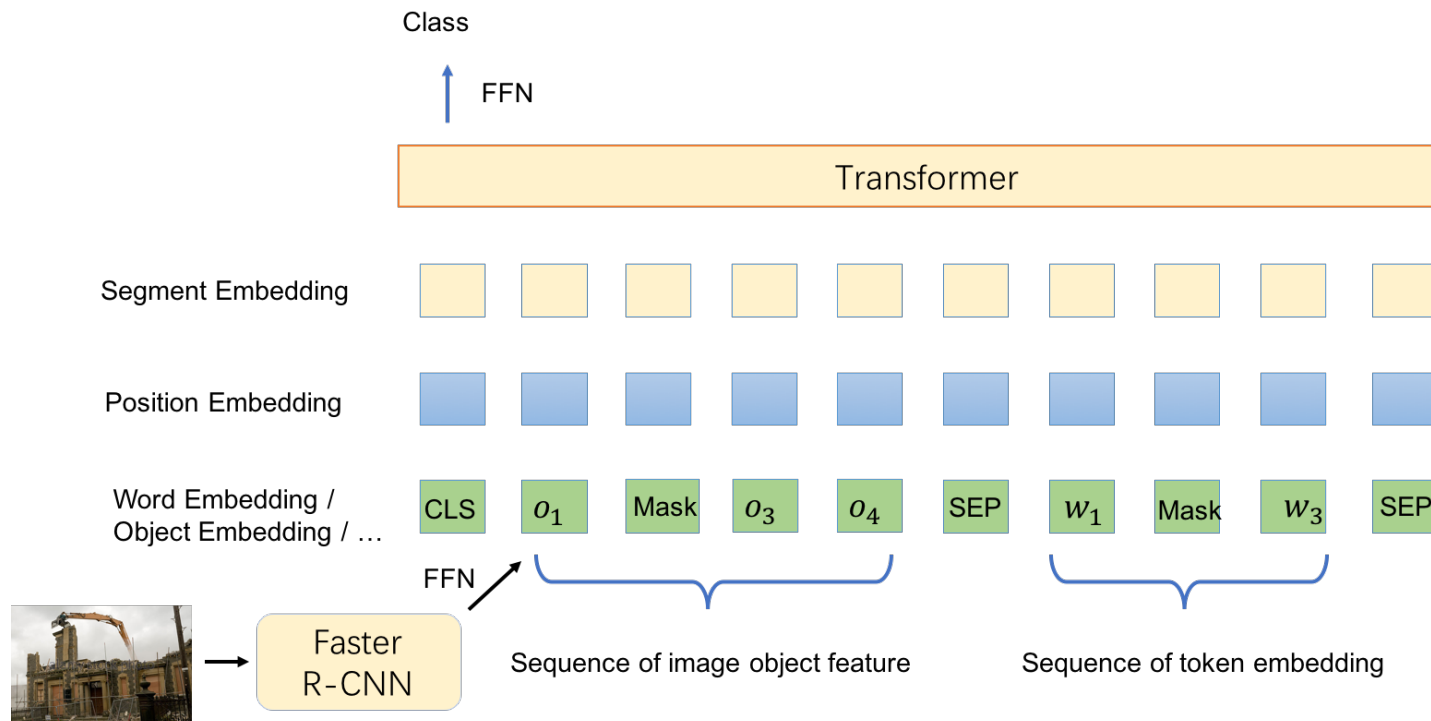
One-stream Architecture



UNITER: UNiversal Image-Text Representation Learning

Our Model

- One-stream 12-layer Transformer (BERT base architecture)
 - Project the image feature and textual feature into the same semantic space
 - Pre-training with COCO caption, VG caption, VG QA, GQA, VQA dataset
 - Bottom up top down feature with faster rcnn



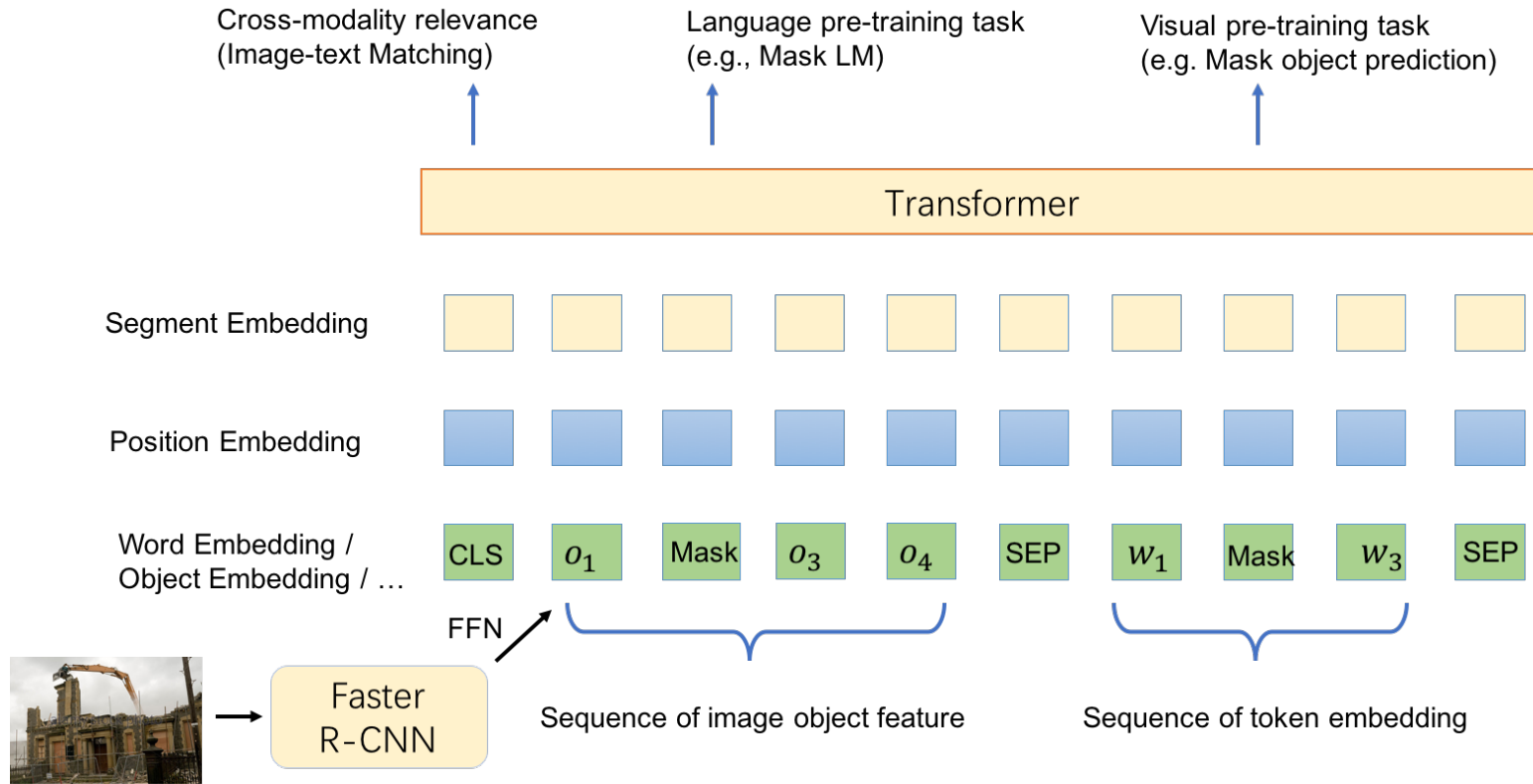
Main Techniques To Improve Performance

- ✓ One-stream v.s. Two-stream
- ✓ Pre-training Tasks (Multi-task Pre-training)
- ✓ Multi-stage Progressive Pre-training
- ✓ Model Ensembling



One-stream v.s. Two-stream

- One-stream can be better with less parameters
 - Masked Cross-Modality LM + ROI Feature Regression + Detected Object Classification + Detected Attribute Classification + Image-Text Matching



	# param	Performance
Two stream (LXMERT)	200M+	72.5
One stream Transformer (12layer base)	130M	72.8



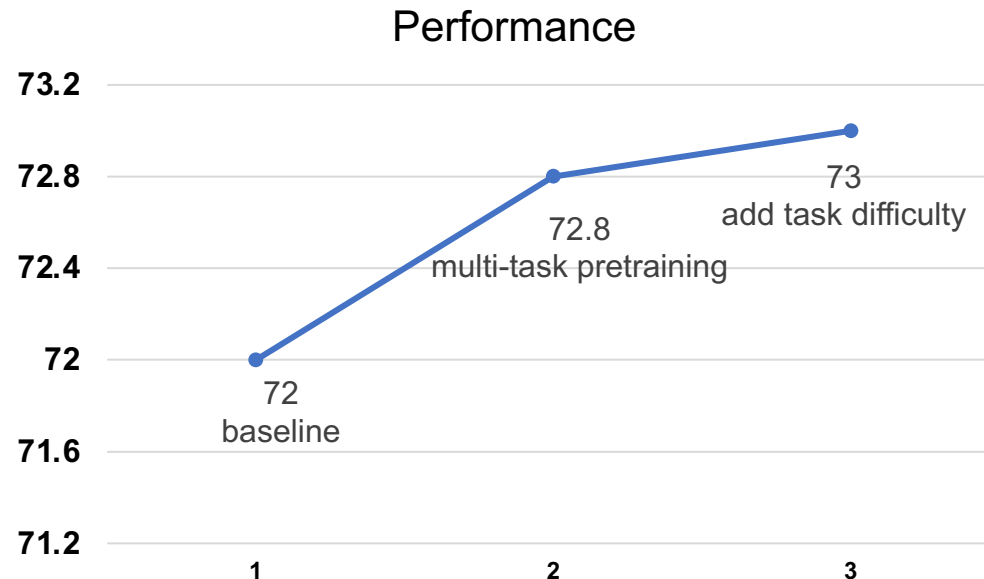
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Improve Pre-training Tasks

- Increase the task difficulty
 - **Language Modality:** use whole word masking to mask continuous word span
 - **Visual Modality:** also mask overlapped Image objects with significant overlap (> 0.5 IoU)
- Multi-task Pre-training
 - Pre-training with all the self-supervised tasks together
 - Add in-domain question-answering data in pre-training can further improve the performance



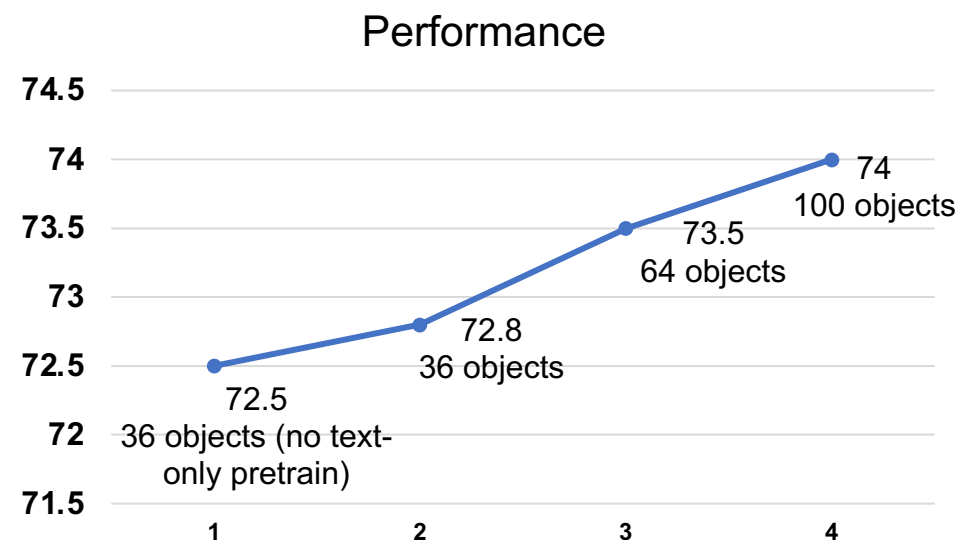
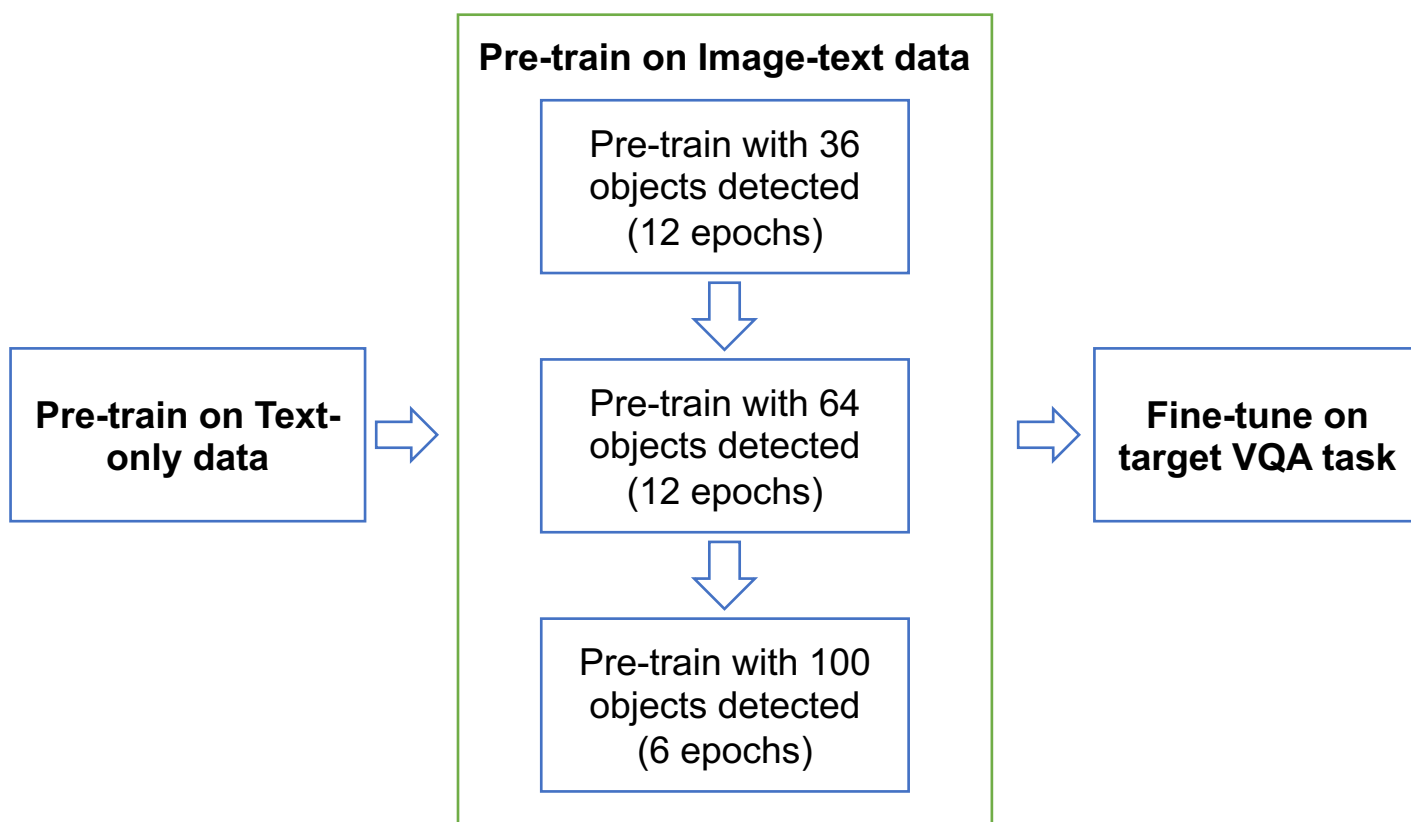
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- ✓ **Multi-stage Progressive Pre-training**
- ✓ Model Ensembling



Multi-stage Progressive Pre-training

- **Progressive Pre-training within Unified Visual-Semantic Space**
 - **Horizontal:** first pre-train on text-only data (helpful in one-stream architecture), and then pre-train image-text pairs
 - **Vertical:** first pre-train on 36 objects, then pre-train on 64 objects and finally pre-train on 100 objects (use faster rcnn to detect more fine-grained objects can promote the performance)



Main Techniques To Improve Performance

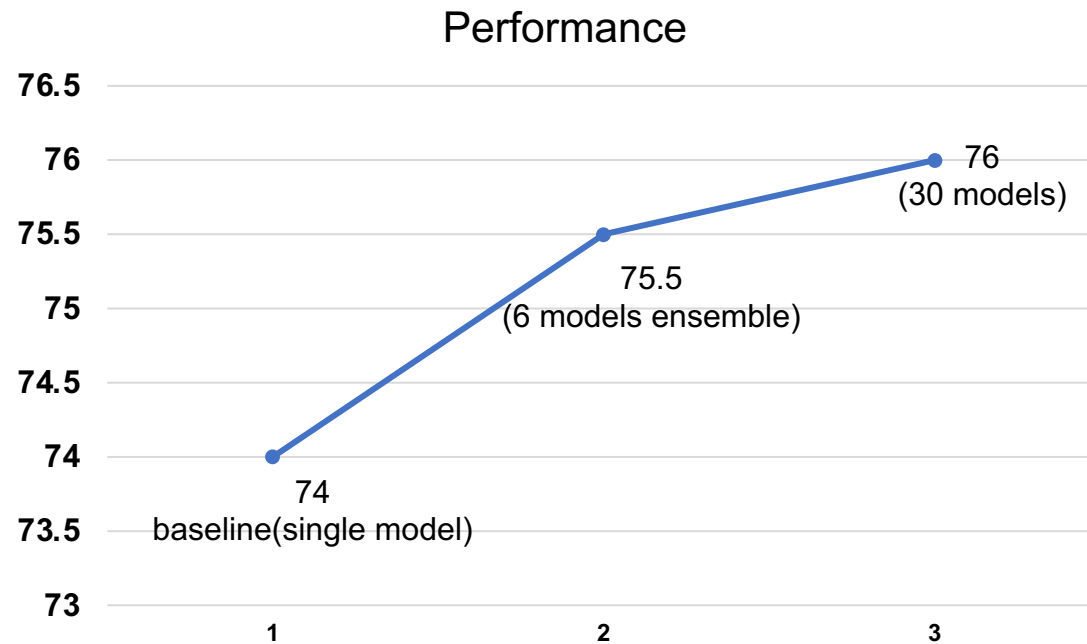
- ✓ One-stream v.s. Two-stream
- ✓ Pre-training Tasks (Multi-task Pre-training)
- ✓ Multi-stage Progressive Pre-training
- ✓ **Model Ensembling**



Model Ensembling

- Diverse Model Ensembling

- **6 Diverse Models:** train with different object numbers (36 objects, 64 objects, 100 objects), one-stream architecture and two-stream architecture, without qa data in pre-training, MCAN model (w/o VLP)
- **24 More Ensemble:** learning rate, seed, checkpoint, etc



Thank you!

