Images and Languages

CS 6384 Computer Vision

Professor Yu Xiang
The University of Texas at Dallas

Image Classification

- ImageNet dataset
  - Training: 1.2 million images
  - Testing and validation: 150,000 images
  - 1000 categories

n02119789: kit fox, Vulpes macrotis
n02100735: English setter
n02096294: Australian terrier
n02066245: grey whale, gray whale, devilfish, Eschrichtius gibbosus, Eschrichtius robustus
n02509815: lesser panda, red panda, panda, bear cat, cat bear, Ailurus fulgens
n02124075: Egyptian cat
n02417914: ibex, Capra ibex
n02123394: Persian cat
n02125311: cougar, puma, catamount, mountain lion, painter, panther, Felis concolor
n02423022: gazelle

https://image-net.org/challenges/LSVRC/2012/index.php

Understand Images with Natural Languages

- Image captioning
- Object grounding
- Visual question answering
- Representation learning with images and languages

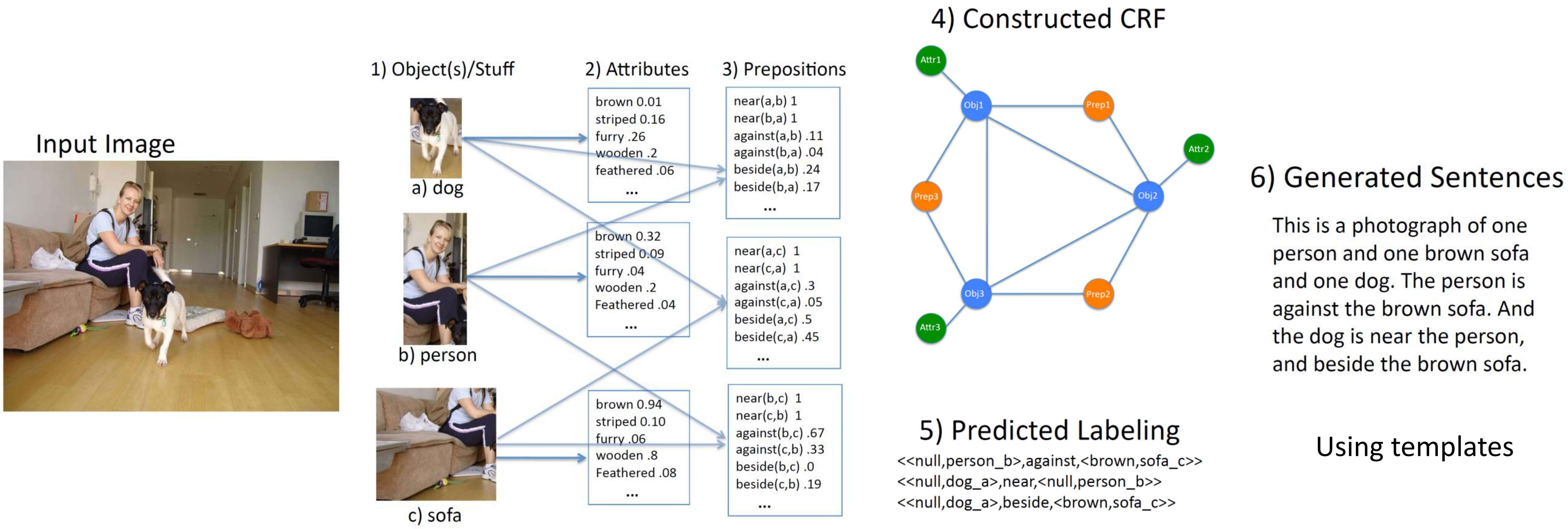
Image Captioning

- Automatically generate texture descriptions of images

the person is riding a surfboard in the ocean

https://www.tensorflow.org/tutorials/text/image_captioning

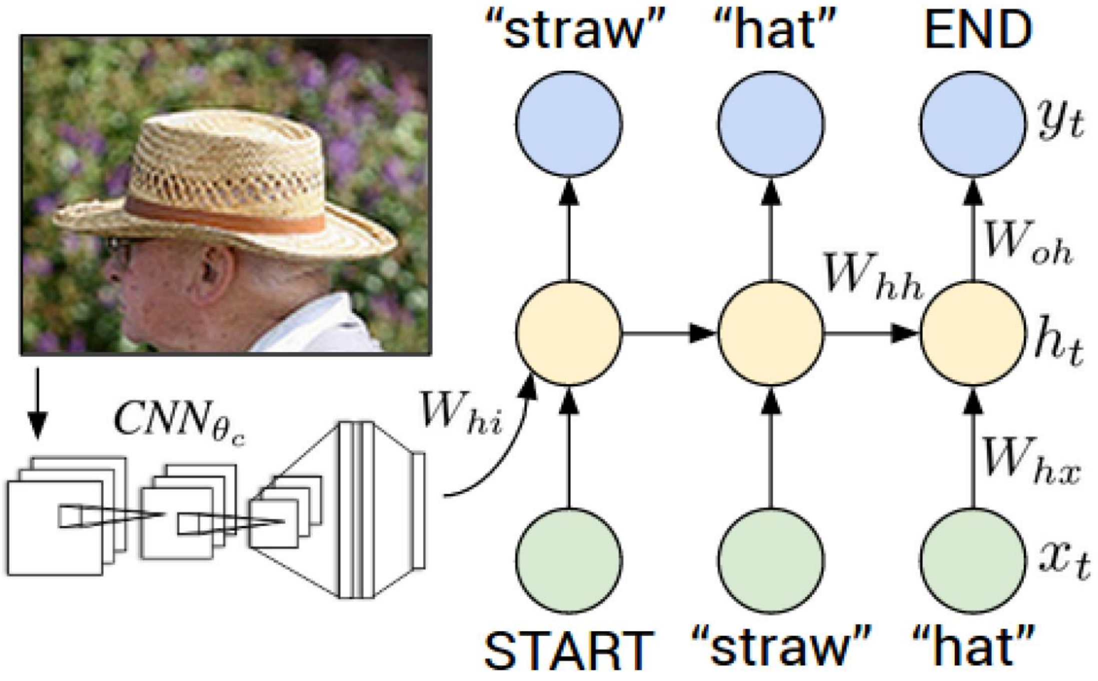
A Traditional Method for Image Captioning



Using templates

Baby Talk: Understanding and Generating Image Descriptions. Kulkarni et al., CVPR, 2011

Image Captioning with RNNs



- Image embedding

$$b_v = W_{hi}[CNN_{\theta_c}(I)]$$

- Hidden state at time t

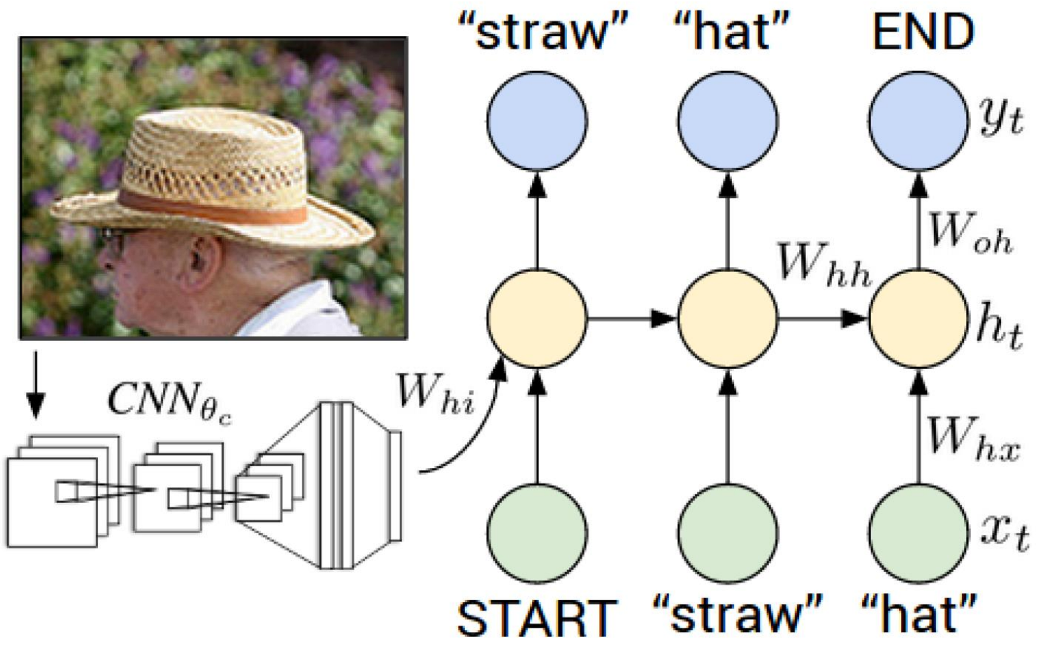
$$h_t = f(W_{hx}x_t + W_{hh}h_{t-1} + b_h + \mathbb{1}(t=1) \odot b_v)$$

Parameters

- Word embedding $x_t = W_w \mathbb{I}_t$
- Output $y_t = softmax(W_{oh}h_t + b_o)$

Deep Visual-Semantic Alignments for Generating Image Descriptions. Karpathy & Fei-fei, CVPR, 2015

Image Captioning with RNNs

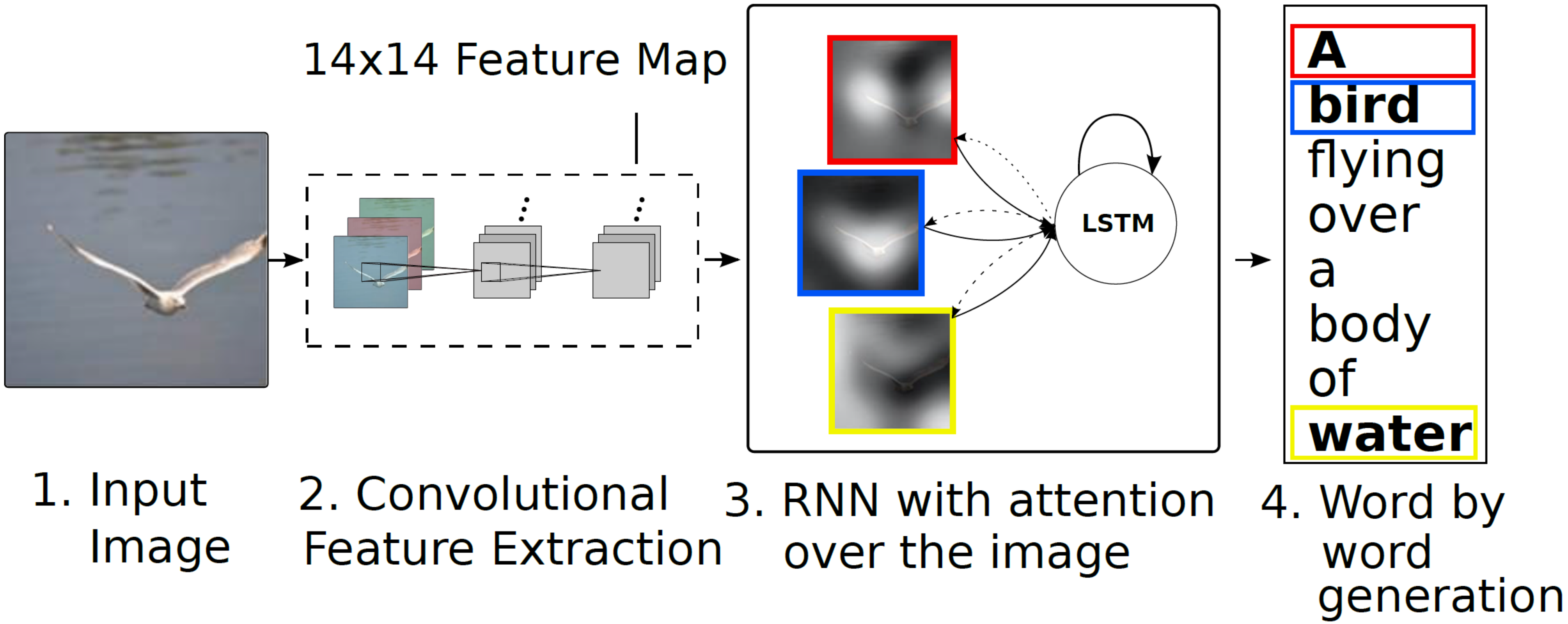


man in black shirt is playing guitar.

construction worker in orange safety vest is working on road.

Deep Visual-Semantic Alignments for Generating Image Descriptions. Karpathy & Fei-fei, CVPR, 2015

Image Captioning with Attentions



Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. Xu et al., PMLR, 2015.

Image Captioning with Attentions

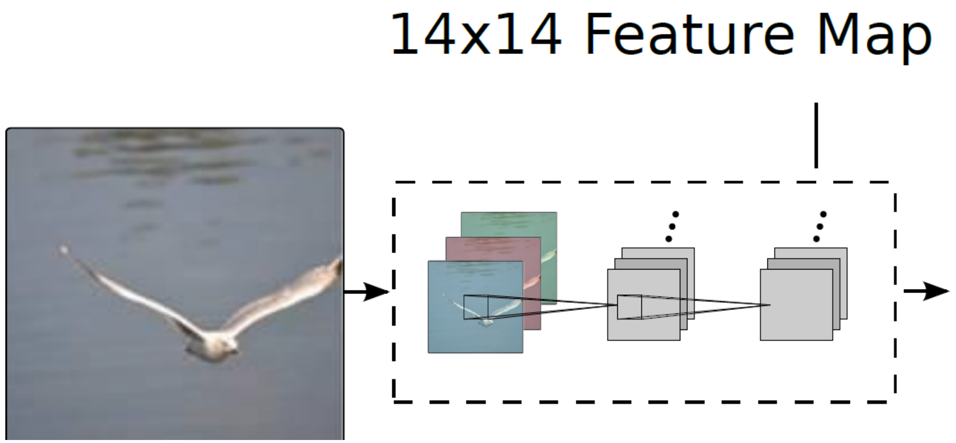


Image features for different locations

$$a = \{\mathbf{a}_1, \ldots, \mathbf{a}_L\}, \ \mathbf{a}_i \in \mathbb{R}^D$$

LSTM for caption generation

$$\begin{pmatrix} \mathbf{i}_t \\ \mathbf{f}_t \\ \mathbf{o}_t \\ \mathbf{g}_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} T_{D+m+n,n} \begin{pmatrix} \mathbf{E}\mathbf{y}_{t-1} \\ \mathbf{h}_{t-1} \\ \hat{\mathbf{z}}_t \end{pmatrix}$$

Word embedding

Context vector

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t).$$

Attention

$$e_{ti} = f_{\text{att}}(\mathbf{a}_i, \mathbf{h}_{t-1})$$

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{k=1}^{L} \exp(e_{tk})}$$

$$\hat{\mathbf{z}}_t = \phi\left(\{\mathbf{a}_i\}, \{\alpha_i\}\right)$$

Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. Xu et al., PMLR, 2015.

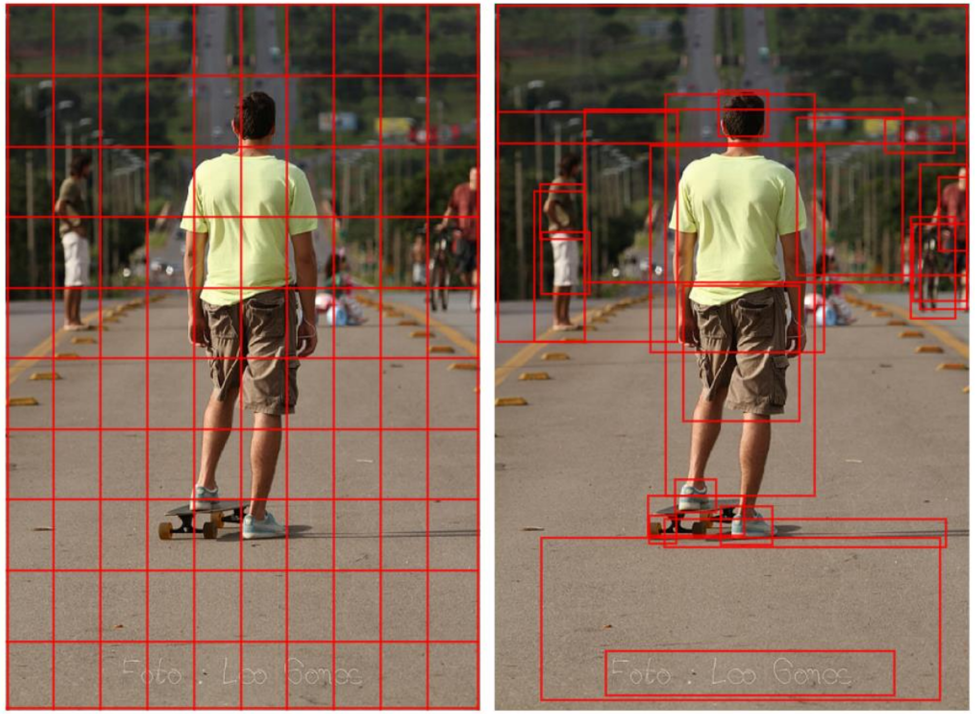
Image Captioning with Attentions

Dataset	Model	BLEU				
		BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR
Flickr8k	Google NIC(Vinyals et al., 2014)$^{\dagger\Sigma}$	63	41	27	—	—
	Log Bilinear (Kiros et al., 2014a)$^{\circ}$	65.6	42.4	27.7	17.7	17.31
	Soft-Attention	**67**	44.8	29.9	19.5	18.93
	Hard-Attention	**67**	**45.7**	**31.4**	**21.3**	**20.30**
Flickr30k	Google NIC$^{\dagger\circ\Sigma}$	66.3	42.3	27.7	18.3	—
	Log Bilinear	60.0	38	25.4	17.1	16.88
	Soft-Attention	66.7	43.4	28.8	19.1	**18.49**
	Hard-Attention	**66.9**	**43.9**	**29.6**	**19.9**	18.46
COCO	CMU/MS Research (Chen & Zitnick, 2014)^{a}	—	—	—	—	20.41
	MS Research (Fang et al., 2014)$^{\dagger a}$	—	—	—	—	20.71
	BRNN (Karpathy & Li, 2014)$^{\circ}$	64.2	45.1	30.4	20.3	—
	Google NIC$^{\dagger\circ\Sigma}$	66.6	46.1	32.9	24.6	—
	Log Bilinear$^{\circ}$	70.8	48.9	34.4	24.3	20.03
	Soft-Attention	70.7	49.2	34.4	24.3	**23.90**
	Hard-Attention	**71.8**	**50.4**	**35.7**	**25.0**	23.04

BLEU (BiLingual Evaluation Understudy)   **METEOR** (**Metric for Evaluation of Translation with Explicit ORdering**)

Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. Xu et al., PMLR, 2015.

Image Captioning with Object Detection



Grid-based attention

Object detection-based attention

Object detection features $\{\boldsymbol{v}_1, \ldots, \boldsymbol{v}_k\}$

RoI pooling from Faster R-CNN

LSTM-based model

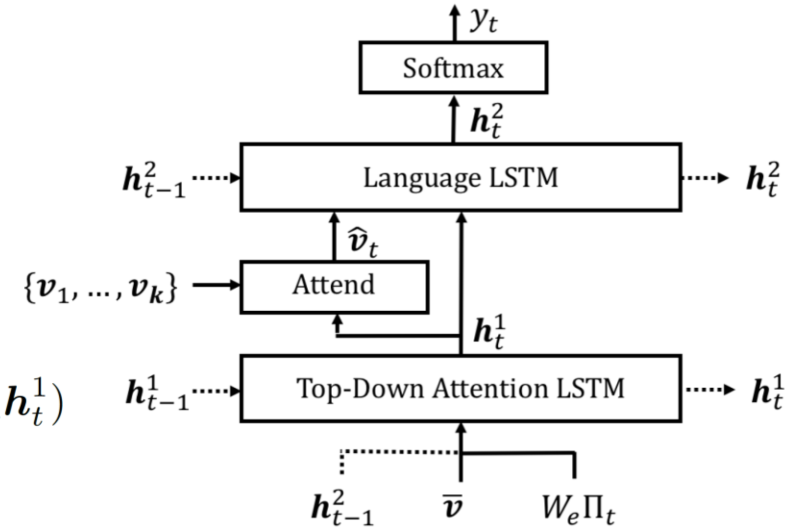
$$\bar{\boldsymbol{v}} = \frac{1}{k} \sum_i \boldsymbol{v}_i$$

Attention

$$a_{i,t} = \boldsymbol{w}_a^T \tanh\left(W_{va}\boldsymbol{v}_i + W_{ha}\boldsymbol{h}_t^1\right)$$

$$\boldsymbol{\alpha}_t = \operatorname{softmax}\left(\boldsymbol{a}_t\right)$$

$$\hat{\boldsymbol{v}}_t = \sum_{i=1}^{K} \alpha_{i,t}\boldsymbol{v}_i$$



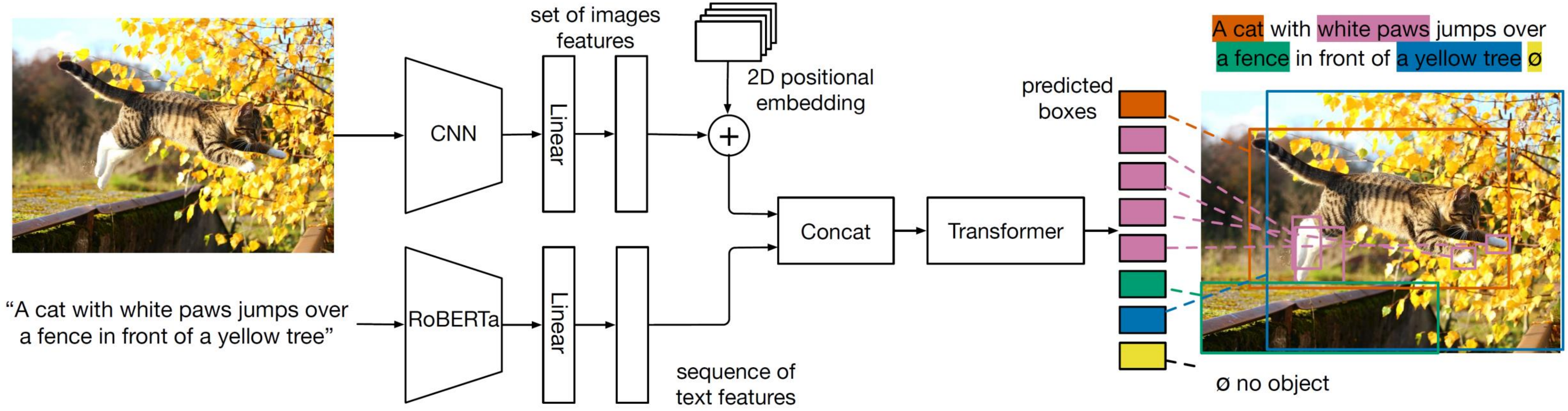
Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering. Anderson et al., CVPR, 2018

Object Grounding

A man with **pierced ears** is wearing **glasses** and **an orange hat**.
A man with **glasses** is wearing **a beer can crotched hat**.
A man with **gauges** and **glasses** is wearing **a Blitz hat**.
A man in **an orange hat** starring at **something**.
A man wears **an orange hat** and **glasses**.

Flickr30k Entities: Collecting Region-to-Phrase Correspondences for Richer Image-to-Sentence Models. Plummer et al., ICCV, 2015.

Object Grounding

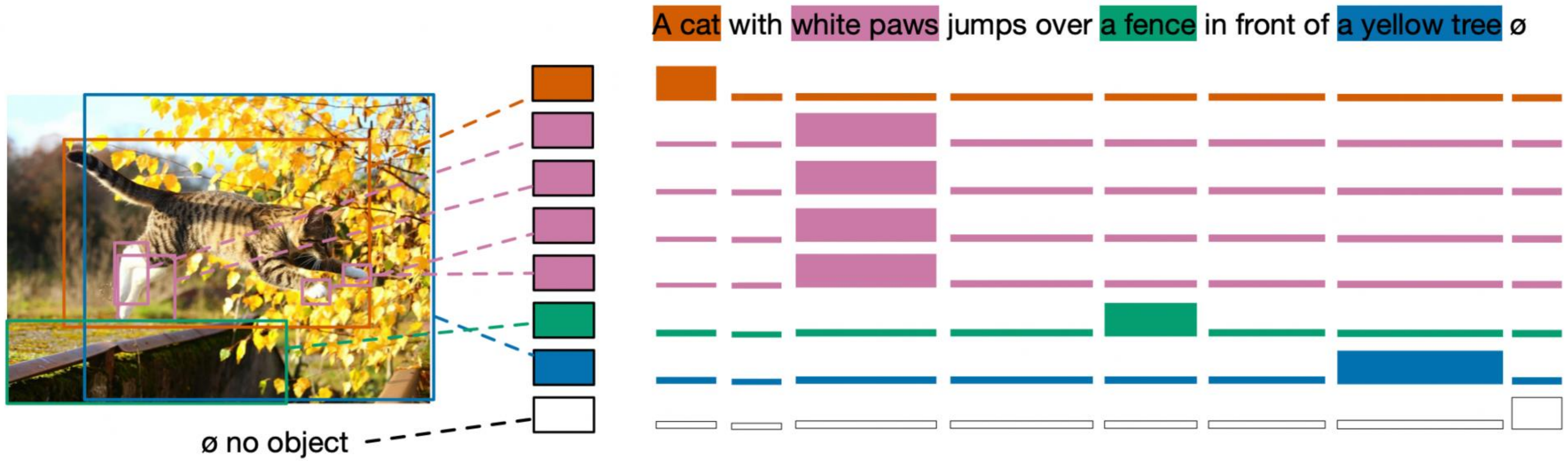


MDETR - Modulated Detection for End-to-End Multi-Modal Understanding. Kamath et al., 2021

Object Grounding

- Soft token prediction
  - For each detected bounding, predict a probability distribution over the tokens in the input phase

maximum number of tokens: 256



MDETR - Modulated Detection for End-to-End Multi-Modal Understanding. Kamath et al., 2021

Object Grounding

(a) "one small boy climbing a pole with the help of another boy on the ground"

(b) "A man talking on his cellphone next to a jewelry store"

(c) "A man in a white t-shirt does a trick with a bronze colored yo-yo"

MDETR - Modulated Detection for End-to-End Multi-Modal Understanding. Kamath et al., 2021

Visual Question Answering

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

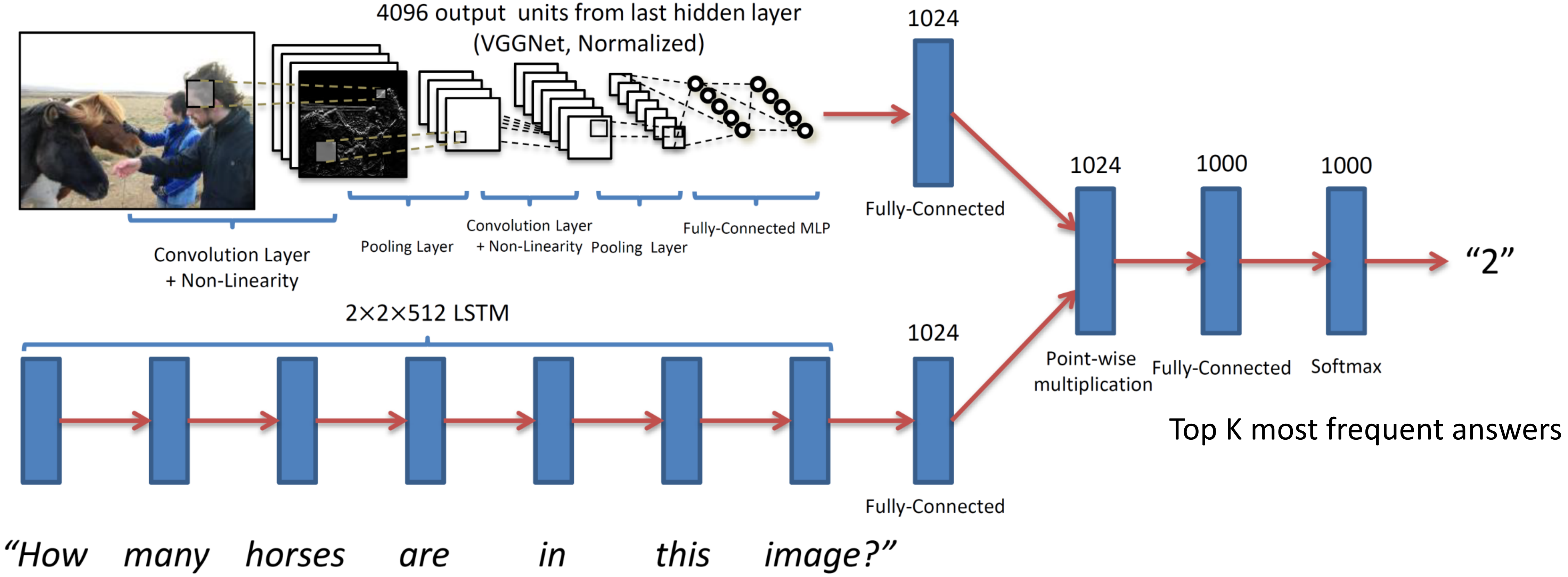
How many slices of pizza are there?
Is this a vegetarian pizza?

- Input
  - An image
  - A free-form, open-ended, natural language question
- Output
  - Case 1: open-ended answer
  - Case 2: multiple-choice task

$$\text{accuracy} = \min\left(\frac{\#\text{ humans that provided that answer}}{3}, 1\right)$$

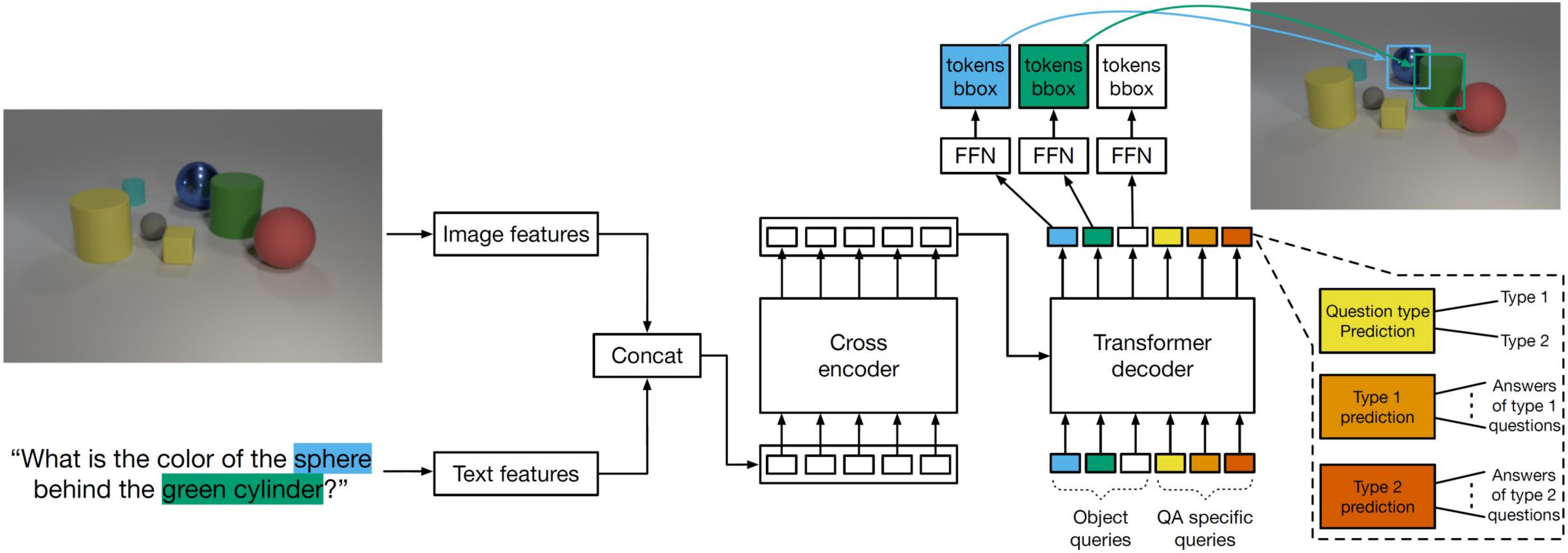
VQA: Visual Question Answering. Agrawal et al., ICCV, 2015

Visual Question Answering



VQA: Visual Question Answering. Agrawal et al., ICCV, 2015

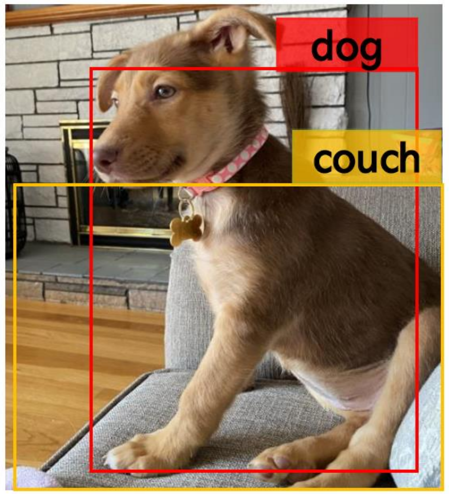
Visual Question Answering



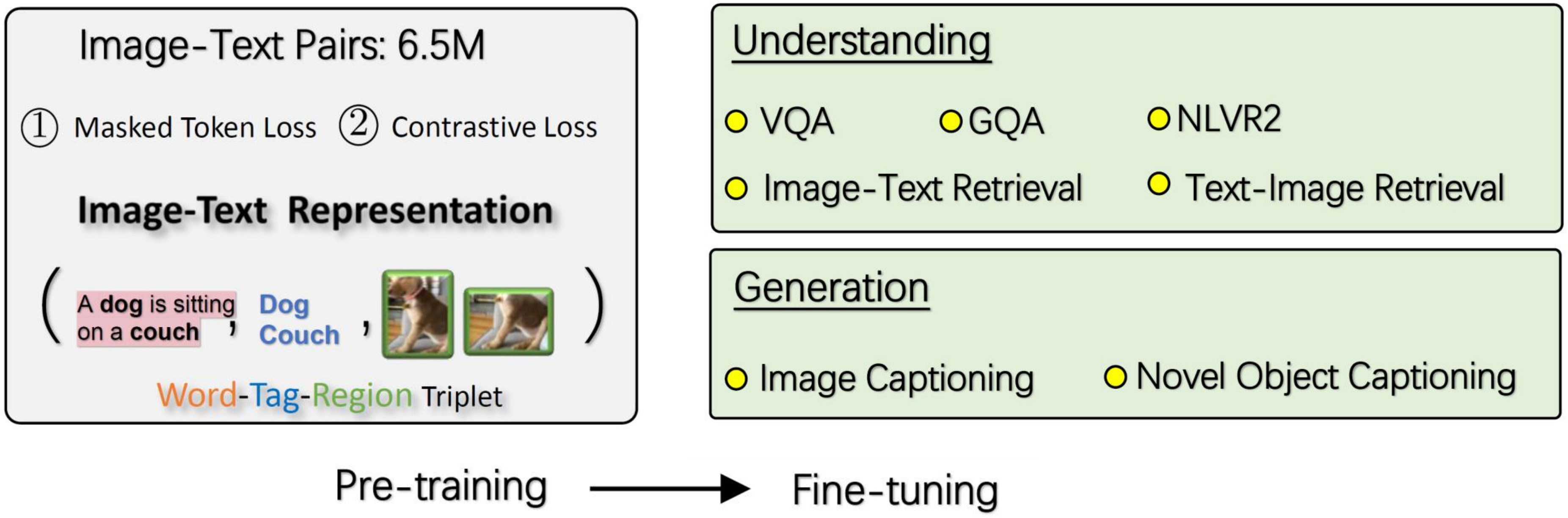
MDETR - Modulated Detection for End-to-End Multi-Modal Understanding. Kamath et al., 2021

Representation Learning

- Can we learn feature representations of images and text that can be useful for various vision-language tasks? (pre-training)



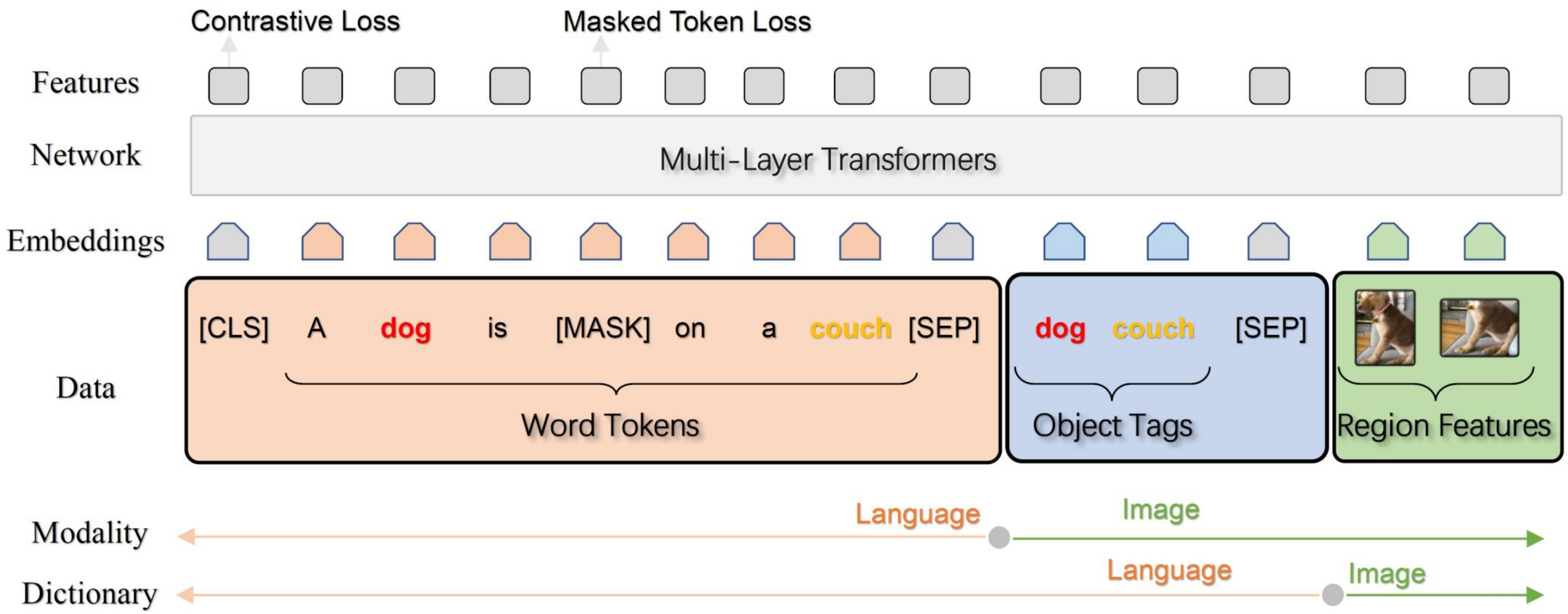
A dog is sitting on a couch



Oscar: Object-Semantics Aligned Pre-training for Vision-Language Tasks. Li et al., ECCV, 2020

Oscar: Object-Semantics Aligned Pre-training

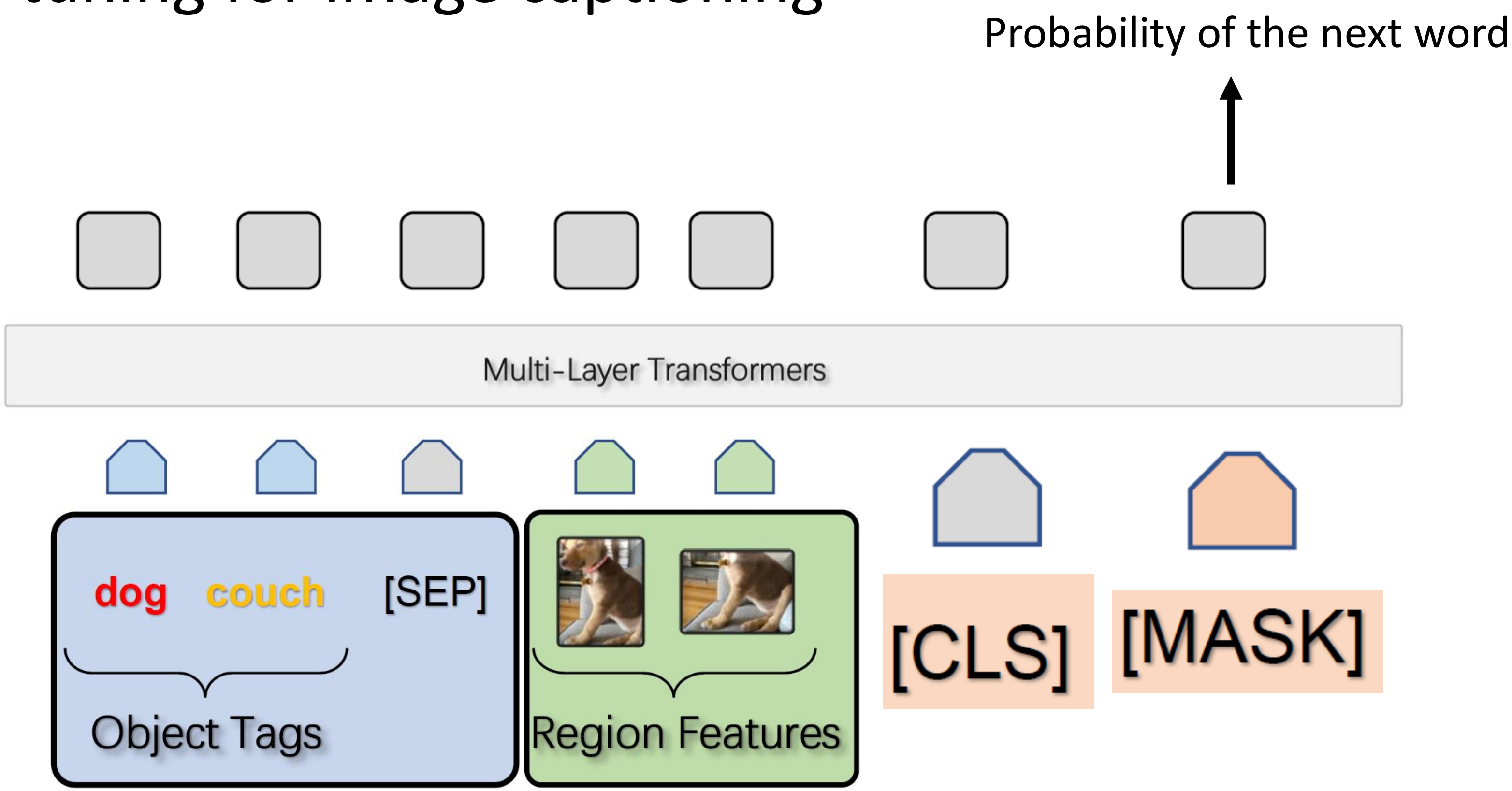
Classify “polluted” triplets with wrong tags



Oscar: Object-Semantics Aligned Pre-training for Vision-Language Tasks. Li et al., ECCV, 2020

Oscar: Object-Semantics Aligned Pre-training

- Fine-tuning for image captioning

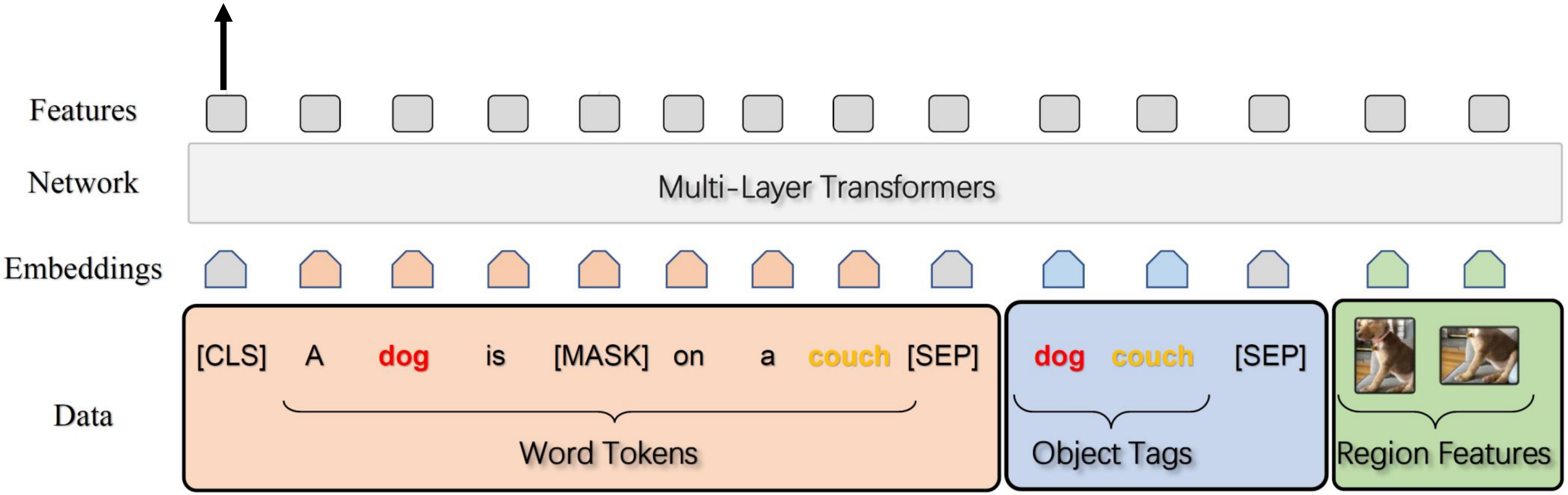


Oscar: Object-Semantics Aligned Pre-training for Vision-Language Tasks. Li et al., ECCV, 2020

Oscar: Object-Semantics Aligned Pre-training

- Fine-tuning for question answering

Classifier to answers (e.g., 3,129 answer set)

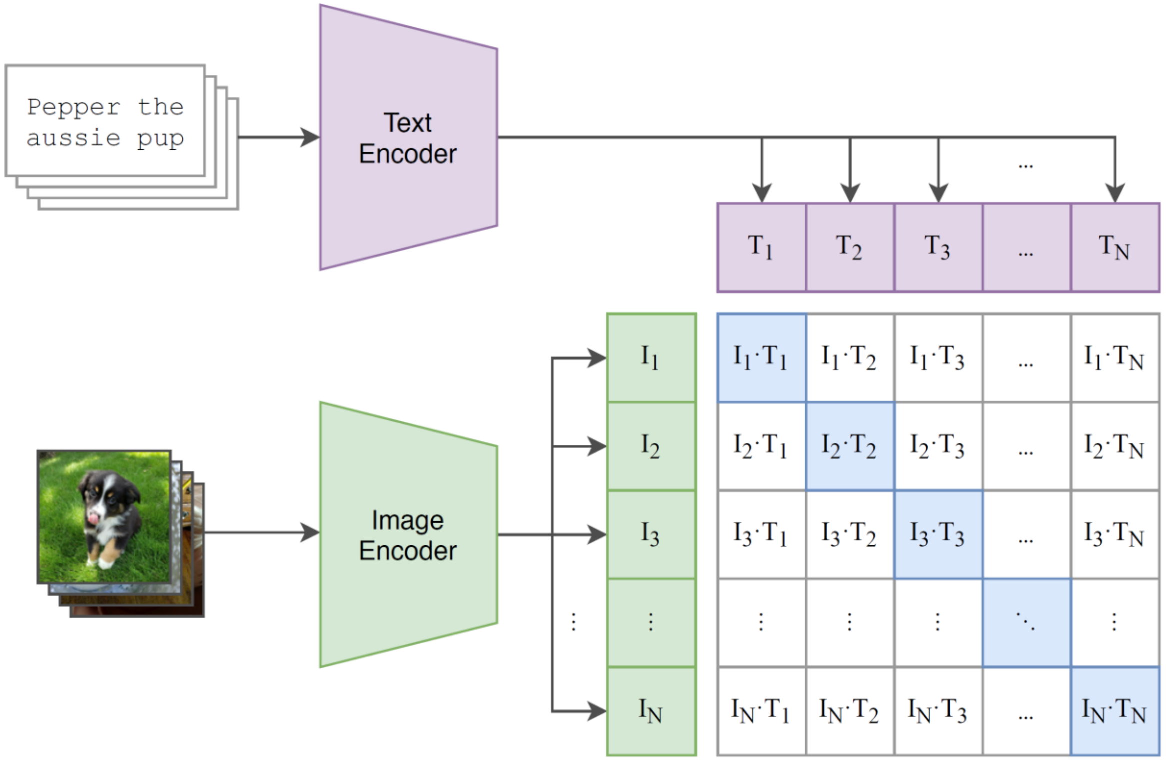


Replace with a Question

Oscar: Object-Semantics Aligned Pre-training for Vision-Language Tasks. Li et al., ECCV, 2020

CLIP: Contrastive Language-Image Pre-Training

- Contrastive pre-training



- 400 million (image, text) pairs from Internet

Learning Transferable Visual Models From Natural Language Supervision. Radford, et al., 2021

CLIP: Contrastive Language-Image Pre-Training

- Contrastive pre-training

```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

Multi-class N-pair Loss

Softmax for multi-class classification

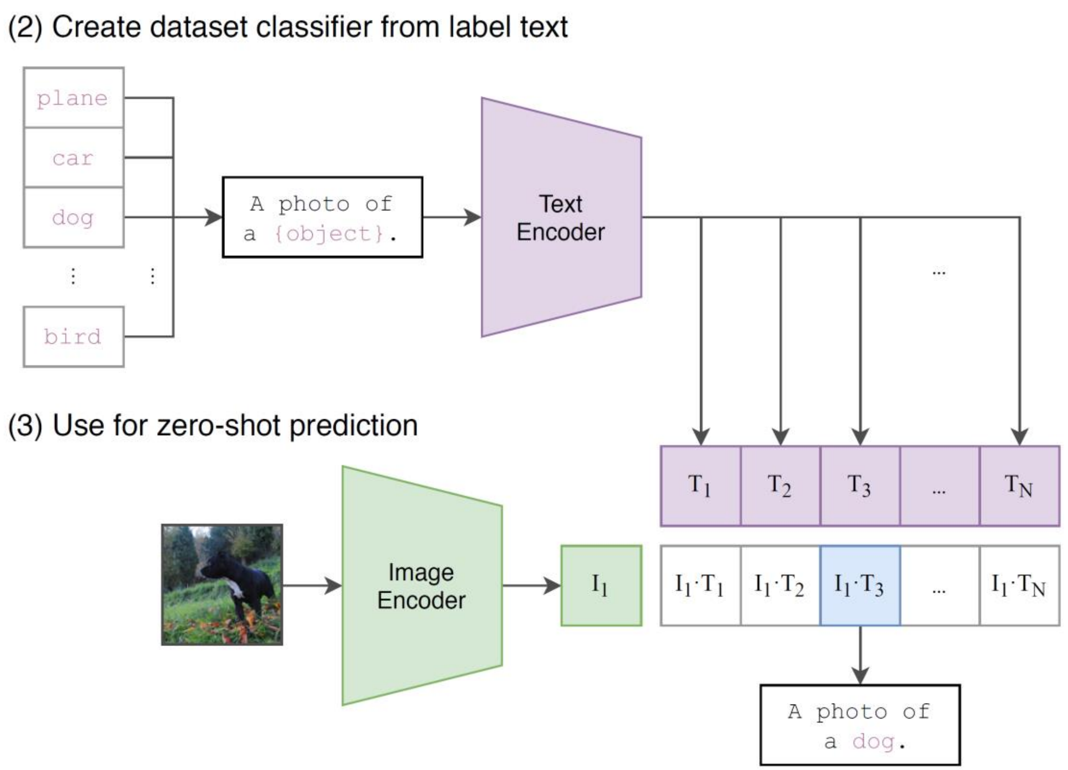
$$\mathcal{L}_{\text{N-pair}}(\mathbf{x}, \mathbf{x}^+, \{\mathbf{x}_i^-\}_{i=1}^{N-1}) = \log\left(1 + \sum_{i=1}^{N-1} \exp(f(\mathbf{x})^\top f(\mathbf{x}_i^-) - f(\mathbf{x})^\top f(\mathbf{x}^+))\right)$$

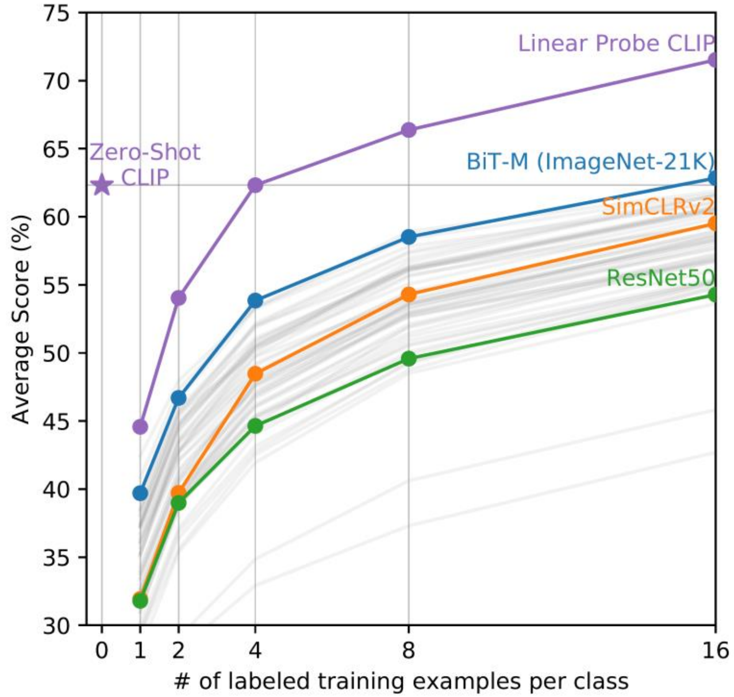
$$= -\log \frac{\exp(f(\mathbf{x})^\top f(\mathbf{x}^+))}{\exp(f(\mathbf{x})^\top f(\mathbf{x}^+)) + \sum_{i=1}^{N-1} \exp(f(\mathbf{x})^\top f(\mathbf{x}_i^-))}$$

Learning Transferable Visual Models From Natural Language Supervision. Radford, et al., 2021

CLIP: Contrastive Language-Image Pre-Training

- Zero-shot classification (no training on target datasets)





CLIP Linear Probe: logistic regression performed on CLIP encoded image features

Learning Transferable Visual Models From Natural Language Supervision. Radford, et al., 2021

Summary

- Vision + language tasks
  - Image captioning
  - Object/phase grounding
  - Visual question answering
  - Image-text retrieval

- Representation learning (Pre-training)
  - Learning image-text representations from large numbers (image, text) pairs
  - Fine-turning for downstream tasks

Further Reading

- Baby Talk: Understanding and Generating Image Descriptions, 2011 http://www.tamaraberg.com/papers/generation_cvpr11.pdf
- Deep Visual-Semantic Alignments for Generating Image Descriptions, 2015 https://arxiv.org/abs/1412.2306
- Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, 2015 https://arxiv.org/abs/1502.03044
- Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering, 2018 https://arxiv.org/abs/1707.07998
- MDETR - Modulated Detection for End-to-End Multi-Modal Understanding, 2021 https://arxiv.org/abs/2104.12763
- VQA: Visual Question Answering, 2015 https://arxiv.org/abs/1505.00468
- Oscar: Object-Semantics Aligned Pre-training for Vision-Language Tasks, 2020 https://arxiv.org/abs/2004.06165
- Learning Transferable Visual Models From Natural Language Supervision, 2021 https://arxiv.org/abs/2103.00020