CS 4644-DL / 7643-A: Lecture 20
Danfei xu

Self-Supervised Learning (Continued)

Large Vision and Language Models

Pretext tasks from image transformations

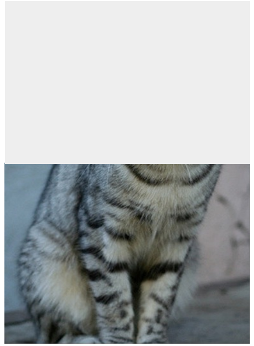


image
completion

rotation
prediction

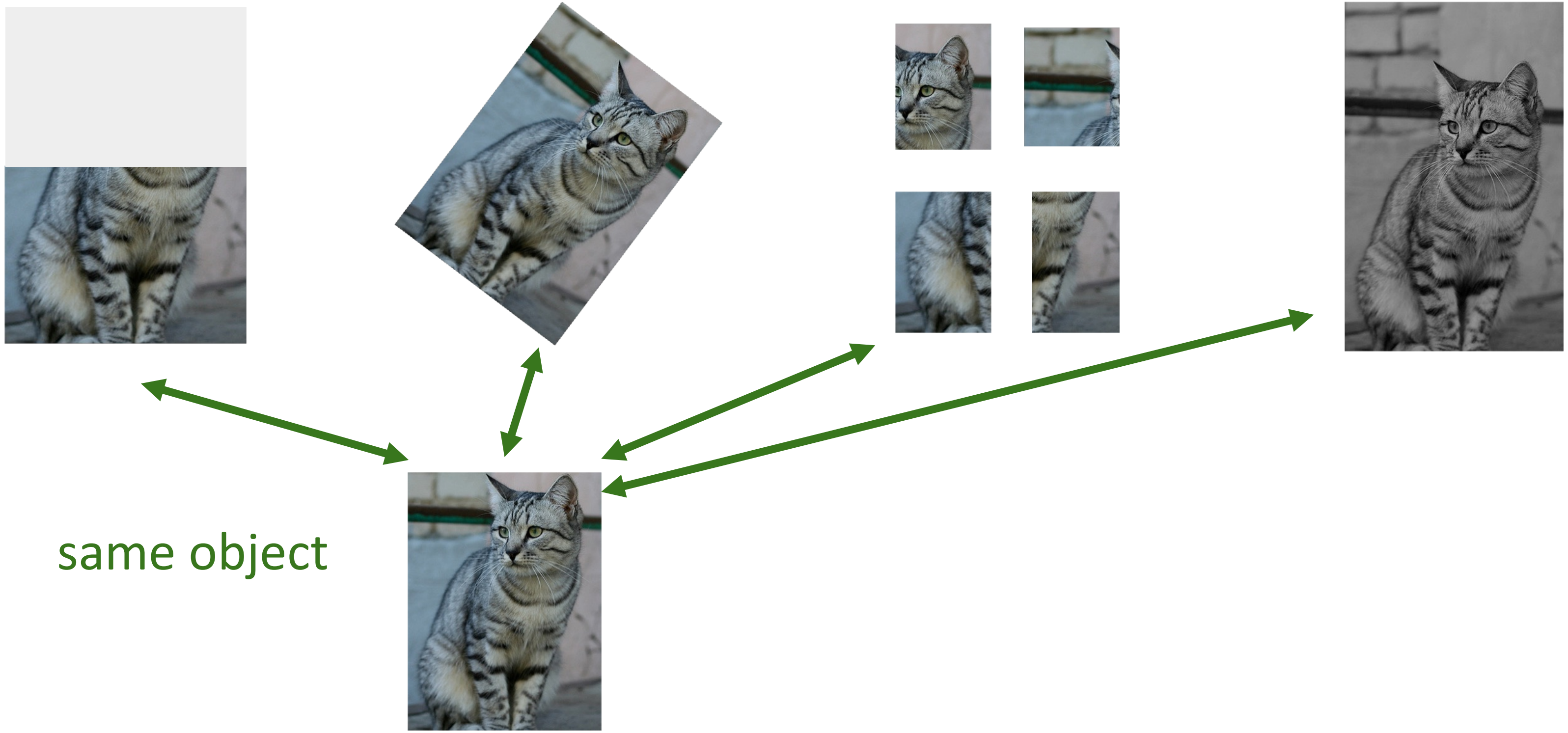
“jigsaw puzzle”

colorization

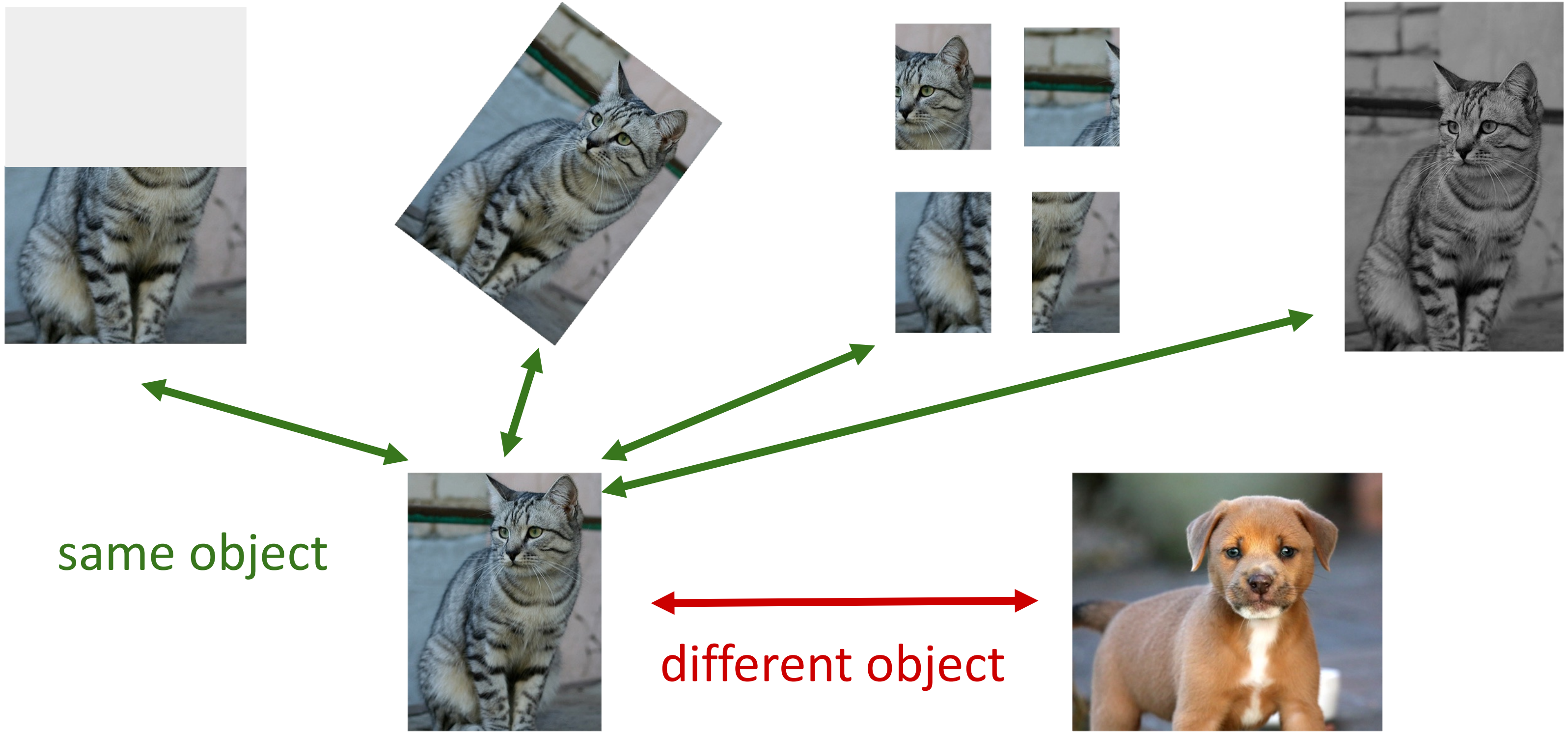
Learned representations may be tied to a specific pretext task!

Can we come up with a more general pretext task?

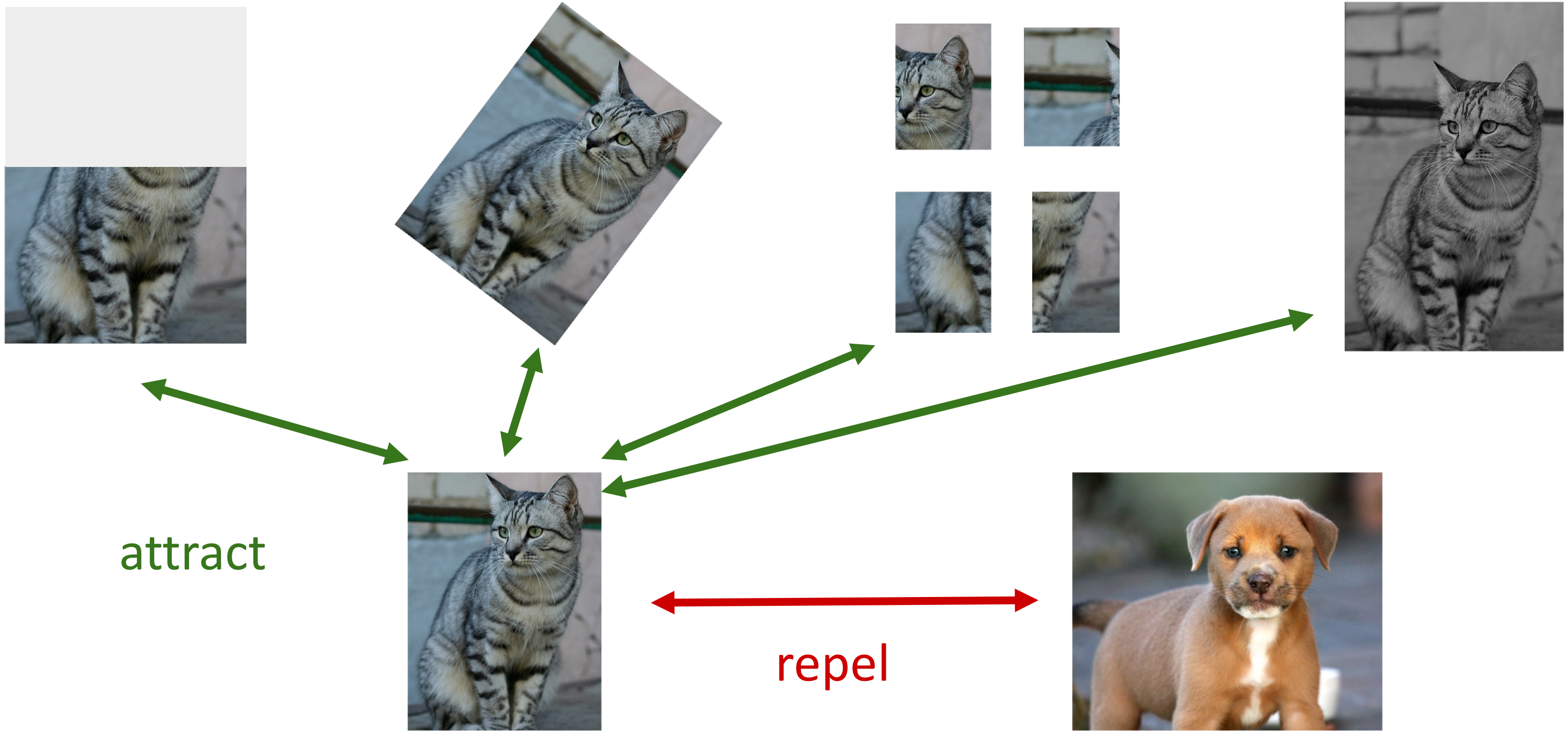
A more general pretext task?



A more general pretext task?



Contrastive Representation Learning

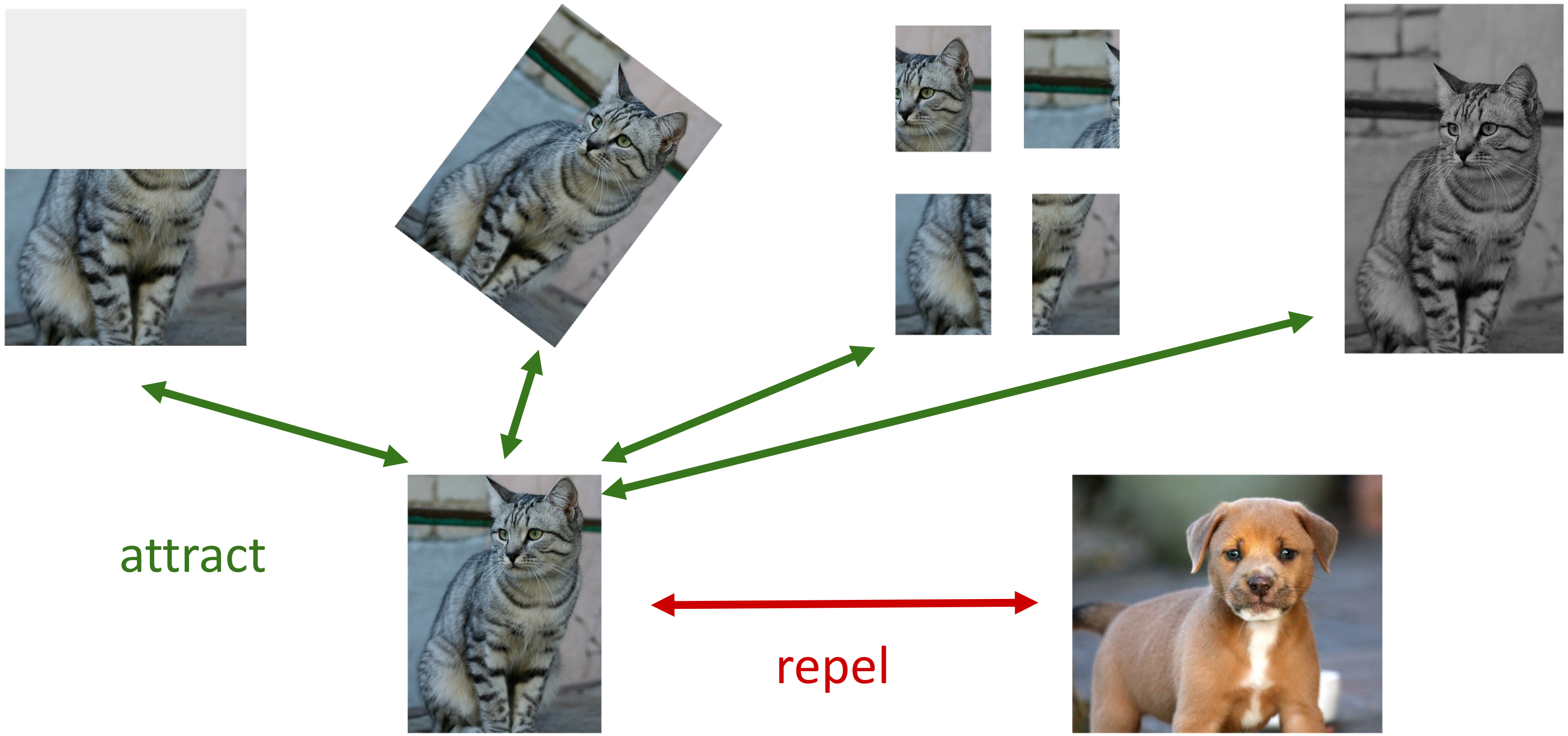


Today's Agenda

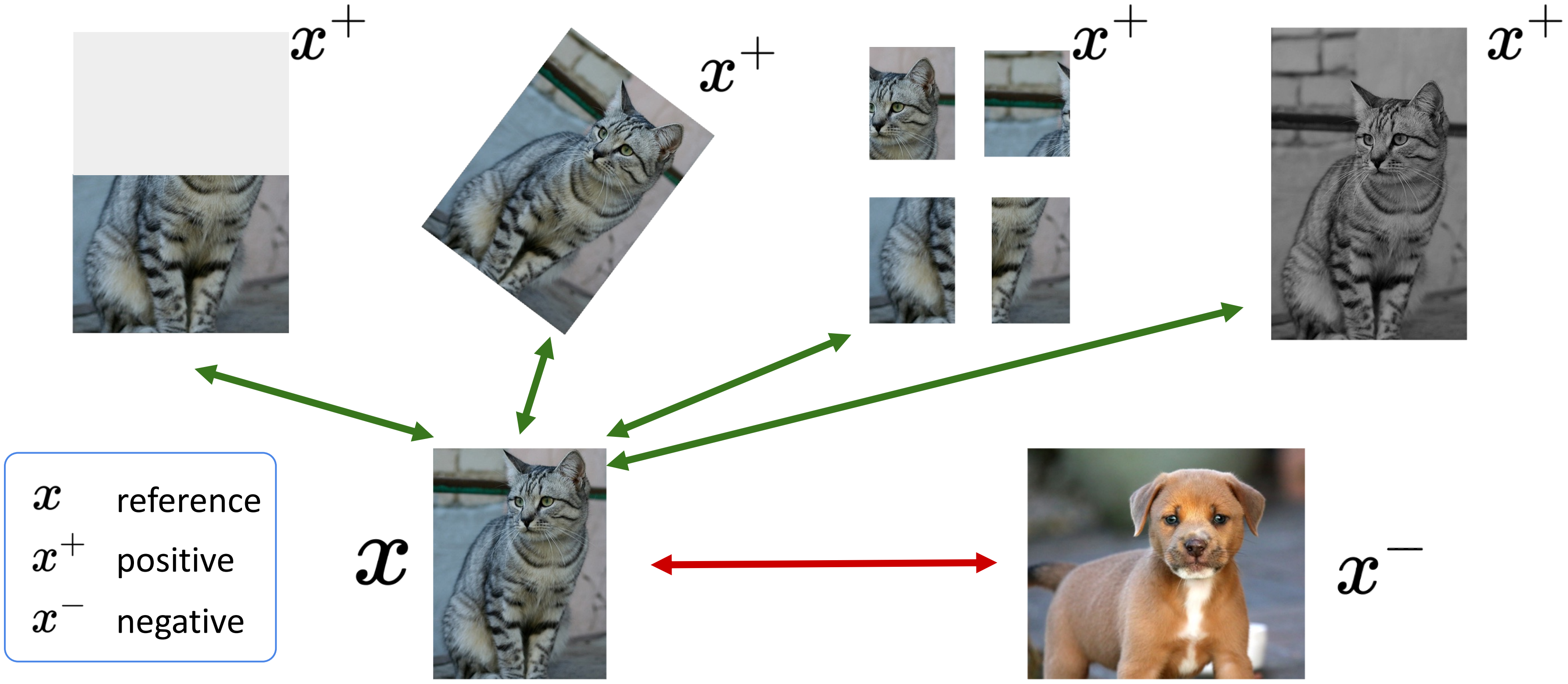
Pretext tasks from image transformations
- Rotation, inpainting, rearrangement, coloring

Contrastive representation learning
- Intuition and formulation
- Instance contrastive learning: SimCLR and MOCO
- Sequence contrastive learning: CPC

Contrastive Representation Learning



Contrastive Representation Learning



A formulation of contrastive learning

What we want:

$$\text{score}(f(x), f(x^+)) >> \text{score}(f(x), f(x^-))$$

x: reference sample; x^+ positive sample; x^- negative sample

Given a chosen score function, we aim to learn an **encoder function** *f* that yields high score for positive pairs (x, x^+) and low scores for negative pairs (x, x^-).

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+)))}{\exp(s(f(x), f(x^+))) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-)))} \right]$$

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+)))}{\exp(s(f(x), f(x^+))) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-)))} \right]$$

x

x^+

x

x_1^-

x_2^-

x_3^-

...

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\overline{\exp(s(f(x), f(x^+)))}}{\underbrace{\exp(s(f(x), f(x^+)))}_{\text{score for the positive pair}} + \underbrace{\sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-)))}_{\text{score for the N-1 negative pairs}}} \right]$$

This seems familiar …

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\overline{\exp(s(f(x), f(x^+))}}{\underbrace{\exp(s(f(x), f(x^+))}_{\text{score for the positive pair}} + \underbrace{\sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))}_{\text{score for the N-1 negative pairs}}} \right]$$

This seems familiar …

Cross entropy loss for a N-way softmax classifier!

I.e., learn to find the positive sample from the N samples

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

Commonly known as the InfoNCE loss (van den Oord et al., 2018)

A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

The larger the negative sample size (*N*), the tighter the bound

Detailed derivation: Poole et al., 2019

SimCLR: A Simple Framework for Contrastive Learning

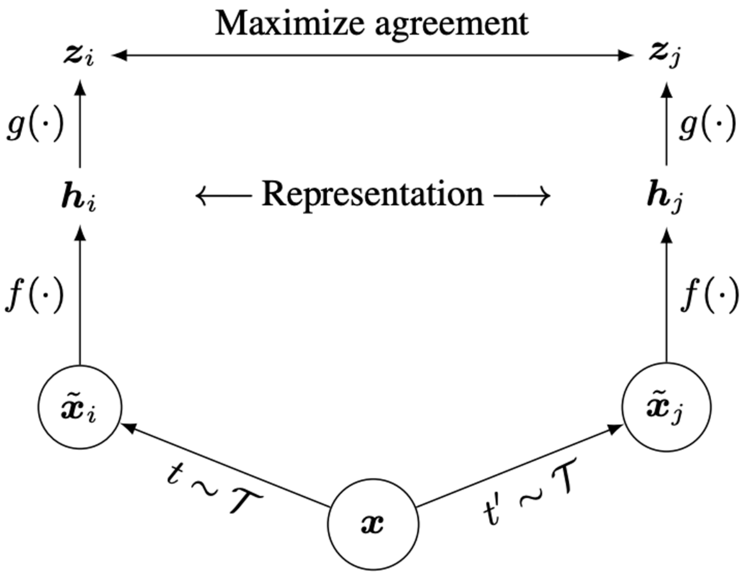
Cosine similarity as the score function:

$$s(u, v) = \frac{u^T v}{||u||||v||}$$

Use a projection network ***h(·)*** to project features to a space where contrastive learning is applied

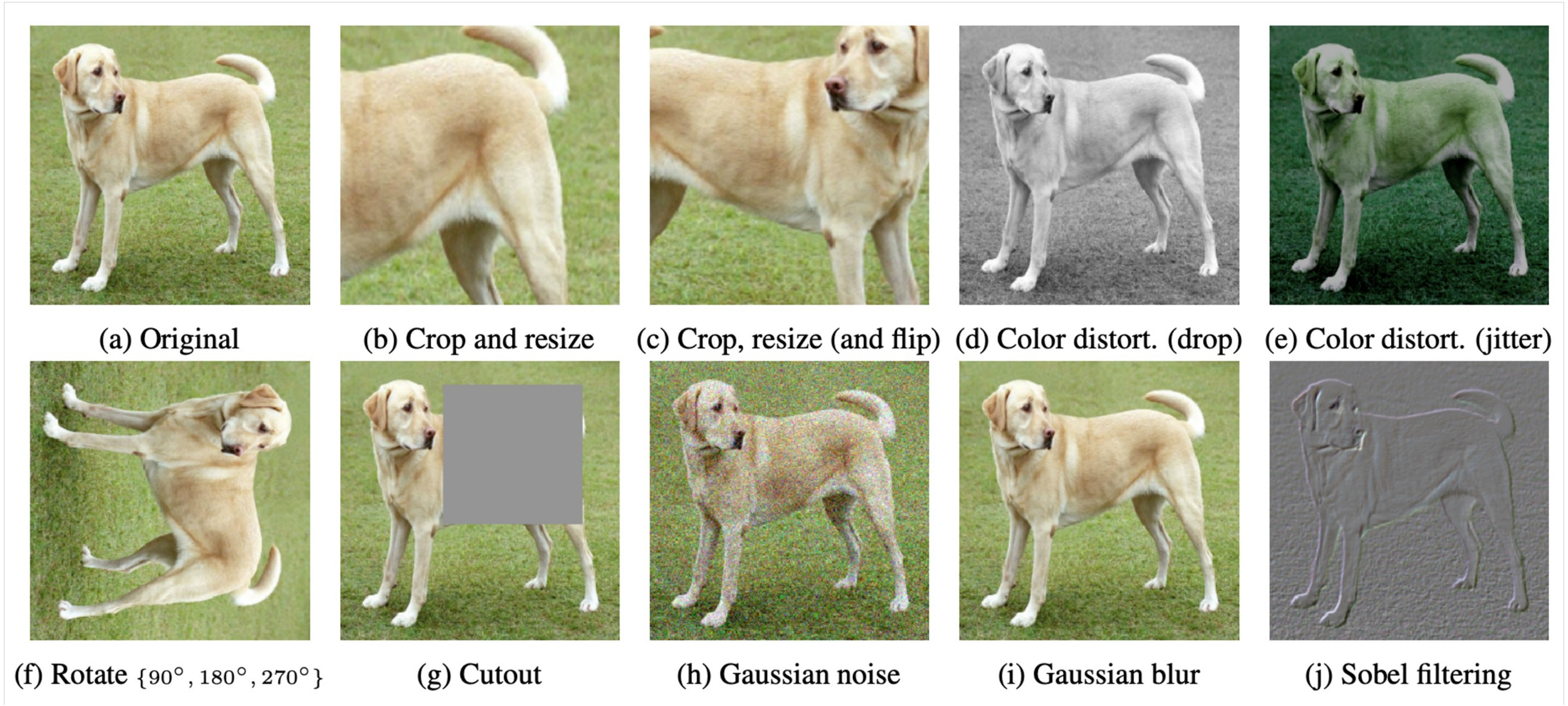
Generate positive samples through data augmentation:

- random cropping, random color distortion, and random blur.



Source: Chen et al., 2020

SimCLR: generating positive samples from data augmentation



Source: [Chen et al., 2020]

SimCLR

Generate a positive pair by sampling data augmentation functions

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    $\boxed{\text{draw two augmentation functions } t \sim \mathcal{T}, t' \sim \mathcal{T}}$
    # the first augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^{\top} \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

Source: [Chen et al., 2020]

SimCLR

Generate a positive pair by sampling data augmentation functions

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    $\boxed{\text{draw two augmentation functions } t \sim \mathcal{T}, t' \sim \mathcal{T}}$
    # the first augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\boxed{\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

InfoNCE loss:
Use all non-positive samples in the batch as x^-

Source: [Chen et al., 2020]

SimCLR

Generate a positive pair by sampling data augmentation functions

Iterate through and use each of the 2N sample as reference, compute average loss

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^N$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    draw two augmentation functions $t \sim \mathcal{T}$, $t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

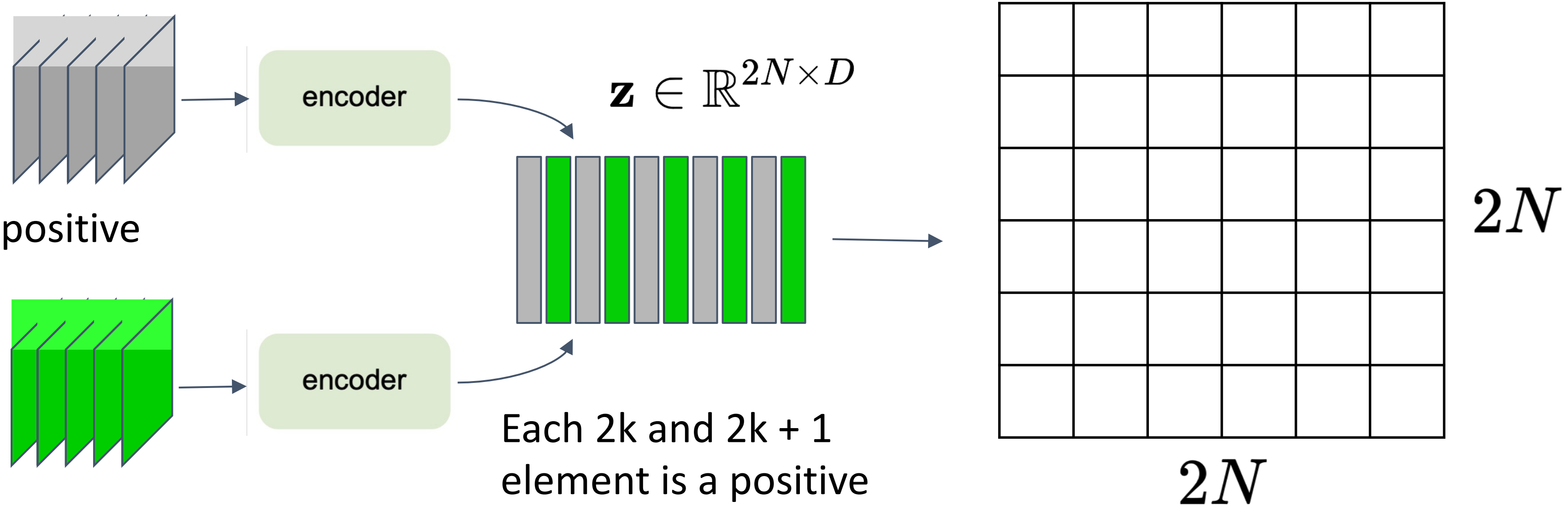
InfoNCE loss:
Use all non-positive samples in the batch as x^-

Source: [Chen et al., 2020]

SimCLR: mini-batch training

$$s_{i,j} = \frac{z_i^T z_j}{||z_i|| \, ||z_j||}$$

"Affinity matrix"



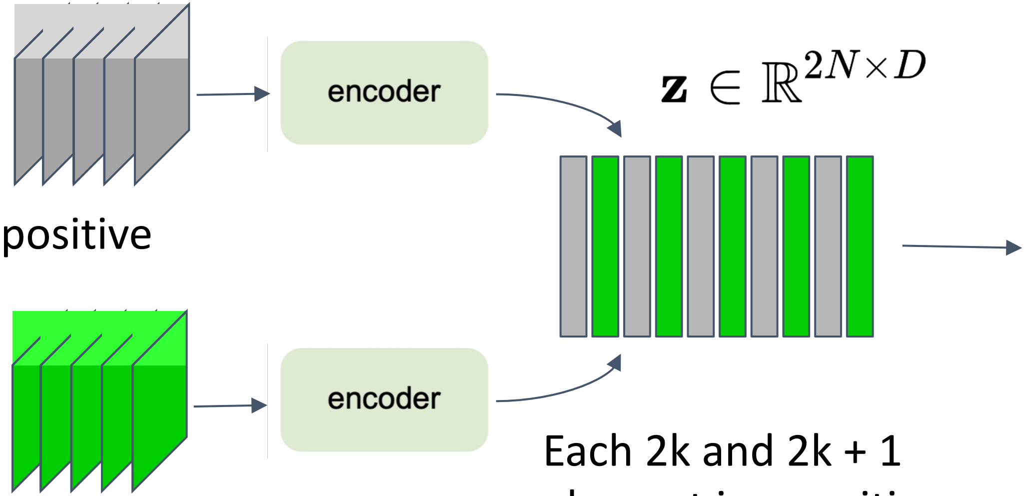
list of positive pairs

Each 2k and 2k + 1 element is a positive pair

SimCLR: mini-batch training

$$s_{i,j} = \frac{z_i^T z_j}{||z_i|| \, ||z_j||}$$

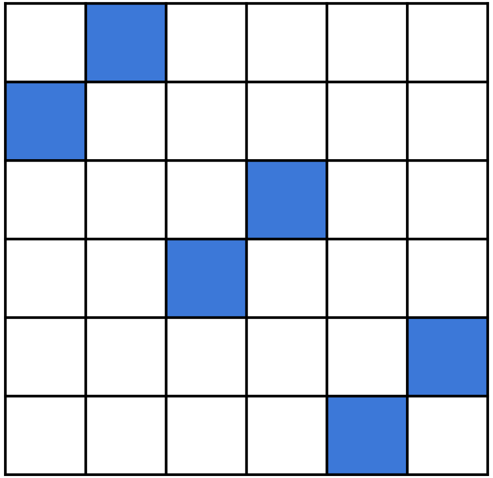
list of positive pairs



$\mathbf{z} \in \mathbb{R}^{2N \times D}$

Each 2k and 2k + 1 element is a positive pair

"Affinity matrix"

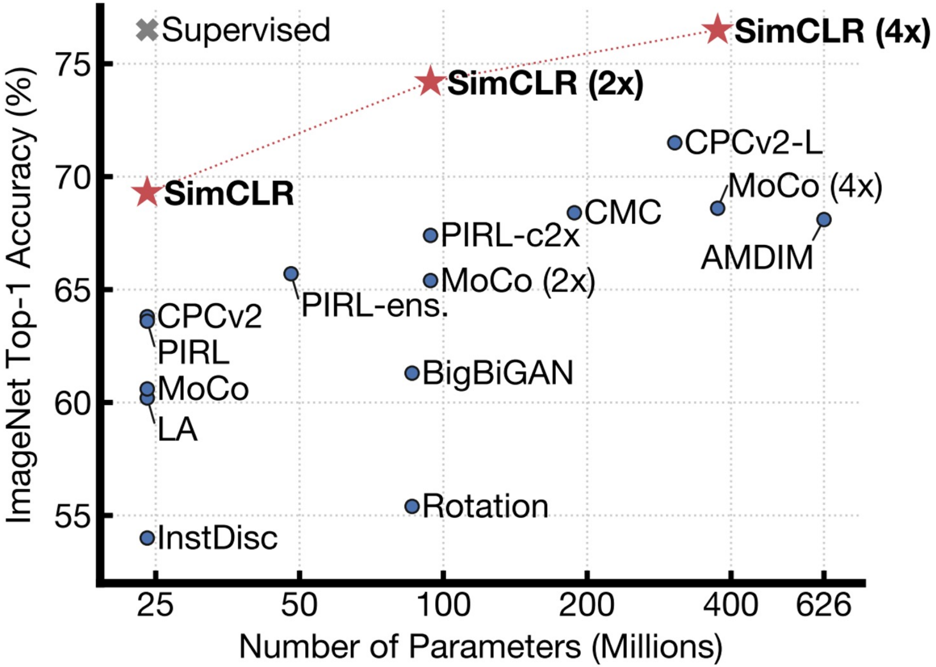


$2N$

$2N$

= classification label for each row

Training linear classifier on SimCLR features



Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Freeze feature encoder, train a linear classifier on top with labeled data.

Source: [Chen et al., 2020]

Semi-supervised learning on SimCLR features

Method	Architecture	Label fraction 1% (Top 5)	Label fraction 10% (Top 5)
Supervised baseline	ResNet-50	48.4	80.4
Methods using other label-propagation:			
Pseudo-label	ResNet-50	51.6	82.4
VAT+Entropy Min.	ResNet-50	47.0	83.4
UDA (w. RandAug)	ResNet-50	-	88.5
FixMatch (w. RandAug)	ResNet-50	-	89.1
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2
Methods using representation learning only:			
InstDisc	ResNet-50	39.2	77.4
BigBiGAN	RevNet-50 (4×)	55.2	78.8
PIRL	ResNet-50	57.2	83.8
CPC v2	ResNet-161(∗)	77.9	91.2
SimCLR (ours)	ResNet-50	75.5	87.8
SimCLR (ours)	ResNet-50 (2×)	83.0	91.2
SimCLR (ours)	ResNet-50 (4×)	**85.8**	**92.6**

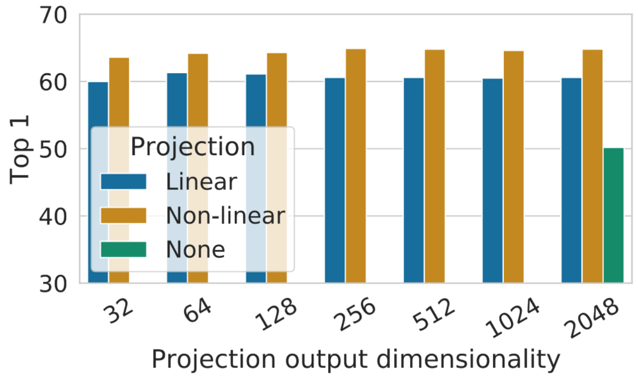
Table 7. ImageNet accuracy of models trained with few labels.

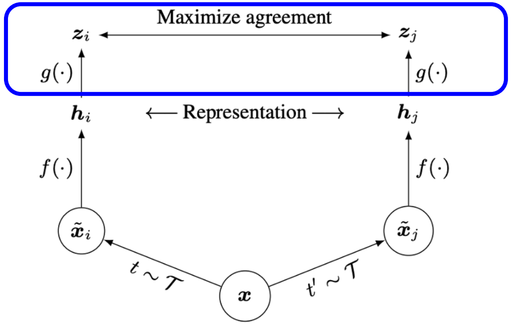
Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Finetune the encoder with 1% / 10% of labeled data on ImageNet.

Source: [Chen et al., 2020]

SimCLR design choices: projection head





Linear / non-linear projection heads improve representation learning.

A possible explanation:

- contrastive learning objective may discard useful information for downstream tasks
- representation space ***z*** is trained to be invariant to data transformation.
- by leveraging the projection head **g(·)**, more information can be preserved in the **h** representation space

Source: [Chen et al., 2020]

SimCLR design choices: large batch size

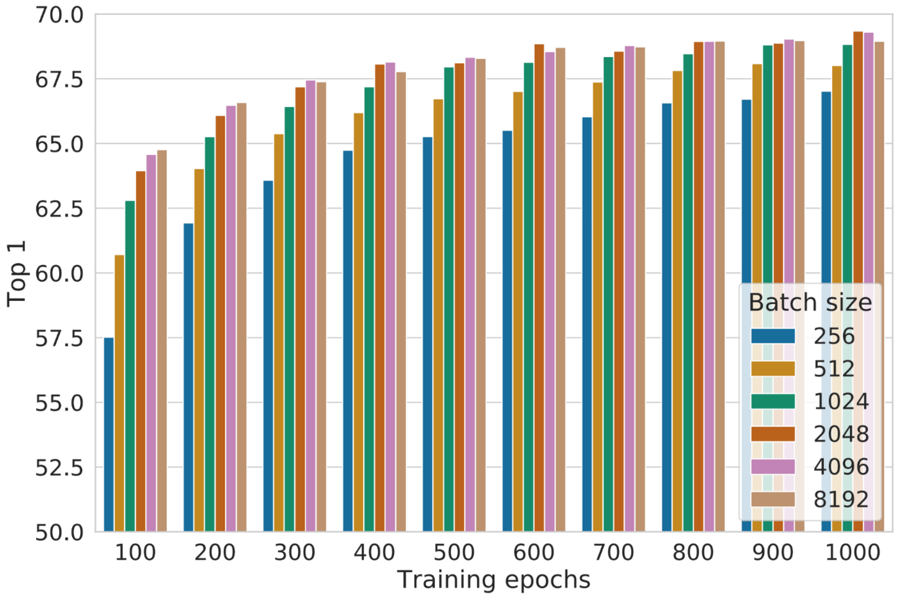


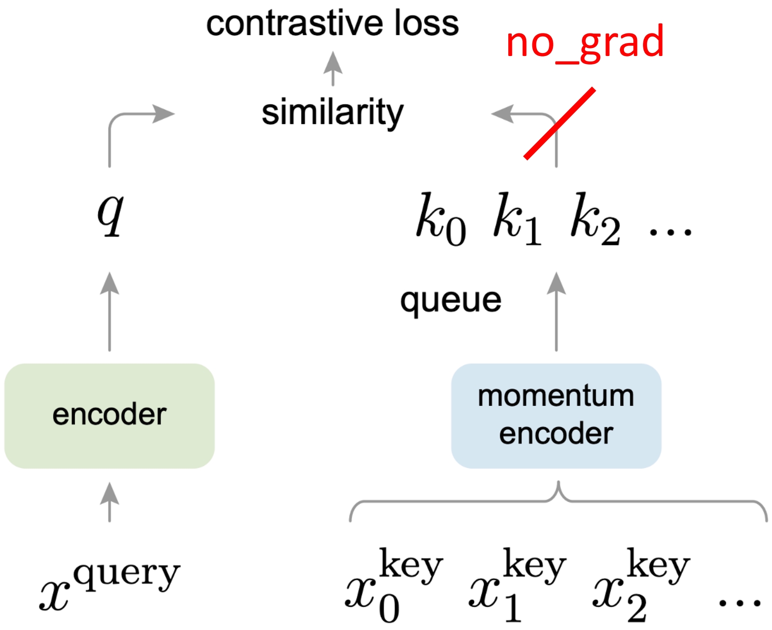
Figure 9. Linear evaluation models (ResNet-50) trained with different batch size and epochs. Each bar is a single run from scratch.[10]

Large training batch size is crucial for SimCLR!

Large batch size causes large memory footprint during backpropagation: requires distributed training on TPUs (ImageNet experiments)

Source: [Chen et al., 2020]()

Momentum Contrastive Learning (MoCo)

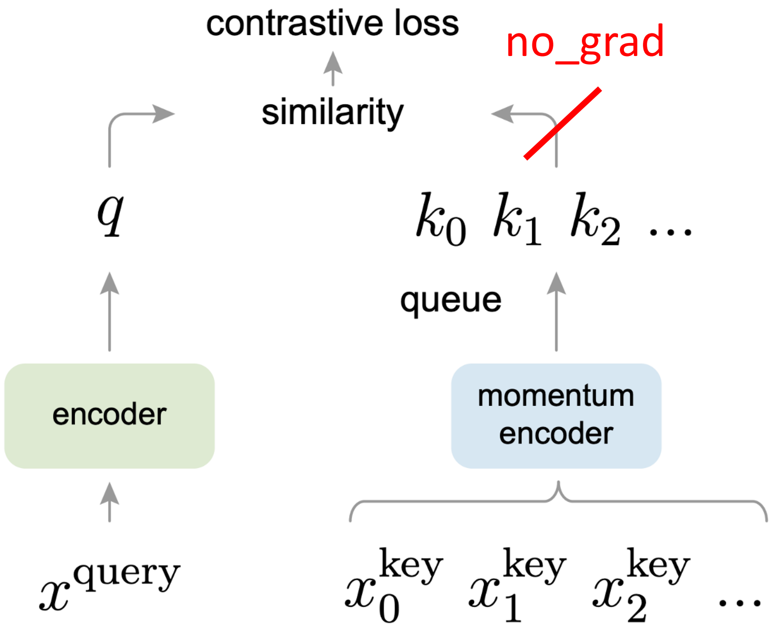


Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.

Source: He et al., 2020

Momentum Contrastive Learning (MoCo)



Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.
- The key encoder is slowly progressing through the momentum update rules:

$$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1 - m)\theta_{\mathrm{q}}$$

Source: He et al., 2020

MoCo

Algorithm 1 Pseudocode of MoCo in a PyTorch-like style.

```
# f_q, f_k: encoder networks for query and key
# queue: dictionary as a queue of K keys (CxK)
# m: momentum
# t: temperature

f_k.params = f_q.params # initialize
for x in loader: # load a minibatch x with N samples
   x_q = aug(x) # a randomly augmented version
   x_k = aug(x) # another randomly augmented version

   q = f_q.forward(x_q) # queries: NxC
   k = f_k.forward(x_k) # keys: NxC
   k = k.detach() # no gradient to keys

   # positive logits: Nx1
   l_pos = bmm(q.view(N,1,C), k.view(N,C,1))

   # negative logits: NxK
   l_neg = mm(q.view(N,C), queue.view(C,K))

   # logits: Nx(1+K)
   logits = cat([l_pos, l_neg], dim=1)

   # contrastive loss, Eqn.(1)
   labels = zeros(N) # positives are the 0-th
   loss = CrossEntropyLoss(logits/t, labels)

   # SGD update: query network
   loss.backward()
   update(f_q.params)

   # momentum update: key network
   f_k.params = m*f_k.params+(1-m)*f_q.params

   # update dictionary
   enqueue(queue, k) # enqueue the current minibatch
   dequeue(queue) # dequeue the earliest minibatch
```

bmm: batch matrix multiplication; mm: matrix multiplication; cat: concatenation.

Generate a positive pair by sampling data augmentation functions

No gradient through the positive sample

Use the running queue of keys as the negative samples

InfoNCE loss

Update f_k through momentum

Update the FIFO negative sample queue

Source: He et al., 2020

"MoCo V2"

Improved Baselines with Momentum Contrastive Learning

Xinlei Chen Haoqi Fan Ross Girshick Kaiming He
Facebook AI Research (FAIR)

A hybrid of ideas from SimCLR and MoCo:

- **From SimCLR**: non-linear projection head and strong data augmentation.
- **From MoCo**: momentum-updated queues that allow training on a large number of negative samples (no TPU required!).

Source: [Chen et al., 2020]

MoCo vs. SimCLR vs. MoCo V2

case	unsup. pre-train MLP	aug+	cos	epochs	ImageNet acc.	VOC detection AP_{50}	AP	AP_{75}
supervised					76.5	81.3	53.5	58.8
MoCo v1				200	60.6	81.5	55.9	62.6
(a)	✓			200	66.2	82.0	56.4	62.6
(b)		✓		200	63.4	82.2	56.8	63.2
(c)	✓	✓		200	67.3	**82.5**	57.2	63.9
(d)	✓	✓	✓	200	67.5	82.4	57.0	63.6
(e)	✓	✓	✓	**800**	**71.1**	**82.5**	**57.4**	**64.0**

Table 1. **Ablation of MoCo baselines**, evaluated by ResNet-50 for (i) ImageNet linear classification, and (ii) fine-tuning VOC object detection (mean of 5 trials). "**MLP**": with an MLP head; "**aug+**": with extra blur augmentation; "**cos**": cosine learning rate schedule.

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.

Source: [Chen et al., 2020]

MoCo vs. SimCLR vs. MoCo V2

case	MLP	aug+	cos	epochs	batch	ImageNet acc.
	unsup. pre-train					
MoCo v1 [6]				200	256	60.6
SimCLR [2]	✓	✓	✓	200	256	61.9
SimCLR [2]	✓	✓	✓	200	8192	66.6
MoCo v2	✓	✓	✓	200	256	**67.5**
*results of **longer** unsupervised training follow:*						
SimCLR [2]	✓	✓	✓	1000	4096	69.3
MoCo v2	✓	✓	✓	800	256	**71.1**

Table 2. **MoCo *vs.* SimCLR**: ImageNet linear classifier accuracy (**ResNet-50, 1-crop 224×224**), trained on features from unsupervised pre-training. "aug+" in SimCLR includes blur and stronger color distortion. SimCLR ablations are from Fig. 9 in [2] (we thank the authors for providing the numerical results).

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).

Source: Chen et al., 2020

MoCo vs. SimCLR vs. MoCo V2

mechanism	batch	memory / GPU	time / 200-ep.
MoCo	256	**5.0G**	**53 hrs**
end-to-end	256	7.4G	65 hrs
end-to-end	4096	93.0G†	n/a

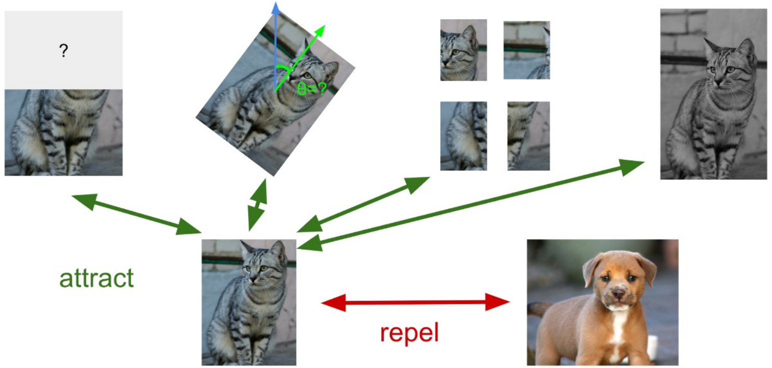
Table 3. **Memory and time cost** in 8 V100 16G GPUs, implemented in PyTorch. †: based on our estimation.

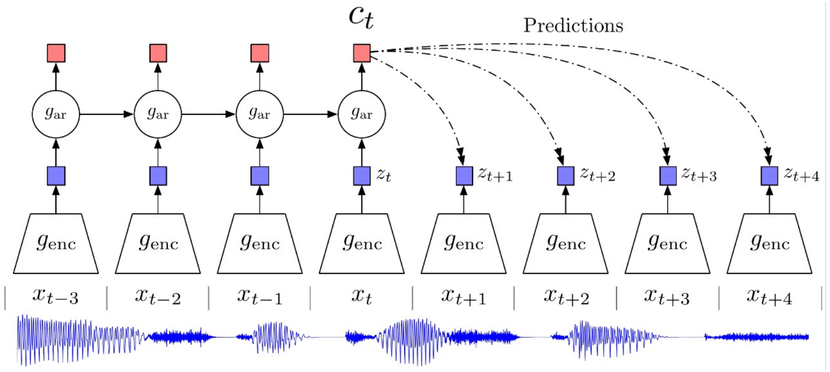
Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).
- … all with much smaller memory footprint! (“end-to-end” means SimCLR here)

Source: [Chen et al., 2020]

Instance vs. Sequence Contrastive Learning



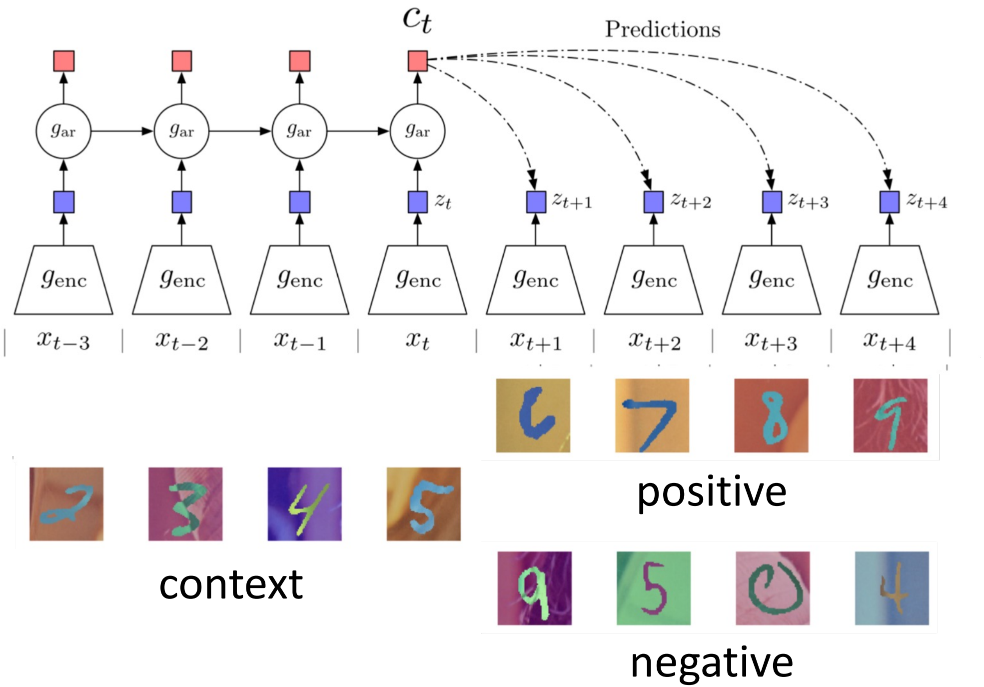


Source: van den Oord et al., 2018

Instance-level contrastive learning: contrastive learning based on positive & negative instances. Examples: SimCLR, MoCo

Sequence-level contrastive learning: contrastive learning based on sequential / temporal orders. Example: **Contrastive Predictive Coding (CPC)**

Contrastive Predictive Coding (CPC)



Contrastive: contrast between "right" and "wrong" sequences using contrastive learning.

Predictive: the model has to predict future patterns given the current context.

Coding: the model learns useful feature vectors, or "code", for downstream tasks, similar to other self-supervised methods.

Figure source

Source: van den Oord et al., 2018,

Contrastive Predictive Coding (CPC)

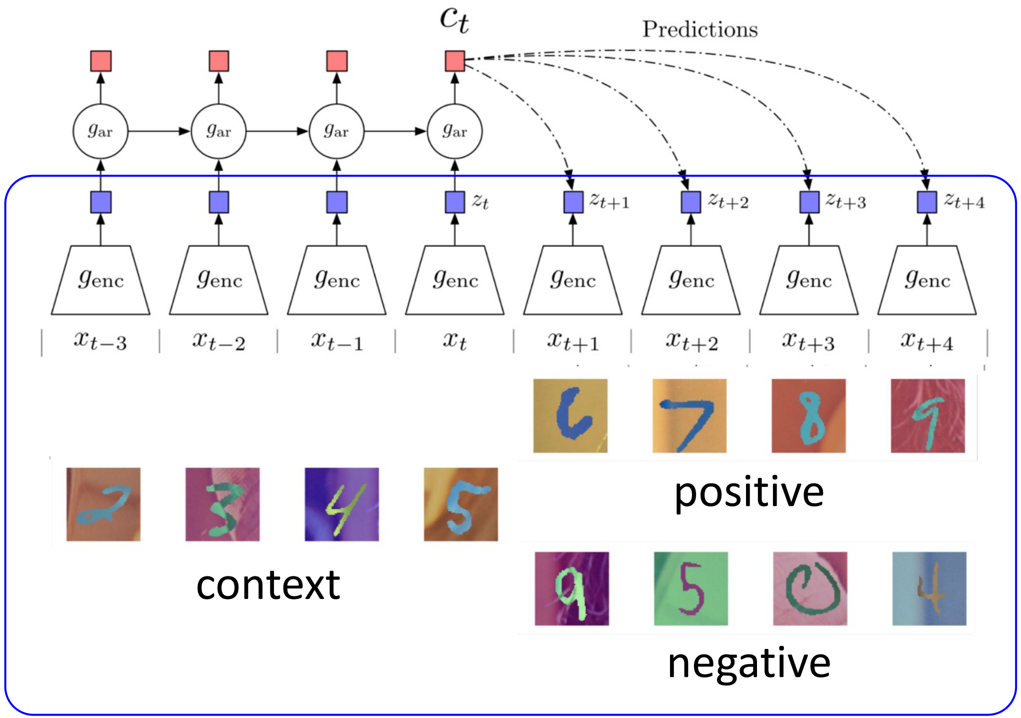
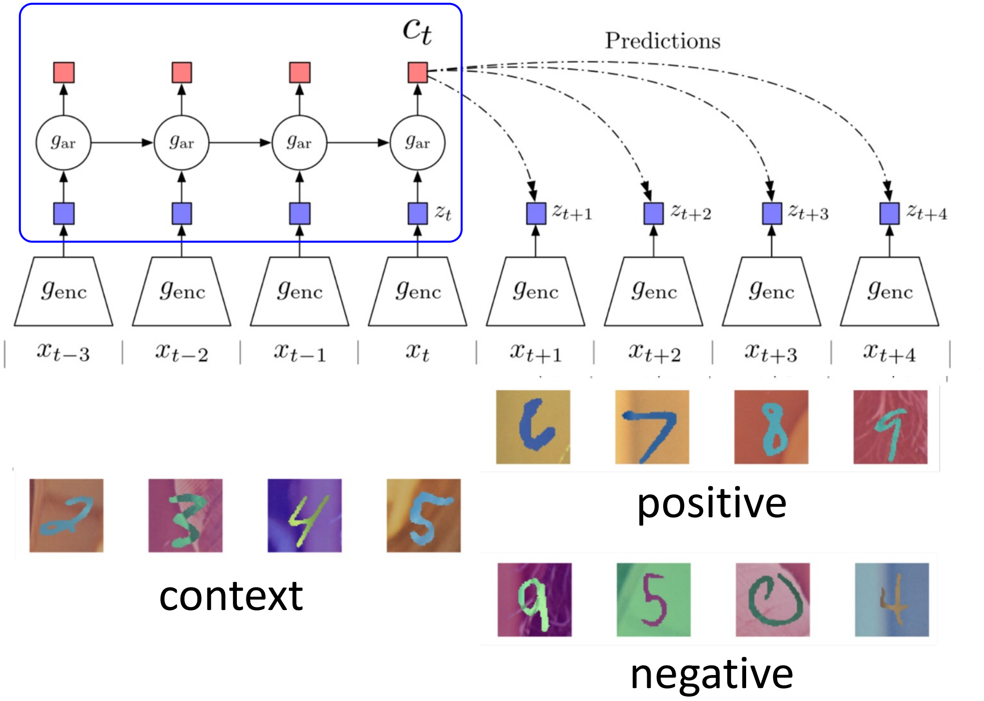


Figure source

1. Encode all samples in a sequence into vectors $\boldsymbol{z_t = g_{enc}(x_t)}$

Source: van den Oord et al., 2018,

Contrastive Predictive Coding (CPC)



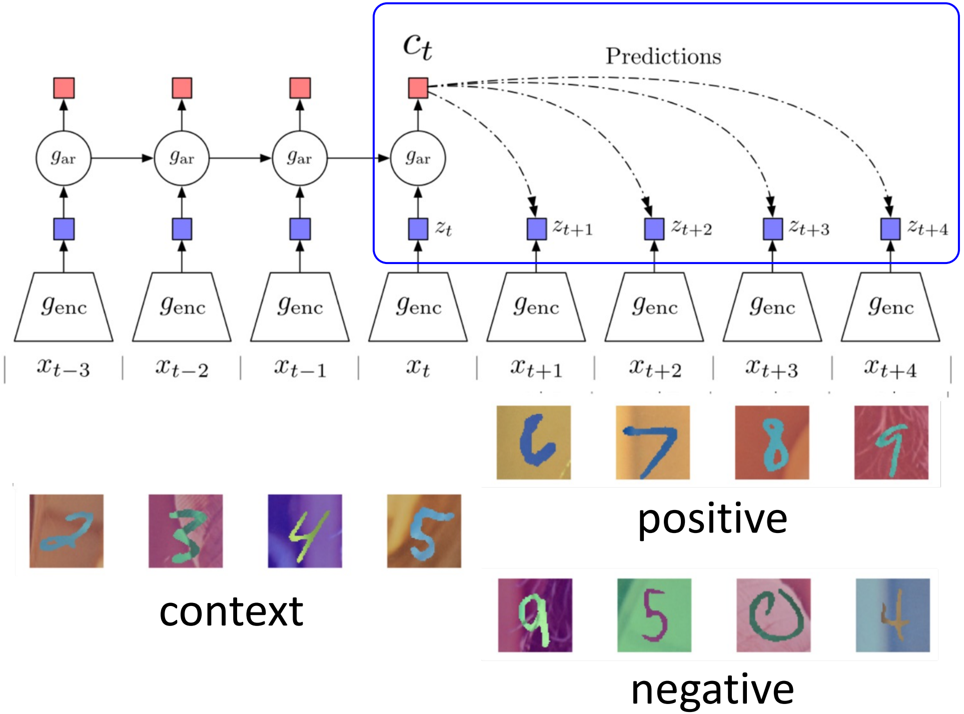
1. Encode all samples in a sequence into vectors $\boldsymbol{z_t = g_{enc}(x_t)}$

2. Summarize context (e.g., half of a sequence) into a context code $\boldsymbol{c_t}$ using an auto-regressive model ($\boldsymbol{g_{ar}}$).

Figure source

Source: van den Oord et al., 2018,

Contrastive Predictive Coding (CPC)



1. Encode all samples in a sequence into vectors $\boldsymbol{z_t = g_{enc}(x_t)}$

2. Summarize context (e.g., half of a sequence) into a context code $\boldsymbol{c_t}$ using an auto-regressive model ($\boldsymbol{g_{ar}}$).

3. Compute InfoNCE loss between the context $\boldsymbol{c_t}$ and future code $\boldsymbol{z_{t+k}}$ using the following time-dependent score function:

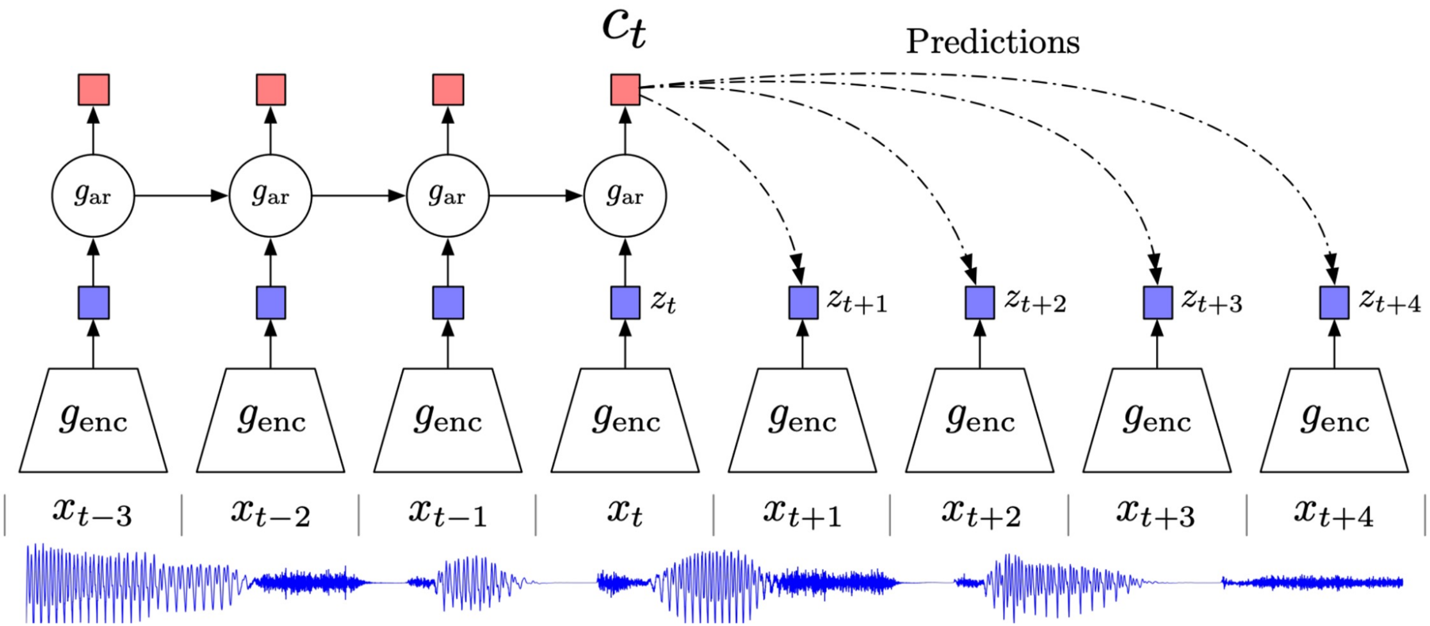
$$s_k(z_{t+k}, c_t) = z_{t+k}^T W_k c_t$$

, where W_k is a trainable matrix.

Figure source

Source: van den Oord et al., 2018,

CPC example: modeling audio sequences



Source: [van den Oord et al., 2018](),

CPC example: modeling audio sequences

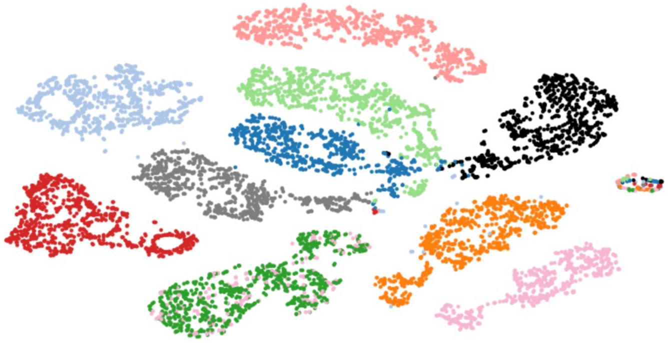


Figure 2: t-SNE visualization of audio (speech) representations for a subset of 10 speakers (out of 251). Every color represents a different speaker.

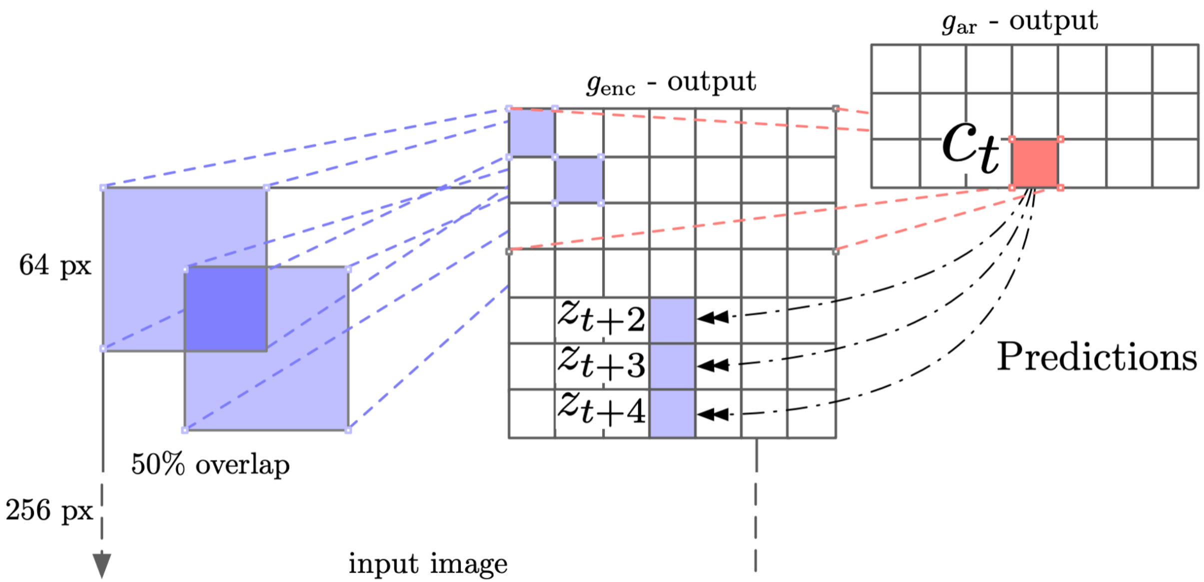
Method	ACC
Phone classification	
Random initialization	27.6
MFCC features	39.7
CPC	64.6
Supervised	74.6
Speaker classification	
Random initialization	1.87
MFCC features	17.6
CPC	97.4
Supervised	98.5

Linear classification on trained representations (LibriSpeech dataset)

Source: van den Oord et al., 2018,

CPC example: modeling visual context

Idea: split image into patches, model rows of patches from top to bottom as a sequence. I.e., use top rows as context to predict bottom rows.



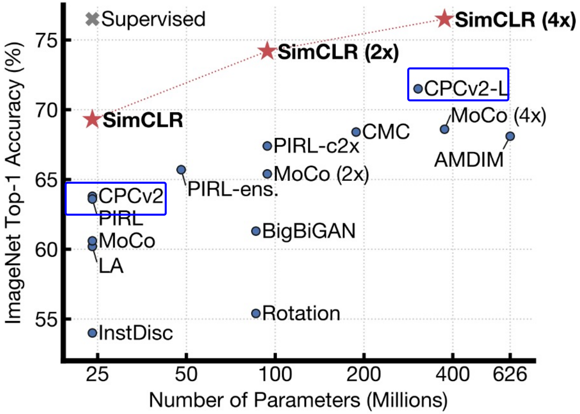
Source: [van den Oord et al., 2018](),

CPC example: modeling visual context

Method	Top-1 ACC
Using AlexNet conv5	
Video [28]	29.8
Relative Position [11]	30.4
BiGan [35]	34.8
Colorization [10]	35.2
Jigsaw [29] *	38.1
Using ResNet-V2	
Motion Segmentation [36]	27.6
Exemplar [36]	31.5
Relative Position [36]	36.2
Colorization [36]	39.6
CPC	**48.7**

Table 3: ImageNet top-1 unsupervised classification results. *Jigsaw is not directly comparable to the other AlexNet results because of architectural differences.

- Compares favorably with other pretext task-based self-supervised learning method.
- Doesn't do as well compared to newer instance-based contrastive learning methods on image feature learning.



Source: van den Oord et al., 2018,

Summary: Contrastive Representation Learning

A general formulation for contrastive learning:

$$\text{score}(f(x), f(x^+)) >> \text{score}(f(x), f(x^-))$$

InfoNCE loss: N-way classification among positive and negative samples

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

Commonly known as the InfoNCE loss (van den Oord et al., 2018)

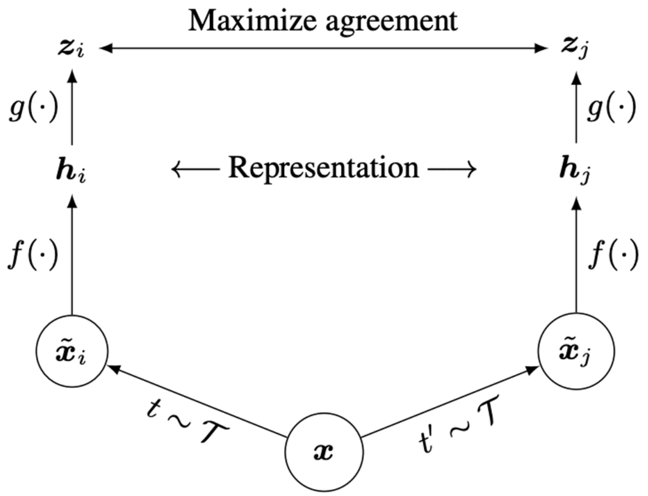
A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

Summary: Contrastive Representation Learning

SimCLR: a simple framework for contrastive representation learning

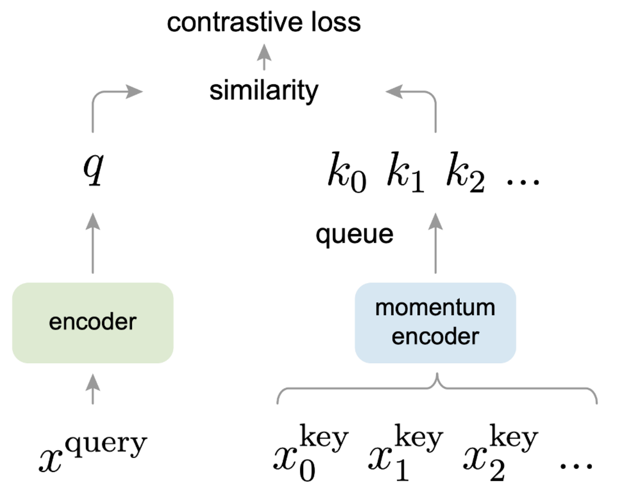
- **Key ideas**: non-linear projection head to allow flexible representation learning
- Simple to implement, effective in learning visual representation
- Requires large training batch size to be effective; large memory footprint



Summary: Contrastive Representation Learning

MoCo (v1, v2): contrastive learning using momentum sample encoder

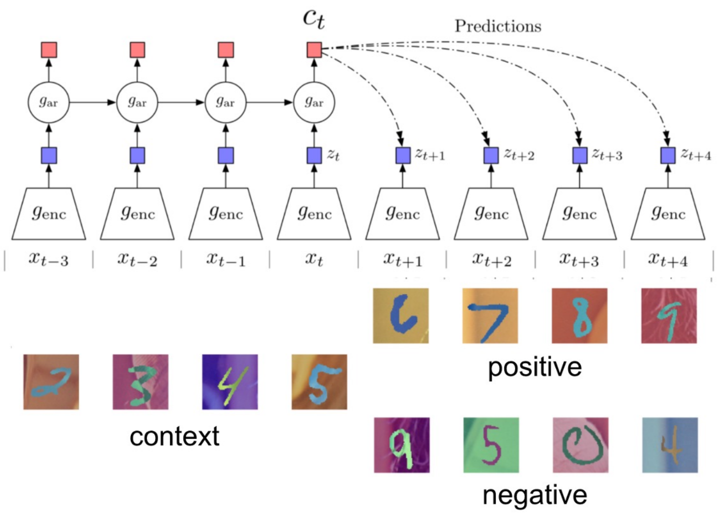
- Decouples negative sample size from minibatch size; allows large batch training without TPU
- MoCo-v2 combines the key ideas from SimCLR, i.e., nonlinear projection head, strong data augmentation, with momentum contrastive learning



Summary: Contrastive Representation Learning

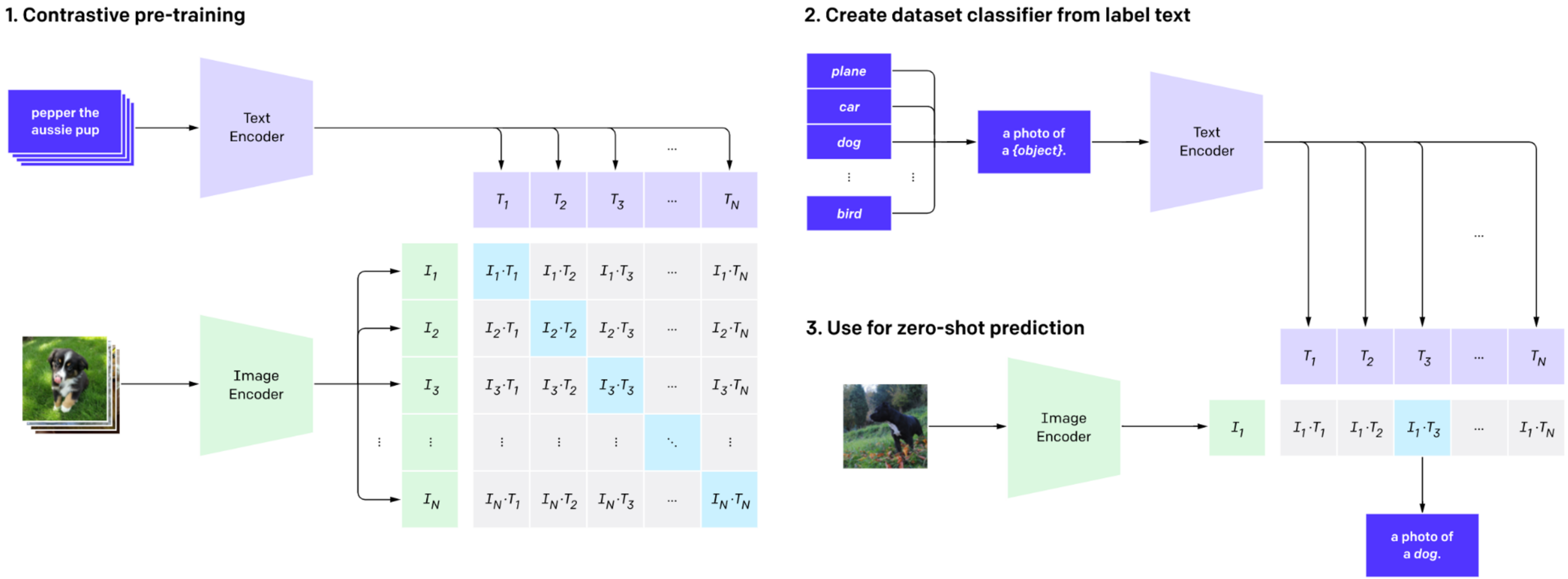
CPC: sequence-level contrastive learning

- Contrast "right" sequence with "wrong" sequence.
- InfoNCE loss with a time-dependent score function.
- Can be applied to a variety of learning problems, but not as effective in learning image representations compared to instance-level methods.



Other examples

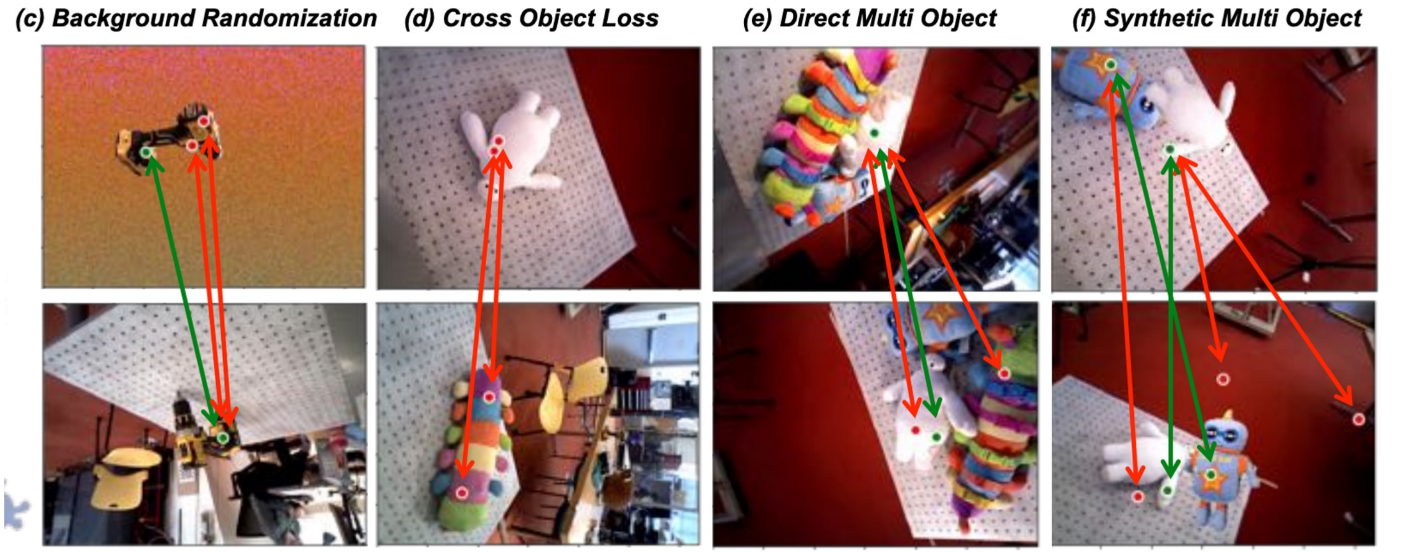
Contrastive learning between image and natural language sentences



CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

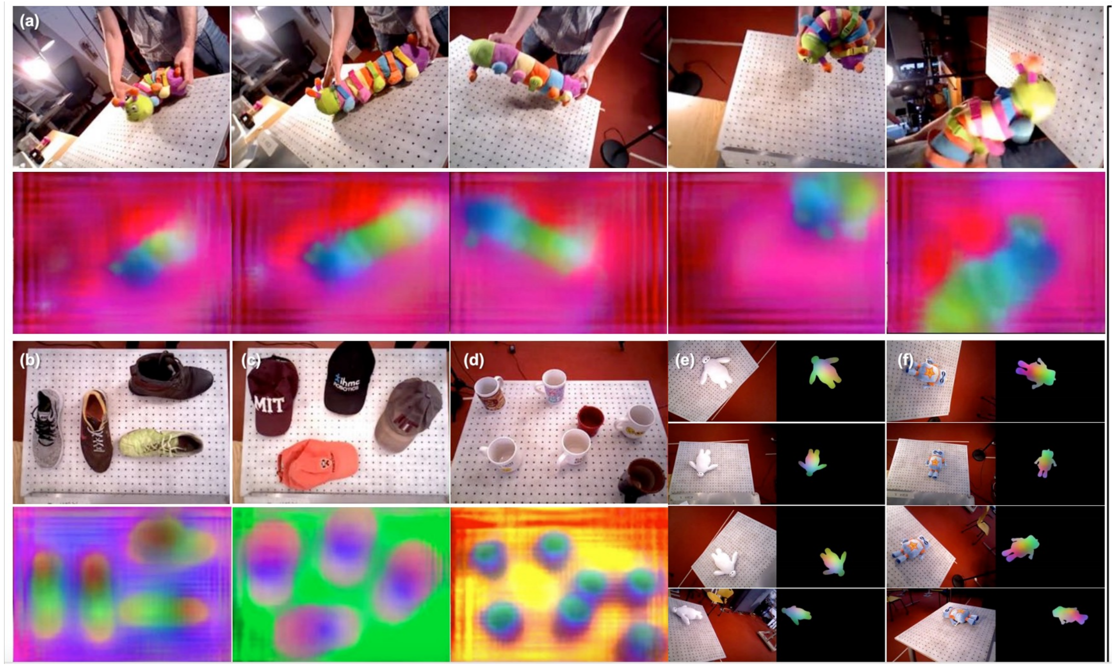
Other examples

Contrastive learning on pixel-wise feature descriptors



Dense Object Net, Florence et al., 2018

Other examples



Dense Object Net, Florence et al., 2018

Vision and Language Models:

Connecting the Pixel and Semantic Worlds at Scale

Why Vision-Language Models?

- Language is the most intuitive interface for an unstructured data space (e.g., natural images)
- Important to ground sensory information to semantic concepts
- Complementary information sources for a given task
- Claim: you cannot learn language without grounding

History: the first captioning model (Ordonez, 2011)

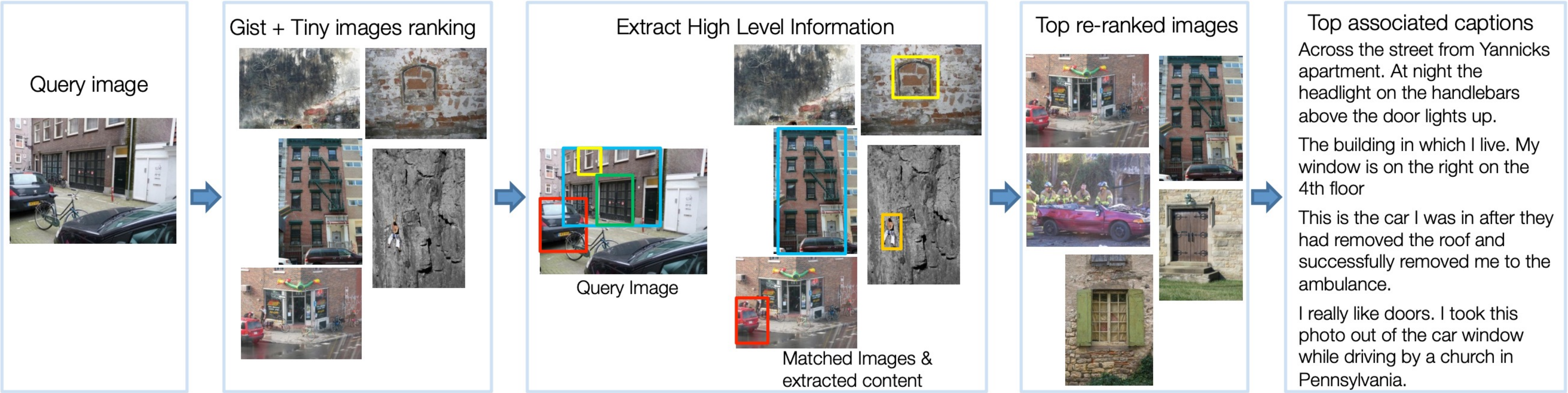
Im2Text: Describing Images Using 1 Million Captioned Photographs

Vicente Ordonez **Girish Kulkarni** **Tamara L Berg**

Stony Brook University
Stony Brook, NY 11794
{vordonezroma or tlberg}@cs.stonybrook.edu

Abstract

History: the first captioning model (Ordonez, 2011)



History: the first deep captioning model (Vinyals, 2015)

Show and Tell: A Neural Image Caption Generator

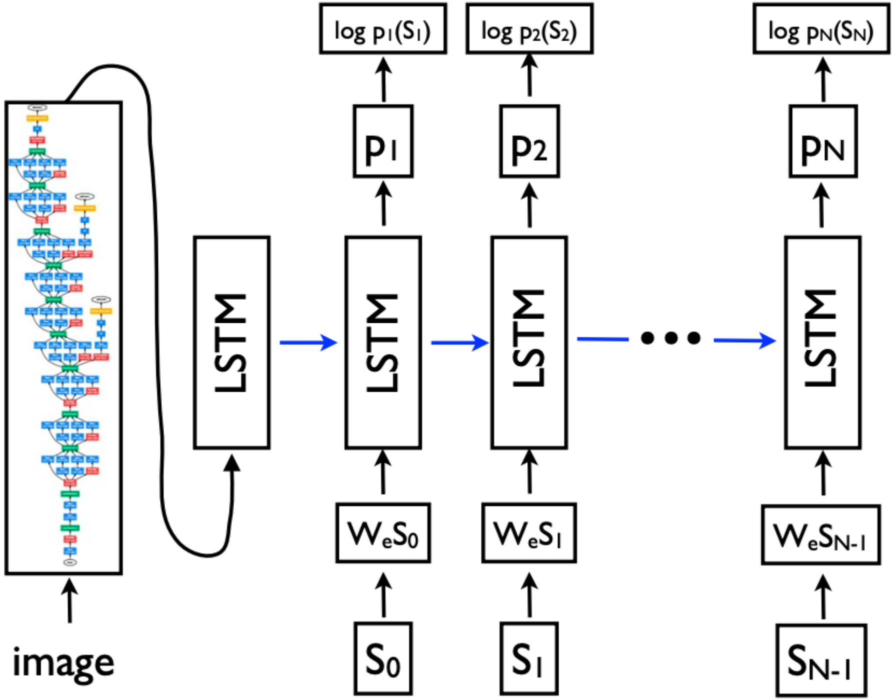
Oriol Vinyals
Google
vinyals@google.com

Alexander Toshev
Google
toshev@google.com

Samy Bengio
Google
bengio@google.com

Dumitru Erhan
Google
dumitru@google.com

History: the first deep captioning model (Vinyals, 2015)



History: the first VQA model (Agrawal, 2015)

VQA: Visual Question Answering

www.visualqa.org

Aishwarya Agrawal*, Jiasen Lu*, Stanislaw Antol*,
Margaret Mitchell, C. Lawrence Zitnick, Dhruv Batra, Devi Parikh

Abstract—We propose the task of *free-form* and *open-ended* Visual Question Answering (VQA). Given an image and a natural language question about the image, the task is to provide an accurate natural language answer. Mirroring real-world scenarios, such as helping the visually impaired, both the questions and answers are open-ended. Visual questions selectively target different areas of an image, including background details and underlying context. As a result, a system that succeeds at VQA typically needs a more detailed understanding of the image and complex reasoning than a system producing generic image captions. Moreover, VQA is amenable to automatic evaluation, since many open-ended answers contain only a few words or a closed set of answers that can be provided in a multiple-choice format. We provide a dataset containing ∼0.25M images, ∼0.76M questions, and ∼10M answers (www.visualqa.org), and discuss the information it provides. Numerous baselines and methods for VQA are provided and compared with human performance. Our VQA demo is available on CloudCV (http://cloudcv.org/vqa).

History: the first VQA model (Agrawal, 2015)

Is something under the sink broken?	yes yes yes	no no no
What number do you see?	33 33 33	5 6 7

Can you park here?	no no no	no no yes
What color is the hydrant?	white and orange white and orange white and orange	red red yellow

What kind of store is this?	bakery bakery pastry	art supplies grocery grocery
Is the display case as full as it could be?	no no no	no yes yes

How many bikes are there?	2 2 2	3 4 12
What number is the bus?	48 48 48	4 46 number 6

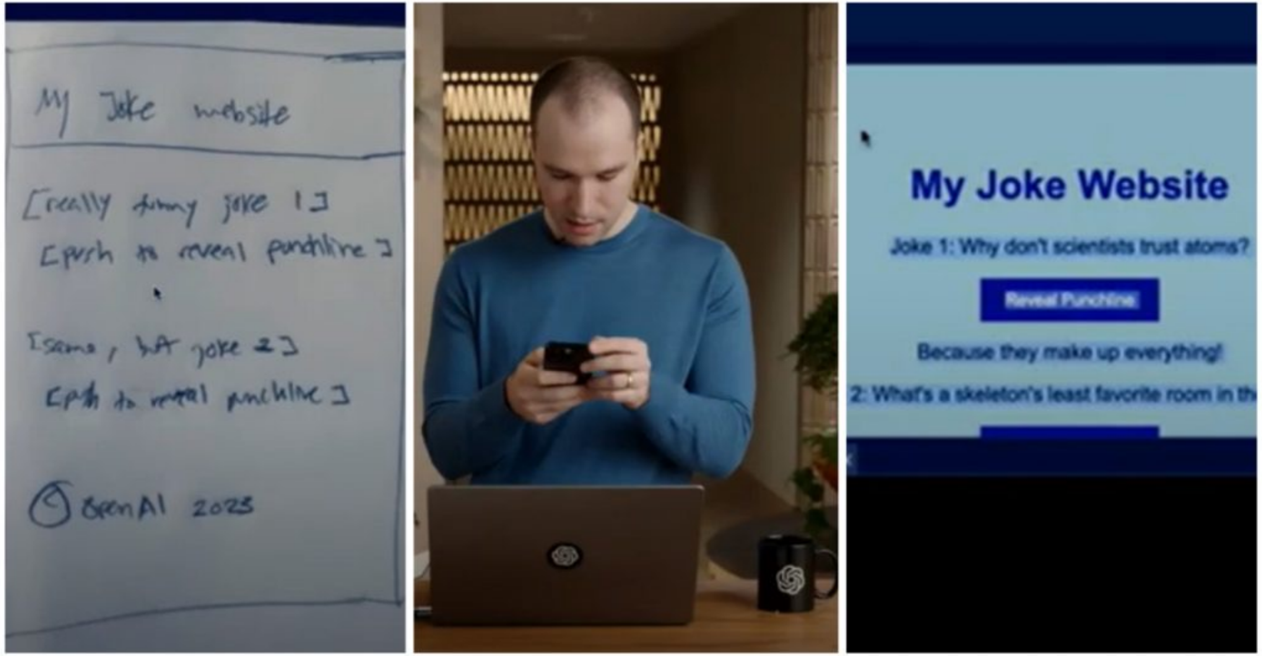
Does this man have children?	yes yes yes	yes yes yes
Is this man crying?	no no no	no yes yes

Has the pizza been baked?	yes yes yes	yes yes yes
What kind of cheese is topped on this pizza?	feta feta ricotta	mozzarella mozzarella mozzarella

How many pickles are on the plate?	1 1 1	1 1 1
What is the shape of the plate?	circle round round	circle round round

What does the sign say?	stop stop stop	stop stop yield
What shape is this sign?	octagon octagon octagon	diamond octagon round

Foundation VLM (2019-)



Hand-drawn sketch to website source code
GPT 4v(ision) (OpenAI, 2023)

Major Areas

- **Representation**: how to convert raw data into meaningful features
- **Translation**: transform one modality to another
- **Alignment**: discover relationships between elements across modalities
- **Fusion**: join features from modalities to support prediction
- **Co-learning**: transferring knowledge from one modality to another

Slide credit: Desmont Elliott

Language->Vision: Language-guided Image Gen

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

riding a horse lounging in a tropical resort in space playing basketball with cats in space

in a photorealistic style in the style of Andy Warhol as a pencil drawing

→

DALL·E 2

https://openai.com/dall-e-2/

Vision->Language: Image Captioning

Captions generated using neuraltalk2

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

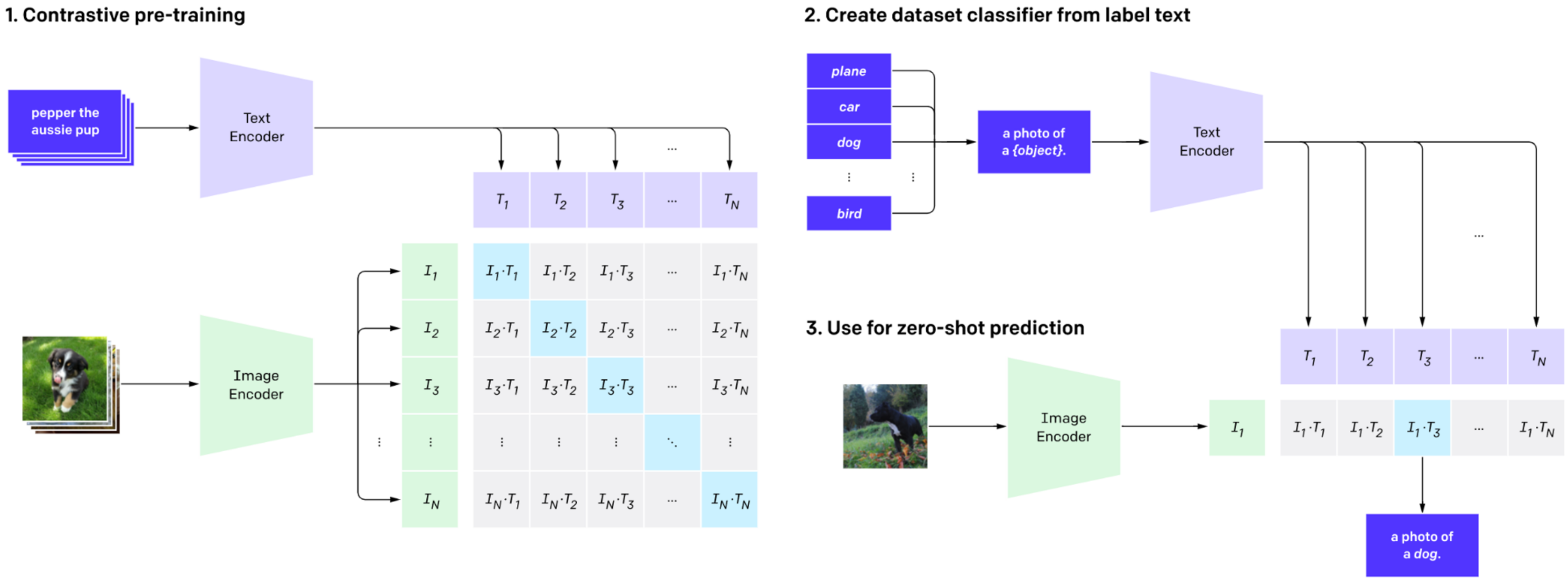
A tennis player in action on the court

Two giraffes standing in a grassy field

A man riding a dirt bike on a dirt track

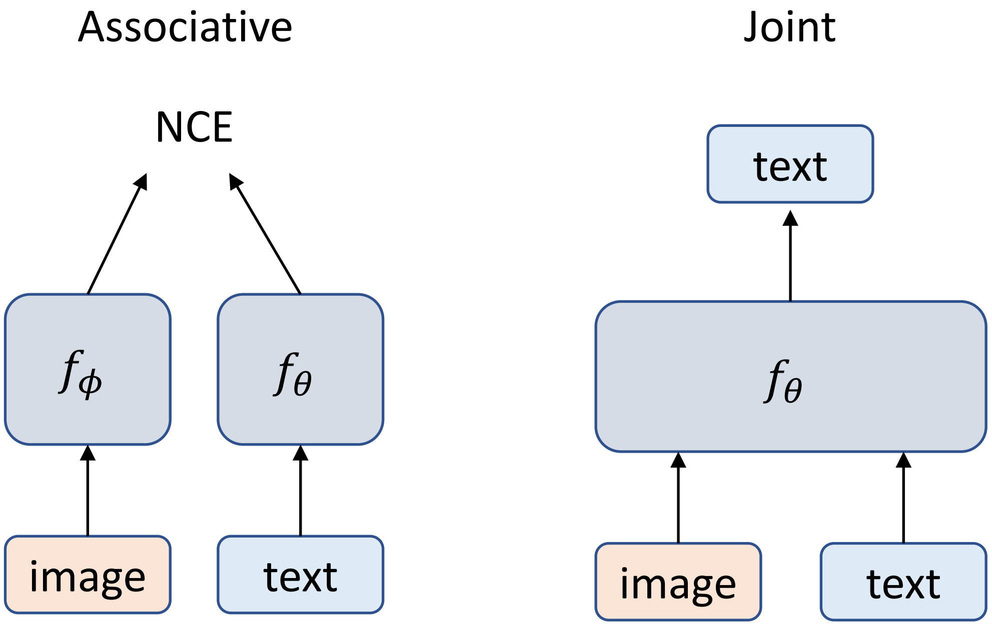
Image – Language Association

Contrastive learning between image and natural language sentences

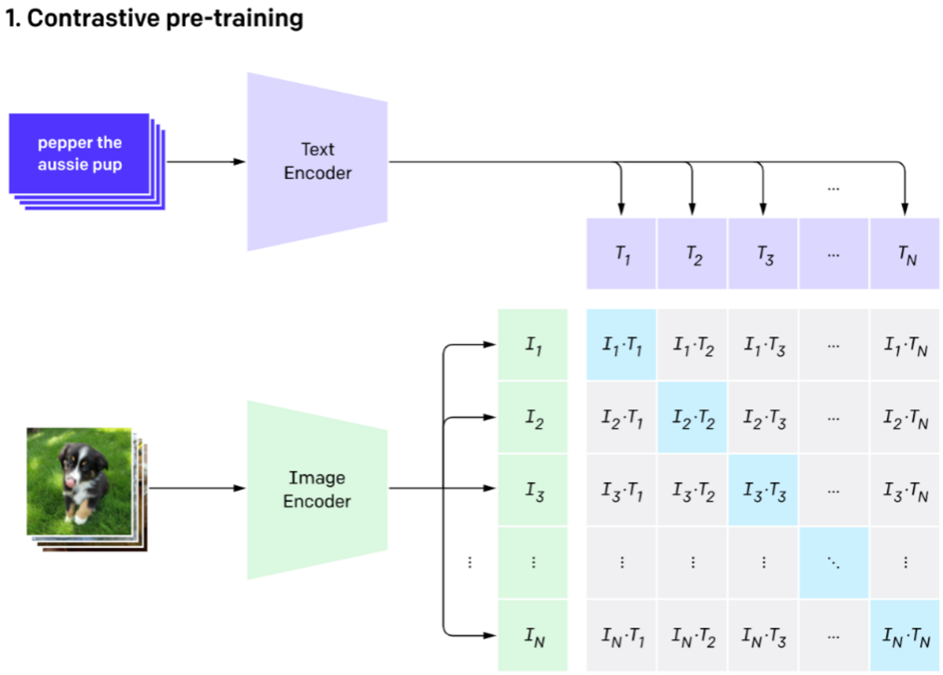


CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

Image – language encoding architectures



CLIP: Associative Encoding



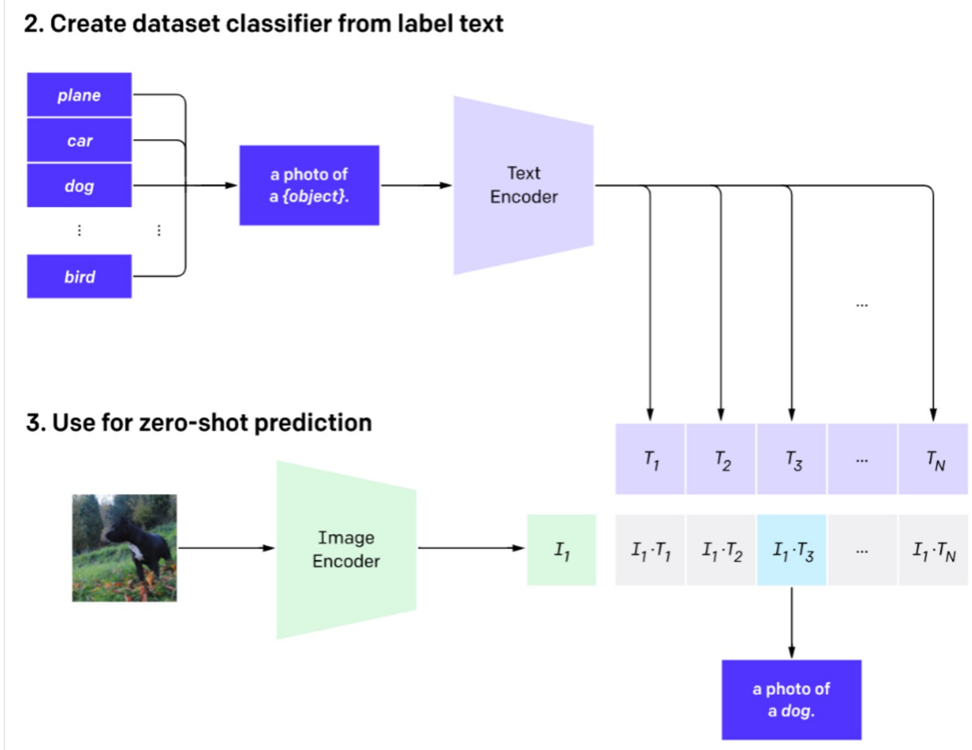
CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

CLIP: 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
```

CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

CLIP: Zero-shot Classification



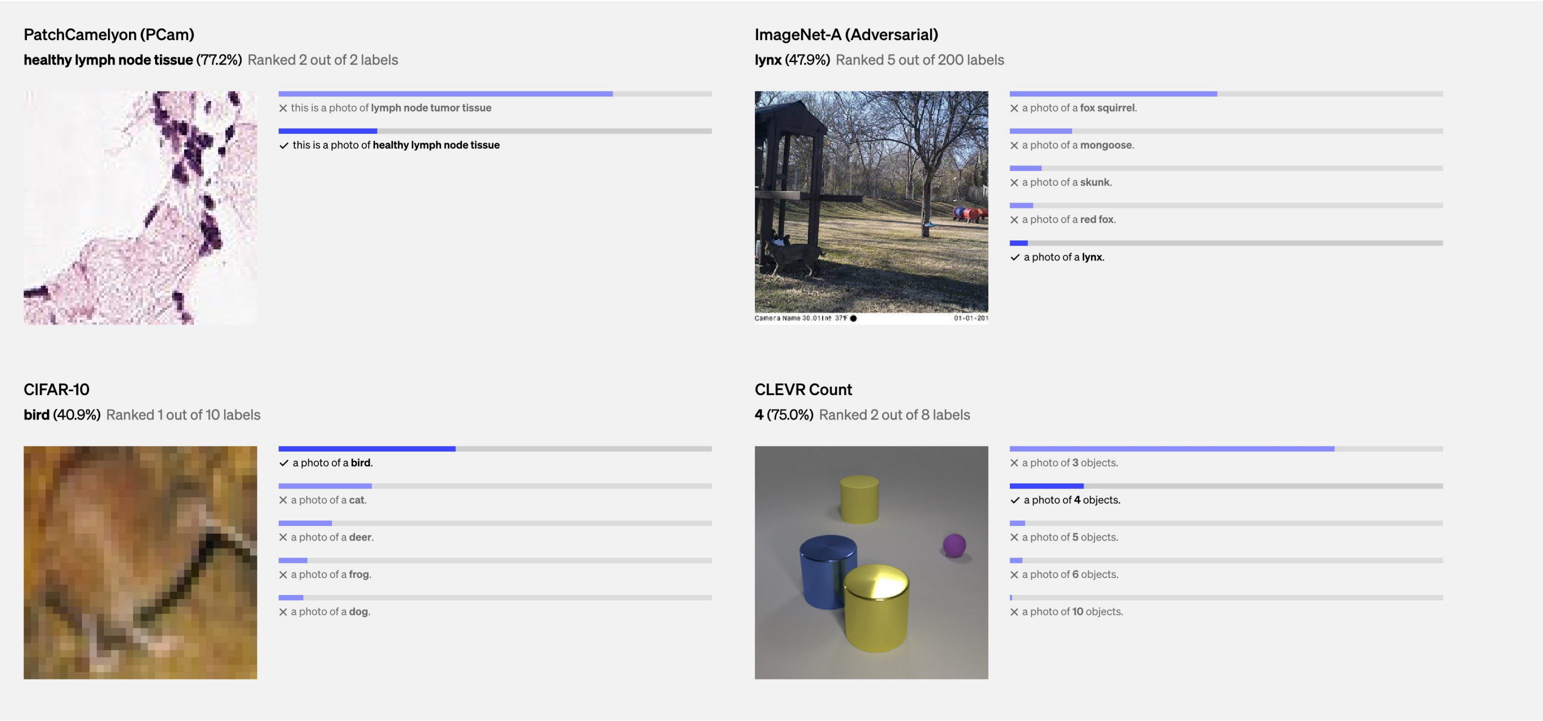
CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

CLIP: Zero-shot Classification

```python
# Load the model
device = "cuda" if torch.cuda.is_available() else "cpu"
model, preprocess = clip.load('ViT-B/32', device)

# Download the dataset
cifar100 = CIFAR100(root=os.path.expanduser("~/.cache"), download=True, train=False)

# Prepare the inputs
image, class_id = cifar100[3637]
image_input = preprocess(image).unsqueeze(0).to(device)
text_inputs = torch.cat([clip.tokenize(f"a photo of a {c}") for c in cifar100.classes]).to(device)

# Calculate features
with torch.no_grad():
    image_features = model.encode_image(image_input)
    text_features = model.encode_text(text_inputs)

# Pick the top 5 most similar labels for the image
image_features /= image_features.norm(dim=-1, keepdim=True)
text_features /= text_features.norm(dim=-1, keepdim=True)
similarity = (100.0 * image_features @ text_features.T).softmax(dim=-1)
values, indices = similarity[0].topk(5)
```

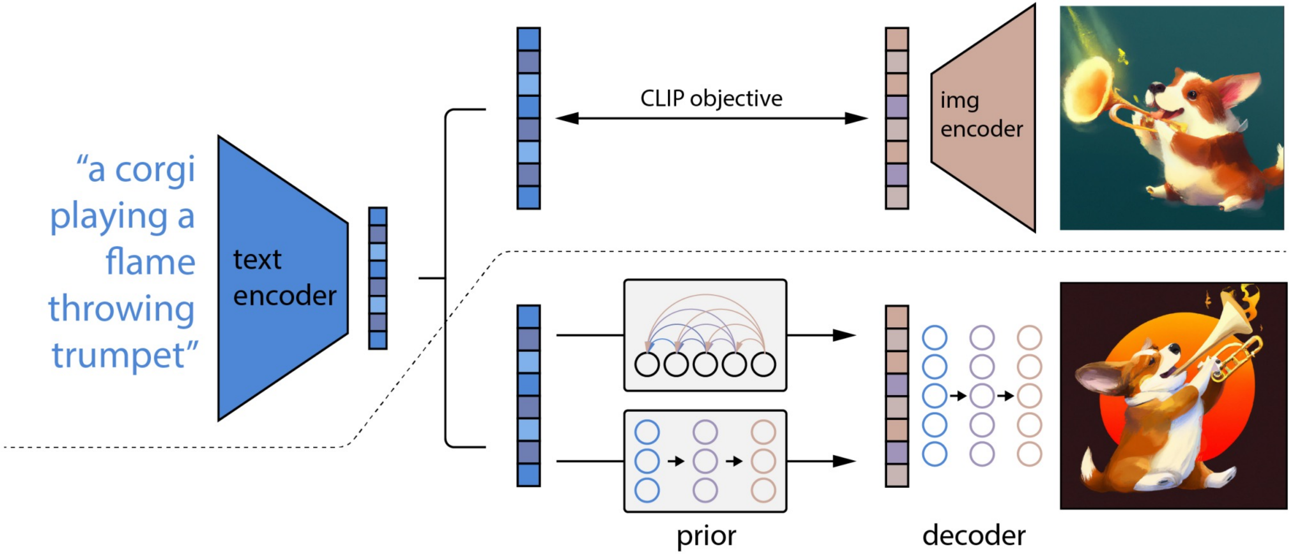
https://github.com/openai/CLIP

CLIP: Zero-shot Classification



CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

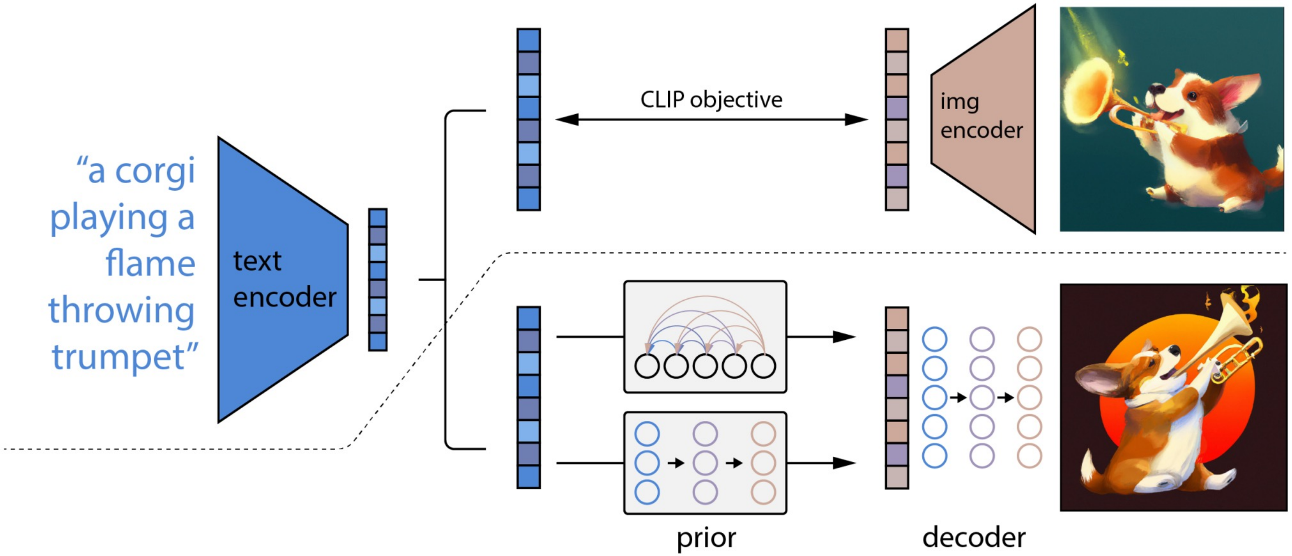
Generating Images from CLIP Latents (DALL-E 2)



- Train image diffusion with classifier-free guidance using CLIP image embedding
- Train another diffusion model to predict CLIP image embedding from the CLIP embedding of the input text.

Hierarchical Text-Conditional Image Generation with CLIP Latents (Ramesh, Dhariwal, Nichol, Chu, Chen, 2022)

Generating Images from CLIP Latents (DALL-E 2)

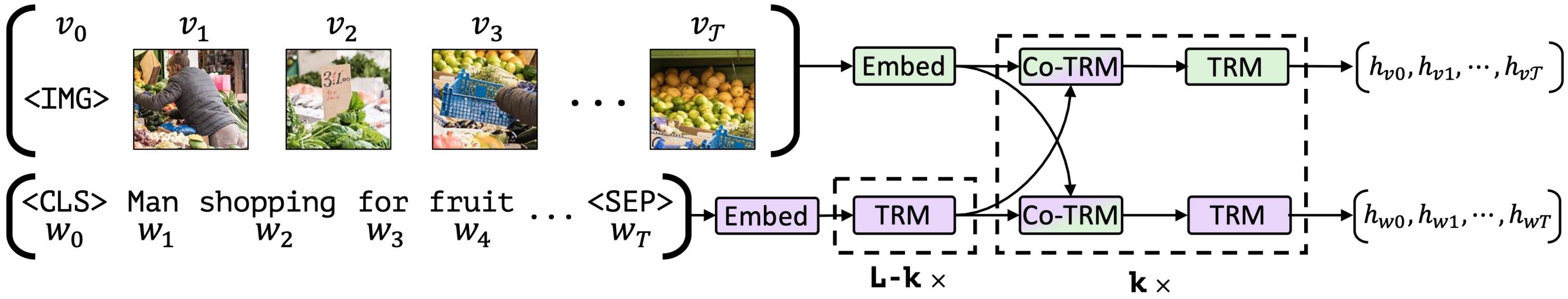


Learning objective for the text to image CLIP embedding diffusion model:

$$L_{\text{prior}} = \mathbb{E}_{t\sim[1,T], z_i^{(t)} \sim q_t}\left[\|f_\theta(z_i^{(t)}, t, y) - z_i\|^2\right]$$

Hierarchical Text-Conditional Image Generation with CLIP Latents (Ramesh, Dhariwal, Nichol, Chu, Chen, 2022)

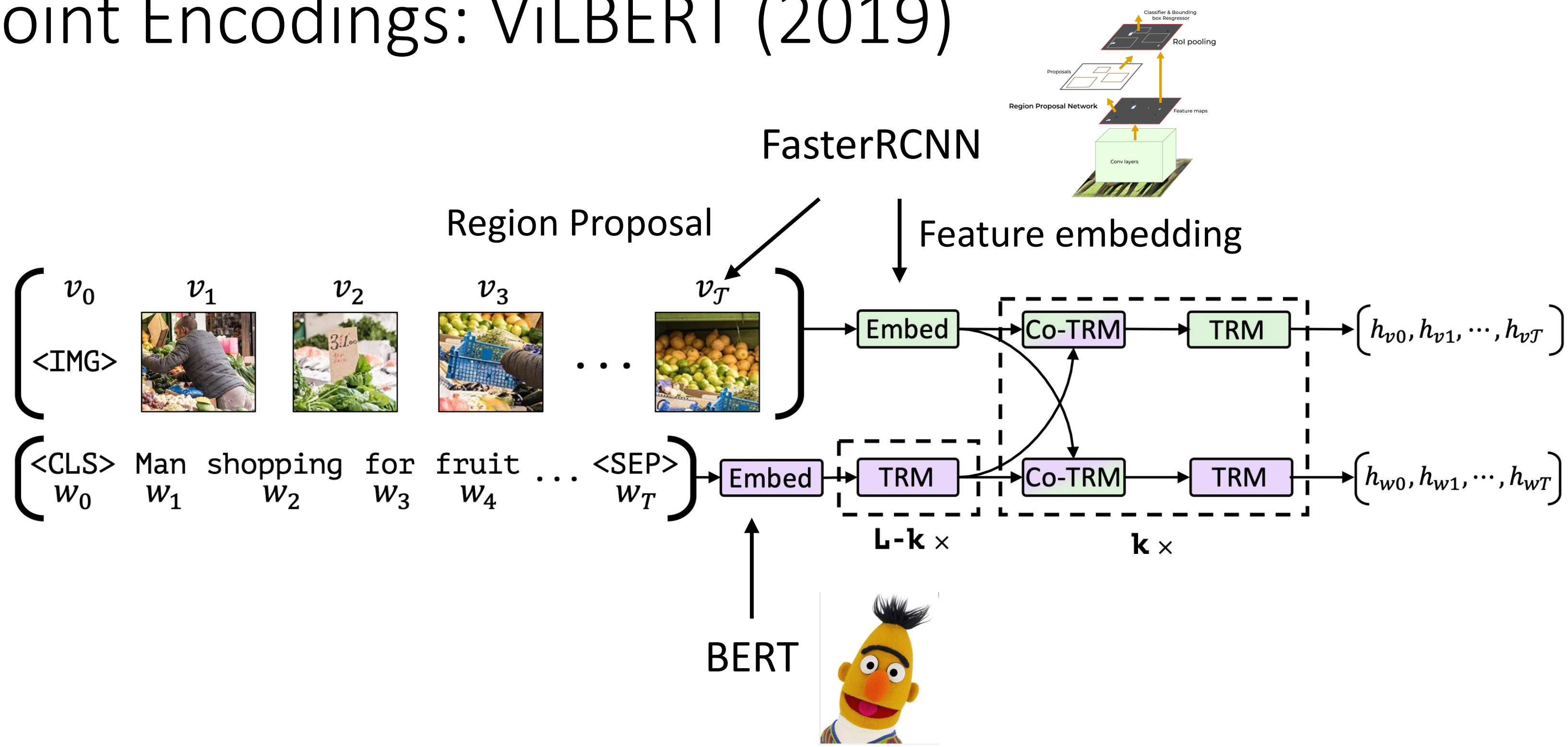
Joint Encodings: ViLBERT (2019)



Vision and Language Joint Pretraining

ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks (Lu et al., 2019)

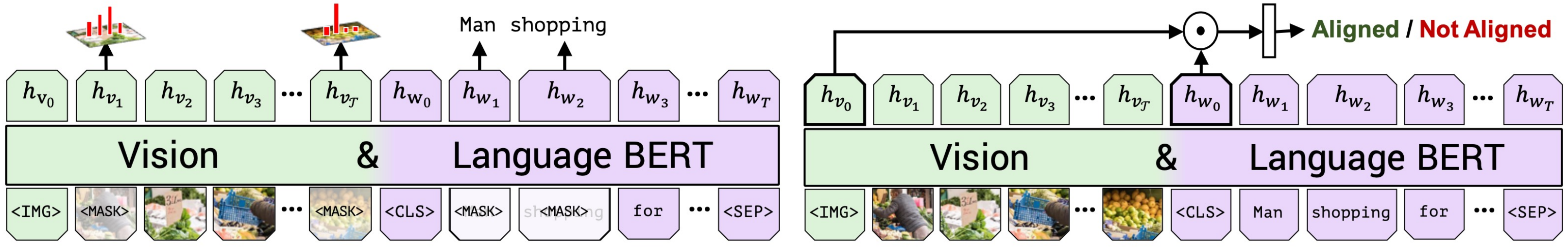
Joint Encodings: ViLBERT (2019)



Vision and Language Joint Pretraining

ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks (Lu et al., 2019)

Joint Encodings: ViLBERT (2019)

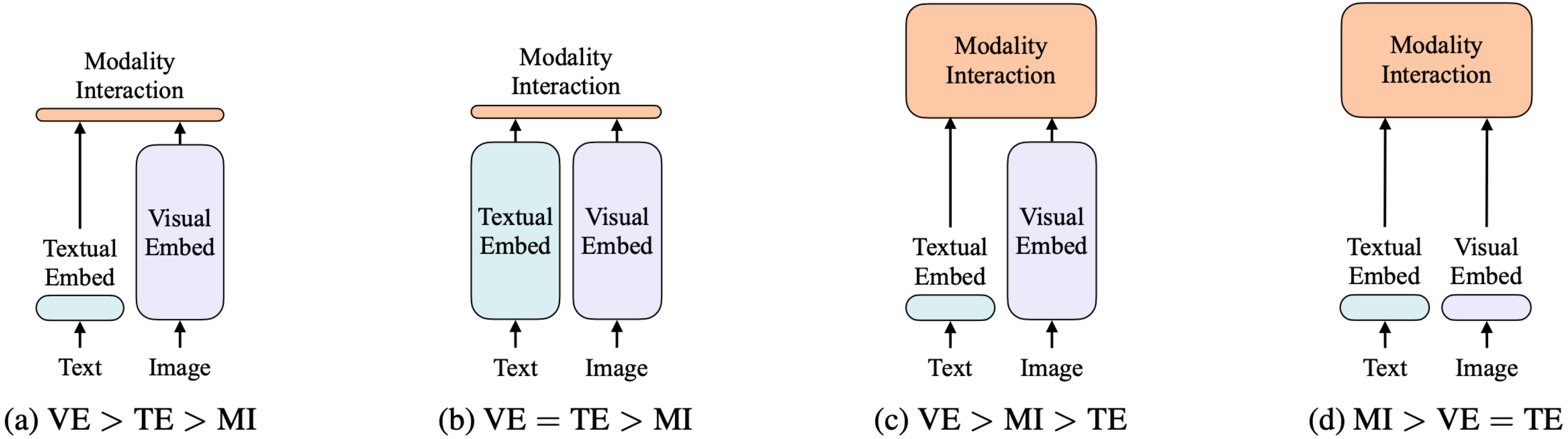


(a) Masked multi-modal learning (b) Multi-modal alignment prediction

Vision and Language Joint Pretraining

ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks (Lu et al., 2019)

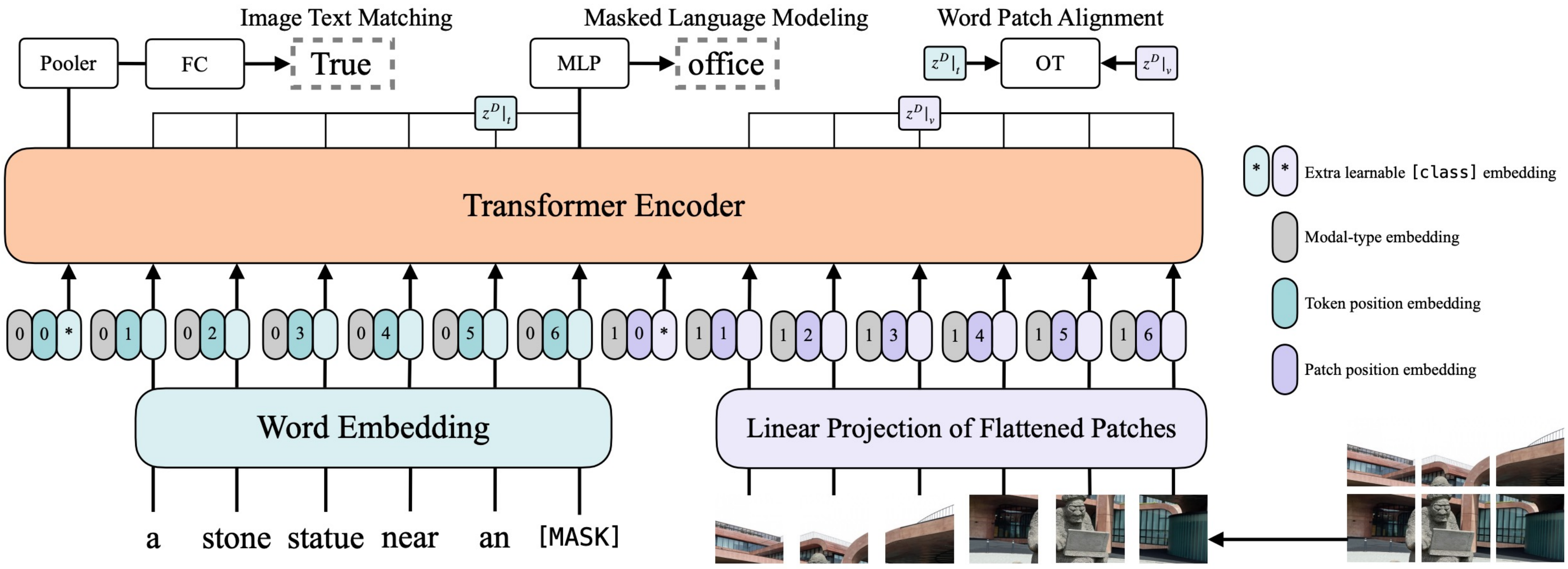
Joint Encodings: ViLT (2021)



Categories of vision-language model in terms of model complexity / capacity

ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision (Kim and Son, 2021)

Joint Encodings: ViLT (2021)



Vision and Language Joint Pretraining

ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision (Kim and Son, 2021)

Data matters

Scaling Up Foundation Vision and Language Models

Pre-foundation model era (2015 – 2020)

Visual Question Answering
(Goyal and Knot, 2017)

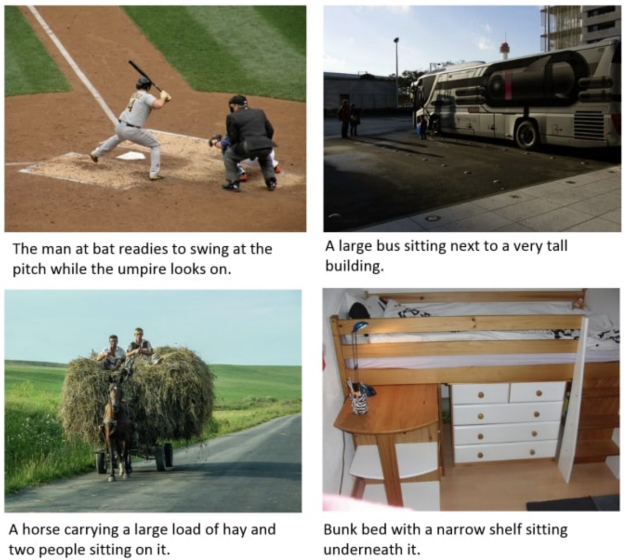
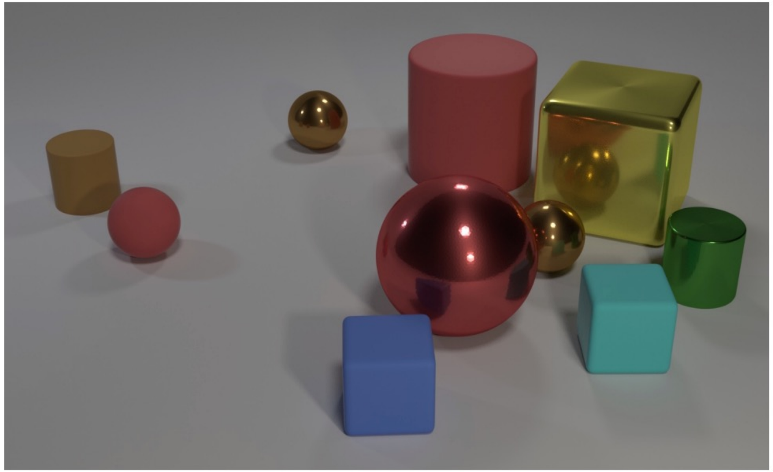


Image Captioning
(MS-COCO)

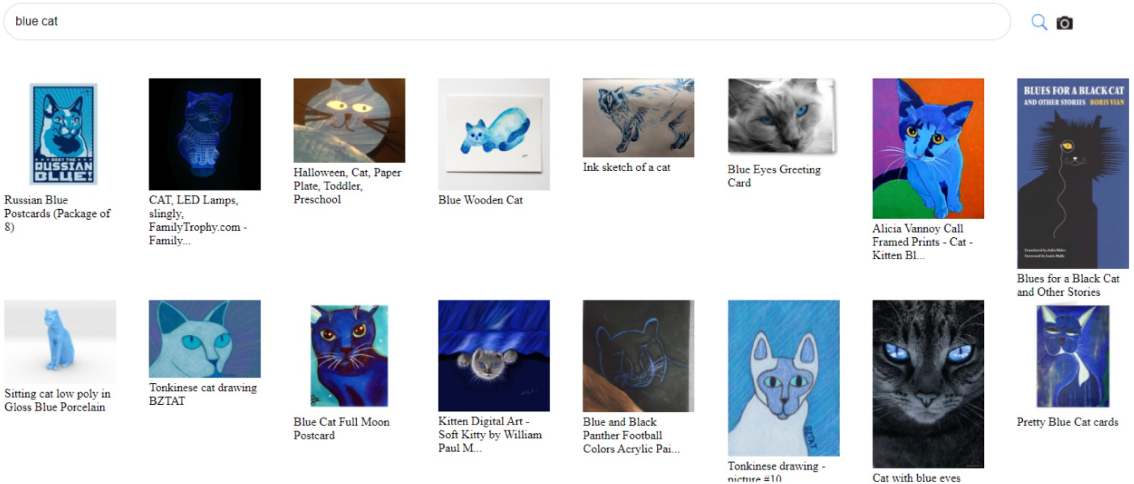
Pre-foundation model era (2015 – 2020)



Q: Are there an equal number of large things and metal spheres? **Q:** What size is the cylinder that is left of the brown metal thing that is left of the big sphere? **Q:** There is a sphere with the same size as the metal cube; is it made of the same material as the small red sphere? **Q:** How many objects are either small cylinders or metal things?

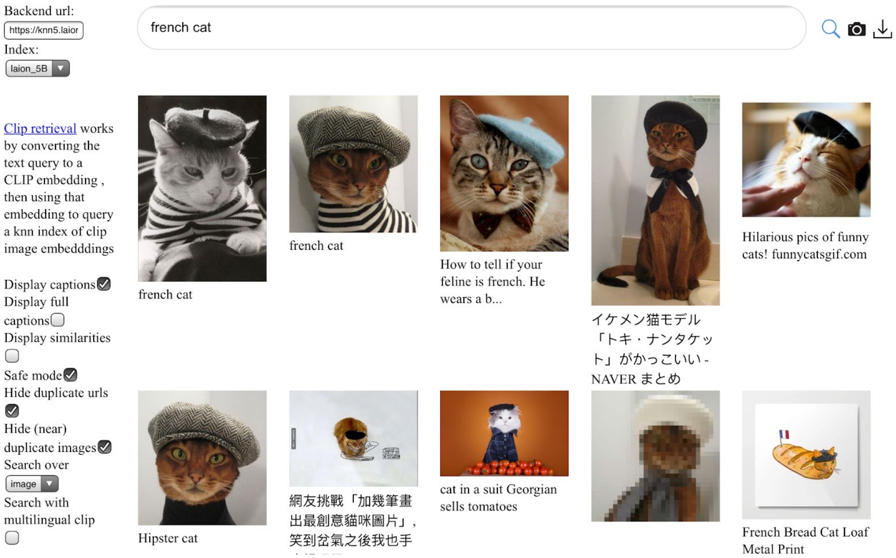
Diagnostic Language and Visual Reasoning
(CLEVR, Johnson et al., 2016)

The “Foundation Model Era” (2020-now)



- **LAION-400M**: 400 million image-text pairs
- Built using Common Crawl datasets,
- Extracting image-text pairs from HTML data.
- Post-processing filters unsuitable pairs using OpenAI's CLIP model.
- A10TB webdataset with CLIP embeddings and kNN indices.

The “Foundation Model Era” (2020-now)



- **LAION-5B**: Significantly larger than LAION-400M
- Crawled using 50 billion webpages + CLIP filtering
- 2.3 billion pairs in English + 2.2 billions in other languages + 1 billion unassignable languages (e.g., names).

The "Foundation Model Era" (2020-now)

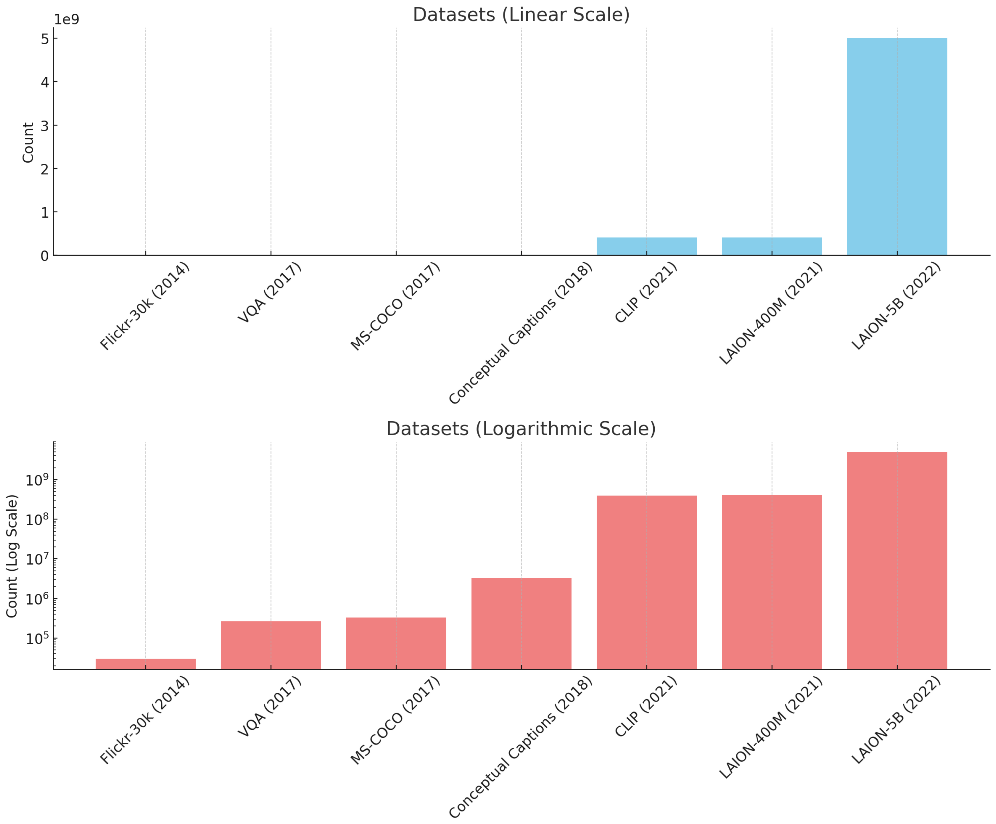
Stable Diffusion

Stable Diffusion was made possible thanks to a collaboration with Stability AI and Runway and builds upon our previous work:

High-Resolution Image Synthesis with Latent Diffusion Models
Robin Rombach*, Andreas Blattmann*, Dominik Lorenz, Patrick Esser, Björn Ommer
CVPR '22 Oral | *GitHub* | *arXiv* | *Project page*

Stable Diffusion is a latent text-to-image diffusion model. Thanks to a generous compute donation from Stability AI and support from LAION, we were able to train a Latent Diffusion Model on 512x512 images from a subset of the LAION-5B database. Similar to Google's Imagen, this model uses a frozen CLIP ViT-L/14 text encoder to condition the model on text prompts. With its 860M UNet and 123M text encoder, the model is relatively lightweight and runs on a GPU with at least 10GB VRAM. See this section below and the model card.

A snapshot of vision-language dataset



Automatic data crawling is great but …

tomclancysthedivision2_gc18images_0001

Enchantments-JUN16-13.jpg

"""""""They Shall Not Grow Old"""". Watching Peter Jackson tinker with WW1 is like watching George Lucas tinker with """"Star Wars"""". Only way more offensive. pic.twitter.com/PkteSrh9tR"""

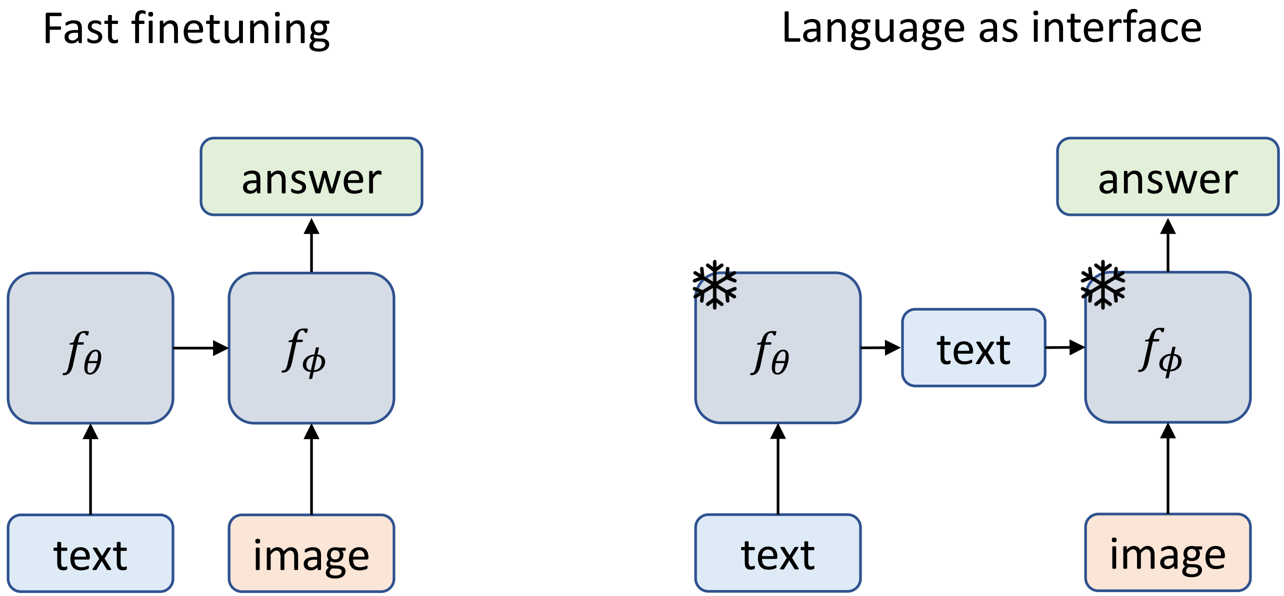
The International Code Council (ICC) has ratified a change to the 2021 International Building Code (IBC) to allow the use of shipping containers in commercial construction. Photo © www.bigstockphoto.com

https://laion-aesthetic.datasette.io/laion-aesthetic-6pls/images?_next=300

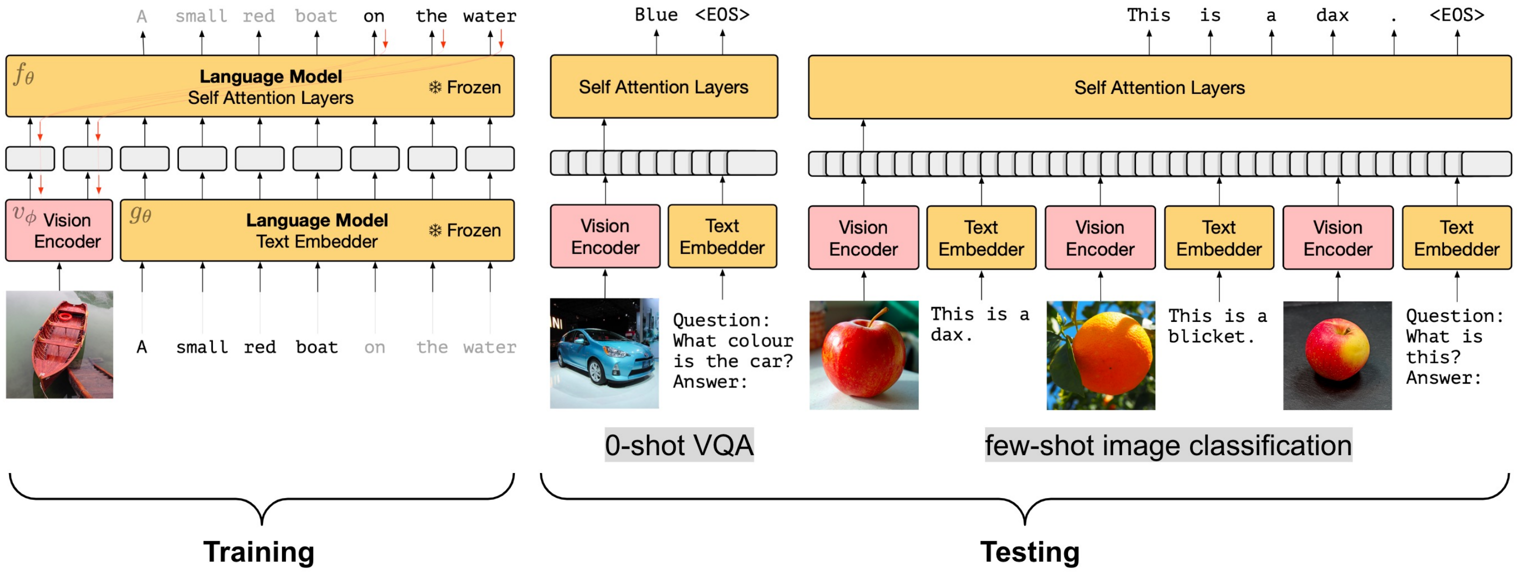
Composing Vision and Language Models

How to compose *trained* L and V models?

How to compose *trained* L and V models?



Finetuning VLM: Frozen LM, finetune VM



- Train image encoder with frozen language model.
- At test time, can do 0-shot VQA or few-shot classification through in-context learning

Multimodal Few-Shot Learning with Frozen Language Models (Tsimpoukelli et al., 2021)

Finetuning VLM: Frozen LM, finetune VM

- Train image encoder with frozen language model.
- At test time, can do 0-shot VQA or few-shot classification through in-context learning

Multimodal Few-Shot Learning with Frozen Language Models (Tsimpoukelli et al., 2021)

Finetuning VLM: Frozen LM, finetune VM

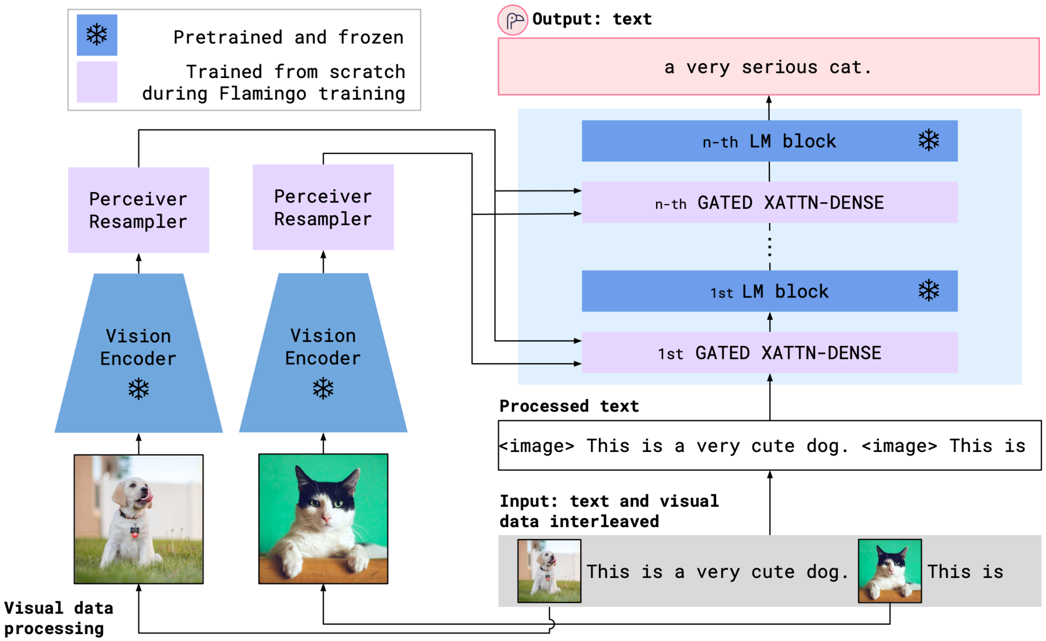
n-shot Acc.	n=0	n=1	n=4	τ
Frozen	29.5	35.7	38.2	✗
Frozen scratch	0.0	0.0	0.0	✗
Frozen finetuned	24.0	28.2	29.2	✗
Frozen train-blind	26.2	33.5	33.3	✗
Frozen VQA	48.4	–	–	✓
Frozen VQA-blind	39.1	–	–	✓
Oscar [23]	73.8	–	–	✓

n-shot Acc.	n=0	n=1	n=4	τ
Frozen	5.9	9.7	12.6	✗
Frozen 400mLM	4.0	5.9	6.6	✗
Frozen finetuned	4.2	4.1	4.6	✗
Frozen train-blind	3.3	7.2	0.0	✗
Frozen VQA	19.6	–	–	✗
Frozen VQA-blind	12.5	–	–	✗
MAVEx [42]	39.4	–	–	✓

- Training large VLM from scratch does not work at all
- Finetuning LM degrades performance
- “Blind” baselines till works, showing the innate power of LM

Multimodal Few-Shot Learning with Frozen Language Models (Tsimpoukelli et al., 2021)

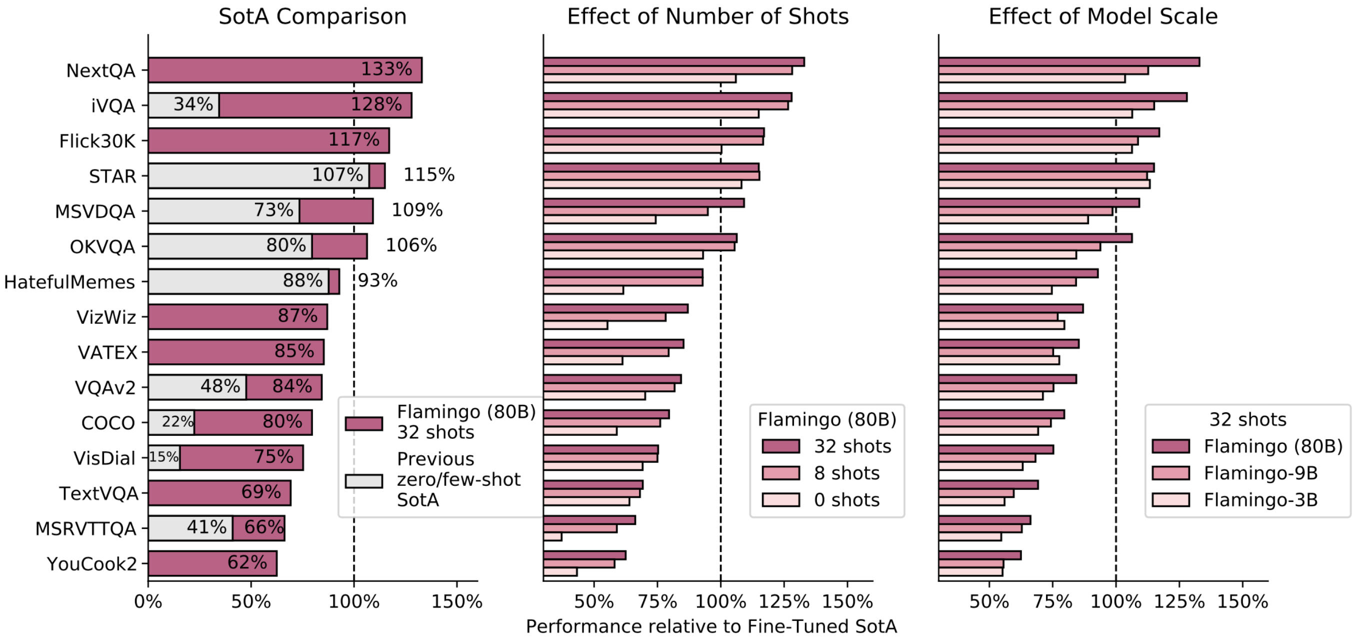
Finetuning VLM: freeze both LM and VM



- Interleaved text-image input
- Only finetune the cross attention (XATTN-DENSE) layers

Flamingo: a Visual Language Model for Few-Shot Learning (Alayrac et al., 2022)

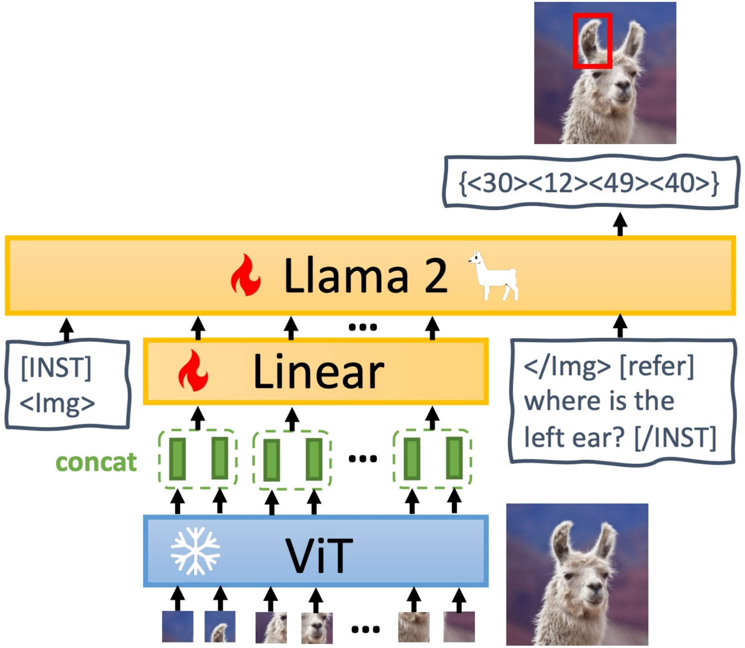
Finetuning VLM: freeze both LM and VM

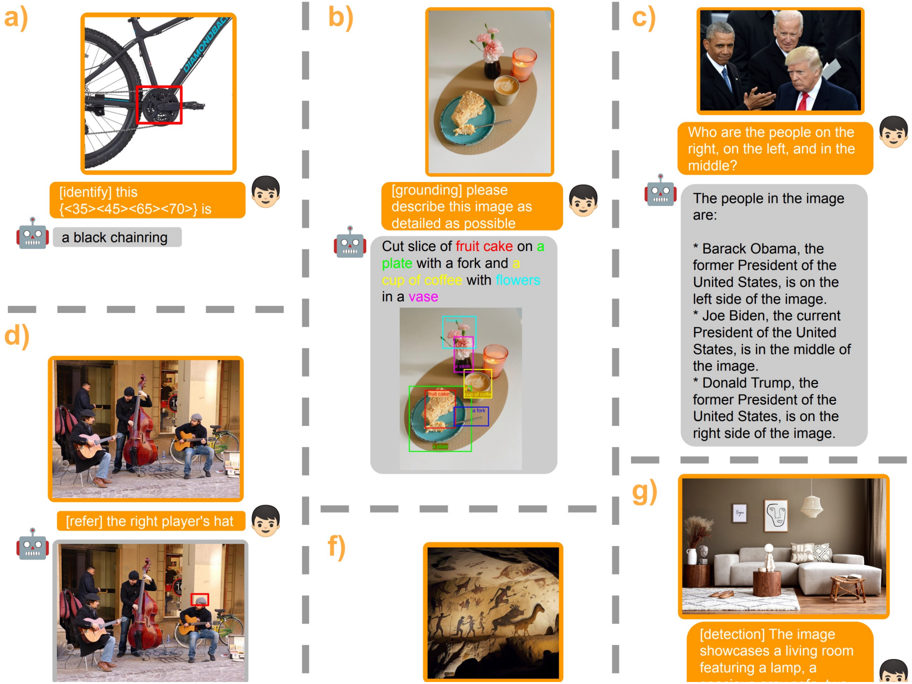


- Largely outperforms previous zero/few shot SotA
- More in-context learning examples do help
- Larger model gives better results

Flamingo: a Visual Language Model for Few-Shot Learning (Alayrac et al., 2022)

Finetuning VLM: freeze both LM and VM





Freeze VM and LM. Train the linear layer and LORA finetune Llama 2

MiniGPT-v2: large language model as a unified interface for vision-language multi-task learning (Chen et al., 2023)

Low-rank finetuning (LORA)

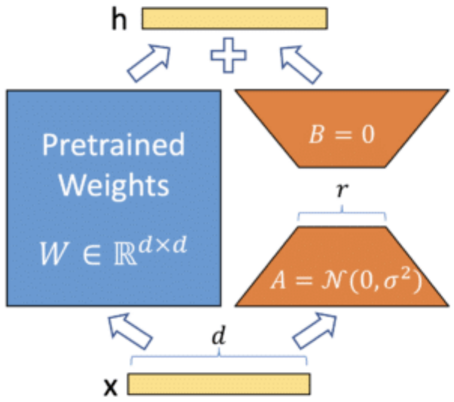
quickly finetune a billion-parameter model

Problem: finetuning still takes a lot of data, especially if the model is huge and/or the domain gap is large.

Fact: finetuning is just adding a W_δ to the existing weight matrix W, i.e., $W^* = W + W_\delta$

Hypothesis: W_δ is *low-rank*, meaning that W_δ can be decomposed into two smaller matrices A and B, i.e., $W_\delta = A^T B$.

So what?: A and B have a lot fewer parameters than the full W. Requires less data and faster to train.



Hu, Edward J., et al. "Lora: Low-rank adaptation of large language models.", 2021

Low-rank finetuning (LORA)

quickly finetune a billion-parameter model

🤗 PEFT

State-of-the-art Parameter-Efficient Fine-Tuning (PEFT) methods

Parameter-Efficient Fine-Tuning (PEFT) methods enable efficient adaptation of pre-trained language models (PLMs) to various downstream applications without fine-tuning all the model's parameters. Fine-tuning large-scale PLMs is often prohibitively costly. In this regard, PEFT methods only fine-tune a small number of (extra) model parameters, thereby greatly decreasing the computational and storage costs. Recent State-of-the-Art PEFT techniques achieve performance comparable to that of full fine-tuning.

Seamlessly integrated with 🤗 Accelerate for large scale models leveraging DeepSpeed and Big Model Inference.

Supported methods:

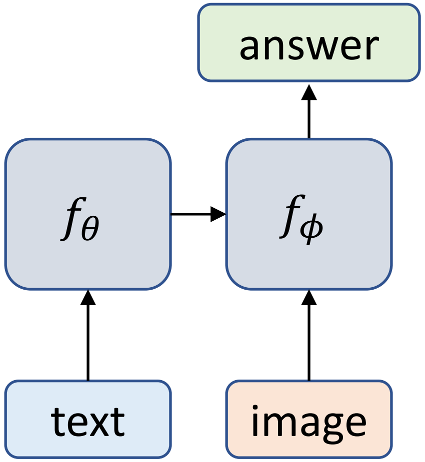
1. LoRA: LORA: LOW-RANK ADAPTATION OF LARGE LANGUAGE MODELS
2. Prefix Tuning: Prefix-Tuning: Optimizing Continuous Prompts for Generation, P-Tuning v2: Prompt Tuning Can Be Comparable to Fine-tuning Universally Across Scales and Tasks
3. P-Tuning: GPT Understands, Too
4. Prompt Tuning: The Power of Scale for Parameter-Efficient Prompt Tuning
5. AdaLoRA: Adaptive Budget Allocation for Parameter-Efficient Fine-Tuning
6. $(IA)^3$: Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning
7. MultiTask Prompt Tuning: Multitask Prompt Tuning Enables Parameter-Efficient Transfer Learning
8. LoHa: FedPara: Low-Rank Hadamard Product for Communication-Efficient Federated Learning
9. LoKr: KronA: Parameter Efficient Tuning with Kronecker Adapter based on Navigating Text-To-Image Customization:From LyCORIS Fine-Tuning to Model Evaluation implementation

```python
import torch
from peft import inject_adapter_in_model, LoraConfig

class DummyModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.embedding = torch.nn.Embedding(10, 10)
        self.linear = torch.nn.Linear(10, 10)
        self.lm_head = torch.nn.Linear(10, 10)

    def forward(self, input_ids):
        x = self.embedding(input_ids)
        x = self.linear(x)
        x = self.lm_head(x)
        return x

lora_config = LoraConfig(
    lora_alpha=16,
    lora_dropout=0.1,
    r=64,
    bias="none",
    target_modules=["linear"],
)

model = DummyModel()
model = inject_adapter_in_model(lora_config, model)

dummy_inputs = torch.LongTensor([[0, 1, 2, 3, 4, 5, 6, 7]])
dummy_outputs = model(dummy_inputs)
```

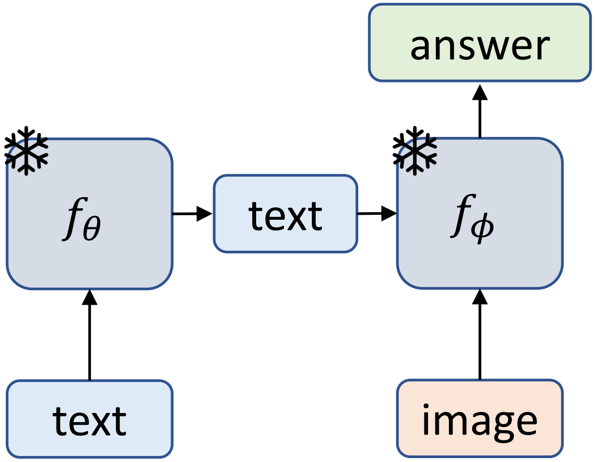
https://github.com/huggingface/peft

How to compose *trained* L and V models?

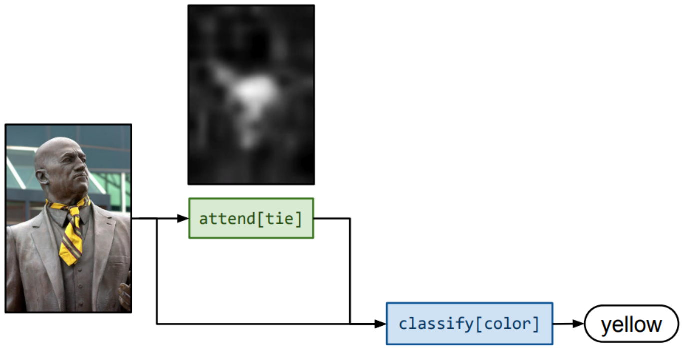
Fast finetuning

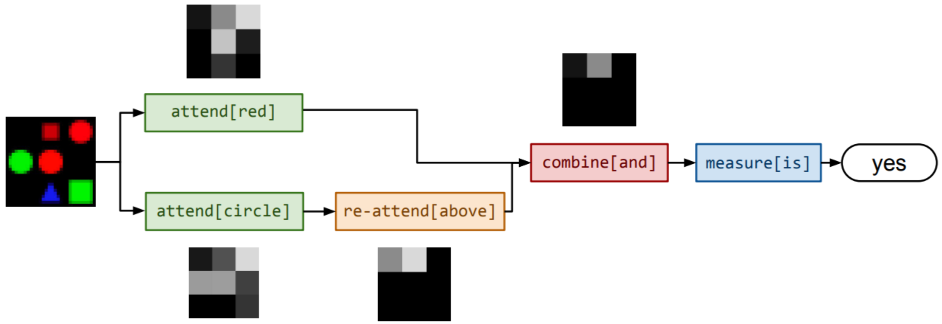


Language as interface



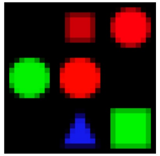
Neural Module Networks (Andreas et al., 2015)





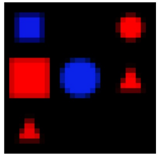
Idea: train modular networks (attend, classify). Use a controller network to decide how to compose the modules together to solve a task

Neural Module Networks (Andreas et al., 2015)

				
how many different lights in various different shapes and sizes?	*what is the color of the horse?*	*what color is the vase?*	*is the bus full of passengers?*	*is there a red shape above a circle?*

`measure[count](`
`attend[light])`
	`classify[color](`
	`attend[horse])`
		`classify[color](`
		`attend[vase])`
			`measure[is](`
			`combine[and](`
			`attend[bus],`
			`attend[full])`
				`measure[is](`
				`combine[and](`
				`attend[red],`
				`re-attend[above](`
				`attend[circle])))`

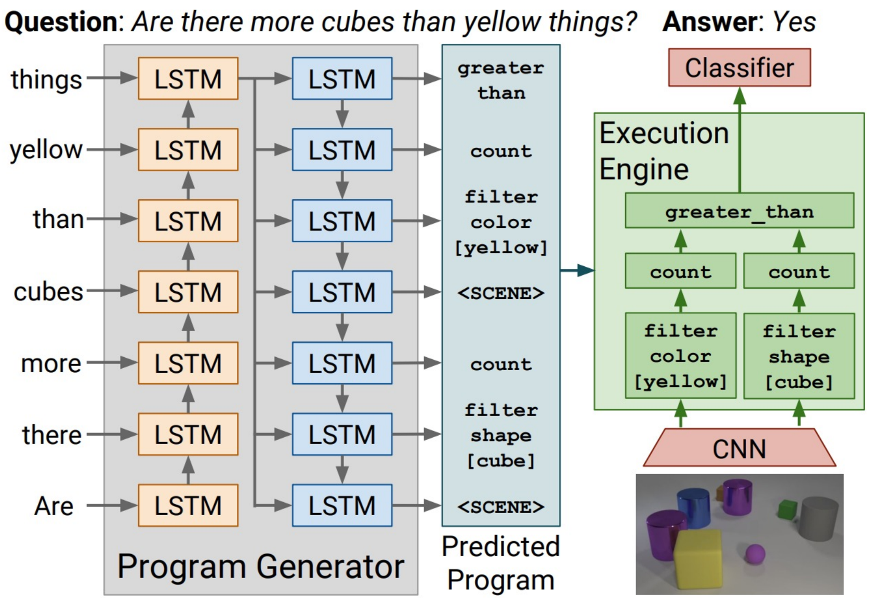
four (four)	brown (brown)	green (green)	yes (yes)	no (no)

				
what is stuffed with toothbrushes wrapped in plastic?	*where does the tabby cat watch a horse eating hay?*	*what material are the boxes made of?*	*is this a clock?*	*is a red shape blue?*

`classify[what](`
`attend[stuff])`
	`classify[where](`
	`attend[watch])`
		`classify[material](`
		`attend[box])`
			`measure[is](`
			`attend[clock])`
				`measure[is](`
				`combine[and](`
				`attend[red],`
				`attend[blue]))`

container (cup)	pen (barn)	leather (cardboard)	yes (no)	yes (no)

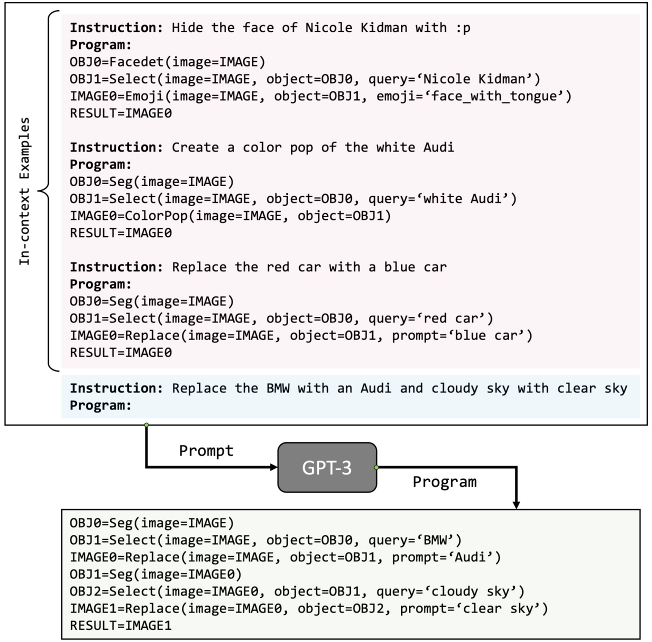
Inferring and Executing Programs for Visual Reasoning (Johnson et al., 2017)

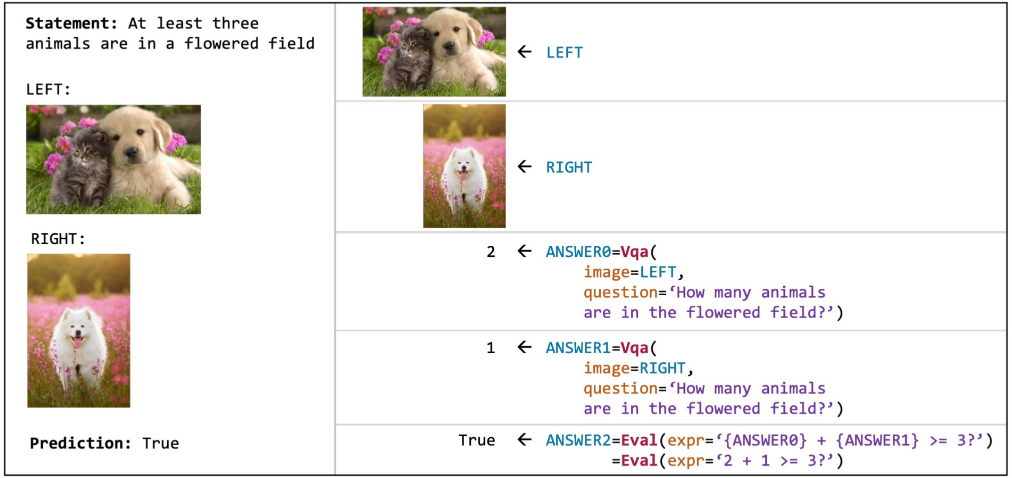


Similar to NMN, but train a *program generator* using REINFORCE

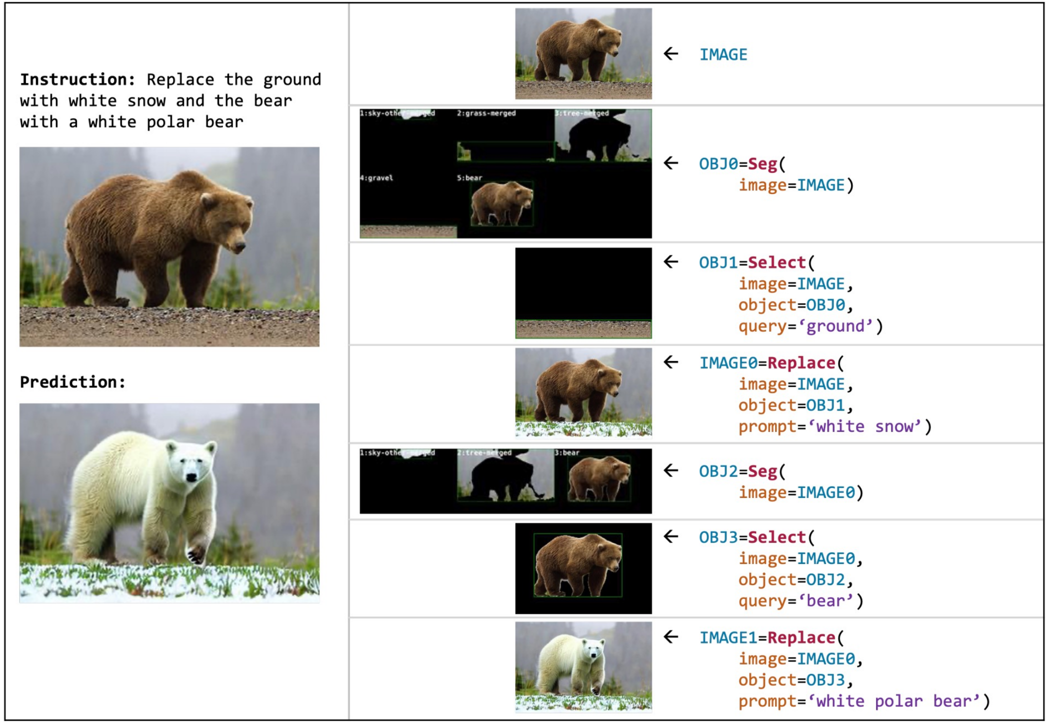
Reward comes from whether the answer is correct

Visual Programming: Compositional visual reasoning without training (Gupta et al., 2023)

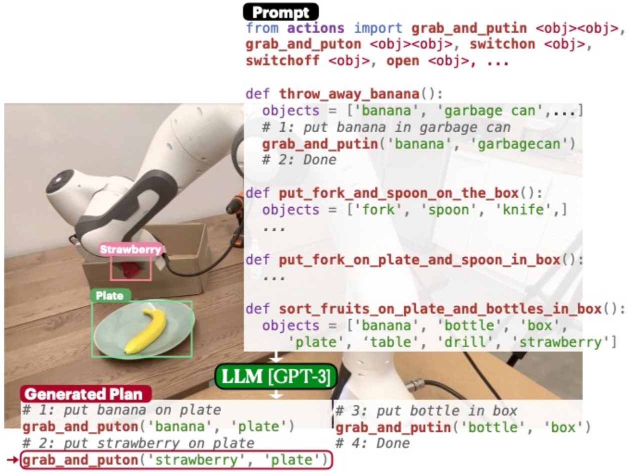


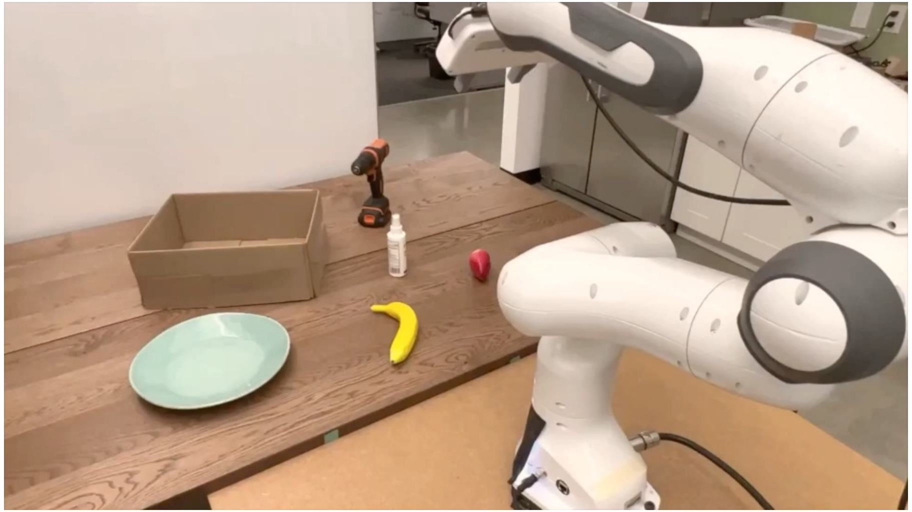


Visual Programming: Compositional visual reasoning without training (Gupta et al., 2023)



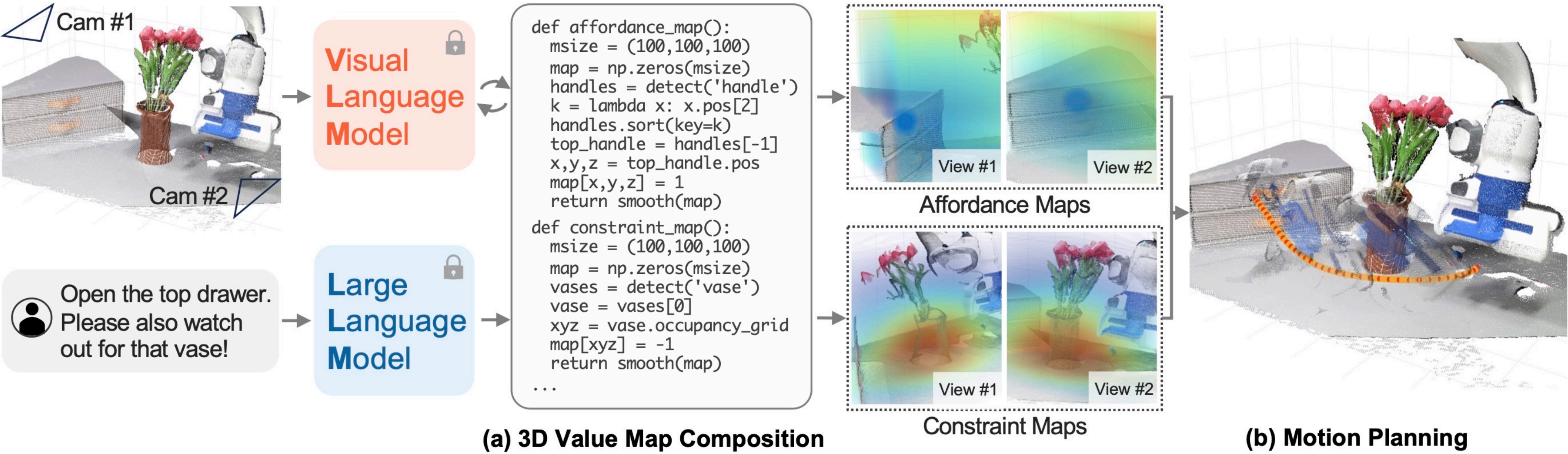
ProgPrompt (Singh et al., 2023): Program to Actions





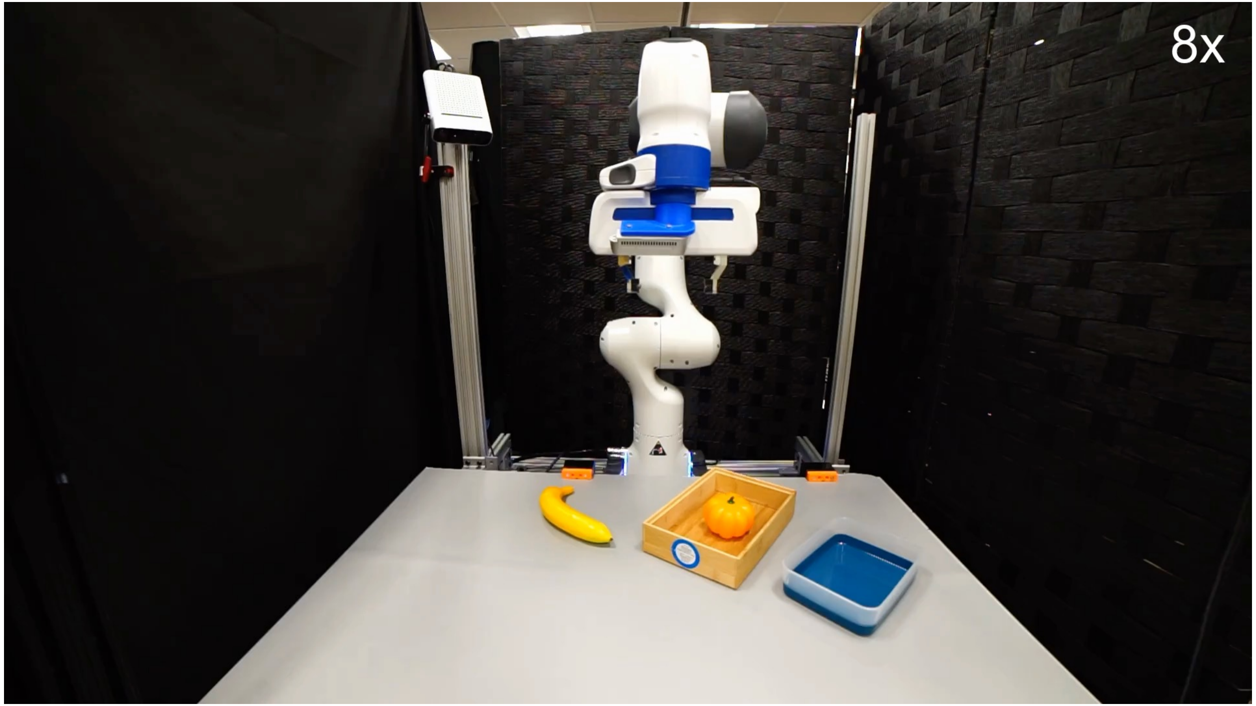
Use large language models (LLMs) to generate program-like semantic plans from natural language command.

VoxPoser (Huang et al., 2023): Program to Grounded Actions



Use LLMs to guide VMs to find where to act next in a 3D scene

VoxPoser (Huang et al., 2023): Program to Grounded Actions



"Sort the paper trash into the blue tray."

Summary: Large Vision and Language Models

- Very active field of research, with a history as long as modern deep learning (2011 -)
- Foundation vision and language models have revolutionized the research paradigm post 2019.
- Trending towards larger model and dataset.
- Many active research on how to finetune / adapt VLMs with small amount of compute / data.
- The future is going to be multimodal.