

RT-2, where are you from?

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Outline

1 Robotics Transformers

- Introduction
- Preliminaries
- Architectures

2 Vision-language-Action Models

- Robotics Transformer 2
- Vision Language Models

3 Reflection & Future Work

- Reflection
- Future Work

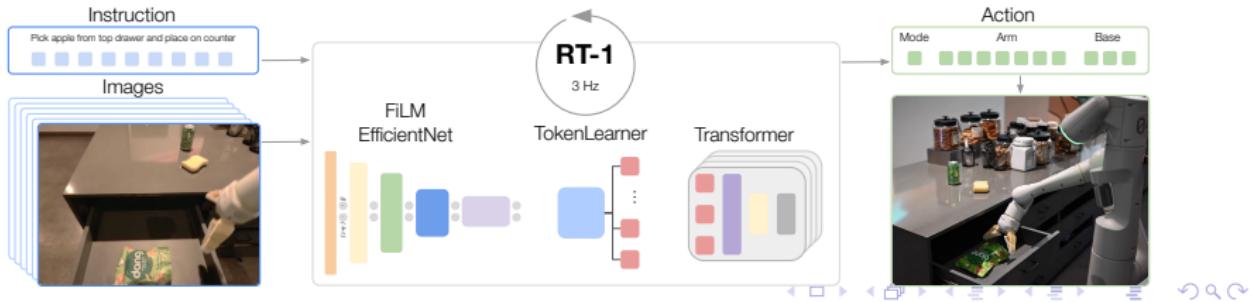
Key features of RT-1 and RT-2

- **end-to-end** robotic control
- express the actions as text tokens
- RT-1: open-ended task-agnostic training + high-capacity architectures
- RT-2: co-fine-tune vision-language models
(vision-language-action)

End-to-end Explained



Figure: Output sequence of skills vs. low-level actions



Robot Learning

- Learn robot policies to solve language-conditioned tasks

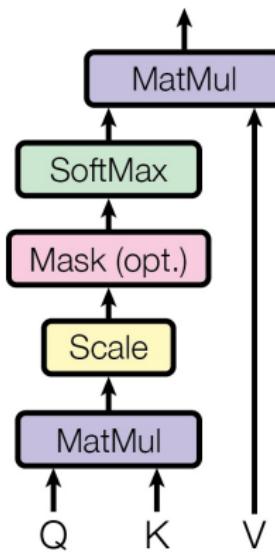
$$a_t \sim \pi(\cdot | i, \{x_j\}_{j=0}^t) \quad (1)$$

- Episode: full interaction $i, \{(x_j, a_j)\}_{j=0}^T$ from $t = 0$ to $t = T$
- Reward: $r \in \{0, 1\}$

A more concrete view of Trajectory

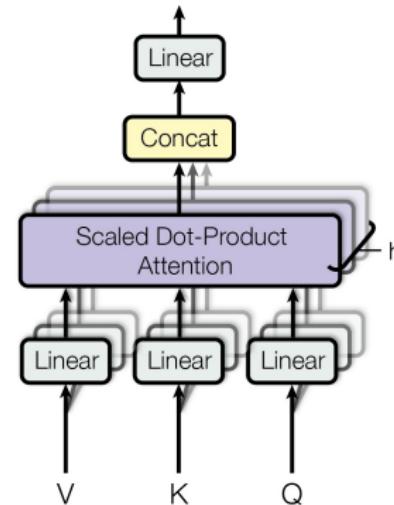
```
class Trajectory(  
    NamedTuple(  
        'Trajectory',  
        [  
            ('step_type', types.SpecTensorOrArray),  
            ('observation', types.NestedSpecTensorOrArray),  
            ('action', types.NestedSpecTensorOrArray),  
            ('policy_info', types.NestedSpecTensorOrArray),  
            ('next_step_type', types.SpecTensorOrArray),  
            ('reward', types.NestedSpecTensorOrArray),  
            ('discount', types.SpecTensorOrArray),  
        ],  
    ):  
:
```

Transformers



(a) scaled dot-product attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



(b) multi-head attention: $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$

Immitation Learning

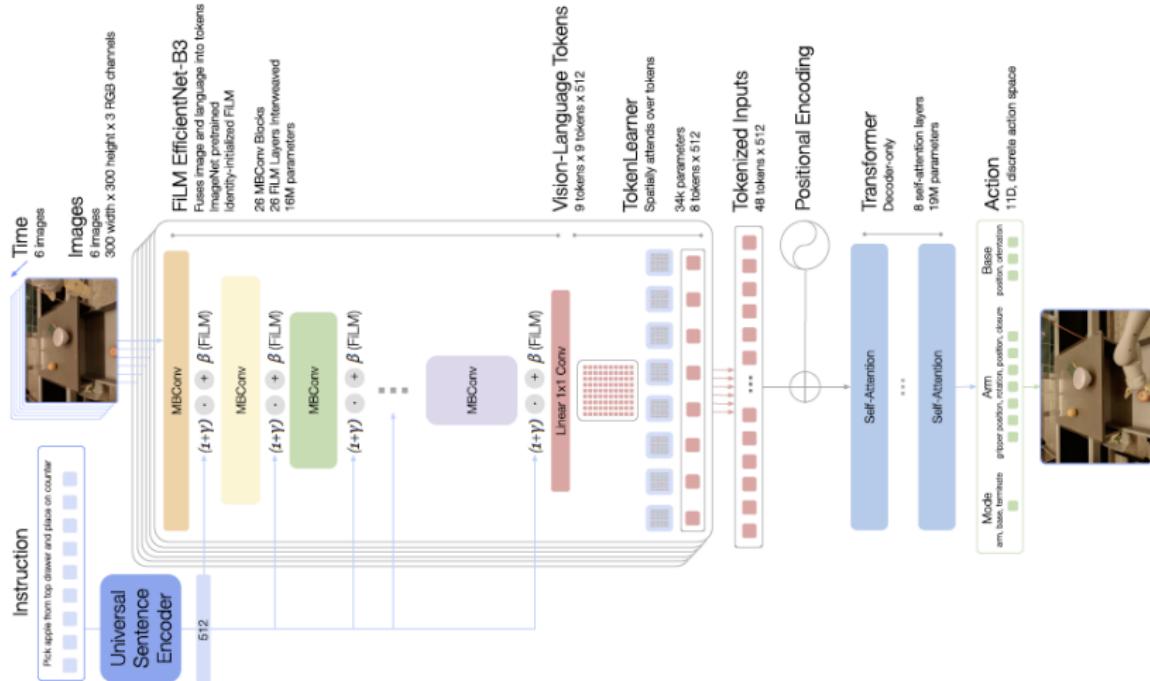
- Given a dataset of episodes:

$$\mathcal{D} = \{(i^{(n)}, \{(x_t^{(n)}, a_t^{(n)})\}_{t=0}^T)\}_{n=0}^N \quad (2)$$

- Learn π using behavioral cloning: directly learn the expert policy

$$\hat{\pi}^* = \arg \min_{\pi} \sum_{(i, \{(x_t, a_t)\}_{t=0}^T) \in \mathcal{D}} L(\pi(i, x_t), \pi^*(i, x_t)) \quad (3)$$

RT-1 architecture



Let's Break It Down

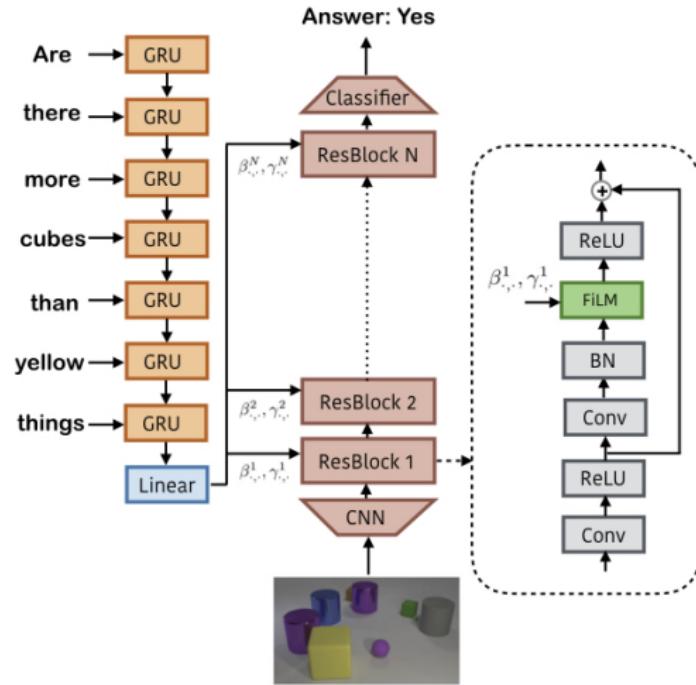
- Input: images, language embedding
- Output: de-tokenized actions

```
observation = {
    'image': tf.constant(tf.squeeze(obs_image).numpy(), shape=image_shape),
    'natural_language_embedding': tf.constant(tf.squeeze(embeded).numpy(), shape=emb_shape),
}
time_step = ts.restart(observation, batch_size=1)
init_state = eval_policy.get_initial_state(batch_size=1)
policy_step = eval_policy.action(time_step, init_state)
print(policy_step.action)
```

```
{'base_displacement_vector': BoundedArraySpec(shape=(2,), dtype=dtype('float32'), name='base_displacement_vector',
                                              minimum=-1.0, maximum=1.0),
 'base_displacement_vertical_rotation': BoundedArraySpec(shape=(1,), dtype=dtype('float32'), name='base_displacement_vertical_rotation',
                                                       minimum=-3.1415927410125732, maximum=3.1415927410125732),
 'gripper_closeness_action': BoundedArraySpec(shape=(1,), dtype=dtype('float32'), name='gripper_closeness_action',
                                               minimum=-1.0, maximum=1.0),
 'world_vector': BoundedArraySpec(shape=(3,), dtype=dtype('float32'), name='world_vector', minimum=-1.0, maximum=1.0),
 'terminate_episode': BoundedArraySpec(shape=(3,), dtype=dtype('int32'), name='terminate_episode', minimum=0, maximum=1), # mode switch
 'rotation_delta': BoundedArraySpec(shape=(3,), dtype=dtype('float32'), name='rotation_delta',
                                     minimum=-1.5707963705062866, maximum=1.5707963705062866)}
```

Image and Language Fusion

- Condition the image tokenizer on the language instruction



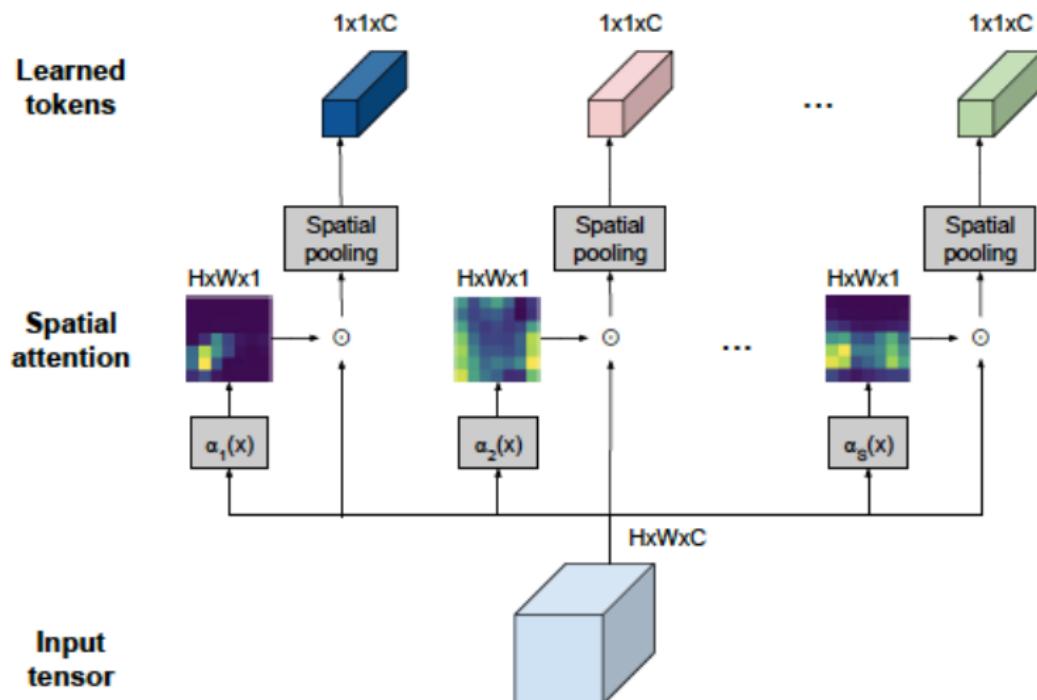
FiLM: Feature-wise Linear Modulation

$$\gamma_{i,c} = f_c(x_i) \quad \beta_{i,c} = h_c(x_i) \quad (4)$$

$$FiLM(\mathbf{F}_{i,c} | \gamma_{i,c}, \beta_{i,c}) = \gamma_{i,c} \mathbf{F}_{i,c} + \beta_{i,c} \quad (5)$$

```
def call(self, conv_filters: tf.Tensor, conditioning: tf.Tensor):  
    tf.debugging.assert_rank(conditioning, 2)  
    projected_cond_add = self._projection_add(conditioning) # beta  
    projected_cond_mult = self._projection_mult(conditioning) # gamma  
  
    # Original FiLM paper argues that 1 + gamma centers the initialization at  
    # identity transform.  
    result = (1 + projected_cond_mult) * conv_filters + projected_cond_add  
    return result
```

TokenLearner



TokenLearner

$$Z = [z_i]_{i=1}^S$$

$$z_i = \rho(X \odot \gamma(\alpha_i(X))) \quad (6)$$

```
def call(self, inputs: tf.Tensor, training: bool = False) -> tf.Tensor:  
    if len(inputs.shape) == 4:  
        bs, h, w, c = inputs.shape  
        inputs = tf.reshape(inputs, shape=[bs, h * w, c])  
    selected = self.layernorm(inputs)  
    selected = self.mlp(  
        *args: selected, is_training=training) # Shape: [bs, h*w, n_token].  
    selected = tf.transpose(selected, perm=[0, 2, 1]) # Shape: [bs, n_token, h*w].  
    selected = tf.nn.softmax(selected, axis=-1)  
    # element-wise operation  
    feat = tf.einsum(equation: "...si,...id->...sd", *inputs: selected, inputs)  
    return feat # Shape: [bs, n_token, c]
```

RT-1 Objective

- Given a sequence of tokens $s_{1:L}$ and parameters θ :

$$\log p_\theta(s_1, \dots, s_L) = \sum_{l=1}^L \log p_\theta(s_l | s_1, \dots, s_{l-1}) \quad (7)$$

- The training loss for a batch \mathcal{B} :

$$\mathcal{L}(\theta, \mathcal{B}) = - \sum_{b=1}^{|\mathcal{B}|} \sum_{l=1}^L m(b, l) \log p_\theta(s_l^{(b)} | s_1^{(b)}, \dots, s_{l-1}^{(b)}) \quad (8)$$

Intuitions Behind RT-1 Model Design

Transformer-based model:

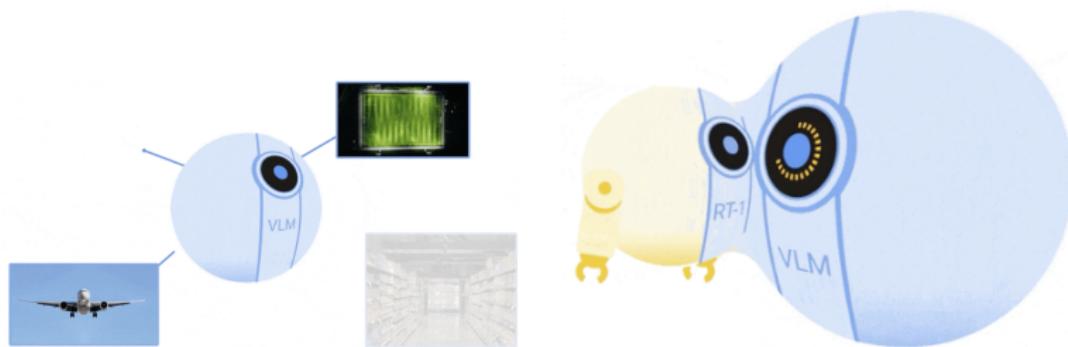
- FiLM-conditioned EfficientNet
- TokenLearner
- Transformer

Intuitions:

- Effective robotic multi-task learning
- Efficient real-time robotic control

From RT-1 to RT-2

- RT-2 learns from both web data and robotics data



Transfer Web Knowledge to Robotic Control

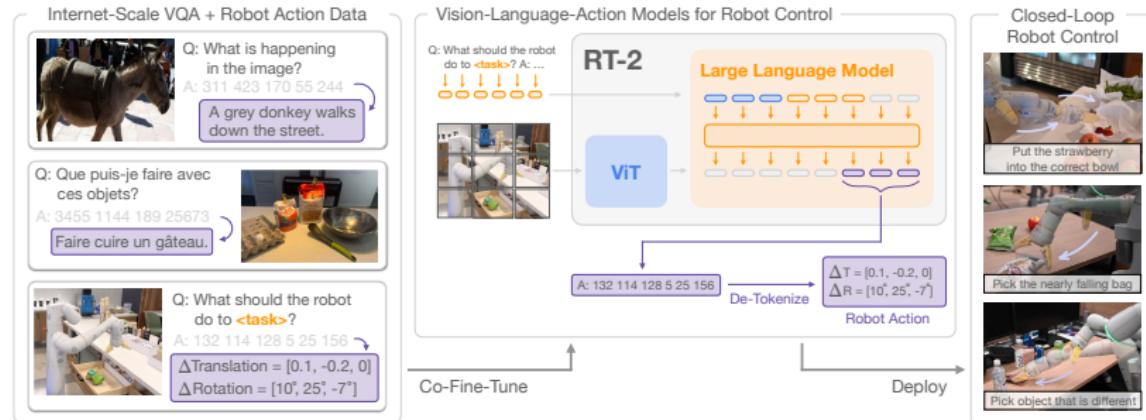


Figure: Present robot actions as another language. The text tokens are de-tokenized into robot actions during inference.

Vision-Language-Action Models

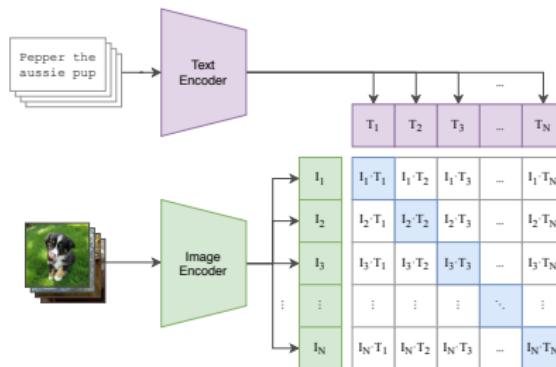
- Learn to map robot observations to actions
- Express robotic actions as text tokens
- Co-fine-tune vision-language models on both robotic trajectory data and Web data



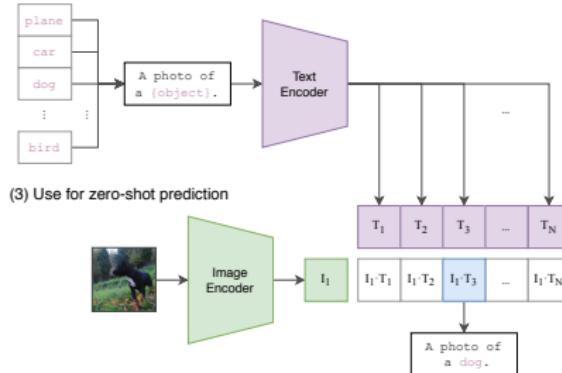
Figure: Robot action token numbers: “1 128 91 241 5 101 127 217”

CLIP: Contrastive Language Image Pre-training

(1) Contrastive pre-training



(2) Create dataset classifier from label text



Contrastive Language Image 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
```

PaLI: Pathways Language and Image Model

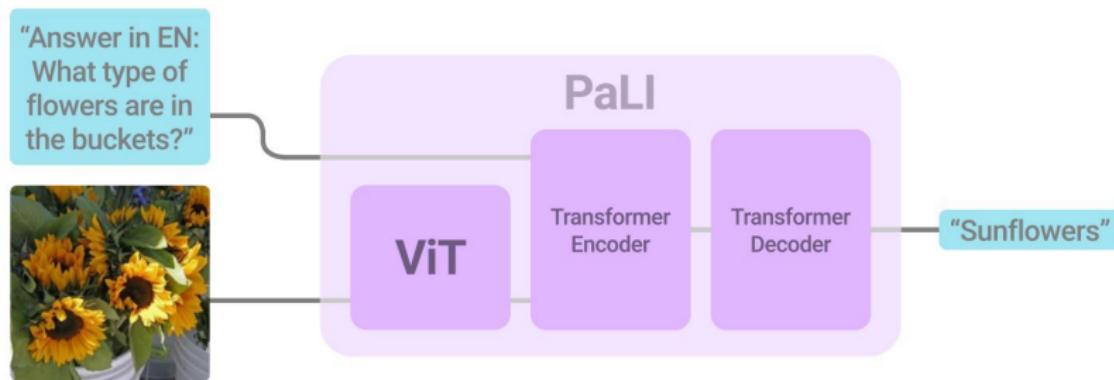


Figure: A simple and scalable architecture.

Pathways Explained

“A next-generation AI architecture”



TODAY'S AI MODELS	PATHSWAYS
Typically trained to do only one thing	Train a single model to do thousands or millions of things
Mostly focus on one sense	Enable multiple senses
Dense and inefficient	Sparse and efficient

PaLM-E

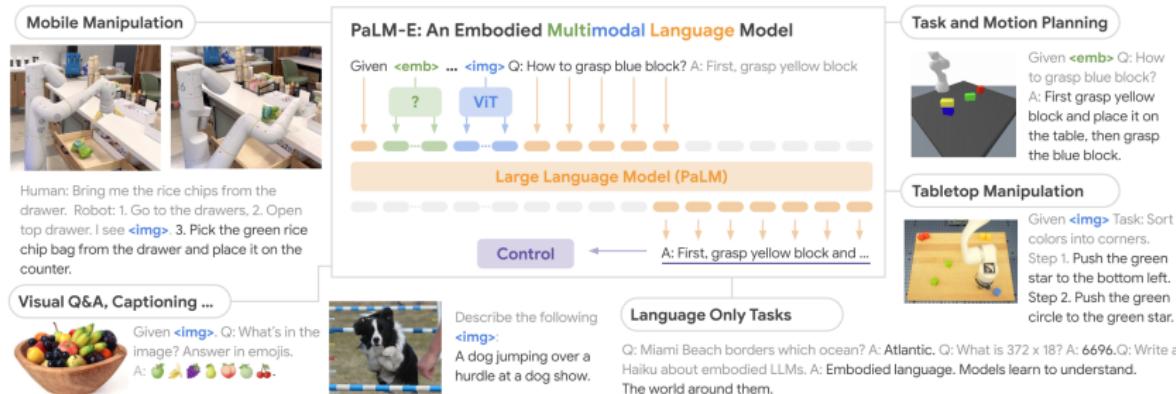
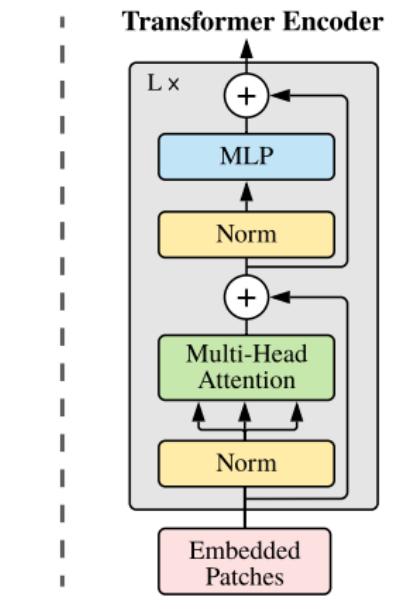
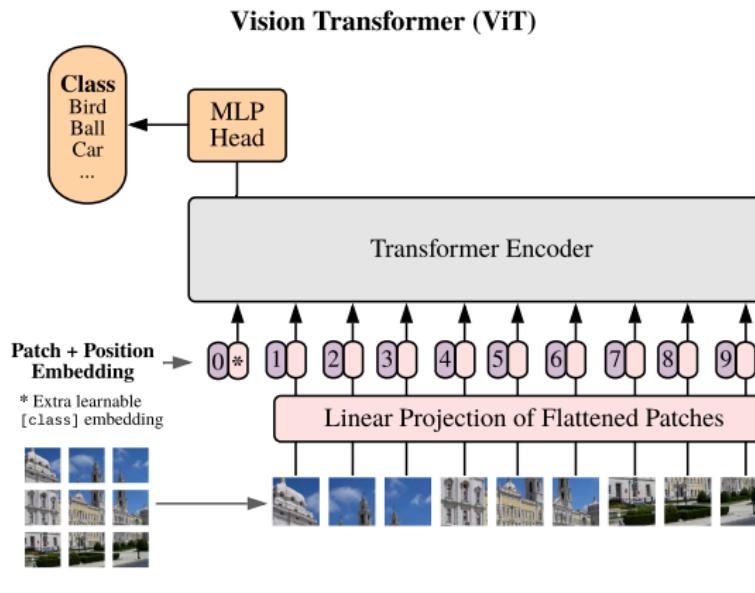


Figure: A single general-purpose multimodal language model.

Vision Transformer



Vision Transformer

$$\begin{aligned} z_0 &= [\mathbf{x}_{class}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \cdots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{pos} \\ \mathbf{E} &\in \mathbb{R}^{(P^2 \cdot C) \times D}, \quad \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D} \end{aligned} \tag{9}$$

$$z_l' = MSA(LN(z_{l-1})) + z_{l-1}, \quad l = 1 \cdots L \tag{10}$$

$$z_l = MLP(LN(z_l')) + z_l' \tag{11}$$

$$y = LN(z_L^0) \tag{12}$$

Vision Transformer

```
# Attention block.  
assert inputs.ndim == 3, f'Expected (batch, seq, hidden) got {inputs.shape}'  
x = nn.LayerNorm(dtype=self.dtype)(inputs)  
x = nn.MultiHeadDotProductAttention(  
    dtype=self.dtype,  
    kernel_init=nn.initializers.xavier_uniform(),  
    broadcast_dropout=False,  
    deterministic=deterministic,  
    dropout_rate=self.attention_dropout_rate,  
    num_heads=self.num_heads)(  
    x, x)  
x = nn.Dropout(rate=self.dropout_rate)(x, deterministic=deterministic)  
x = x + inputs  
  
# MLP block.  
y = nn.LayerNorm(dtype=self.dtype)(x)  
y = MlpBlock(  
    mlp_dim=self.mlp_dim, dtype=self.dtype, dropout_rate=self.dropout_rate)(  
    y, deterministic=deterministic)  
  
return x + y
```

Reflection

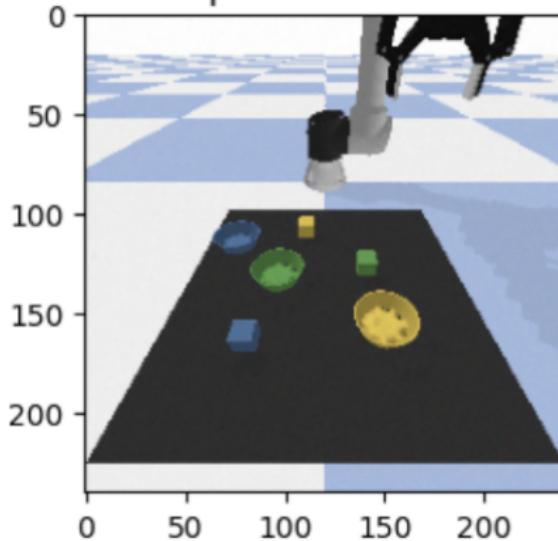
- If **few** equations, then conduct **extensive** experiments
- Multi-modal fusion happens in the embedding space
- Image and text inputs are processed in similar way

Multimodal Learning

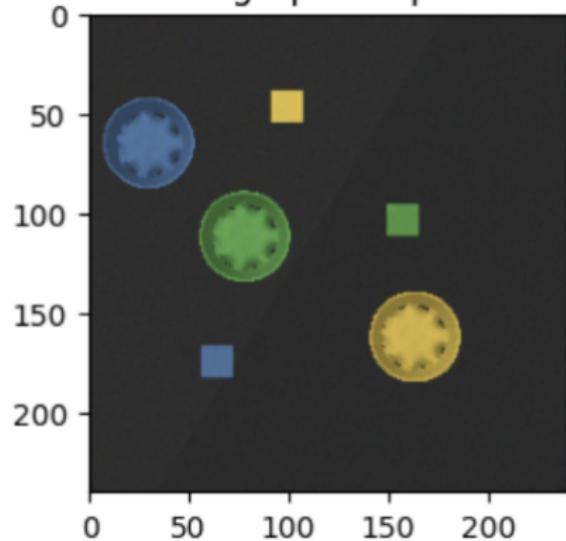
- Explore **inter-modal** and **intra-modal** relations from a statistical perspective
- Aim for **task-agnostic** multimodal representations
- **Robust** and **efficient** enough for a robotic system

Simulation Environment

Perspective side-view



Orthographic top-view



Thank you very much!
Q&A