Recent Developments in Vision-Language Transformers

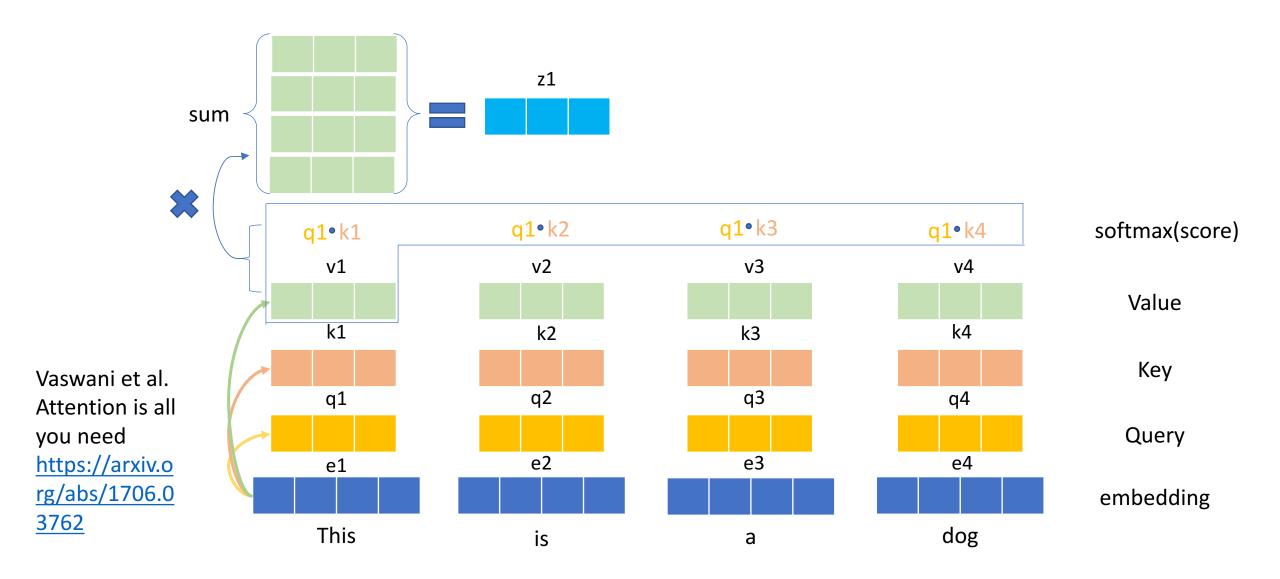
VisualBERT, PixelBERT, VILT and ALBEF



Today

- Review: Attention is All you Need!
- Review: BERT
- VisualBERT
- PixelBERT
- ViLT
- ALBEF

Attention is All you Need

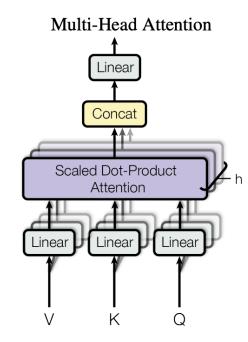


Multi-head Attention: Do not settle for just one set of attention weights.

Vaswani et al. Attention is all you need https://arxiv.org/abs/1706.0
3762

$$\begin{aligned} \text{MultiHead}(Q, K, V) &= \text{Concat}(\text{head}_1, ..., \text{head}_h) W^O \\ \text{where head}_i &= \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \end{aligned}$$

Where the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

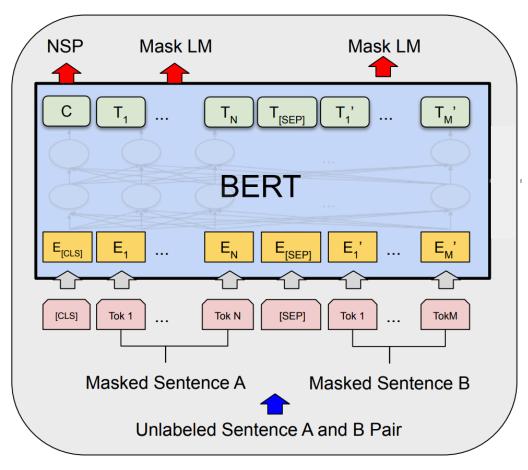


The BERT Encoder Model

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding . https://arxiv.org/abs/1810.04805

Important things to know

- No decoder
- Masking Language Modeling (MLM): Train the model to fill-in-the-blank by masking some of the input tokens and trying to recover the full sentence.
- The input is not one sentence but two sentences separated by a [SEP] token.
- Next Sentence Prediction (NSP): Also try to predict whether these two input sentences are consecutive or not.

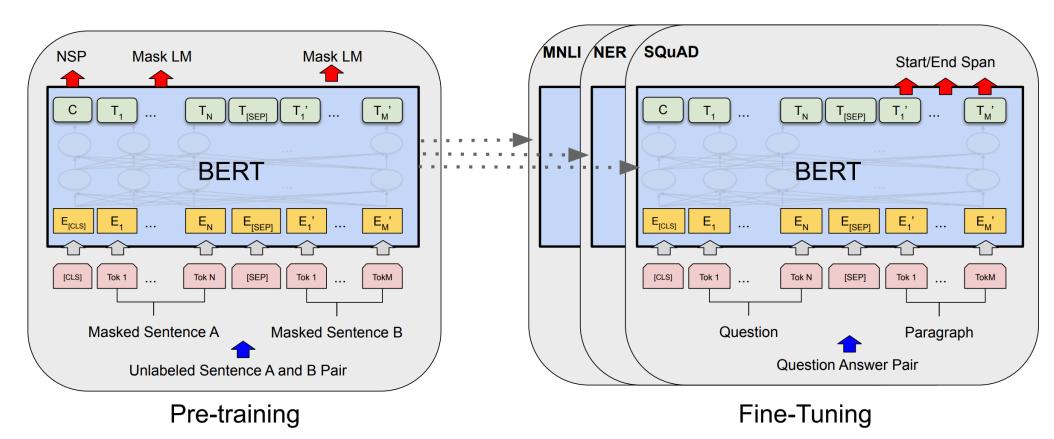


Pre-training

The BERT Encoder Model

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language

Understanding . https://arxiv.org/abs/1810.04805



Datasets

MSCOCO:



a umbrella stuck into sand at a beach with boats and hills in the background. a beach umbrella with a backpack underneath it is on the beach. an umbrella on a beach with a backpack and bag under it. a green umbrella sitting on top of a sandy beach. an umbrella provides shade on a beach in front of the water.

SBU:



My dog playing with her favorite ball in the snow.

Visual Genome:



frisbee flying above tree line green frisbee with white cloud sky is gray and cloudy

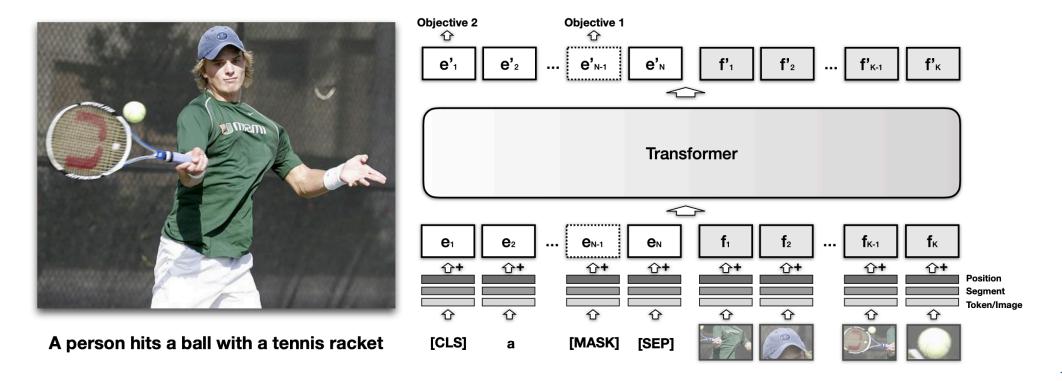
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VisualBERT

Li, Liunian Harold, et al. Visualbert: A simple and performant baseline for vision and language. https://arxiv.org/pdf/1908.03557.pdf

Important things to know

- Input: paired image + two sentences
- Faster-RCNN image features
- Objective 1: Masking Language Modeling (MLM)
- Objective 2: Sentence Image Prediction: predict whether both sentences are describing the input image.



VisualBERT

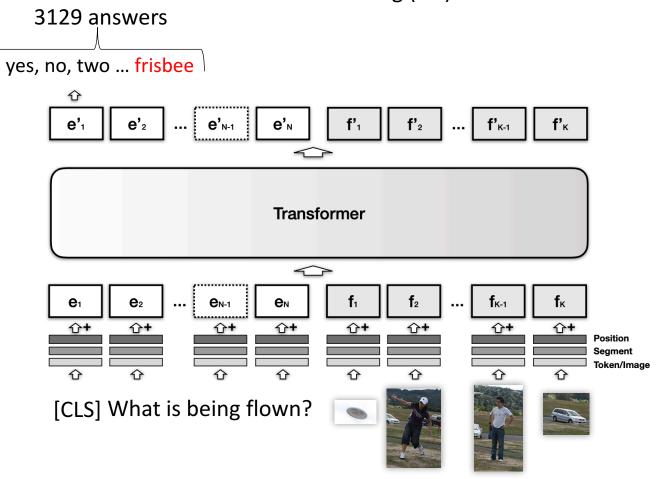
Li, Liunian Harold, et al. Visualbert: A simple and performant baseline for vision and

language. https://arxiv.org/pdf/1908.03557.pdf



Downstream tasks

- Visual Question Answering (VQA)
- Visual Commonsense Reasoning (VCR)
- Natural Language for Visual Reasoning (NLVR)
- Visual Grounding (VG)



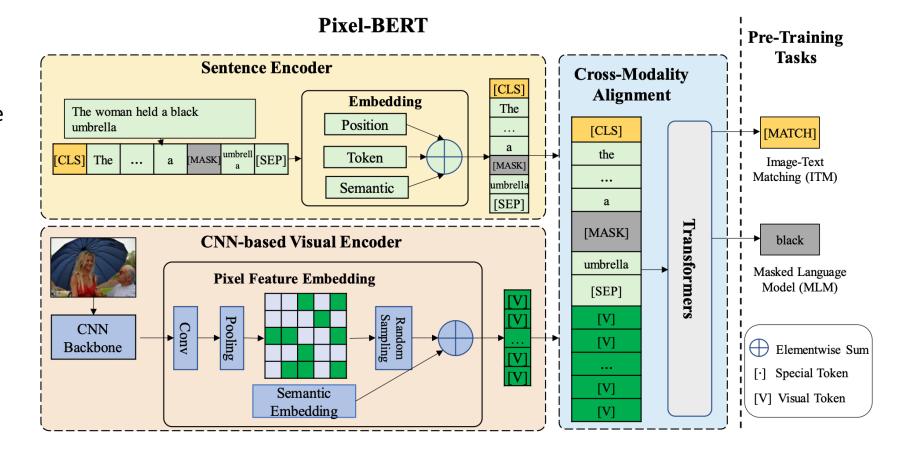
PixelBERT

Huang, Zhicheng, et al. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers.

https://arxiv.org/pdf/2004.00849.pdf

Important things to know

- Input: paired image + sentence
- CNN image features
- Masking Language Modeling (MLM)
- Image Text Matching (ITM): predict if the input image and text are matched



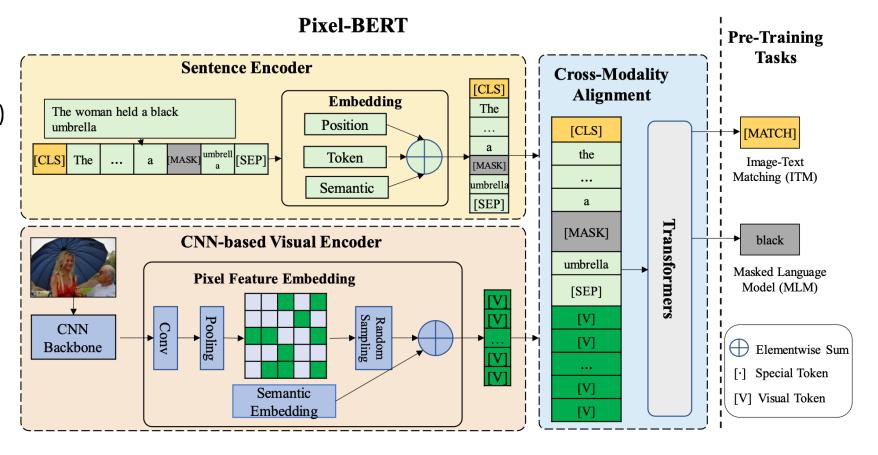
PixelBERT

Huang, Zhicheng, et al. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers.

https://arxiv.org/pdf/2004.00849.pdf

Downstream tasks

- Visual Question Answering (VQA)
- Natural Language for Visual Reasoning (NLVR)
- Image Retrieval & Text Retrieval (IR & TR)

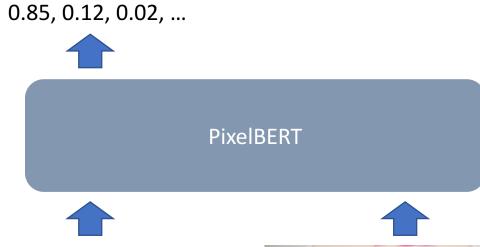


PixelBERT

Huang, Zhicheng, et al. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers. https://arxiv.org/pdf/2004.00849.pdf

Downstream tasks

- Visual Question Answering (VQA)
- Natural Language for Visual Reasoning (NLVR)
- Image Retrieval & Text Retrieval (IR & TR)



Positive: a fluffy brown cat is laying in a bathroom sink.

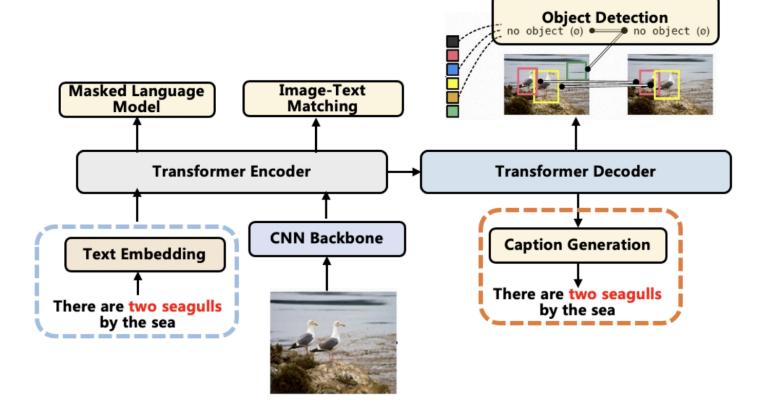
Negative: an image of a cat looking out the window a man stands in front of an elephant a white building that is a medical clinic.

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Reading for you: E2E-VLP

Xu, Haiyang, et al. E2E-VLP: End-to-End Vision-Language Pre-training Enhanced by Visual Learning. https://arxiv.org/abs/2106.01804



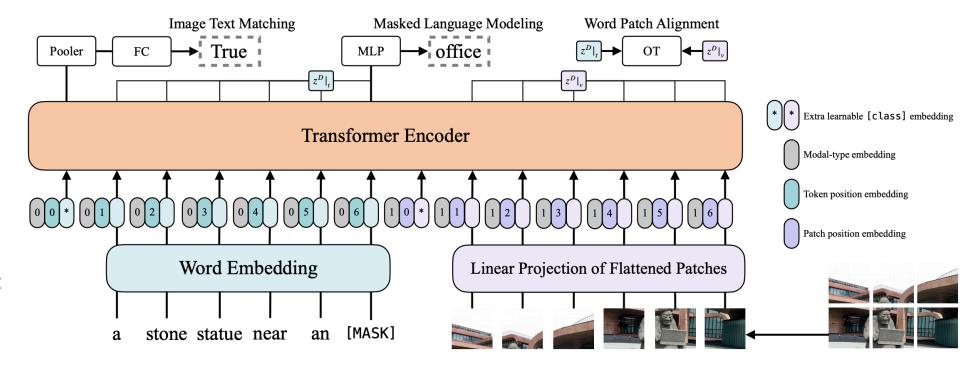


Kim, Wonjae, et al. ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision

https://arxiv.org/pdf/2102.03334.pdf

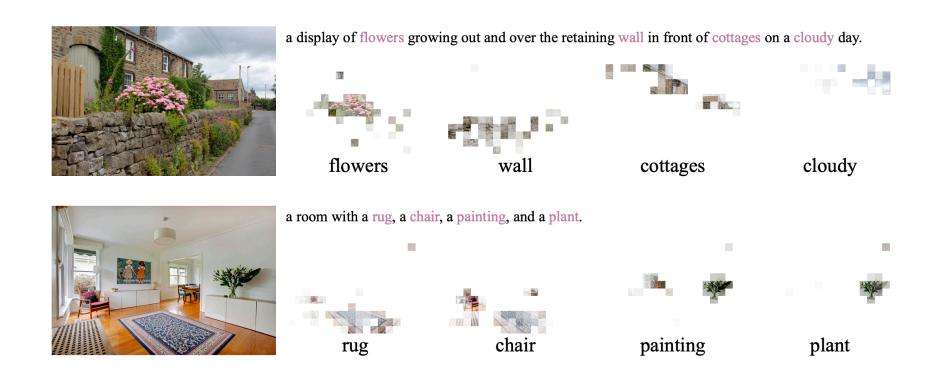
Important things to know

- Input: paired image + sentence
- Image inputs are flattened patches
- Masking Language Modeling (MLM)
- Image Text Matching (ITM)
- Word Patch Alignment (WPA): predict if the patch and the token are matched



ViLT

inexact proximal point method for optimal transports (IPOT)



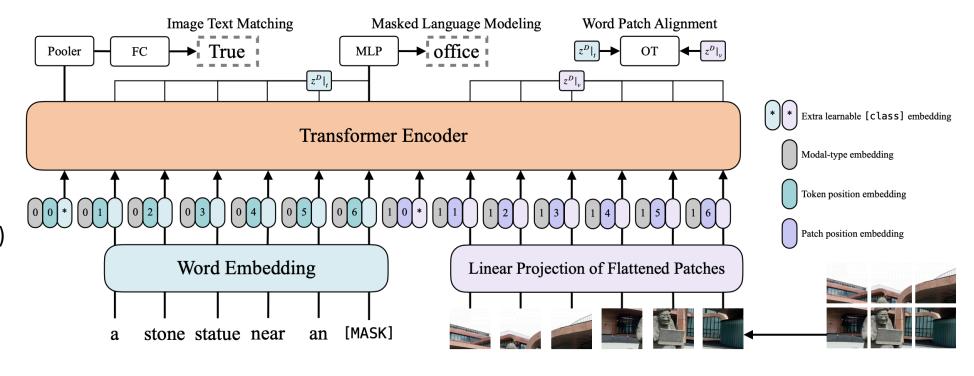


Kim, Wonjae, et al. ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision

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Downstream tasks

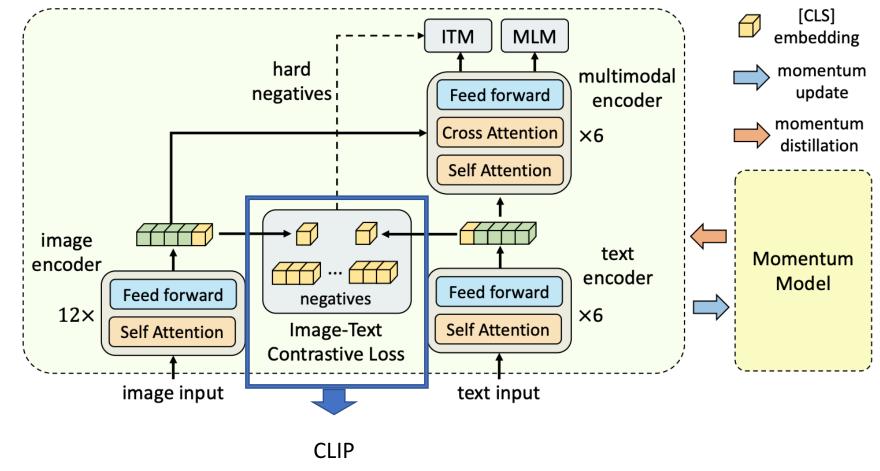
- Visual Question Answering (VQA)
- Natural Language for Visual Reasoning (NLVR)
- Image Retrieval & Text Retrieval (IR & TR)



Li, Junnan, et al. Align before Fuse: Vision and Language Representation Learning with Momentum Distillation https://arxiv.org/pdf/2107.07651.pdf

Important things to know

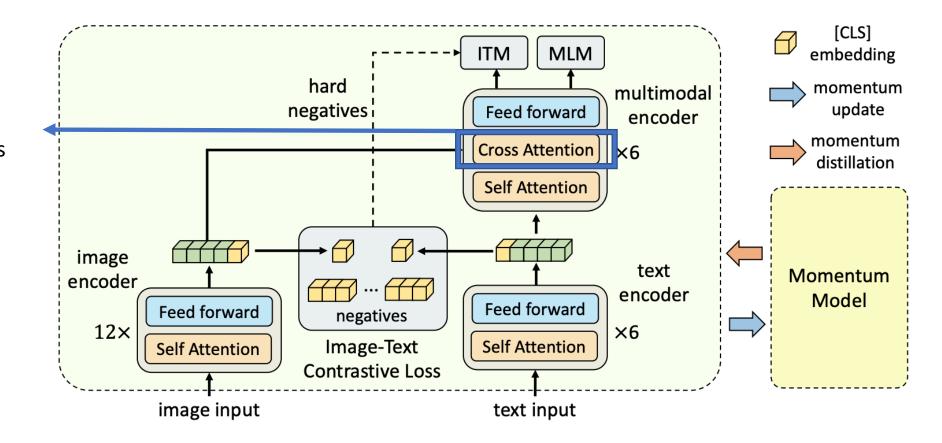
- Input: paired image + sentence
- Use ViT to encode images
- Masking Language Modeling (MLM)
- Image Text Matching (ITM)
- Image-Text Contrastive loss: make positive image-text pairs similar to each other



Li, Junnan, et al. Align before Fuse: Vision and Language Representation Learning with Momentum Distillation https://arxiv.org/pdf/2107.07651.pdf

Query: text vector

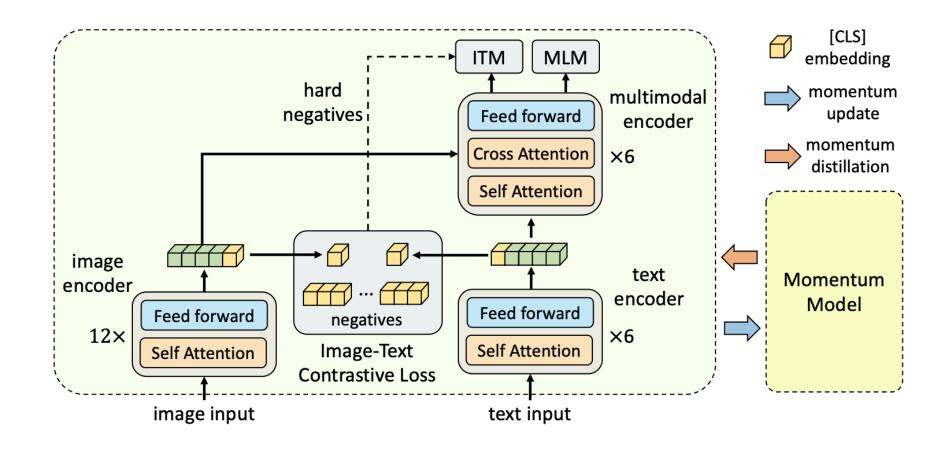
Key, Value: image vectors



Li, Junnan, et al. Align before Fuse: Vision and Language Representation Learning with Momentum Distillation https://arxiv.org/pdf/2107.07651.pdf

Downstream tasks

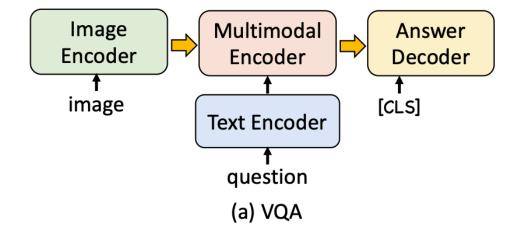
- Visual Question Answering (VQA)
- Natural Language for Visual Reasoning (NLVR)
- Image Retrieval & Text Retrieval (IR & TR)
- Visual Entailment (VE)
- Visual Grounding (VG)



Li, Junnan, et al. Align before Fuse: Vision and Language Representation Learning with Momentum Distillation https://arxiv.org/pdf/2107.07651.pdf

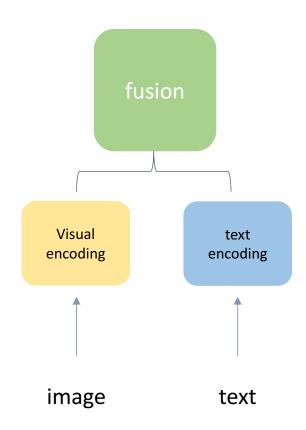
Downstream tasks

- Visual Question Answering (VQA)
- Natural Language for Visual Reasoning (NLVR)
- Image Retrieval & Text Retrieval (IR & TR)
- Visual Entailment (VE)
- Visual Grounding (VG)



Summary

- Image encoding:
 - CNN
 - Object detectors
 - Patches
 - Visual Transformer
 - etc.
- Text encoding:
 - BERT
 - Word embedding
 - etc.



Download

- VisualBERT: https://github.com/uclanlp/visualbert
- VILT: https://github.com/dandelin/vilt
- ALBEF: https://github.com/salesforce/ALBEF

```
from functools import partial
from models.vit import VisionTransformer
from models.xbert import BertConfig, BertModel
from models.tokenization bert import BertTokenizer
import torch
from torch import nn
from torchvision import transforms
import json
class VL_Transformer_ITM(nn.Module):
    def init (self,
                 text encoder = None,
                 config bert = ''
                 ):
        super().__init__()
        bert config = BertConfig.from json file(config bert)
        self.visual encoder = VisionTransformer(
            img size=384, patch size=16, embed dim=768, depth=12, num heads=12,
            mlp ratio=4, qkv bias=True, norm layer=partial(nn.LayerNorm, eps=1e-6))
        self.text_encoder = BertModel.from_pretrained(text_encoder, config=bert_config, add_pooling_layer=False)
        self.itm head = nn.Linear(768, 2)
    def forward(self, image, text):
        image embeds = self.visual encoder(image)
        image atts = torch.ones(image embeds.size()[:-1],dtype=torch.long).to(image.device)
        output = self.text encoder(text.input ids,
                                attention mask = text.attention mask,
                                encoder_hidden_states = image_embeds,
                                encoder attention mask = image atts,
                                return dict = True,
        vl embeddings = output.last hidden state[:,0,:]
        vl output = self.itm head(vl embeddings)
        return vl output
```

```
import torch
import yaml
from models.vit import interpolate pos embed
from models.tokenization bert import BertTokenizer
model path = 'ALBEF.pth'
bert config path = 'configs/config bert.json'
checkpoint = torch.load(model_path, map_location='cpu')
state dict = checkpoint['model']
#### Model ####
print("Creating model")
tokenizer = BertTokenizer.from pretrained('bert-base-uncased')
model = VL Transformer ITM(text encoder='bert-base-uncased', config bert=bert config path)
# reshape positional embedding to accommodate for image resolution change
pos embed reshaped = interpolate pos embed(state dict['visual encoder.pos embed'], model.visual encoder)
state dict['visual encoder.pos embed'] = pos embed reshaped
for key in list(state dict.keys()):
    if 'bert' in key:
        encoder key = key.replace('bert.','')
        state dict[encoder key] = state dict[key]
        del state dict[key]
msg = model.load state dict(state dict,strict=False)
print('load checkpoint from %s'%model path)
print(msg)
```

```
from PIL import Image
import cv2
import numpy as np
from torchvision import transforms
from skimage import transform as skimage transform
from scipy.ndimage import filters
from matplotlib import pyplot as plt
normalize = transforms.Normalize((0.48145466, 0.4578275, 0.40821073), (0.26862954, 0.26130258, 0.27577711))
transform = transforms.Compose([
                                                                  import re
    transforms.Resize((384,384),interpolation=Image.BICUBIC),
    transforms.ToTensor(),
                                                                  def pre caption(caption, max words=50):
    normalize,
                                                                     caption = re.sub(
                                                                         r"([,.'!?\"()*#:;~])",
])
                                                                         caption.lower(),
image path = 'examples/image0.jpg'
                                                                     ).replace('-', '').replace('/', '')
image pil = Image.open(image path).convert('RGB')
image = transform(image pil).unsqueeze(0)
                                                                     caption = re.sub(
                                                                         r"\s{2,}",
caption = 'the woman is working on her computer at the desk'
text = pre caption(caption)
                                                                         caption,
text input = tokenizer(text, return tensors="pt")
                                                                     caption = caption.rstrip('\n')
                                                                     caption = caption.strip(' ')
                                                                     #truncate caption
                                                                     caption words = caption.split(' ')
                                                                     if len(caption words)>max words:
                                                                         caption = ' '.join(caption words[:max words])
```

return caption

```
image embeds = model.visual encoder(image)
print('Visual Transformer output shape is: ', image embeds.shape)
image atts = torch.ones(image embeds.size()[:-1],dtype=torch.long).to(image.device)
output = model.text encoder(text input.input ids,
                           attention mask = text input.attention mask,
                           encoder hidden states = image embeds,
                           encoder attention mask = image atts,
                           return dict = True,
vl embeddings = output.last hidden state[:,0,:]
print('Visual Language Transformer output shape is: ', vl embeddings.shape)
vl output = model.itm head(vl embeddings)
print(vl output)
Visual Transformer output shape is: torch.Size([1, 577, 768])
Visual Language Transformer output shape is: torch.Size([1, 768])
tensor([[-3.1364, 3.2983]], grad fn=<AddmmBackward>)
```

Questions?