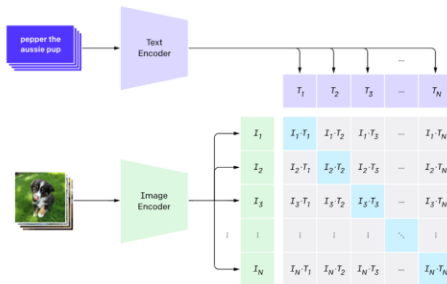


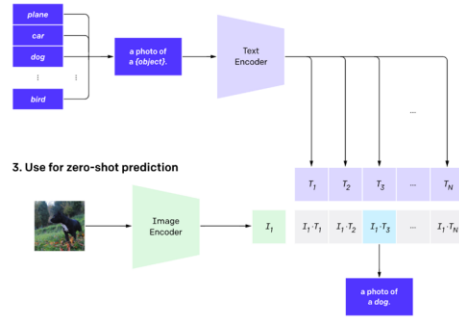
Open World Image Semantic Segmentation

- Introduction to **CLIP** (Contrastive Language-Image Pre-training)
- Aligns the CLS token of image and text encoder via InfoNCE
- Zero-shot image classification

1. Contrastive pre-training



2. Create dataset classifier from label text



3. Use for zero-shot prediction

$$\mathcal{L}_{\mathbf{x}} = \frac{1}{k} \sum_{i=1}^k \left(\frac{e^{\phi(\mathbf{x}_i, \mathbf{y}_i)}}{\sum_{j=1}^k e^{\phi(\mathbf{x}_i, \mathbf{y}_j)}} \right) \quad f_v : \mathbb{R}^{C,H,W} \rightarrow \mathbb{R}^{D_v} \text{ and } f_t : \mathbb{R}^l \rightarrow \mathbb{R}^{D_t}$$

$$\mathcal{L}_{\mathbf{y}} = \frac{1}{k} \sum_{i=1}^k \left(\frac{e^{\phi(\mathbf{x}_i, \mathbf{y}_i)}}{\sum_{j=1}^k e^{\phi(\mathbf{x}_j, \mathbf{y}_i)}} \right) \quad e_v : \mathbb{R}^{D_v} \rightarrow \mathbb{R}^D \text{ and } e_t : \mathbb{R}^{D_t} \rightarrow \mathbb{R}^D$$

$$\phi(\mathbf{x}, \mathbf{y}) = \left(\frac{e_v(f_v(\mathbf{x}))}{|e_v(f_v(\mathbf{x}))|} \cdot \frac{e_t(f_t(\mathbf{y}))}{|e_t(f_t(\mathbf{y}))|} \right)$$

$$\mathcal{L}_{\text{InfoNCE}} = 1/2(\mathcal{L}_{\mathbf{x}} + \mathcal{L}_{\mathbf{y}}).$$

Attentive Mask CLIP

A-CLIP

- Main idea:
 - Drop irrelevant tokens!!
 - Drop almost $\geq 50\%$
- Random dropping degrades performance though
 - Masked Image Modeling (MIM) works with random dropping but not CLIP, why?

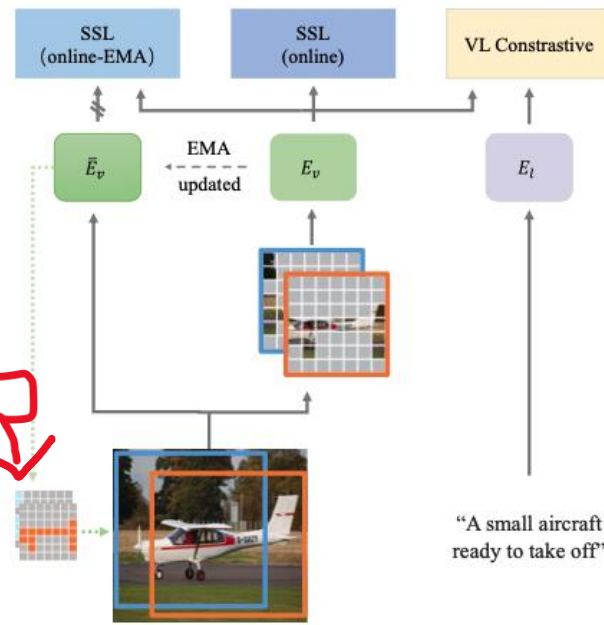


Attentive Mask

$$s_P = \frac{1}{HL} \sum_{l=1}^L \sum_{h=1}^H \text{Softmax} \left(\frac{\mathbf{f}_{lh}^q(CLS) \cdot \mathbf{f}_{lh}^k(P)}{\sqrt{C}} \right)$$

- Low strategy – discard low s_p score, high strategy: use high s_p scores, mixture strategy
- EMA for attention score computation
 - A-CLIP-eff: half-res for speed as it does not need to be very accurate
- Shared EMA scored map for multiple views, efficiency
- Multiple masked views
 - Auxiliary contrastive learning
 - Between a masked view and EMA feature (BYOL)
 - Between masked views (SIMCLR)

where l denotes the layer index; h denotes the attention head index; $\mathbf{f}_{lh}^q(CLS)$ denotes the query embedding of the $[CLS]$ token at Layer l and Head h ; $\mathbf{f}_{lh}^k(P)$ denotes the key embedding of Layer l and Head h for an image token at location P ; C is the number of channels for the query and key embedding.



Strong correlation to text

importance of token



Sigmoid Loss based CLIP

SGLIP

- Recall:

$$\mathcal{L}_{\mathbf{x}} = \frac{1}{k} \sum_{i=1}^k \left(\frac{e^{\phi(\mathbf{x}_i, \mathbf{y}_i)}}{\sum_{j=1}^k e^{\phi(\mathbf{x}_i, \mathbf{y}_j)}} \right)$$


$$\mathcal{L}_{\mathbf{y}} = \frac{1}{k} \sum_{i=1}^k \left(\frac{e^{\phi(\mathbf{x}_i, \mathbf{y}_i)}}{\sum_{j=1}^k e^{\phi(\mathbf{x}_j, \mathbf{y}_i)}} \right)$$



Inefficient and prevents large batch size (usually 32768, N positive pairs, N x N – N negative pairs)

SGLIP

- Instead of global normalization as in CLIP, separate pair processing
- A lot of negative pairs causing a lot of imbalance during optimization
 - Massive over-correction in the training results
- Added a bias term and temperature
- Z_{ij} is the label (1 for positive pair and -1 otherwise)
- Batch size can go up to a million, but typically 32k

$$-\frac{1}{|\mathcal{B}|} \sum_{i=1}^{|\mathcal{B}|} \sum_{j=1}^{|\mathcal{B}|} \underbrace{\log \frac{1}{1 + e^{z_{ij}(-t\mathbf{x}_i \cdot \mathbf{y}_j + b)}}}_{\mathcal{L}_{ij}}$$


Allows for chunking

Attendance



Assignment Due 9/18

- Dataset: Human Action Recognition (HAR)
 - Same train/test split
- Fine tune on HAR and compare CLIP, A-CLIP and SGLIP
- Report performance, speed and memory consumption
 - SGLIP is able to load very large batch size, use 32k
 - For CLIP, A-CLIP (4096)
- Report, code, video to be submitted