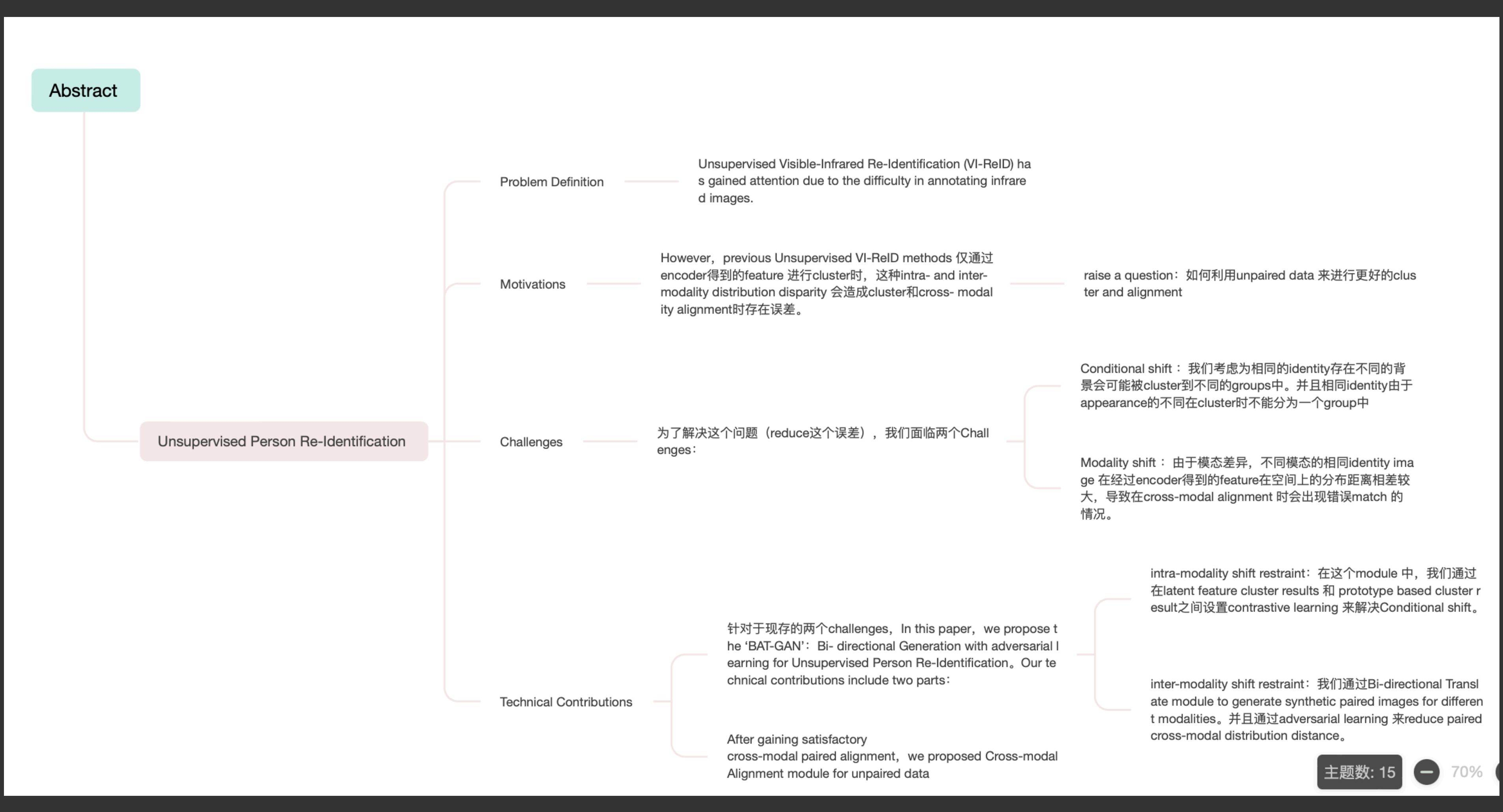
In the experimental section:

While keeping the cwcon-filterthresh at 0.00240, I changed prec_nums from '1,5,15' to '1,5,10' because according to the dataset, the maximum number of images for each identity in the infrared/visible pair is 10.

```
Domain A->B: P@1: 0.558252427184466; P@5: 0.4514563106796116; P@10: 0.4611650485436893
Domain B->A: P@1: 0.6067961165048543; P@5: 0.5339805825242718; P@10: 0.5631067961165048
```

Judging from the results, the accuracy of the retrieval is not bad, and the role of each loss in the paper has been utilized

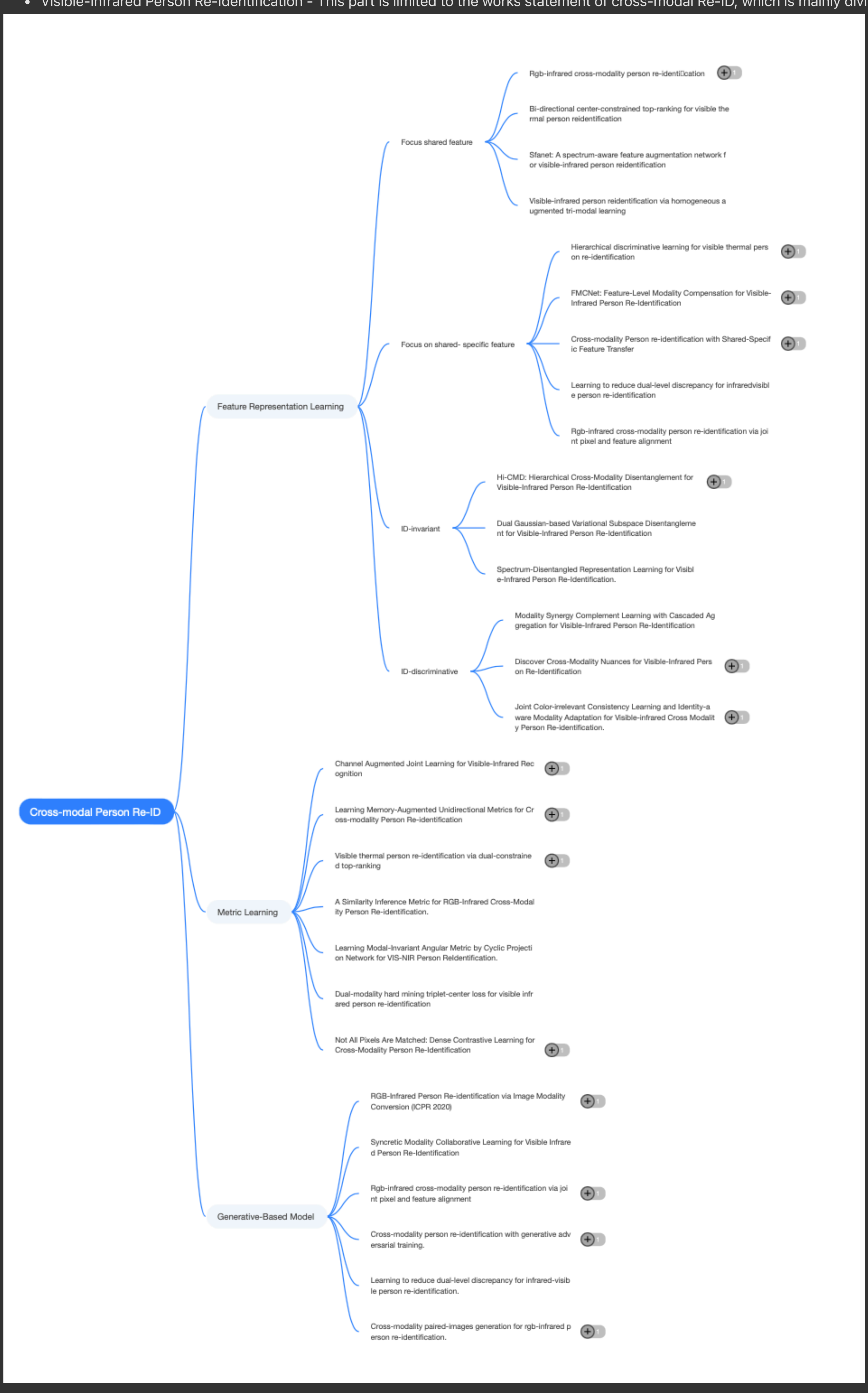
Logically sort out the Abstract



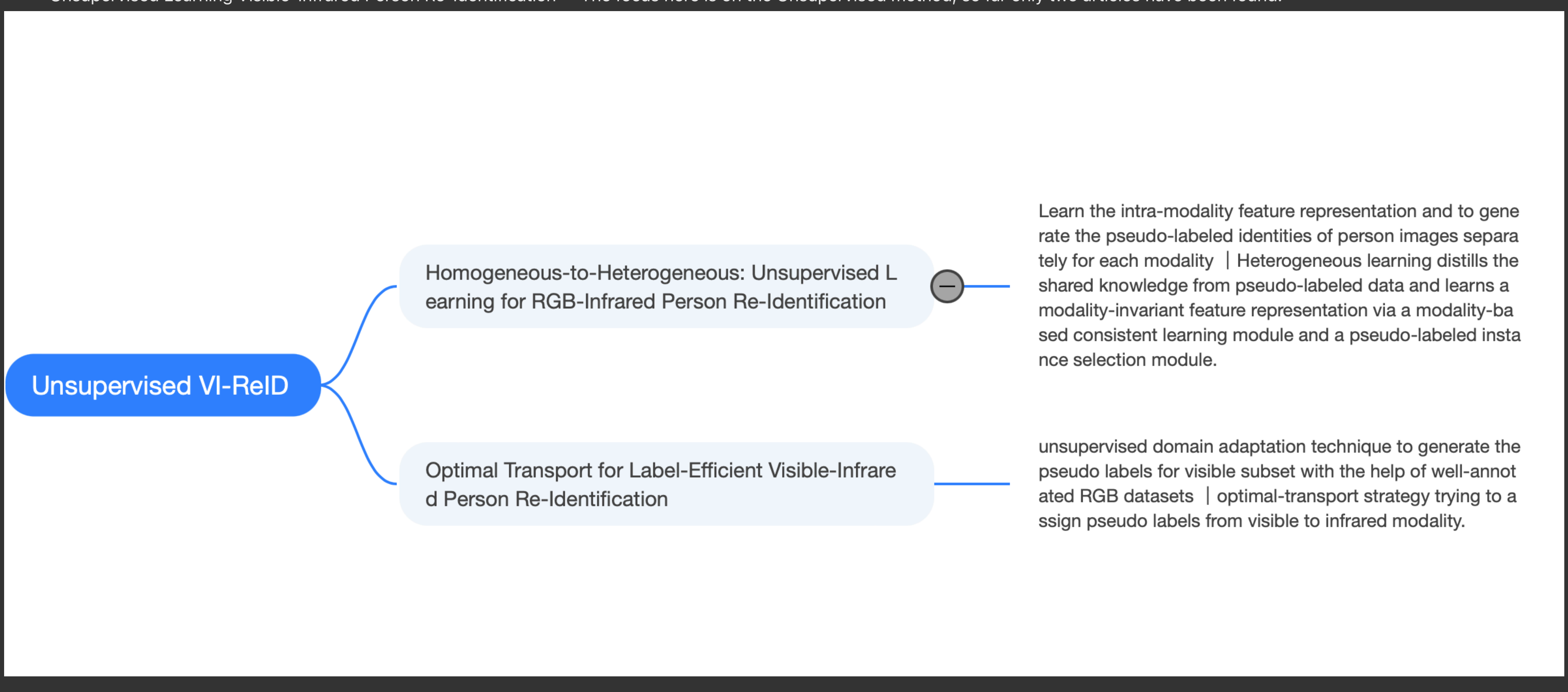
Organize Literature Review

For the Literature Review, I plan to divide it into three parts:

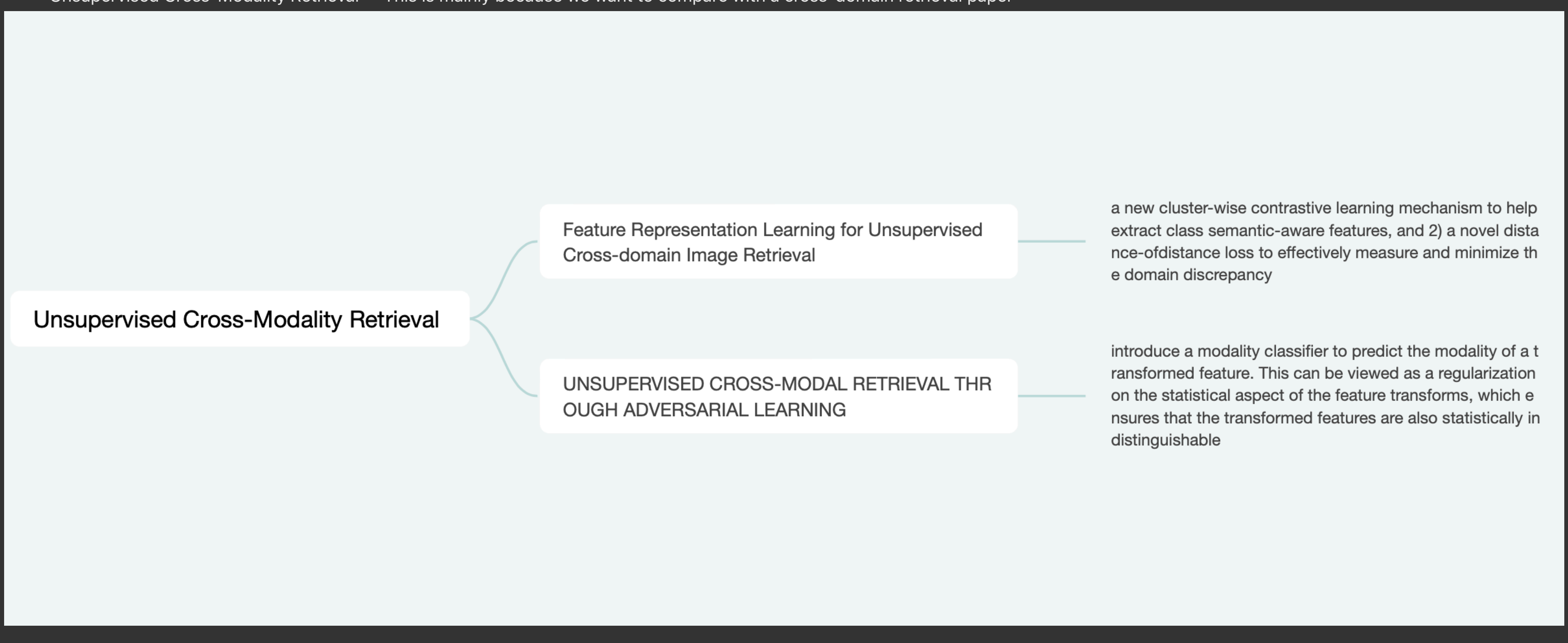
- Visible-Infrared Person Re-Identification - This part is limited to the works statement of cross-modal Re-ID, which is mainly divided into the following parts:



- Unsupervised Learning Visible-Infrared Person Re-Identification — The focus here is on the Unsupervised method, so far only two articles have been found:



- Unsupervised Cross-Modality Retrieval — This is mainly because we want to compare with a cross-domain retrieval paper



New expression learned: inevitably reduces feature distinctiveness. — suitable for saying match pedestrians across modalities using modality alignment solely

ignoring the valuable identity information, which may cause the feature misalignment of some identities and weaken the discrimination of features. — from 'Joint Color-irrelevant Consistency Learning and Identity-aware Modality Adaptation for Visible-infrared Cross Modality Person Re-identification' （AAAI 2021）

Write the draft of Abstract and related works, and modify the framework figure.

From Haotian's sharing class, I learned that reinforcement learning and nerf can be combined!

The latest paper found so far (only two in total):

Reinforcement learning with neural radiance fields

NeRF-RL (Driess et al., 2022) extends the prior study and firstly introduces NeRF-based architecture to the general model-free RL framework.

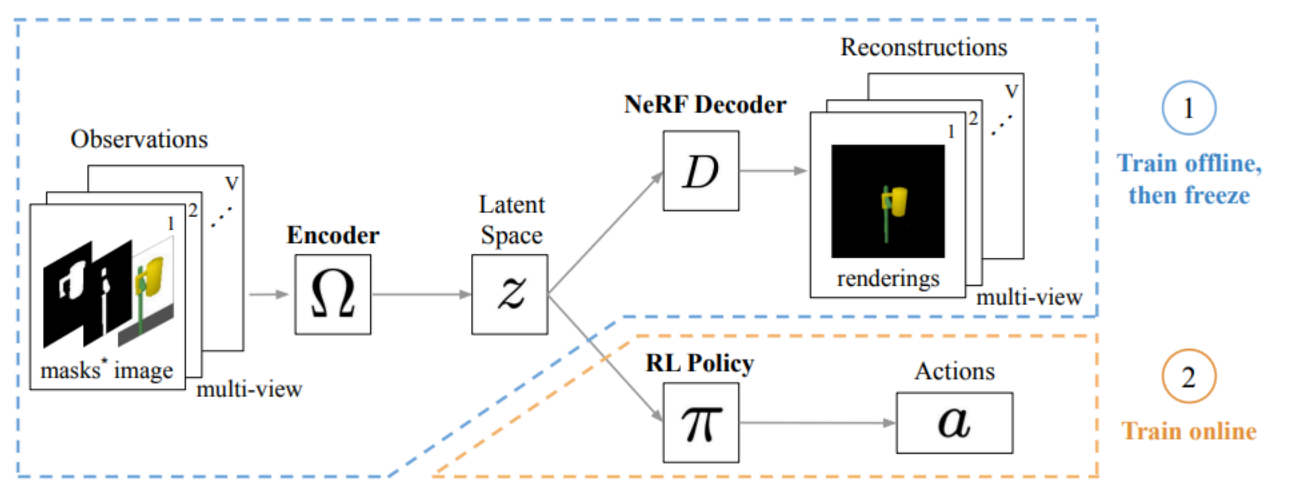


Figure 1: State representation learning for RL with NeRFs. First, the encoder and NeRF decoder are trained with supervision from a multi-view reconstruction loss on an offline dataset. Then, the encoder's weights are frozen, and the latent space is used as state input to train a policy with RL. *Masks of individual objects are only required for the compositional variant of our encoder.

However, they could not learn semantic features due to the limited RGB supervision with na¨ıve NeRF. To learn object-centric representation only with RGB supervision, NeRF-RL presents compositional NeRF with object-individual masks, but requiring masks during the deployment of RL agents seems to be a strong assumption.
The RL agents in NeRF-RL require object-individual masks during training and deployment to utilize semantic representations, which is quite unrealistic.

SNeRL: Semantic-aware Neural Radiance Fields for **Reinforcement Learning**

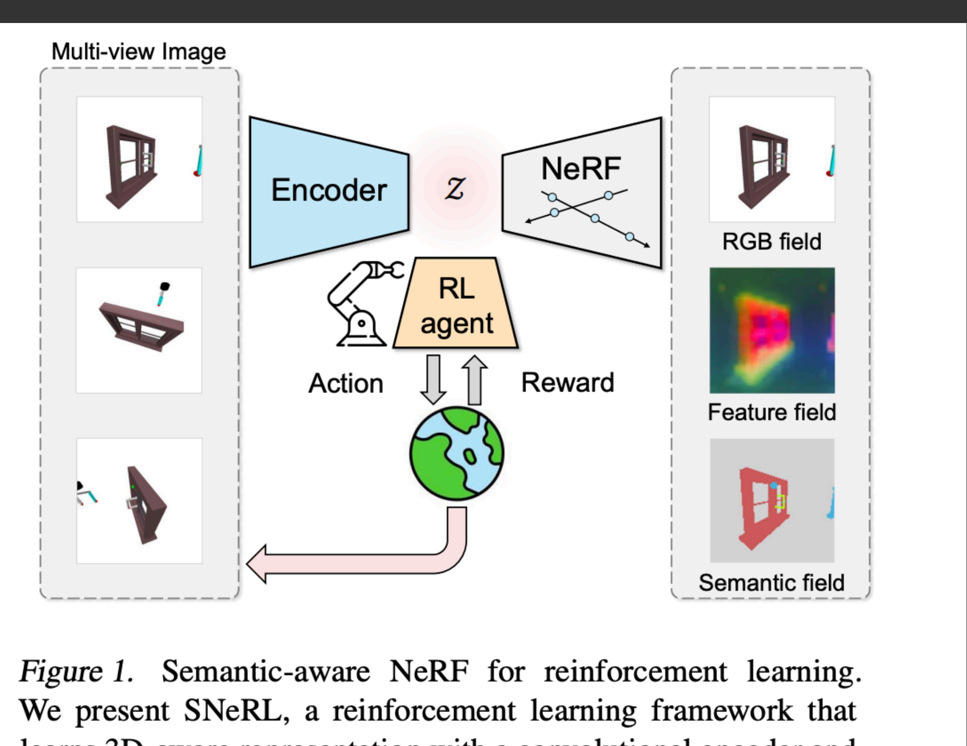


Figure 1. Semantic-aware NeRF for reinforcement learning. We present SNeRL, a reinforcement learning framework that learns 3D-aware representation with a convolutional encoder and semantic-aware NeRF decoder. The latent vectors from the encoder are propagated to the policy network to generate an action for RL agents.

In this paper, they propose SNeRL which learns both geometric and semantic information with RGB, semantic, and distilled feature supervision for RL downstream tasks without any object masks during the inference phase.

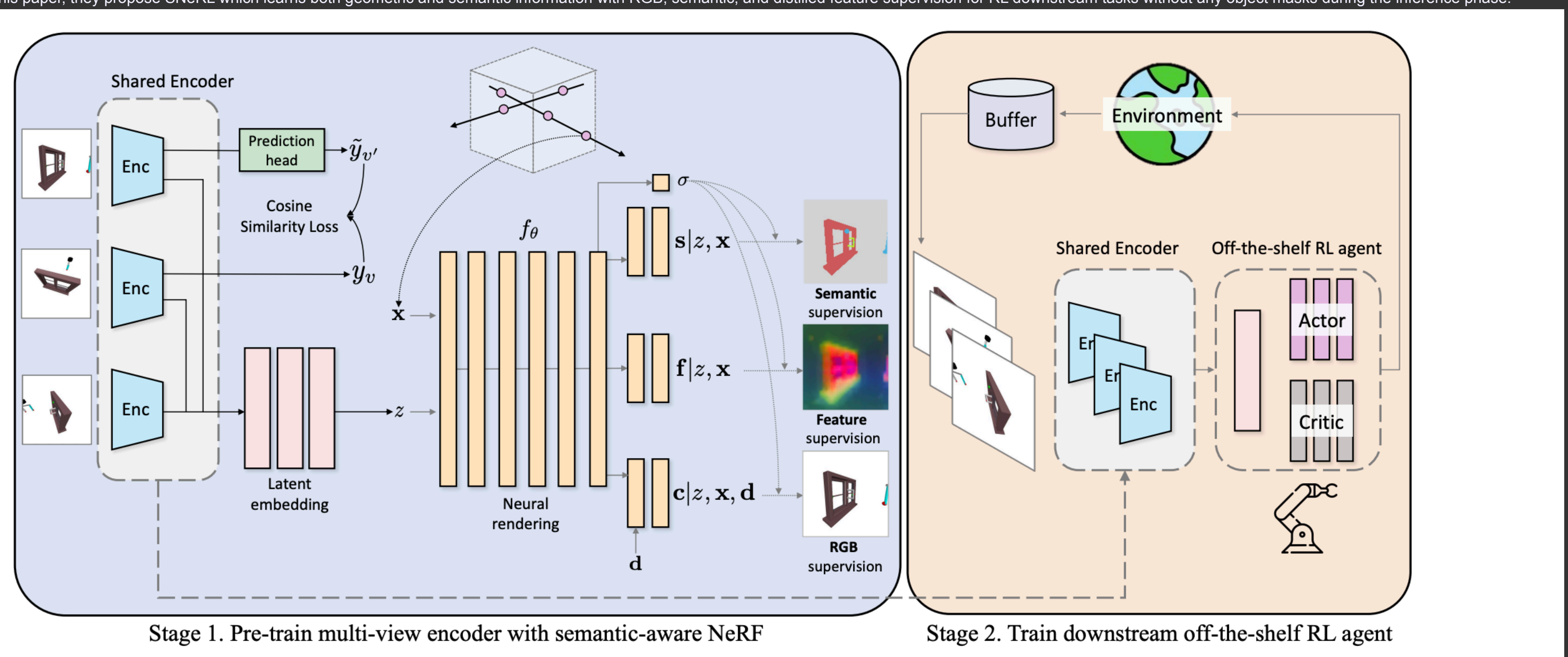


Figure 2. SNeRL Overview. SNeRL consists of two stages, which are pre-training NeRF-based autoencoder and fine-tuning to the downstream RL tasks, respectively. With observations from three different camera views, an encoder produces a single latent vector z, and a decoder with neural rendering function f_θ takes the position $\mathbf{x}$, viewing direction $\mathbf{d}$ in the 3D coordinates and z as inputs to synthesize three different fields in the arbitrary views. An auxiliary multi-view self-prediction loss is applied to enable view-invariant representation. Then, the encoder and the decoder are jointly optimized in a supervised manner with an offline dataset. The pre-trained encoder is utilized as a feature extractor to train the policy with off-the-shelf RL algorithms.

Limitation： First of all, SNeRL requires multi-view offline data, and collecting an offline dataset covering the state space in some complex control tasks might be challenging. Also, the NeRF decoder that consumes more computational budget than CNN, so there might be limitations in extending their method to an online setup which trains the encoder concurrently with RL agents.

Future work: The combination of Asynchronous Advantage Actor Critic strategy and NeRF can be explored. The advantage is that the maximum exploration can be achieved through the asynchronous update of actors, and the correlation between training data can be eliminated.