Continual Semantic Segmentation via Repulsion-Attraction of Sparse and Disentangled Latent Representations

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Our Focus: Class-Incremental Continual Learning in Semantic Segmentation
Continual Segmentation - Different Setups

- Image
- Ground Truth
- Sequential
- Disjoint
- Overlapped

- Car
- Bike
- Person
- Dog
- Background
  - Unlabeled

- Learned
- Current
- Future

- Not present

Software: Image Ground Truth Disjoint Overlapped
**SDR Architecture**

**SDR:** Sparse and Disentangled Representations

We combine task-related cross entropy loss with 4 constraints:

- **Not trainable**
- **Trainable**

**Contrastive**
- Attractive force
- Repulsive force

**Prototypes Matching**
- On-batch prototypes
- { , } prototypes

**Sparsity**
- Activation value
  - low
  - high

before

after

Output-level Knowledge Distillation [1,2]

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[1] Michieli, U., et al., "Incremental learning techniques for semantic segmentation" ICCVW, 2019.

[2] Cermelli, F. et al., "Modeling the background for incremental learning in semantic segmentation" CVPR, 2020.
**SDR Architecture**

\[
\mathcal{L}_{pm} = \frac{1}{\left|\mathcal{C}_{k-1}\right|} \left\| \hat{p}_c - p_c \right\|_F \quad c \in \mathcal{C}_{k-1}
\]

→ **On-batch prototypes** constrained to be close to representations learned from previous steps

- Attractive: \[\mathcal{L}_{cl}^a = \frac{1}{|c_j \in y_n^*|} \sum_{c_j \in y_n^*} \sum_{f_i \in \mathcal{F}_n} \left\| (f_i - p_{c_j}) \mathbb{I}[y_i^* = c_j] \right\|_F\]

Features of the same class tightly clustered around prototype

- Repulsive: \[\mathcal{L}_{cl}^r = \frac{1}{|c_j \in y_n^*|} \sum_{c_j \in y_n^*} \sum_{c_k \in y_n^* \backslash c_j} 1 \left\| \hat{p}_{c_j} - \hat{p}_{c_k} \right\|_F\]

Features of different classes separated from each other

\[
\mathcal{L}_{sp} = \frac{1}{|f_i \in \mathcal{F}_n|} \sum_{f_i \in \mathcal{F}_n} \sum_j \exp\left( \frac{f_{i,j}}{\sigma} \right)
\]

Set of active channels is narrowed, letting room for the representation of upcoming classes

features normalized with respect to the class-conditional maximum value
More challenging
→ SDR outperforms competitors, especially when multiple steps are involved.
Conclusion

✓ We propose 3 novel latent space shaping techniques to avoid forgetting and promote learning of new concepts:
  - prototype matching
  - contrastive learning
  - sparsity

✓ We jointly tackle sequential, disjoint and overlapped scenarios

✓ We achieve state-of-the-art results on a variety of tasks and datasets

Paper website: https://lttm.dei.unipd.it/paper_data/SDR/

Code available: https://github.com/LTTM/SDR