Self-Supervised Learning for Jigsaw Puzzles

Self-Supervised Learning for Jigsaw Puzzles is a research project that focuses on leveraging self-supervised learning techniques to train deep models for solving visual jigsaw puzzles. Self-supervised learning aims to learn meaningful representations from unlabeled data by defining pretext tasks that provide supervision signals during training. This project involves designing novel pretext tasks specifically tailored for jigsaw puzzles, such as predicting the relative positions of puzzle pieces or learning embeddings that capture the semantic information of the puzzle images.

1. Relative Position Prediction: In this pretext task, the deep model is trained to predict the relative positions of puzzle pieces. Each puzzle image is divided into multiple patches, and the model is tasked with predicting the correct spatial relationships between these patches. By solving this task, the model learns spatial awareness and develops an understanding of how the pieces should be arranged.

2. Contextual Embeddings: This approach focuses on learning embeddings that capture the semantic information of puzzle images. The deep model is trained to encode each puzzle piece or patch into a low-dimensional embedding space, where similar pieces are mapped closer together. The embeddings can be learned using contrastive learning, where the model aims to maximize the similarity between embeddings of different views of the same puzzle image while minimizing similarity with other puzzle images. This encourages the model to learn representations that capture meaningful information about the puzzle pieces' content.

References

[1] Paumard MM, Picard D, Tabia H. Deepzzle: Solving visual jigsaw puzzles with deep learning and shortest path optimization. IEEE Transactions on Image Processing. 2020 Jan 7;29:3569-81.

[2] Paumard MM, Picard D, Tabia H. Image reassembly combining deep learning and shortest path problem. InProceedings of the European conference on computer vision (ECCV) 2018 (pp. 153-167).

[3] Paumard MM, Picard D, Tabia H. Jigsaw puzzle solving using local feature co-occurrences in deep neural networks. In2018 25th IEEE International Conference on Image Processing (ICIP) 2018 Oct 7 (pp. 1018-1022). IEEE.

[4] Besbes MD, Tabia H, Kessentini Y, Hamed BB. Progressive Learning With Anchoring Regularization For Vehicle Re-Identification. In2021 IEEE International Conference on Image Processing (ICIP) 2021 Sep 19 (pp. 1154-1158). IEEE.

[5] Mahmoudi MA, Chetouani A, Boufera F, Tabia H. Taylor series Kernelized layer for fine-grained recognition. In2021 IEEE International Conference on Image Processing (ICIP) 2021 Sep 19 (pp. 1914-1918). IEEE.

[6] Heuillet A, Tabia H, Arioui H, Youcef-Toumi K. D-DARTS: Distributed differentiable architecture search. arXiv preprint arXiv:2108.09306. 2021 Aug 20.

[7] Mahmoudi MA, Chetouani A, Boufera F, Tabia H. Deep kernelized network for fine-grained recognition. InNeural Information Processing: 28th International Conference, ICONIP 2021, Sanur, Bali, Indonesia, December 8–12, 2021, Proceedings, Part III 28 2021 (pp. 100-111). Springer International Publishing.

[8] Mahmoudi MA, Chetouani A, Boufera F, Tabia H. Kernel-based convolution expansion for facial expression recognition. Pattern Recognition Letters. 2022 Aug 1;160:128-34.

[9] Heuillet A, Tabia H, Arioui H. NASiam: Efficient Representation Learning using Neural Architecture Search for Siamese Networks. arXiv preprint arXiv:2302.00059. 2023 Jan 31.

[10] Mahmoudi M, Chetouani A, Boufera F, Tabia H. Kernel function impact on convolutional neural networks. arXiv preprint arXiv:2302.10266. 2023 Feb 20.