SELF-SUPERVISED LEARNING

Mohammadreza Ahmadi Teshnizi
Sajad Sabzi

DATA AUGMENTATION (NO SPECIFIC RELEASE YEAR)

Data augmentation involves creating new training examples by applying various transformations to the original data. This helps the model learn to be invariant to these transformations and extract more meaningful features. Common data augmentation techniques include rotation, cropping, flipping, and color jittering.

CONTRASTIVE LEARNING (AROUND 2020)

Contrastive learning is a popular technique in self-supervised learning. It involves training a model to bring similar samples closer together in the feature space while pushing dissimilar samples apart. This is typically done using a contrastive loss function, such as the triplet loss or the InfoNCE loss.

TEMPORAL OR SPATIAL CONTEXT (NO SPECIFIC RELEASE YEAR)

In self-supervised learning for sequences or images, temporal or spatial context is often used. For example, in video understanding, a model may predict the next frame in a video given previous frames. This forces the model to learn temporal dependencies.

TRANSFORMERS (2017)

Transformers, originally designed for natural language processing tasks, have been adapted for self-supervised learning in various domains. They can capture contextual information effectively and have achieved state-of-the-art results in many self-supervised tasks.

SIAMESE NETWORKS (1994)

Siamese networks are used in self-supervised learning to learn similarity between pairs of data points. They consist of two identical subnetworks that share the same weights. These networks are trained to minimize the distance between similar data points and maximize the distance between dissimilar ones.

AUTOENCODERS (1980)

Autoencoders are neural networks that are trained to map data from a high-dimensional input space to a lower-dimensional latent space and then back to the input space. Self-supervised learning can be done by training an autoencoder to minimize the reconstruction error.

PRETEXT TASKS (NO SPECIFIC RELEASE YEAR)

In self-supervised learning, models are often trained on pretext tasks, which are tasks created specifically to generate labels for the unlabeled data. These pretext tasks can include predicting missing parts of an image, predicting the relative order of shuffled data, or any other task that enforces the model to learn useful features.

TRANSFER LEARNING (2013-2014)

After training on a self-supervised task, the learned representations can be transferred to downstream tasks with limited labeled data. Fine-tuning the pretrained model on the target task often leads to improved performance.

EVALUATION METRICS (NO SPECIFIC RELEASE YEAR)

Evaluating the quality of learned representations is crucial. Common evaluation metrics include top-1 and top-5 accuracy for image classification tasks or performance on downstream tasks, such as object detection or sentiment analysis.

LARGE-SCALE DATA (2010S)

Self-supervised learning often benefits from training on large-scale datasets. Large datasets help in learning more generalized representations, which can be transferred to various downstream tasks.