Easy Guide: Self-Supervised, Semi-Supervised & Contrastive Learning Explained

Self-supervised learning and semi-supervised learning are two types of learning approaches in machine learning that leverage a combination of labeled and unlabeled data. Here's an overview of each approach along with easy examples to help you understand the differences:

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Self-supervised learning: In self-supervised learning, the model learns by using its own predictions to create labels for the unlabeled data. It doesn't require any external supervision, as the learning task is designed in such a way that the model can generate its own supervision signal from the input data.

Example: Imagine you have a collection of images without any labels. A self-supervised learning task might involve predicting a missing part of the image or reordering shuffled image patches. The model learns by predicting the missing parts or the correct order of the patches using the information present in the rest of the image. The correct answer is already present in the data, so no external supervision is required.

Semi-supervised learning: In semi-supervised learning, the model is trained using a small amount of labeled data and a larger amount of unlabeled data. The idea is to leverage the structure and patterns in the unlabeled data to improve the performance of the model on the labeled data.

Example: Suppose you have a dataset of 1,000 cat and dog images, but only 100 of them have labels (i.e., "cat" or "dog"). In semi-supervised learning, you'd train a model using the 100 labeled images and also make use of the 900 unlabeled images. The model might first be trained on the labeled data and then refined using the unlabeled data, for instance, by using clustering techniques to group similar images together. The model can then predict labels for the unlabeled data and use those predictions to improve its overall performance.

> In summary, self-supervised learning creates its own supervision signal from the input data, while semi-supervised learning uses a combination of labeled and unlabeled data to improve model performance.

On the other hand, Contrastive learning is a specific technique used in self-supervised learning, where the model learns to differentiate between similar and dissimilar data points by comparing their representations in a high-dimensional space.

The main idea behind contrastive learning is to encourage the model to learn useful representations by making the representations of similar data points closer in the high-dimensional space while pushing dissimilar data points further apart. This is achieved by optimizing a contrastive loss function, which measures the difference between the representations.

Example: Imagine you have a dataset of images without any labels. In a contrastive learning task, you might create pairs of images consisting of an "anchor" image and a "positive" or "negative" image. The positive image is a slightly transformed version of the anchor image (e.g., by applying a random crop, rotation, or brightness change), while the negative image is a different image altogether.

The model aims to learn a representation such that the distance between the anchor image and the positive image is minimized, and the distance between the anchor image and the negative image is maximized. By doing this, the model learns to recognize and extract useful features from the images, which can later be used for various downstream tasks, such as classification or object detection.

So, contrastive learning is a specific technique within the broader self-supervised learning framework. It helps the model learn useful representations by comparing and contrasting similar and dissimilar data points.
