**Reading Notes: Ravid Shwartz-Ziv and Yann LeCun (2023), To Compress or Not to Compress - Self-Supervised Learning and Information Theory: A Review. arXiv: 2304.09355**

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**Summary**

In this paper, the authors address the problem of self-supervised learning, done with Deep Neural Networks (DNNs) from an information-theoretic perspective, with a focus on multi-view applications (cases where multiple sources of information are available about one object of interest, e.g. audio and video data of public situations, where the goal is identification of persons). Specifically, the authors have two objectives: Providing an overview and information-theoretic synthesis of existing approaches to self- and semi-supervised learning, and investigation of how recent models optimize information-theoretic terms.

They start by summarizing typical learning tasks in ML:

* Supervised learning: predictor data and corresponding labels are available. The goal is optimal prediction of labels given predictors through a model. The model is trained for optimal predictive skill with the predictor-label data. To ensure good generalization, i.e. out-of-sample performance, split-sampling approaches and/or model size constraints are applied.
* Unsupervised learning: only predictor data are available. Goal is identification of patterns in the data. This can be realized by training a model with the goal to optimally predict the predictor data from themselves through a model. The model then represents the underlying patterns in the data. The model is trained for an optimal tradeoff between quality of reconstruction of the data by the model (should be high), and size of the model (should be small), thus achieving generality and avoiding a trivial solution of simply passing the input to the output.
* semi-supervised learning: special case of supervised learning, where only for a subset of predictor data corresponding labels exist. The goal is optimal prediction of labels given predictors through a model. Label-free predictor data can e.g. be used to provide better estimates of the marginal distribution of predictors, which can be used to guide/improve the supervised learning part.
* self-supervised learning (SSL): special case of supervised learning, where labels can be self-generated from the predictors themselves. These are then used for supervised learning. E.g. to learn natural language processing, single words can be removed from text. The goal is then optimal re-infilling of these words by a model, using the removed words themselves as labels. A precondition for self-supervised learning is that both the predictor and the targets of interest are contained in the available data. There are two main architectures for SSL: First, generative architectures (auto-encoders), where data are transformed to a latent variable and then reconstructed with the joint objective of maximizing reconstruction quality and smallness of the latent space to ensure generality. Second, joint embedding architectures (JEA).

The authors go on by explaining multi-view learning, and representation learning, i.e. the extraction of relevant information from available data and representing it in a compressed manner, thus reducing computational efforts and the Curse of Dimensionality of high-dimensional data sets. A good representation is a minimal sufficient statistic (MSS) of the data. For cases where labels are known for the data, the information bottleneck (IB) method is a guide towards the optimal balance between accurate prediction of the target and size of the representation (the smaller the more efficient and general), and thus serves as a real-world approximation of the MSS principle. However, application of IB becomes difficult or questionable for the frequent case where labels are lacking and have to be guessed.

In the next section , the authors give an overview on how information-theoretic objective functions are used in a broad range of learning scenarios (supervised, unsupervised, self-supervised, single- and multiview). They illustrate this by setting up a common framework for the mentioned scenarios for a multiview setting, and then explaining the various objective functions, and mapping existing objective functions from literature into the framework. They point out that while the IB is a rigorous method for supervised singleview settings, it is not directly applicable to multiview problems. They also show that many autoencoders used in unsupervised learning are special cases of unsupervised IB, but that the objectives in supervised and unsupervised learning are different: While in the former, the latent representation should be a sufficient statistic of the target variable, which usually allows very small representations, for the latter it should be a sufficient statistic of the input (=target), which can lead to representations as large as the data themselves (in the trivial case). Ensuring sufficient compression is the key problem in this setting, and it also applies to self-supervised learning, which is discussed in the next section. One of the first objectives used in this context, the Infomax principle, maximizes information transfer from the input to the latent representation, but does not ensure compression (although it does in practice). To overcome this shortcoming, the multiview IB framework was proposed, which contains the Multiview assumption stating that relevant information is the information shared by all views. This however places a high and often unwarranted constraint, as relevant information could also be contained in information unshared among views. In summary, therefore, the Multiview assumption seems overly restrictive for many purposes, and for particular settings the question which information measure to minimize or maximize remains non-trivial and subject of further research.

The authors then address the practical but important question of how to estimate information measures from deterministic and/or high-dimensional data and limited sample size, and terminate by naming future research directions. These comprise replacing the Multiview assumption, integrating further learning methods, and information measures considering computational constraints, or moving from information measures based on integrated probabilities to the wider, more flexible and non-integrated class of energy measures.

**How this might be useful**

* The authors convincingly show that information-theoretic measures can be used to characterize data and data-relations, and to set up objective functions across the full range of ML-tasks, thus facilitating inter-disciplinary and inter-problem communication and collaboration.
* Beware of the multiview assumption: Often it is overly limiting and contradicts the idea the useful sources of information are as independent from each other as possible.

**Open questions**

* Where in the Earth Sciences do we encounter cases of self-supervised learning? If our goal is integrated earth system modeling in general (i.e. no particular target in mind), can we approach it as a self-supervised learning problem operating on high-dimensional observational data sets, partly relaxing existing causal chains constraints for the learning process? Will this help overcoming the problem of limited observational data and missing target data?
* How can we extend current objective functions in ML, focusing on predictive performance or pattern recognition, towards explicitly incorporating cause-and-effect structures?
* Is there a principal difference between learning about static and dynamical systems (e.g. image classification and radar-image forecasting), or can we use the same set of tools for both?