Towards transferability metrics

explored in the context of image denoising

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1 Context

In this and the latter half of last semester I've been working with Vimal (ai20mtech12001@iith.ac.in) towards trying to formulate an generic transferability metric.

Vimal handles the collaboration front with KLA tencor and we both meet regularly to discuss the next approaches.

This is a summary of our meets directed towards the above to be applied in the context of image denoising.

1.1 Motivation

Transfer learning is an important stream of exploration in the context of machine learning due to the following:

- there is a huge overlap in several tasks that artificial intelligence is directed in solving
- compute (in the context of deep learning specifically) is expensive (effort wise (energy and time))

From the first point, not trying to find a common epistemological core between different tasks is a missed opportunity - the second point further incentivizing this stream of exploration.

1.2 Existing Work and Differences

As of now, transferability metrics have been mostly explored in the context of supervised learning: specializing further into the discrete version (classification).

The task that we intend to devise a metric for in this case is Image denoising. Elaborating, the task model simply takes as input a noisy image and is required to output a cleaned up version of the same. The specific approaches taken to do this were not of relevance to the core objective of my mini-project this past semester, but for completeness we use the Noise2Noise[1] model.

The way one gauges the quality of the task model is via different versions noise-to-signal ratios: one of them being PSNR[2]. Now, consequent to the context presented above, we try to find out the applicability of a denoiser (the task model in our case) trained upon a certain dataset on another dataset (semantically similar but different in terms of the inherent noise in it).

This, therefore, cannot be bucketted under the pre-existing work relevant to supervised transferability metrics.

[1]:`https://arxiv.org/abs/1803.04189`
[2]: `https://en.wikipedia.org/wiki/Peak_signal-to-noise_ratio`

2 Objective

We wish to formulate an efficient transferability metric, preferably a generic one. We start out with image denoising as our prototypical task and soon wish to branch out into the general umbrella of unsupervised learning.

2.1 Parameters to keep in mind

2.1.1 Computation limitations

One of the functions of a good transferability metric is to provide the insight into utility of a particular dataset for another dataset **quickly**.

This means that amount of compute dedicated to gauge the transferability has to be a preferably smaller fraction of what is required to train the model itself for the concerned task.

This further cuts down on the approaches we may pursue.

2.1.2 Interpretability

The transferability metric should be semantically sensible. For instance, in the context of image denoising, the transferability score between two subsets of the same dataset (sampled from the same underlying distribution) should be very close to 1.

Similarly, there should be some sense of order between a set of intentionally hand-crafted domains. Say we have a base domain and create a series a domains by injecting noise of similar nature but with greater intensity.

The transferability metric should then portray a correspondingly decreasing score, between the base domain and the series of domains generated.

2.1.3 Symmetric (Questionable)

The distance from A to B need not be the same as that from B to A. For instance, if A is a subset of B, the model trained on B will perform well on A as well but not the other way around.

2.2 Assumptions

- One potential point of failure here is the assumption that the distance between two domains can be captured by a scalar ranging from zero to one.

- This imposes certain restrictions on the nature of the "transferability" hyperplane and its structure but we have to start somewhere ..

3 Progress

We have only recently started experimenting with a particular approach and this is a summary of the same (presented in a generic manner - only focusing on the relevant details).

Given domains A and B: the objective being to find the usability of the model trained on domain A towards that of denoising domain B

1. we first train a denoiser on domain A.

2. we try modelling the noise nature of A (in a functional manner (black box) and not a parametric way)

3. we then sample some passes of B through the model trained on A

4. we then obtain the contextual noise nature of B
5. finally we try formulating the distance between the noise distributions of the two domains

The final formulation of the score is still under construction. We are yet to obtain any results.