Research Statement

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The notion of a curriculum as it applies to human learning is a familiar one. Most formal instruction employs this to impose structure upon the task of learning, presenting concepts at different times and building upon existing knowledge to teach more complex abstractions. As an example, in the case of adults learning a new language, a human may be presented with the simplest nouns and verbs followed by short phrases before being asked to learn to form complete sentences or tackle other grammatical nuances (Richards, 1984).

The idea of whether such a curriculum learning would be useful to *machine* learners was first formally addressed by Bengio et al. (2009), who defined it as *the task of designing the order of presentation of training samples.* They defined the expected benefits from such a curriculum on machine learning as, (i) improved speed of convergence of the training process and (ii) improved performance and quality of the local minimum obtained post-training. Inspired by humans and the way they learn, most initial research in this field focused on presenting easy examples to the learning machine first and gradually increasing their complexity during training.

My research builds upon this initial work and focuses on the following questions:

Q1. What is an ideal curriculum for training a machine learning model and how does this change based on the properties of the task and the dataset? Can the curriculum itself be learned, instead of relying on hand-designed versions?

Q2. Do we expect human intuition about learning via curricula to translate to machine learning? Specifically, does training of models stand to gain (performance or speed) from knowledge of how humans learn through gradual exposure from easy to more complex examples?

Q3. How does one define the notion of an easy or hard example with respect to the training of machine learning models? Do human-designed heuristics for determining sample *difficulty* work and is it possible to do away with the need for such heuristics?

My past work attempts to seek answers to these questions in the context of Neural Machine Translation (NMT) (Sutskever et al., 2014). Using artificial neural networks, NMT attempts to learn models which can translate sentences (sequences of words) from one language (source) to another (target). NMT is a good test case for curriculum learning, as training is very computationally expensive in large data conditions required to reach good performance. Additionally, training data for large-scale NMT models are typically very heterogeneous (varying in characteristics such as domain, translation quality, and degree of linguistic difficulty), are often derived from noisy web-crawls, and can contain hundreds of millions of sentence pairs, not all of which may be useful or non-redundant. Finally, as with other machine learning applications, some hand-designed curricula have shown significant improvement in translation performance of NMT systems. The most commonly encountered and extreme versions are *data filtering* (e.g., Moore and Lewis (2010)), only exposing the model to a selected portion of the dataset during training, and *fine-tuning* (e.g. Luong and Manning (2015)), training the model to convergence on one subset of the dataset and then further training this (converged) model on another carefully chosen subset.

A brief summary of my previous work in this research area follows. It is worth nothing that while these works use NMT and speech translation (denoising, domain adaptation, low resource multi-task) as application areas, this research applies more generally to most machine learning applications.

Empirical exploration of curriculum learning

Our work in Zhang et al. (2018) examines various hand-designed curricula and their effect on translation performance and training speed of NMT systems. We explore difficulty criteria based on auxiliary NMT model scores as well as linguistic properties and consider a wide range of schedules, based not only on the easy-to-difficult ordering, but also on strategies developed independently from curriculum learning, such as dynamic sampling and boosting . Our experiments on a German-English translation task confirm that curriculum learning can improve convergence speed without loss of translation quality, and show that viewing curriculum learning more flexibly than strictly training on easy samples first has some benefits. We also demonstrate that hand-designed curricula are highly sensitive to hyperparameters, and no single strategy emerges as clearly or uniformly the experiments. Our work in Zhang et al. (2019) extends this approach and shows gains on domain adaptation for NMT.

Reinforcement learning based curriculum learning

Instead of relying on hand-designed curricula, our work in Kumar et al. (2019) focuses on *meta-learning* a curriculum for the task of training an NMT system on extremely noisy French-English and German-English datasets. We attempt to match the performance of a state-of-the-art non-trivial reference curriculum proposed by Wang et al. (2018b), in which training gradually focuses on increasingly cleaner data, as measured by an external scoring function. To effectively search through the large space of possible curricula, we use a reinforcement-learning (RL) approach involving a learned agent whose task is to select data representing a given noise level, at each NMT training step to optimize eventual translation performance. We demonstrate that this approach can learn a curriculum which significantly outperforms a random-curriculum baseline and match the performance of the strongest hand-designed curriculum. Interestingly, it does so using a different strategy from the best hand-designed curriculum. Our work in Kumar et al. (2021b) takes this one step further by training RL agents using evidence gathered from multiple training runs and shows gains on the task of low-resource multilingual NMT.

Learning sample usefulness for curriculum learning

As discussed earlier, determining sample usefulness for training can be a hard task. Kumar et al. (2021a) describes our effort to do away with an explicit notion of usefulness and instead backs off to representing each sample as a set of features that may be correlated to usefulness. Using feedback from the training of multiple NMT systems, we instead *learn* an interpolation of the features which serves as a score to define a fixed filtering-based curriculum. Our experiments, which apply this method to building NMT systems for a noisy Estonian-English dataset, show that it outperforms a strong single-feature filtering-curriculum and hand-designed feature interpolation. Additionally, we show that this method is robust in the presence of the kinds of noise most prevalent in web-crawled datasets.

Curriculum learning has the potential to benefit machine learning training and while our work has looked at some portion of this space, several interesting questions remain. Some are listed here:

- Can curriculum learning benefit all machine learning tasks?
- Can learned curricula for one task be *transferred* to other (possibly low resource) tasks?
- What are the effective ways of obtaining feedback (reward) from and summarizing (for observations) machine learning models for reinforcement learning agents? How do we study and compare these?
- Models trained with curriculum learning can serve as good starting points for fine-tuning (Kumar et al., 2021a). Can we use these curricula generally for pre-training?
- Does this research inform and complement research in automated machine learning (AutoML)?

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