Abstract

Curriculum learning strategies in prior multi-task learning approaches arrange datasets in a difficulty hierarchy either based on human perception or by exhaustively searching the optimal arrangement. However, human perception of difficulty may not always correlate well with machine interpretation leading to poor performance and exhaustive search is computationally expensive. Addressing these concerns, we propose two classes of techniques to arrange training instances into a learning curriculum based on difficulty scores computed via model-based approaches. The two classes i.e Dataset-level and Instance-level differ in the granularity of arrangement. We conduct comprehensive experiments with 12 datasets and show that instance-level and dataset-level techniques lead to an average performance improvement of 4.17% and 3.15% over their respective baseline methods. Furthermore, we find that most of this improvement comes from correctly answering the difficult instances, implying a greater efficacy of our techniques on difficult tasks.

Prior work has shown that presenting training instances ordered by difficulty level benefits not only humans but also machines (Elman, 1993; Xu et al., 2020). Arranging instances in a difficulty hierarchy i.e Curriculum Learning (easy to hard) and Anti-Curriculum Learning (hard to easy) has been studied in MTL setup (McCann et al., 2018; Pentina et al., 2015). These techniques arrange datasets either based on human perception of difficulty or by exhaustively searching the optimal arrangement. However, both these approaches have several limitations. Firstly, human perception of difficulty may not always correlate well with machine interpretation, for instance, a dataset that is easy for humans could be difficult for machines to learn or vice-versa. Secondly, exhaustive search is computationally expensive and becomes intractable as the number and size of datasets increase.

In this work, we propose two classes of techniques that enable models to form their own learning curriculum in a difficulty hierarchy. The two classes i.e Dataset-level and Instance-level differ in the granularity of arrangement. In dataset-level techniques, we arrange datasets based on the average difficulty score of their instances and train the model sequentially such that all the instances of a dataset are learned together. In instance-level techniques, we relax the dataset boundaries and order instances solely based on their difficulty scores. We leverage two model-based approaches to compute the difficulty scores (Section 2).

We experiment with 12 datasets covering various sentence pair tasks and show the efficacy of instance and dataset-level techniques with an average performance gain of 4.17% and 3.15% over their respective baseline methods. Furthermore, we analyze model predictions and find that difficult instances contribute most to this improvement implying greater effectiveness of our techniques on difficult tasks. We note that our techniques are generic and can be employed in any MTL setup.
In summary, our contributions are as follows:

(i) **Incorporating Machine Interpretation of Difficulty in MTL**: We introduce a novel framework for MTL that goes beyond human intuition of sample difficulty and provides model the flexibility to form its own curriculum at two granularities: instance-level and dataset-level.

(ii) **Performance Improvement**: We experiment with 12 varied datasets and show that instance and dataset-level techniques lead to a significant performance improvement of 4.17% and 3.15%.

(iii) **Findings and Benefits for the Community**: We conduct experiments in a limited training data regime and find that the proposed techniques are most effective on difficult instances. This finding makes our techniques more applicable for real-world tasks as they are often more difficult than abstract toy tasks and provide limited training instances. Furthermore, we analyze difficulty scores and find that approximately one-third instances of existing datasets get assigned a very low difficulty score i.e very easy-to-learn instances, hinting at presence of dataset artifacts or inherent easiness of a large portion of the datasets. These findings will help the community in developing high-quality and hard datasets.

## 2 Difficulty Score Computation

In this section, we describe two model-based difficulty computation methods based on recent works.

### 2.1 Cross Review Method

Xu et al. (2020) proposed a method that requires splitting the training dataset \( D \) into \( N \) equal meta-datasets \( \{M_1, \ldots, M_N\} \) and training a separate model on each meta-dataset with identical architecture. Then, each training instance is inferred using the models trained on other meta-datasets and the average prediction confidence is subtracted from 1 to get the difficulty score. Mathematically, score of instance \( i \in M_k \) is calculated as,

\[
s_i = 1 - \frac{\sum_{j \neq k} c_{ji}}{N - 1}
\]

where \( c_{ji} \) is prediction confidence on instance \( i \) given by the model trained on \( M_j \).

### 2.2 Average Confidence Across Epochs

In this method, the difficulty score is computed by simply averaging the prediction confidences across epochs of a single model and subtracting it from 1.

\[
s_i = 1 - \frac{\sum_{j=1}^{E} c_{ji}}{E}
\]

where the model is trained till \( E \) epochs and \( c_{ji} \) is prediction confidence of the correct answer given by the model at \( j^{th} \) checkpoint. This method is based on a recent work (Swayamdipta et al., 2020) that analyses the behavior of model during training i.e “training dynamics”.

### Algorithm 1: General Training Structure

**Input:**

\( D \): the training dataset, 
\{\( S_1, \ldots, S_K \)\}: splits created from \( D \)
\( frac \): fraction of previous split

**Initialization:** Model \( M \)

for \( i \leftarrow 1 \) to \( K \) do

\( train\_data = S_i \)

for \( j \leftarrow 1 \) to \( i - 1 \) do

\( sampled\_S_j = \text{Sampler}(S_j, frac) \)

\( train\_data += sampled\_S_j \)

end

Train \( M \) with \( train\_data \)

end

Train \( M \) with \( D \)

## 3 Proposed Techniques

Addressing the limitations of current approaches highlighted in Section 1, we propose two classes of techniques to arrange training instances that allow models to form the learning curriculum based on their own difficulty interpretation. The technique classes i.e Dataset-Level and Instance-Level leverage difficulty scores computed using methods described in section 2 and follow the general training structure shown in Algorithm 1. The training dataset \( D \) is divided into \( K \) splits \( \{S_1, \ldots, S_K\} \) based on the difficulty score, and model \( M \) is trained sequentially on these ordered splits. Furthermore, while training the model on split \( S_i \), a fraction \( (frac) \) of instances from previous splits \( \{S_j (j < i)\} \) is also included in training to avoid catastrophic forgetting (Carpenter and Grossberg, 1988) i.e forgetting the previous splits while learning a new split. Note that \( D \) is a collection of multiple datasets in the MTL setup. The final step requires training on the entire dataset \( D \) as the evaluation sets often contain instances of all tasks and difficulty levels. Dataset-level and Instance level techniques vary in the way splits \( \{S_1, \ldots, S_K\} \) are created as described below:
we show in Figure 3 that the number of instances
where, $s_i$ (QQP (Iyer et al., 2017), MRPC (Dolan and Brock
difficulty scores. For evaluation
Equate (Ravichander et al., 2019)). For evaluation
varies greatly across difficulty scores.
2019)), and Numerical Reasoning (Stress Test of
et al., 2018)), Dialogue NLI (DNLI (Welleck et al.,
ial NLI (Nie et al., 2020)), Paraphrase Identification
sensitive Reasoning (Winogrande (Sakaguchi et al.,
ating various sentence pair tasks, namely, Natural
Language Inference (SNLI (Bowman et al.,
MultiNLI (Williams et al., 2018), Adversarial
LNI (Nie et al., 2020)), Paraphrase Identification
(QQP (Iyer et al., 2017), MRPC (Dolan and Brockett,
PAWS (Zhang et al., 2019)), Common-
sense Reasoning (Winogrande (Sakaguchi et al.,
Question Answering NLI (QNLI (Wang et al., 2018)), Dialogue NLI (DNLI (Welleck et al.,
) and Numerical Reasoning (Stress Test of
Equate (Ravichander et al., 2019)). For evaluation
on robustness and generalization parameters, we
use HANS (McCoy et al., 2019) and Stress Test
(Naik et al., 2018) datasets.

**Setup:** We experiment in a low-resource regime
limiting the number of training instances of each
dataset to 5000. This enables evaluating our tech-
niques in a fair and comprehensive manner as trans-
former models achieve very high accuracy when
given large datasets. Furthermore, inspired by
decaNLP (McCann et al., 2018), we reformulate all
the tasks in our MTL setup as span identification
Question Answering tasks
tasks. This allows creating a single model to solve the tasks that originally have
different output spaces.

**Implementation Details:** We use three values of
frac: 0, 0.2, and 0.4 (refer Algorithm 1), $N = 5$
in (Cross Review method), and $E = 5$ (Average
Confidence method). For distribution-based split-
ing, we experiment by dividing $D$ into 3 and 5
splits. These hyper-parameters are selected based
on development dataset performance.

**Baseline Methods:** In MTL, heterogeneous
batching where all the datasets are combined and a batch
is randomly sampled has been shown to be much
everse than homogeneous and partitioned
batching strategies (Gottumukkala et al., 2020).
Therefore, we use it as the baseline for instance-
level techniques. For dataset-level techniques, we
generate multiple dataset orders and take the aver-
age performance as the baseline. We average these
baseline scores across 3 different runs.

5 Results:

Table 1 shows the efficacy of our proposed curricu-
um learning techniques.

**Performance Improvement:** Instance and
Dataset-level techniques achieve an average im-
provement of 4.17% and 3.15% over their respec-
tive baseline methods. This improvement in con-
sistent across all the datasets and also outperforms
single-task performance in most cases. Furth-
more, we find that models leveraging Average Con-
idence method (2.2) outperform their counterparts
using the Cross Review method (2.1) rendering
Average Confidence approach as more effective
both in terms of performance and computation as
Cross Review requires training multiple models
(one for each meta-dataset).

**Uniform Vs Distribution based splitting:** In
instance-level experiments, distribution-based split-
ing shows slight improvement over uniform split-
ing. We attribute this to the superior inductive bias

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1 Refer Supplementary for details
resulting from the collation of instances with similar difficulty scores to the same split.

**Effect of adding instances from previous splits:**
For dataset-level techniques, we find that it does not provide any improvement. This is because all the instances of a dataset are grouped in a single split therefore, adding instances from other splits doesn’t contribute much to the inductive bias. Furthermore, in the case of instance-level, it leads to a performance improvement because previous splits contain instances of the same dataset hence, providing the inductive bias.

**Difficulty Scores Analysis:** Figure 3 shows the distribution of training instances of all datasets with difficulty scores computed using Average Confidence (2.2) method. This distribution reveals that instances across datasets and within every dataset vary greatly in difficulty as they are widely spread across the difficulty scores. Comparing the average difficulty score of all datasets (shown in legends of Figure 3) shows that Equate and QNLI are easy-to-learn while PAWS and Winogrande are relatively difficult-to-learn. Furthermore, around 32% of the training instances get assigned a difficulty score of $\leq 0.1$ hinting at either the presence of dataset artifacts or the inherent easiness of these instances. A similar observation is made with Cross Review artifacts or the inherent easiness of a large portion of the existing datasets. We hope that our techniques and findings will foster development of stronger MTL models and high-quality hard datasets.

**Test Set Analysis:** We also compute difficulty scores of test instances and plot the performance improvement achieved by our approach over the baseline method for every difficulty score bucket in Figure 2. We find that our technique is effective especially on instances with high difficulty scores.
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### Table 2: Statistics of our test set.

| Dataset         | Size  | Dataset         | Size  |
|-----------------|-------|-----------------|-------|
| SNLI            | 9824  | MNLI            | 19645 |
| Winogrande      | 1654  | QNLI            | 5650  |
| PAWS qqp        | 671   | PAWS wiki       | 7987  |
| MRPC            | 1630  | ANLI R1         | 1000  |
| ANLI R2         | 1000  | ANLI R3         | 1000  |
| DNLI            | 16408 | HANS            | 30000 |
| Equate          | 696   | QQP             | 40371 |
| Stress Test     | 136464|                 |       |

Table 2 shows the statistics of the test sets used in our experiments.

## B Implementation Details:

We use the huggingface implementation of BERT-Base model, batch size 16, learning rate $5e^{-5}$ for our experiments. We use three values of $\text{frac}$: 0, 0.2, and 0.4 (refer Algorithm 1), $N = 5$ (in Cross Review method), and $E = 5$ (in Average Confidence method). For distribution based splitting, we experiment by dividing $D$ into 3 and 5 splits. The results reported in the paper are for 3 splits. These hyper-parameters are selected based on performance on the dev dataset. We adjust the per gpu training batch size and gradient accumulation accordingly to fit in our 4 Nvidia V100 16GB GPUs. We keep the maximum sequence length of 512 for our experiments to ensure that the model uses the full context.

## C Dataset Examples

Table 3 shows examples of datasets used in this work.

## D Difficulty Scores

Figure 3 shows the distribution of difficulty scores computed using Cross Review and Average Confidence approach.

## E Results

Table 4 shows the results of instance-level and dataset-level techniques.

## F Analysis

Table 5 shows the comparison of comparison of performance across difficulty scores for instance-level approaches.

## G Limitations

Our method involves computing the difficulty scores of training instances which requires additional computation. However, this computation is only required during training and not required during inference. Hence, it does not add any computational overhead when deployed in an application.
C: Kyle doesn’t wear leg warmers to bed, while Logan almost always does. he is more likely to live in a colder climate. **false**, or true ?
Q: Kyle is more likely to live in a colder climate.

C: In order for an elevator to be legal to carry passengers in some jurisdictions it must have a solid inner door. **false**, or true ?
Q: What is another name for a freight elevator? Does the context sentence contain answer to this question ?

C: What makes a great problem solver? false, or **true**?
Q: How can I be a fast problem solver? Are the two sentences semantically equivalent?

C: i sell miscellaneous stuff in local fairs. **contradiction**, or neutral, or entailment ?
Q: i used to work a 9 5 job as a telemarketer . Consistency of the dialogues ?

C: 205 total Tajima’ s are currently owned by the dealership. **contradiction**, or neutral, **entailment** ?
Q: less than 305 total Tajima’ s are currently owned by the dealership.

C: Two collies are barking as they play on the edge of the ocean **contradiction**, or neutral, or **entailment** ?
Q: Two dogs are playing together.

| **Context – Question** | **Datasets** |
|------------------------|--------------|
| C: Kyle doesn’t wear leg warmers to bed, while Logan almost always does. he is more likely to live in a colder climate. **false**, or true ? | Winogrande |
| Q: Kyle is more likely to live in a colder climate. | |
| C: In order for an elevator to be legal to carry passengers in some jurisdictions it must have a solid inner door. **false**, or true ? | QNLI |
| Q: What is another name for a freight elevator? Does the context sentence contain answer to this question ? | |
| C: What makes a great problem solver? false, or **true**? | QQP, MRPC, |
| Q: How can I be a fast problem solver? Are the two sentences semantically equivalent? | PAWS |
| C: i sell miscellaneous stuff in local fairs. **contradiction**, or neutral, or **entailment** ? | DNLI |
| Q: i used to work a 9 5 job as a telemarketer . Consistency of the dialogues ? | |
| C: 205 total Tajima’ s are currently owned by the dealership. **contradiction**, or neutral, **entailment** ? | SNLI, MNLI, |
| Q: less than 305 total Tajima’ s are currently owned by the dealership. | ANLI |
| C: Two collies are barking as they play on the edge of the ocean **contradiction**, or neutral, or **entailment** ? | |
| Q: Two dogs are playing together. | |

Table 3: Examples context-question pairs of various types of training datasets used in our experiments. Answers are highlighted in bold.

| **Datasets** | **Instance-Level** | **Dataset-Level** |
|--------------|--------------------|-------------------|
|              | Uniform Splitting + Prev | Proposed Order with frac=0.4 | AC on Proposed Order |
| **EM** | **F1** | **EM** | **F1** | **EM** | **F1** |
| SNLI | 76.19 | 76.2 | 77.09 | 77.11 | 77 | 77.02 |
| MNLI Mismatched | 64.54 | 64.55 | 65.83 | 65.85 | 65.36 | 65.41 |
| MNLI Matched | 63.63 | 63.64 | 66.06 | 66.08 | 64.72 | 64.77 |
| Winogrande | 50.48 | 50.48 | 50.6 | 50.94 | 48.43 | 49.79 |
| QNLI | 68.16 | 68.17 | 71.24 | 71.25 | 72.23 | 72.26 |
| EQUATE | 99.71 | 99.71 | 99.43 | 99.43 | 99.57 | 99.57 |
| QQP | 77.61 | 77.61 | 79.32 | 79.32 | 79.68 | 79.71 |
| MRPC | 72.15 | 72.15 | 76.07 | 76.07 | 77.55 | 77.55 |
| PAWS Wiki | 52.11 | 52.13 | 69.48 | 69.48 | 52.92 | 52.95 |
| PAWS QQP | 68.7 | 68.7 | 69.75 | 69.75 | 66.62 | 66.69 |
| ANLI R1 | 41.9 | 41.93 | 43.8 | 43.88 | 44.7 | 44.8 |
| ANLI R2 | 37.8 | 37.85 | 36.8 | 36.83 | 37.4 | 37.5 |
| ANLI R3 | 37.58 | 37.62 | 36.5 | 36.53 | 36.83 | 36.83 |
| DNLI | 82.55 | 82.58 | 83.64 | 83.66 | 81.83 | 81.93 |
| HANS | 49.76 | 49.77 | 48.24 | 48.28 | 50.25 | 50.26 |
| Stress Test | 56.07 | 56.09 | 57.55 | 57.57 | 58.79 | 58.87 |
| Average | 62.43 | 62.45 | 64.46 | 64.5 | 63.37 | 63.49 |

Table 4: Results on test sets.
Figure 3: Distribution of instances based on difficulty score.

| Difficulty Score | Instances | Random Order | Proposed Order |
|------------------|-----------|--------------|----------------|
| 0.1              | 63736     | 94.86        | 93.77          |
| 0.2              | 18703     | 87.8         | 85.55          |
| 0.3              | 28035     | 81.85        | 79.85          |
| 0.4              | 17238     | 74.5         | 72.81          |
| 0.5              | 21502     | 65.03        | 65.84          |
| 0.6              | 17338     | 57.69        | 57.94          |
| 0.7              | 21255     | 46.75        | 48.92          |
| 0.8              | 18058     | 38.36        | 44.05          |
| 0.9              | 22327     | 26.8         | 33.07          |
| 1                | 46008     | 9.17         | 14.05          |

Table 5: Performance comparison across difficulty scores for instance level techniques.