Improving Machine Learning Ability with Fine-Tuning

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Abstract
Item Response Theory (IRT) allows for measuring ability of Machine Learning models as compared to a human population. However, it is difficult to create a large dataset to train the ability of deep neural network models (DNNs). We propose fine-tuning as a new training process, where a model pre-trained on a large dataset is fine-tuned with a small supplemental training set. Our results show that fine-tuning can improve the ability of a state-of-the-art DNN model for Recognizing Textual Entailment tasks.

1. Introduction
Machine Learning models require task-specific data from which the models can learn. Traditionally for supervised ML a model is trained on some dataset, where the output of the model is compared to the correct label provided as part of the dataset. Learning involves updating parameters of the model to minimize some loss function. This training process assumes that each gold standard label is correct and additionally, that each item is independently and equally important in the updating of parameters in the model.

Recent studies have shown that ML models can be compared to the intelligence (or ability) of a human population using Item Response Theory (IRT). IRT models characteristics of individual examples (called “items”) such as difficulty and discriminatory ability to estimate ability as a function of correctly answered items. IRT estimated ability relies on which items in a test set are answered correctly, not just how many, and compares NLP models to human ability directly. High performance in terms of traditional evaluation metrics (e.g. recall, precision, accuracy) does not mean that the ML model is of high ability (Lalor et al., 2016), due to characteristics of the test set and parameters of the items that are answered correctly. To achieve a high performance in ability, it is therefore important to train ML models by updating parameters based on ability.

Ideally, a ML model could be trained on such items directly to maximize the performance using the estimated item parameters to improve performance with regards to ability. However, IRT datasets require a large number of human-generated response patterns, and the sets of items to be labeled need to be kept short to avoid drops in annotator performance due to boredom, fatigue, etc. Therefore, the size of the IRT datasets is small, making it impossible to be used to directly train a ML model, especially for a DNN model which requires a large amount of data for training.

In this paper we propose an innovative fine-tuning approach to training that incorporates a specific subsection of data as a supplemental training set for a pre-trained learning model. Our hypothesis is that for a pre-trained model that has already learned a representation of a particular NLP task introducing additional carefully selected supplemental training data can improve performance. In this study, we show that by introducing additional carefully selected supplemental training data we improved the ability of a NLP system as measured by IRT. By fine-tuning with a carefully selected subset of data, we can influence the parameters learned on the original full data set with a small amount of data. Our results show that the fine-tuning process is a simple and effective way to improve model ability without requiring a large amount of additional data for training.

We evaluate our approach on Recognizing Textual Entailment (RTE) with the Stanford Natural Language Inference (SNLI) data set (Bowman et al., 2015). For fine-tuning data we use the IRT evaluation scales for RTE data (Lalor et al., 2016), and data from the Sentences Involving Compositional Knowledge (SICK) data set, another widely used RTE data set (Marelli et al., 2014). By supplementing training with the IRT data, we can improve model performance with regards to a human population, while avoiding overfitting normally associated with updating parameters on a small data set. Evaluation includes overall accuracy on the original SNLI test set as well as using IRT to model ability in terms of a human population.

The supplemental IRT training data has two qualities that make it desirable as training data: (i) the data were identified because of their local independence from each other in the process of fitting an evaluation metric to measure latent...
ability, and (ii) each example in the data has a large number (approx. 1000) of human-annotated responses which can be interpreted as a probability distribution over the potential labels. The supplemental SICK data was generated entirely independently of the source data set and can be considered an alternative to the original training set.

By introducing supplemental data from a separate data set the model is able to update its representations to boost performance in some test scenarios. Interestingly, our results show that by introducing a small set of examples from a separate dataset the model can improve performance in certain situations. In contrast, fine-tuning with a large supplemental training set has a negative effect on performance. When testing on more difficult items, it is not helpful to fine-tune with easier items as identified by IRT. However, introducing examples from a new data set does improve performance. The fine-tuning process therefore requires different data for the particular purpose.

Our contributions are as follows: (i) we show that fine-tuning parameter weights for a memory-augmented neural network (Munkhdalai & Yu, 2017) with a specialized supplemental training set improves model performance for certain tasks when compared with a human population, (ii) this fine-tuning does not overfit on the supplemental data and therefore does not negatively affect generalization in terms of accuracy, and (iii) we motivate the use of supplemental training data as a way to improve performance in terms of ability with regards to a human population.

2. Background

2.1. Item Response Theory

Item Response Theory is a psychometric methodology for scale construction and evaluation (Baker & Kim, 2004). IRT is widely used in educational testing both for designing tests and analyzing human responses (graded as right or wrong) to a set of questions (called “items”).

IRT jointly models an individual’s ability and item characteristics to predict performance. IRT models make the following assumptions: (i) individual performance can be modeled as an unobserved latent trait dimension (called “ability” or “factor”), (ii) the probability of correctly answering an item is a function of the person’s ability, (iii) responses to different items are independent of each other for a given ability level (local independence), and (iv) responses from different individuals are independent of each other (Lalor et al., 2016).

With IRT, one models the ability of a respondent as a function of the characteristics of the individual items in a data set. IRT fits a model of ability according to the response patterns to a set of items provided by a human population. According to the two parameter logistic (2PL) single-factor model, the probability for an individual $j$ with latent ability $\theta_j$ to answer item $i$ correctly can be modeled as:

$$p_{ij}(\theta_j) = \frac{1}{1 + e^{-a_i(\theta_j - b_i)}}$$

(1)

Items can be screened according to a sequential process: local dependence and item fit are tested, and items that either do not fit the model well or have local dependence with other items are removed. This results in a calibrated set of examples that constitute a test set for measuring the specified latent ability factor.

When selecting the items, it is beneficial to consider items that can discriminate according to ability at different levels. For this reason the set of items in the the calibrated IRT set are interesting to consider in the context of machine learning. Each item in the set has a specific difficulty and discriminatory parameter, such that individuals at different ability levels have different probabilities of answering the items correctly. This is in contrast to the large data sets that are usually used for training in ML models. Those training sets, particularly in classification tasks, do not consider different parameters of the items, and treat the examples in aggregate and do not consider the items individually.

It is important to note here that IRT ability is associated with a single dimension related to the items in the specific IRT test set. Items retained for an IRT analysis constitute a set of items that are locally independent in the sense that their interdependence is only due to the common latent ability dimension, and taken as a whole can reliably measure a latent ability trait. For example, the G4-Contradiction IRT group can be considered a test set that measures a human’s (or ML model’s) ability to recognize contradiction when presented with a P-H pair.

Lalor et al. (2016) introduced IRT for the evaluation of NLP models, showing that evaluation performance with respect to a human population provided more information than classification accuracy. For example, a high performing model in terms of accuracy can exhibit ability similar to that of average human performance if the test set is inherently easy. A DNN model that answered 96% of the IRT test items correctly for identifying the entailment label scored in the 44th percentile in terms of ability because the set of items was very easy for the human population. The same model scored in the 96th percentile of ability for a more difficult test set to identify contradiction with only 79% accuracy (Lalor et al., 2016).

Martínez-Plumed et al. (2016) used IRT for ML models’ responses to classification tasks and found that many assumptions that are made in IRT translate well to the analysis of machine learning models.


**Table 1.** Examples of sentence pairs from the IRT data sets, their corresponding label and difficulty as measured by IRT. Refer to §2.1 for how to interpret difficulty values.

| Premise                                                                 | Hypothesis                  | Label       | Difficulty |
|------------------------------------------------------------------------|-----------------------------|-------------|------------|
| People were watching the tournament in the stadium                     | The people are sitting outside on the grass | Contradiction | 0.51       |
| Two girls on a bridge dancing with the city skyline in the background  | The girls are sisters.      | Neutral     | -1.92      |
| A little girl eating a sucker                                           | A child eating candy        | Entailment   | -2.74      |
| A young boy in a sweatshirt is doodling on a piece of paper             | The class pictures are on display | Contradiction | 0.78       |
| A couple plays frisbee in a green field with trees in the background   | A couple fixes dinner in their kitchen | Contradiction | -0.82      |
| A girl in a newspaper hat with a bow is unwrapping an item              | The girl is going to find out what is under the wrapping paper | Entailment | -2.69      |
| A scene of snow and water                                               | A snow and water scene at sunset | Neutral | -1.01      |

### 2.2. Learning Techniques

There have been a number of approaches to organizing training data to improve classification performance and generalization.

Boosting is a learning procedure that attempts to reduce classification error in a training set by iteratively focusing more on misclassified items in a training set (Freund & Schapire, 1997; Schapire & Singer, 1999). More weight is assigned to the incorrectly classified items, such that later classifiers have a higher probability of training on these misclassified examples. Boosting in neural networks has also shown promise (Schwenk & Bengio, 2000).

Our approach differs from boosting in that we do not assume that misclassified items are inherently more difficult for a classifier. We model difficulty explicitly using IRT. Item difficulty parameters are models from a set of human responses, and are interpretable in the sense that they have a direct relation to the ability level of a test-taker.

Bengio et al. (2009) introduced curriculum learning as a training procedure. Training with simple concepts and gradually introducing more complex concepts when training a neural network can improve generalization and speed up convergence. They demonstrate the effectiveness of curriculum learning on several toy tasks and draw a comparison with boosting and active learning as well. Here we have an explicit measure of difficulty in examples as modeled by IRT. Instead of selecting examples in order of difficulty, we use the specialized test sets to refine pre-trained models.

Finally, this work is related to transfer learning and domain adaptation (Caruana, 1995; Bengio et al., 2011; 2012; Yosinski et al., 2014), but with an important distinction. Transfer learning and domain adaptation focus on repurposing representations learned for a source domain to facilitate learning in a target domain. In this paper we want to improve performance in the source domain by fine-tuning with a specialized set of supplemental data. The fine-tuning data is associated with the source domain, and comes from either a specific subset of the domain data set or from another data set associated with the same task.

### 2.3. Modeling Item and User Parameters

Bachrach et al. (2012) presented the DARE model to jointly infer item difficulty and individual ability using a graphical model framework (Koller & Friedman, 2009) in the context of crowdsourcing. The DARE model is able to infer correct answers for unknown labels given the item’s difficulty and the ability estimates for individuals that have provided possible labels. In this work we assume that the gold standard labels provided are correct, and we model ability of test-takers (human or ML model) in order to rank the test-taker with respect to the population.

Bruce & Wiebe (1999) modeled latent traits of data points to identify a correct label. There has also been work in modeling individuals to identify poor annotators Hovy et al. (2013), but neither jointly model the ability of individuals and data points, or apply the resulting metrics to NLP models. Passonneau & Carpenter (2014) model the probability a label is correct along with the probability of an annotator to label an item correctly according to the Dawid & Skene (1979) model, but do not consider difficulty or discriminatory ability of the data points.

### 2.4. Terminology

In keeping with previous work using IRT, we here define common IRT terms as they are applied to RTE.

An _item_ refers to a P-H pair and its correct label (entailment, contradiction, or neutral). A vector of responses to some set of items (each graded as correct or incorrect) is a _response pattern_ for that set of items. An _evaluation scale_ is a specific set of items that has been calibrated by fitting an IRT model to some large set of response patterns. An evaluation scale can be administered as a test set to mea-
sure the latent ability common to the items in the evaluation scale. New respondents (either human or ML model) supplies a response pattern for the evaluation set (e.g., an output of predicted labels for the items), which is then used to estimate an ability score (or theta score) to the respondent. This ability score indicates how far from average performance the respondent is in terms of the original population. For this work we report ability in terms of the percentage of the original population the respondent outperformed.

3. Fine-Tuning with Specialized Data

We would like to understand the effect of a carefully selected set of items on a pre-trained learning model. Can a small set of examples that have been selected for a particular purpose be used to improve overall performance in a model that has already been trained with a large training set? In our experiment we fine-tune a high-performing neural network model with a selection of supplemental data sets in order to identify where and how additional training data can improve performance, both in terms of accuracy and latent ability.

3.1. Data and Model

We conduct our experiment on the Recognizing Textual Entailment (RTE) task (Dagan et al., 2006). In RTE, for a given Premise (P) and Hypothesis (H) sentence pair, a model must classify the relationship between the pair as entailment, contradiction, or neutral.

For this experiment we use a Neural Semantic Encoder (NSE) (Munkhdalai & Yu, 2017), a memory augmented neural network. NSE uses read, compute, and write operations to maintain an external memory during training. The model was selected as it has one of the highest test set accuracies at the time of writing on the SNLI test set.

The model is trained on the Stanford Natural Language Inference (SNLI) data set (Bowman et al., 2015). SNLI is an order of magnitude larger than previously available RTE data sets, and it consists entirely of human-generated P-H pairs. Table 1 presents examples of P-H pairs retained in the IRT test sets, their corresponding labels, and the difficulty value as modeled with IRT. The first pair in Table 1, for example, is of a difficulty that an individual with latent ability of -1.92 would have a 50% chance of correctly labeling the pair as neutral. Most of the items in the IRT test sets have difficulty parameters below 0 (or close to 0), which is appropriate for evaluating ML models (Lalor et al., 2016).

For the IRT data, we use the evaluation sets created by Lalor et al. (2016). They obtained 1000 labels from a set of Amazon Mechanical Turk (AMT) annotators for a random sample of items from SNLI, and used IRT to select items and construct evaluation scales to measure latent ability. Their selected items were in five groups according to the correct label and the number of quality-control annotators who agreed on the label: entailment with 5 of 5 annotator agreement (G5-Entailment), contradiction with 5 of 5 annotator agreement (G5-Contradiction), neutral with 5 of 5 annotator agreement (G5-Neutral), contradiction with 4 of 5 annotator agreement (G4-Contradition), and neutral with 4 of 5 annotator agreement (G4-Neutral). Each test set consists of 20-30 P-H pairs, and each set is an independent scale for evaluating latent ability with regards to the ability to identify the relevant RTE label.

3.2. Experiments

To test our hypothesis we performed the following experiment. We trained the memory augmented neural network (NSE) on a randomly selected subset of the SNLI training set (100, 1k, 2k, 10k, 100k, 200k, and the full 550k training set). These models were then “fine-tuned” with 4 of the 5 IRT test sets. This fine-tuning was done with both one-hot categorical cross entropy and mean squared error as loss functions. The fine-tuned models were tested on the original SNLI test set (10k examples) for accuracy and the held-out IRT test set for latent ability.

Our goal with this experiment is to understand what effect, if any, a specialized training set has on a fully trained model in terms of performance.

To evaluate the hypothesis, we report the mean accuracy averaged across the results for the 5 held out test sets at each training set size. In addition, we report IRT ability percentile scores, which represent the percentage of the human population that the model outperformed with respect to ability for the held out test set.

Evaluation for these experiments was done with cross-validation, where each model was trained with 4 of the 5 IRT test sets, and tested on the 5th.

We compare our results to the pre-trained models with no fine-tuning, and also with fine-tuning using a random selection of data from the SICK training set (Marelli et al., 2014). This way we can compare performance between the specialized tuning set and a random tuning set. When using SICK as the fine-tuning set, training was done with categorical cross-entropy as the loss function, as there is not a large set of human annotations for this data.

We now explicitly define the training procedure. Let $X_{\text{train}}^N$ be a random selection of $N$ examples from the SNLI training set, and let $X_{\text{test}}$ be the 10k example SNLI test set. Let $IRT = \{4N, 4C, 5N, 5C, 5E\}$ be the 5 IRT evaluation sets. $IRT_{\text{test}}$ is the held-out IRT set used.

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1We followed the original NSE training parameters and hyper-parameters (Munkhdalai & Yu, 2017)
for testing. $FT_{train}$ is the fine-tuning training set, consisting of either 4 of the 5 subsets in IRT, $FT_{train} = IRT \setminus IRT_{train}$, or a random selection of $N$ examples from the SICK training set, $SICK_{train}$

The fine-tuning procedure is defined in Algorithm 1.

**Algorithm 1 Fine-Tuning Procedure**

Input: NumEpochs $e$, $X^N_{train}$, $X_{test}$, $FT_{train}$, $IRT_{test}$, Loss Function $l$
for $i = 1$ to $e$
do
Train NSE with $X^N_{train}$ with loss function CCE
end for
for $i = 1$ to $e$
do
Train NSE with $FT_{train}$ with loss function $l$
end for
calculate accuracy for $X_{test}$
calculate ability for $IRT_{test}$

We now elaborate on the motivation for the choices of loss functions in our experiments.

### 3.3. Overfitting on a Selection of Items

The IRT test sets consist of a selection of items that were identified as being a good set of items for evaluating the latent ability trait associated with Recognizing Entailment. Our hypothesis here can then be thought of as “studying just for the test,” where the pre-trained model (which already has some representation of entailment) is fine tuned according to this specific subset of items. By overfitting on this subset after the model has already been trained, we would like to see improved performance as the model learns specific information about these items.

Our loss function in this case is Categorical Cross-Entropy (CCE). If a model outputs a length $N$ vector of probabilities $\hat{y}$ for a particular training example where the correct output vector is $y$, CCE is calculated as:

$$L_i = -\sum_{j \in N} y_{ij} \log(\hat{y}_{ij})$$

(2)

In the case where a single element in the output vector $y_i$ has probability 1, CCE loss is simply

$$L_i = -\log(\hat{y}_i)$$

(3)

Loss is averaged over all of the training examples.

By fine-tuning on the IRT sets using categorical cross-entropy as the loss function, we are effectively asking the network to memorize this small subset of items.

Pushing the probability of the correct label towards 1 is a rough proxy of training to increase ability score for those answers. Number correct is positively correlated with ability score, but it is not an exact approximation, as different response patterns with the same number of correct answers can result in different estimates of ability. If the pre-trained network learns the supplemental training data such that it is able to classify most (or all) of the examples correctly, this implies a high ability score for those factors. The held out test set does not necessarily align with the supplemental training set in terms of the latent factor that is being evaluated, but because all of the examples deal with recognizing entailment in some fashion, one would expect that the supplemental training set has some positive effect on performance.

One distinction to be made with regards to the IRT sets is the difficulty of items in each set. Lalor et al. (2016) showed that the G4 groups are more difficult on average than the G5 groups. This is true with regards to the difficulty parameters as modeled by IRT, but it also follows when you consider what G4 and G5 represent. If 5 out of 5 annotators agree on a gold standard label, there is little to no disagreement about which label is correct. However, if only 4 of 5 annotators agreed, then there was some additional discrepancy which led to one of the annotators choosing a different label. In this sense, the G4 items are more difficult than the G5 items.

With this in mind, we can think about the fine-tuning process in the context of the held-out IRT test set. If a G4 set is held out for testing, we know that these items are more difficult than the items in the G5 sets, which are being used for training (along with one other G4 set). Therefore one hypothesis is that performance in terms of ability with regards to the held out set would not improve, given that learning easier items does not necessarily help when tested on harder items.

The opposite hypothesis is relevant when we hold out one of the G5 groups for testing. If we train with the more difficult examples (in this case the G4 items), then we would expect that the fine-tuned models will perform better in terms of ability on the held out set, as learning the more difficult items would be beneficial when tested on an easier test set.

### 3.4. Learning from the Crowd

This hypothesis is similar to the previous one, but in this case we do not want to completely overfit on the IRT items. Instead, we treat the human responses obtained from Amazon Mechanical Turk (AMT) as an estimate of the probability distribution over labels for the items:

$$p(X = x) = \frac{N_x}{N}$$

(4)

Where $N_x$ is the count of occurrences where $X$ is labeled
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Figure 1. Theta percentile scores for each IRT test set. For all but G4-Neutral, fine-tuning results in improved performance.

$x$ and $N$ is the total number of labels.

We now use Mean Squared Error (MSE) instead of cross-entropy as our loss function, where we minimize the difference between the estimated probabilities learned by the model and the empirical distributions obtained from AMT.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)$$

In this case, we are attempting to move the NSE model predictions closer to the AMT distribution of responses. We are not necessarily trying to push predicted probability values to 1, which is a departure from the standard understanding of single-label classification. In our case, we hypothesize that by updating weights according to differences in the observed probability distributions can improve the model by preventing it from updating too much for more difficult items (that is, examples where the empirical distribution is spread across the three labels).

Training with MSE in this scenario assumes that the crowdsourced distribution of responses is a better measure of correctness than a single gold-standard label for the set of items (§3.3). The crowd distribution over labels gives a fuller understanding of the items being used for training. The model being fine-tuned can update parameters to move closer to this distribution without making large parameter updates under the assumption that a single correct label should have probability 1.

If we assume that ML performance is not at the level of an average human (which is reasonable in many cases), then fine-tuning with MSE as a loss function can help pull models towards average human behavior in the sense that if the model updates parameters to minimize the difference between its predictions and the distribution of responses provided by AMT workers, then the model predictions should look like that of the average AMT user. Therefore the resulting response patterns should score close to 50% in terms of IRT percentile.

When ML model performance is better than the average AMT user, there is a risk that performance in terms of IRT percentile may suffer. The model may have learned a set of parameters that better models the data than the human population, and updating parameters to reflect the human distribution could lead to a drop in performance.
4. Results

4.1. IRT Ability

We first report theta scores for the different fine-tuning data sets. Figure 1 plots theta percentile scores for each IRT test set as a function of training size (log scale). Theta scores are similar (or worse) for very small training set sizes, however at the large training set sizes (200K and 500K), there is more separation between the theta scores between the fine-tuning approaches.

For the G4 test sets (Contradiction and Neutral), fine-tuning with the rest of the IRT data does not improve performance. This is expected, as the G4 groups are more difficult than the G5 groups. By training on additional easy items, the model is not able to improve performance over the baseline model. However, fine-tuning with a sample of examples from the SICK data set does lead to a higher theta percentile score for the G4 contradiction set. Fine-tuning with easier data does not improve ability, but the introduction of data from an unseen dataset has a positive affect on ability.

For the easier test sets (G5), fine-tuning does improve ability performance. Both IRT and SICK fine-tuning lead to improvements. For IRT, one would expect that fine-tuning with examples that are of a comparable difficulty (the other G5 groups) and items that are more difficult (the G4 items) would lead to improved performance, which is what we see. For G5-Contradiction and G5-Neutral, fine-tuning using CCE or MSE with the IRT data leads to similar performance.

For G5-Entailment, training with MSE as the loss function substantially improves performance. The G5-Entailment group is very “easy” in the sense that most of the examples’ difficulty parameters are very low. High performance on this subset of data in terms of accuracy does not imply a high theta score, as most of the AMT population labeled most of these items correctly (Lalor et al., 2016). Because initial performance was so low to start, training with MSE as the loss function means that the model can significantly improve performance by moving closer to the empirical distribution as estimated by the AMT population.

Note the improvement for the G5-Contradiction group when fine-tuning on MSE. Our original hypothesis was that using MSE as a loss function would pull the model performance towards the average human performance. However, performance in terms of theta was originally above the average human (about 60%), and after fine-tuning performance jumped to 70%. This result is unexpected given what the loss function states, so we must think about why this is the case. One explanation could be that the original learned parameters are situated such that in order to move closer to the crowd distribution the model can only get to a point that is actually better than the crowd before settling to a new local minimum. In this case the fact that performance in terms of theta improved is a surprising result.

Fine-tuning with the full SICK training set negatively impacts performance in all cases, while fine-tuning with a random sample from SICK improves performance over the original model in all cases except G4-Neutral, where the original model performed best. By introducing only a subset of new data to the model in the fine-tuning phase, the model is able to update its parameters without completely re-learning based on the new data. It is able to pick up patterns in the new data that it can apply to its existing representations instead of replacing them, as seems to be the case when fine-tuned with the entire SICK data set.

Table 2 shows the accuracy scores for the fine-tuning procedures on the NSE model pre-trained with the full SNLI training set. Each IRT test set is short (between 20-30 items), so accuracies are sensitive to the response patterns. However we can see that in several cases, multiple fine-tuning procedures result in the same accuracy, but Figure 1 shows that the models have different ability scores. Even though the number of correct answers were the same, the specific response patterns result in different estimates of ability.

4.2. Generalization with Fine-Tuning

![Figure 2. Accuracy scores for the SNLI test set (10k examples)](image)

We next plot accuracy results for the baseline models and both fine-tuned models at each training set size. We report mean accuracy results for each fine-tuning loss function used (MSE and CCE). Figure 2 plots accuracy as a function of training size (log scale). As Figure 2 shows,
accuracy generally does not improve after fine-tuning the models. However, performance does not drop significantly as a result of fine-tuning. One explanation is that the models have already reached a strong point in terms of local minimum, so there is only so much damage the additional overfitting could do in terms of reducing accuracy. Indeed, most results were obtained very early in the training process (around epoch 4 or so), which indicates that there was not too much overfitting.

One exception is when the full SICK training set is used for fine-tuning. In this case test accuracy is significantly lower than the other fine-tuned models. The introduction of a new, large set of data may have led to the NSE model learning patterns in the SICK data that do not translate well to the SNLI test set. The other fine-tuning sets are small enough that they do not substantially alter the initial learned representations.

5. Discussion

By using fine-tuning on a high-performing model, we can improve performance in terms of latent ability without decreasing accuracy due to overfitting. In different subsets of test data, different fine-tuning methods lead to better performance. In this scenario there is no clear preferred training set with regards to selecting the best data set for fine-tuning a fully trained model. However, fine-tuning does improve performance in most cases, especially when initial performance is much lower than the average human ability.

Our results show performance improvements with respect to ability as estimated using IRT. IRT ability is a measure of how well an individual (or in our case, an ML model) performs with respect to some human population. While IRT performance is positively correlated with accuracy, it is not always true that higher accuracy implies a higher theta score. Items in an IRT test set have varying difficulty and discriminatory parameters which affect an ability estimate. Which items are answered correctly is more important than how many.

Training a model to directly maximize ability is a difficult proposition due to the small size of IRT data. However, we have shown that by using IRT data to fine-tune a pre-trained DNN model, performance in terms of ability can be significantly improved. At the same time, using this fine-tuning approach does not have a significant negative effect on generalization, and only very small decreases in test set accuracy.

Most surprising is the fact that fine-tuning using MSE can show significant IRT performance improvement for a model that was already above the average human performance. Our original assumption was that there was a risk that using MSE might pull the model’s performance towards the average human, meaning theta score would decrease. However we found that theta percentile actually improved in the G5-Contradiction case. It could be the case that the local minimum that the NSE model settled on in the original training was such that pulling towards the average when fine-tuning with MSE actually lead to a better position in terms of model weights.

Using IRT as an evaluation metric allows us to directly compare ML performance to a human population. This is an important prerequisite to being able to compare human and machine performance directly and build machines that learn in a similar fashion to human learning (Lake et al., 2016). There have been ML systems that have surpassed human performance (Campbell et al., 2002; Ferrucci et al., 2010; Stadie et al., 2015; Silver et al., 2016), but for most tasks and with regards to general intelligence ML systems are still not performing as well as humans.

6. Conclusion and Future Work

In this paper we have introduced a novel fine-tuning approach to training that can improve performance for a state of the art DNN. Fine-tuning leads to improved performance in terms of IRT ability scores, without negatively impacting generalization due to overfitting.

There are limitations to this work. IRT test sets are small because a large number of human annotators are necessary to sufficiently model the item and ability parameters. Crowdsourcing platforms make recruiting annotators relatively inexpensive compared to expert annotators, but asking crowd workers to label a large set of examples can lead to deteriorating performance as the time required increases. In addition, our fine-tuning performance relies on the initial pre-trained model, and therefore performance improvements are tied to the representations learned by the original model.

Areas for future work may include investigating why certain fine-tuning sets lead to better performance in certain scenarios. Further experiments with different loss functions and different fine-tuning sets can help to understand how fine-tuning affects the representations learned by a model. With regards to the IRT items themselves, if a larger set of IRT items was fit to model ability, these items could incorporate a wider variety that could further improve performance as a fine-tuning set. The improvements using MSE suggest that future work training DNNs to learn a distribution over labels can lead to further performance improvements.
Martínez-Plumed, Fernando, Prudíncio, Ricardo B. C., Us, Adolfo Martínez, and Hernández-Orallo, Jos. Making sense of item response theory in machine learning. In ECAL, volume 285 of Frontiers in Artificial Intelligence and Applications, pp. 1140–1148. IOS Press, 2016. doi: 10.3233/978-1-61499-672-9-1140. URL http://dblp.uni-trier.de/db/conf/ecai/ecai2016.html#Martinez-Plumed16.

Munkhdalai, Tsendsuren and Yu, Hong. Neural semantic encoders. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2017.

Passonneau, Rebecca J. and Carpenter, Bob. The benefits of a model of annotation. Transactions of the Association of Computational Linguistics, 2:311–326, 2014. URL http://aclweb.org/anthology/Q14-1025.

Schapire, Robert E. and Singer, Yoram. Improved Boosting Algorithms Using Confidence-rated Predictions. Machine Learning, 37(3):297–336. December 1999. ISSN 0885-6125, 1573-0565. doi: 10.1023/A:1007614523901. URL https://link.springer.com/article/10.1023/A:1007614523901.

Schwenk, Holger and Bengio, Yoshua. Boosting neural networks. Neural Computation, 12(8):1869–1887, 2000. URL http://www.mitpressjournals.org/doi/abs/10.1162/089976600300015178.

Silver, David, Huang, Aja, Maddison, Christopher J., Guez, Arthur, Sifre, Laurent, van den Driessche, George, Schrittwieser, Julian, Antonoglou, Ioannis, Panneershelvam, Veda, Lanctot, Marc, Dieleman, Sander, Grewe, Dominik, Nham, John, Kalchbrenner, Nal, Sutskever, Ilya, Lillicrap, Timothy, Leach, Madeleine, Kavukcuoglu, Koray, Graepel, Thore, and Hassabis, Demis. Mastering the game of go with deep neural networks and tree search. Nature, 529:484–503, 2016. doi: 10.1038/nature16961.

Stadie, Bradley C., Levine, Sergey, and Abbeel, Pieter. Incentivizing exploration in reinforcement learning with deep predictive models. CoRR, abs/1507.00814, 2015. URL http://arxiv.org/abs/1507.00814.

Yosinski, Jason, Clune, Jeff, Bengio, Yoshua, and Lipson, Hod. How transferable are features in deep neural networks? In Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N. D., and Weinberger, K. Q. (eds.), Advances in Neural Information Processing Systems 27, pp. 3320–3328. Curran Associates, Inc., 2014.