QuExEnt: Improved Zero-Shot Classification from Explanations Through Quantifier Modeling and Curriculum Learning

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Abstract

A hallmark of human intelligence is the ability to learn new concepts purely from language. While recent advances in training machine learning models via natural language explanations show promise, these approaches still fall short on modeling the the intricacies of natural language (such as quantifiers) or in mimicking human behavior in learning a suite a tasks with varying difficulty. In this work, we aim to improve the paradigm of learning from explanations by using two strategies - (1) model the semantics of quantifiers present in explanations, potentially leveraging ordinal relationships between quantifiers and (2) curriculum learning from tasks with simple explanations to tasks with complex explanations. Our model, QuExEnt, trained through this improved training setup outperforms prior work on the recently proposed CLUES benchmark in generalizing better to novel classification tasks.

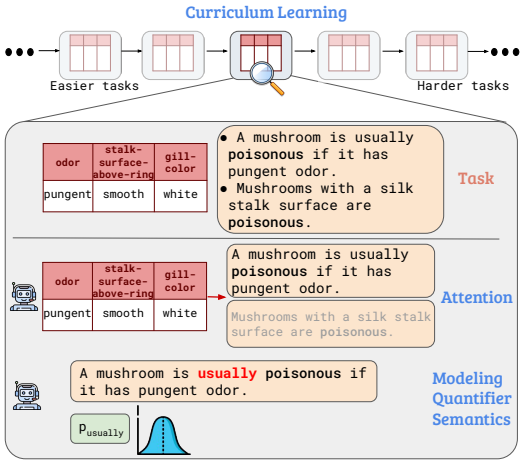

Figure 1: We present improved techniques to learn classifiers from natural language explanations. Our proposed techniques makes use of Curriculum Learning to progressively learn easy to hard tasks, Attention to identify the most salient explanations for classifying an example, and Modeling Quantifier Semantics to account for explanation confidences.

1 Introduction

Learning from language is a new paradigm of machine learning whereby machines are taught to perform tasks through language instructions/explanations (Arabshahi et al., 2020). Remarkably, this form of language supervision to train classification models has been shown to be effective in few-shot (Srivastava et al., 2017; Hancock et al., 2018), and zero-shot settings (Srivastava et al., 2018). More recently, Menon et al. (2022) introduce a benchmark, CLUES and a model, ExEnt to learn generalizable classifiers guided by explanations.

While recent approaches like ExEnt show promise in learning from explanations, they still fall short on modeling the intricacies of natural language or in mimicking human behaviour in learning a suite a tasks with varying difficulty. First, ExEnt fails to capture semantics of quantifiers present in the explanations. Quantifiers are an ubiquitous part of natural language and can dictate the vagueness and perceived confidence of relations expressed in a statement (Solt, 2009; Moxey and Sanford, 1986). Second, prior work does not completely mimic human learning, where humans learn 'simpler' concepts first and then gradually build towards 'harder' concepts (Newport, 1990). While curriculum learning (Bengio et al., 2009) has been shown to be a fruitful in numerous machine learning tasks (Platanios et al., 2019; Tay et al., 2019; Narvekar et al., 2017), it is yet to be explored in the context of learning from explanations. The deteriorating generalization performance of classifiers with increasing complexity of explanations in prior work (Menon et al., 2022) further motivates the need of curriculum learning in the context of training classifiers from explanations.

We address the above shortcomings by formalizing two strategies to improve the paradigm of learning classifiers from language. To address the first shortcoming, we present QuExEnt that extends ExEnt by modeling quantifier semantics explicitly.

We explore learning quantifier semantics directly from labeled classification data and use weak supervision in the form of ordinal relations describing the relative strengths of quantifiers (e.g. 'always' > 'often'). Additionally `QuExEnt` also uses an attention mechanism for aggregating the effect of different explanations corresponding to a task. Second, we consider different axes of explanation complexities and empirically evaluate the utility of curriculum learning on three different curricula. Through experiments on the `CLUES` benchmark we demonstrate the effectiveness of our introduced strategies. Our model, `QuExEnt` outperforms prior work on generalising better to novel classification tasks.

2 Background

2.1 Setup

We employ a cross-task generalization setup (Mishra et al., 2021; Sanh et al., 2022, *inter alia*), and train models using multi-task training over a set of tasks $\mathcal{T}_{seen}$ and evaluate for zero-shot generalization on a new task, $t \in \mathcal{T}_{novel}$ ($\mathcal{T}_{novel} \cap \mathcal{T}_{seen} = \phi$). For experiments, we utilize the recently proposed `CLUES` benchmark (Menon et al., 2022) . In `CLUES`, the inputs are structured in nature, i.e., they are collection of attribute name-attribute value pairs. We encode each structured data example, x, as a text sequence of attribute-name and attribute-value pairs separated by [SEP] tokens (referred to as 'Features-as-Text' or 'FaT' in Menon et al. (2022)). Additional details on `CLUES` can be found in App. A.

2.2 Dataset

We use the synthetic and real-world classification datasets from `CLUES` Benchmark (Menon et al., 2022). On analysis, we observed that preconditions of the explanations were satisfied for only 30% of the samples on average in `CLUES-Synthetic`. In other words, using explanations we can only classify 30% of the samples and thus only this fraction of samples would be effective for learning quantifier semantics. Our initial experiments revealed a need for more samples where explanations would be applicable. Thus, we re-created the synthetic tasks, now with around 50-60% of the samples where explanations are applicable.

2.3 `ExEnt`

In the cross-task generalization setting, Menon et al. (2022) identified that a simple concatenation of explanations with the input was insufficient to endow pre-trained language models with the ability to generalize to novel tasks. Hence, they introduce `ExEnt`, a model which uses NLI[1] as an intermediate step. The operations in `ExEnt` can be broadly grouped into three steps: **(a) NLI step**: obtain scores from an entailment prediction model (RoBERTa+MNLI-finetuned) for the alignment between the input and each explanation available for a task; **(b) Entailment → Classification scores conversion**: convert the entailment scores for each input-explanation pair into classification scores based on the nature of the explanation; and **(c) Aggregation**: aggregate classification scores from each input-explanation pair using mean to obtain an overall score for classification. The aggregated scores are then converted to probabilities using softmax, and we train the model using cross-entropy loss. For further details, we refer the reader to Menon et al. (2022).

3 Improved strategies

3.1 `QuExEnt`

Quantifiers are an ubiquitous part of natural language that help in expressing varying strength of relations in a statement. Prior work has either not modeled quantifiers or modeled their semantics only for a limited number of domains. In this work we build over `ExEnt` by adding a domain-agnostic module to model quantifier semantics.

3.1.1 Adding quantifier semantics to `ExEnt`

`QuExEnt` builds over `ExEnt` by explicitly modeling quantifier semantics. The inputs to the NLI step in `QuExEnt` are same as `ExEnt`. Differing from `ExEnt`, we additionally learn a probability value, p_{quant}, corresponding to each quantifier that denotes the confidence on the predictions from the NLI step. For an explanation, e_j, let us assume the output of the NLI model (that takes as input $[\text{FaT}(x); e_j]$) are the entailment, neutral, and contradiction scores (p_e^j, p_n^j, and p_c^j respectively). In `QuExEnt`, quantifier semantics play a role in the assignment of scores from the NLI model to the set of class labels (say, L for a task) as follows, if:

- **Explanation e_j mentions to assign a label 'l'**:
  Logit assigned to l : $p_{quant} \times p_e^j + (1 - p_{quant}) \times p_c^j$
  Logit assigned to $L \setminus \{l\}$: $p_{quant} \times p_c^j + (1 - p_{quant}) \times p_e^j$
  Divide p_n^j equally among all labels in L.
  Note: If quantifiers are absent, p_{quant} is 1.

[1] Natural Language Inference

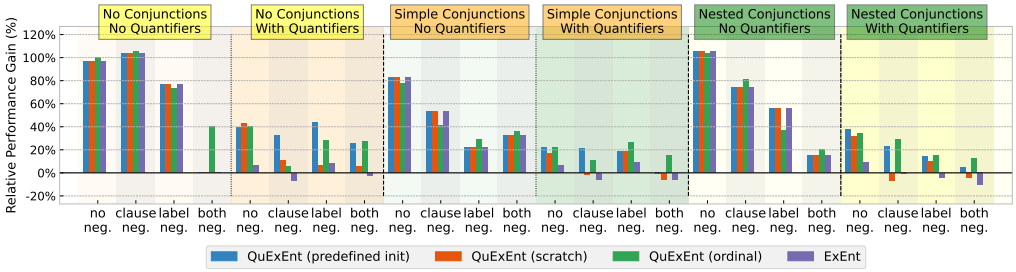

Figure 2: Performance of QuExEnt as compared to the baseline models. We see that QuExEnt outperforms ExEnt (Menon et al., 2022) on the synthetic datasets that contain explanations with quantifiers.

- **Explanation e_j mentions to NOT assign a label 'l'**: The roles of p_c^j and p_e^j as described in the aforementioned operations are reversed.

We refer to the logit assigned to a label l corresponding to an explanation e_j as z_j henceforth.

3.1.2 Approaches to learn quantifier semantics

We model semantics of a quantifier using a probability values that denotes the strength of the quantifier towards the relations expressed in the explanation. We experiment with the following approaches to learn these probabilities:

- **Finetuning pre-defined probability values**: We initialize the quantifier probability values (p_{quant}) then fine-tuning them while training QuExEnt. These initial probabilities can be specified from domain knowledge or by an expert. In this work, we adopt the pre-defined quantifier values from LNQ (Srivastava et al., 2018).
- **Learning probability values for the quantifiers from scratch**: We start from random initialization and then learn the probability values of each quantifier while training the classifier. Technically, we learn a real-valued number corresponding to each quantifier and then map it to range [0,1] to model probability associated with the corresponding quantifier.
- **Weak supervision in form of ordinal ranking**: We explore a weaker form of supervision by specifying ordinal ranks between quantifiers based on their relative strengths ('always' > 'likely'). We start from random initialization of the probability values and leverage ordinal relations in the form of a ranking loss. Following Pavlakos et al. (2018) we define our ranking loss for a pair of quantifiers q_i and q_j as :
  - If strength of q_i is greater than strength of q_j: $\log(1 + \exp(p_{q_i} - p_{q_j}))$
  - If strength of q_i is equal to strength of q_j: $(p_{q_i} - p_{q_j})^2$

  The total ranking loss is sum of ranking loss for all distinct pairs. The final loss is a weighted sum of classification and ranking losses.

3.1.3 Performance of QuExEnt on synthetic tasks

We experiment on the expanded set of synthetic tasks in CLUES-Synthetic (i.e., 80 train and 20 test datasets per synthetic complexity) to judge the effectiveness of modeling quantifier semantics explicitly. Figure 2 shows the results of different variants of QuExEnt and baselines across the different synthetic task types. We find that explicit modeling of quantifier semantics is generally helpful and outperforms prior work in most of the task types containing quantifiers. Note that QuExEnt and ExEnt perform same on task types not containing quantifiers as p_{quant} is 1 in such cases making QuExEnt functionally same as ExEnt. The generalization ability of the models decrease with the increasing complexity of explanations due to changes in structure of explanations or presence of negations.We leave modeling of negations to future work.

3.2 Improving aggregation across explanations using attention

By design, using mean to aggregate class logits resulting from different explanations corresponding to an input considers all explanations to be equally important for classifying the input. In order to model the varying importance of each explanation towards deciding the class label, we use an attention mechanism for the aggregation step (see §2.3). We obtain the attention weights by using a feed-forward network over the [CLS] representations obtained from the intermediate NLI model. The attention weights are then normalized using softmax. The final aggregated class logits for the label l is $\sum_{j=1}^{m} a_j z_j$, where a_j is the attention weight for each explanation e_j, and z_j denotes the classification logits resulting from e_j (see §3.1.1).

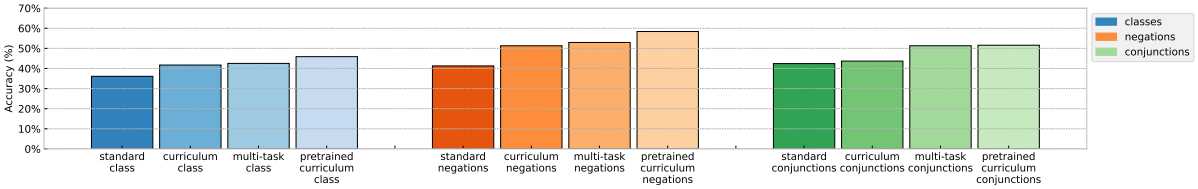

Figure 3: Averaged generalization accuracy on novel synthetic classification tasks of the 'most difficult' task types across three curricula. For pre-trained curricula results, quantifier semantics are pre-trained on the simplest synthetic binary tasks (no negations/conjunctions/disjunctions). Curriculum learning while effective in all the three curricula, shows maximum gains when handling negations. Here, 'standard' corresponds to the scenario where we train solely on datasets of the hardest synthetic task type in a particular curricula and 'multi-task' refers to training on the entire set of easy and hard tasks in a multi-task setting.

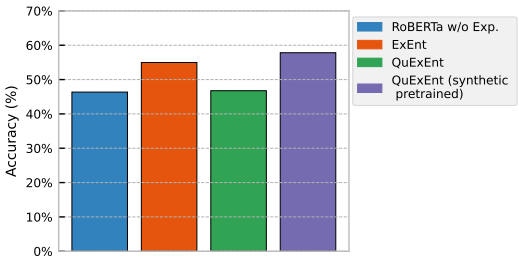

Figure 4: Classification accuracy on novel real-world classification tasks in `CLUES-Real`.

We train two variants of `QuExEnt` (scratch), one using mean and the other using attention to aggregate over explanations. We find that `QuExEnt` with attention has better generalization (relative improvement of 10%) than `QuExEnt` using mean for aggregation over explanations.

4 Curriculum learning

We define 'complexity' of an explanation under three axes - (1) type of classification task (binary vs multiclass), (2) presence of negations, and (3) structure of the explanation (presence of conjunction/disjunctions or nested clauses). Drawing motivation from success of curriculum learning (Bengio et al., 2009) in training on an array of increasingly complex tasks, we explore its utility when learning a classifier from explanations. We empirically evaluate if pre-training on a classification task with 'easier' explanations gives any advantage when learning a task with 'hard' explanations on the following curriculums:

- Binary to multiclass : We first train classifiers on binary classification tasks and then finetune them on multiclass classification tasks.
- No-negations to negations : We begin with tasks that have no negations in their explanations. Gradually, we add tasks with explanations containing negations.
- Simple explanations to explanations containing conjunctions/disjunctions or nested clauses: We train first on tasks without any conjunctions/disjunctions in their explanations. Following this, we train on tasks having explanations that contain one conjunction/disjunction and then on tasks with explanations that contain nested clauses.

Figure 3 shows the results of curriculum learning on the synthetic tasks of `CLUES`. We find that curriculum learning is effective in all the three curricula when we pre-train the quantifier semantics on the simplest binary task with quantifiers and keep the semantics fixed for the remaining curriculum. Notably, we find curriculum learning to be most effective in handling negations.

5 Performance on real-world tasks

Figure 4 shows the performance of `QuExEnt` and the baselines on the tasks of `CLUES-Real`. We find that `QuExEnt` fails to surpass the baselines. The comparatively low number of explanations in `CLUES-Real` hinders the model to jointly learn quantifier semantics and classification from explanations. To alleviate this issue, we pre-train on the synthetic tasks and map the new quantifiers in real-world to the already learned quantifiers from synthetic data. Following this, we fine-tune just the classifier on the `CLUES-Real`. We find this variant to perform best on tasks in `CLUES-Real`.

6 Conclusion

We present two strategies to improve the training paradigm of learning classifiers from natural language explanations. Our strategies focus on modeling quantifier semantics and mimicking human behaviour through curriculum learning setting. Our model, `QuExEnt` trained under this improved setup outperforms prior work showing better generalizing on tasks of the `CLUES` benchmark. Future work can explore other open challenges such as better handling of negations, conjunctions and disjunctions for learing from explanations.

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A Details on CLUES

CLUES (Menon et al., 2022) is a recently proposed benchmark of classification tasks paired with natural language explanations. The benchmark consists of 36 real-world classification tasks (CLUES-Real) as well 144 synthetic classification tasks (CLUES-Synthetic). The explanations for the real-world tasks are obtained through crowdsourcing while they are programmatically generated for CLUES-Synthetic. In this work, we follow the train and test splits for CLUES-Real from Menon et al. (2022). Additionally, we train on 70% of the labeled examples of the seen tasks and perform zero-shot generalization test over the 20% examples of each task in CLUES-Real. For the extremely small Wikipedia tasks, similar to (Menon et al., 2022), we use the entire set of examples for zero-shot testing.

B Training details

In this section we proved details about implementation such as hyperparameter details, and details about hardware and software used along with an estimate of time taken to train the models.

B.1 Hyper-parameter settings

For all the transformer based models we use the implementation of HuggingFace library (Wolf et al., 2020). All the model based hyper-parameters are thus kept default to the settings in the HuggingFace library. We use the publicly available checkpoints to initialise the pre-trained models. For RoBERTa based baselines we use 'roberta-base' checkpoint available on HuggingFace. For our intermediate entailment model in ExEnt, we finetune a pretrained checkpoint of RoBERTa trained on MNLI corpus ('textattack/roberta-base-MNLI')

When training on CLUES-Synthetic, we use a maximum of 64 tokens for our baseline RoBERTa w/o Exp. and ExEnt.

We used the AdamW (Loshchilov and Hutter, 2019) optimizer commonly used to fine-tune pre-trained Masked Language Models (MLM) models. For fine-tuning the pre-trained models on our benchmark tasks, we experimented with a learning rate of $1e-5$. Batch sizes was kept as 2 with gradient accumulation factor of 8. The random seed for all experiments was 42. We train all the models for 20 epochs. Each epoch comprises of 100 batches, and in each batch the models look at one of the tasks (in a sequential order) in the seen split.

B.2 Hardware and software specifications

All the models are coded using Pytorch 1.4.0[2] (Paszke et al., 2019) and related libraries like numpy (Harris et al., 2020), scipy (Jones et al., 2001–) etc. We run all experiments on a Tesla V100-SXM2 GPU of size 16GB, 250 GB RAM and 40 CPU cores.

B.3 Training times

- Training on CLUES-Real: The baseline RoBERTa w/o Exp model typically takes 3 seconds on average for training on 1 batch of examples. In 1 batch, the model goes through 16 examples from the tasks in seen split.
- Training on CLUES-Synthetic: All the models take comparatively much lesser time for training on our synthetic tasks owing to lesser number of explanations on average for a task. For training on 1 batch, all models took 1 seconds or less to train on 1 batch of examples from CLUES-Synthetic.

[2] https://pytorch.org/