L2R²: Leveraging Ranking for Abductive Reasoning

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ABSTRACT
The abductive natural language inference task (aNLI) is proposed to evaluate the abductive reasoning ability of a learning system. In the aNLI task, two observations are given and the most plausible hypothesis is asked to pick out from the candidates. Existing methods simply formulate it as a classification problem, thus a cross-entropy log-loss objective is used during training. However, discriminating true from false does not measure the plausibility of a hypothesis, for all the hypotheses have a chance to happen, only the probabilities are different. To fill this gap, we switch to a ranking perspective that sorts the hypotheses in order of their plausibilities. With this new perspective, a novel L2R² approach is proposed under the learning-to-rank framework. Firstly, training samples are reorganized into a ranking form, where two observations and their hypotheses are treated as the query and a set of candidate documents respectively. Then, an ESIM model or pre-trained language model, e.g. BERT or RoBERTa, is obtained as the scoring function. Finally, the loss functions for the ranking task can be either pair-wise or list-wise for training. The experimental results on the ART dataset reach the state-of-the-art on the public leaderboard.

KEYWORDS
Learning to rank; abductive reasoning; natural language inference

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1 INTRODUCTION
Abduction is considered to be the only logical operation that can introduce new ideas [9]. It contrasts with other types of inference such as entailment, which refers to the well-known natural language inference tasks (NLI), that focuses on inferring only such information that is already provided in the premise. Therefore, abduction reasoning is an important inference type deserved to be explored. A new reasoning task, namely the abductive natural language inference task (aNLI), is proposed to test the abductive reasoning capability of an AI system [1]. Different from traditional NLI tasks, aNLI first provides two pieces of narrative text treated as a start observation and an end observation. The most plausible explanation is then asked to pick out from the candidate hypotheses.

Many models have been successfully developed for the NLI tasks and directly adopted in the new proposed aNLI task. These methods for NLI tasks treat the entailment between two sentences from a classification perspective, also treat aNLI task as a binary-choice question answering problem, which selects one plausible hypothesis from two. However, discriminating true from false does not measure the plausibility of a hypothesis in abductive reasoning task, where all the hypotheses have a chance to happen with their probabilities, though some of their values are close to zero. As we can see in Figure 1, from a tidy room (observation O₁) to a mess room (observation O₂), we do not know what has happened. Thus, four hypotheses are proposed, where ‘thief broke into the room’ is the most likely happened, and ‘cat slipped into the room’ is also a potential answer. Nevertheless, even for the hypothesis ‘earthquake’ is also reasonable, just with a very small probability. It is hard to draw a line to determine which one is true from others. Depending on these insights, we argue that aNLI is better to be treated as a ranking problem. From the ranking perspective, binary-choice question answering setting in the recent aNLI task is just an incomplete pair-wise ranking scenario that only considers partial plausible order of given hypotheses. In order to fully model the plausibility of the hypotheses, we switch to a complete ranking perspective and propose a novel learning to rank for reasoning (L2R²) approach for aNLI task. L2R² adopts the mature learning-to-rank framework, which first reorganizes training instances into a ranking form. Specifically, two observations O₁ and O₂ can be view as a query, and the candidate hypotheses can be view as a set of candidate documents. The relevance degree between a query and each document represents the plausible probability between

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†The source code is available at https://github.com/cydc/L2R2.
observations and each hypothesis. Then, two parts of the learning-to-rank framework, scoring function and loss function are designed for αNLI task. Two types of scoring functions are chosen in this paper, the matching model ESIM [5] and the pre-trained language models, e.g. BERT [6] and RoBERTa [8]. Besides, pair-wise and list-wise loss functions are applied to train the ranking task. The experimental results show that our L2R² approach achieves a new state-of-the-art accuracy on the blind test set of ART. Further analyses illustrate that the benefit of the ranking perspective is to assign a proper plausibility to each hypothesis, instead of either 0 or 1.

2 TASK FORMALIZATION

The task of αNLI contains two major concepts, observation and hypothesis. The observation describes the state of the scene, while the hypothesis is the imaginary cause that transforms one observation to another. The famous Piaget’s cognitive development theory tells us that our world is a dynamic system of continuous change, which involves transformations and states. Therefore, predicting the transformation is the core of the αNLI task.

In detail, two observations are given \( O_1, O_2 \in O \), where \( O \) is the space of all possible observations. The goal of αNLI task is to predict the most plausible hypothesis \( H^* \in \mathcal{H} \), where \( \mathcal{H} \) is the space of all hypotheses. Note that the happening time of observation \( O_1 \) is earlier than \( O_2 \). Inspired by the traditional NLI task, where the hypothesis is regarded to be directly entailed from the premise. However, the relation between two observations and hypotheses in αNLI task is in a totally different way,

\[
H^* = \arg \max_{H^i} P(H^i | O_1, O_2) = \arg \max_{H^i} P(O_2 | O_1, H^i) P(H^i | O_1),
\]

where hypothesis \( H^i \) is depended on the first observation \( O_1 \) and the last observation \( O_2 \) is depended on \( O_1 \) and \( H^i \). The best hypothesis \( H^* \) is the one to max the score of these two parts. It can be modeled by a scoring function that treats \( O_1, O_2 \) and \( H^i \) as input, and outputs a real value \( s_j \), e.g. scoring function: \( f : O \times H \times O \to \mathbb{R} \).

For easy model adaptation, αNLI in the ART dataset is originally defined as a binary-choice question answering problem, whose goal is to choose the most plausible hypothesis from two candidates \( H^1 \) and \( H^2 \). From the classification perspective, it can be formalized as a discriminative task that distinguishes the category of \( s_1 < s_2 \). The positive indicates \( H^1 \) is more plausible than \( H^2 \), while the negative is the opposite. We argue that it is an incomplete pair-wise approach only suited for absolute judgment, we only explore pair-wise and list-wise loss functions in this work.

Therefore, we reformulate this task from the ranking perspective and adopt the learning-to-rank framework. In this framework, observations \( O_1 \) and \( O_2 \) can be regarded as a query, and their candidate hypotheses \( \mathcal{H} = \{H^i\}_{i=1}^N \) can be viewed as the corresponding candidate document set labeled with plausibility scores \( y = (y_j)_{j=1}^N \), where \( N \) is the number of candidate hypotheses. The loss function is a key part of the learning-to-rank framework, where point-wise, pair-wise and list-wise are three commonly used loss function types. In this paper, we only consider pair-wise and list-wise loss function, because point-wise is just a classification loss that does not take the order of the hypotheses into consideration. Given the plausibility scores, we can make all possible hypotheses pairs, when plausibility scores are different, in order to train on a pair-wise loss function.

We also use a list-wise loss function by treating the candidate hypotheses as an ordered list, which measures the error on a whole ranking list.

3 OUR APPROACH

Under the ranking formalization, we proposed our learning to rank for reasoning (L2R²) approach, which is an implementation of the learning-to-rank framework for the αNLI. The learning-to-rank framework typically consists of two main components, e.g. a scoring function used to generate a real value score for a query-document pair and a loss function used to examine the accurate prediction of the ground truth rankings.

3.1 Scoring Function

The scoring function \( f \) can be implemented in different forms, for example, the deep text matching models and the pre-trained language models can be employed as the scoring functions.

ESIM is a strong NLI model that uses Bi-LSTM to encode tokens within each sentence and perform cross-attention on these encoded token representations, whose performance on entailment NLI is close to state-of-the-art. Thus, it is a good choice to implement as a scoring function. ESIM takes two sentences \textit{premise} and \textit{hypothesis} as input. For αNLI task, the concatenation of \( O_1 \) and \( H \) is treated as the \textit{premise}, and \( O_2 \) is treated as the \textit{hypothesis}. ESIM outputs a scalar score indicating the relevance between them.

In scoring functions based on pre-trained language models such as BERT or RoBERTa. For αNLI task, the observations \( O_1, O_2 \) and hypothesis \( H \) are first concatenated into a narrative story with a delimiter token and a sentinel token. Then, it feeds into the pre-trained language model to get a contextual embedding for each token. After that a mean pooling is applied to obtain the feature vector of the observations-hypothesis pair ((\( O_1, O_2 \), \( H \)). Finally, a dense layer is stacked upon to get the plausible score \( f(O_1, H, O_2) \).

3.2 Loss Function and Inference

Though the implementation can be different, all scoring functions are optimized by minimizing the empirical risk as follow:

\[
\mathcal{R}(f) = \frac{1}{m} \sum_{i=1}^{m} L(y^{(i)}, s^{(i)}),
\]

where \( L \) is the loss function utilized to evaluate the prediction scores \( s^{(i)} \) for a single query. Since point-wise loss functions are only suited for absolute judgment, we only explore pair-wise and list-wise loss functions in this work.

Pair-wise loss functions are defined on the basis of pairs of hypotheses whose labels are different, where ranking is reduced to a classification on hypotheses pairs. Here, the pairwise loss functions of Ranking SVM [7], RankNet [2] and LambdaRank [3] are used.

Hinge loss used in Ranking SVM and logistic (cross entropy) loss used in RankNet both have the following form:

\[
L^p(y, s) = \sum_{y_j > y_k} \phi(s_j - s_k),
\]

where the \( \phi \) functions are hinge function \( \phi(z) = \max(0, 1 - z) \) and logistic function \( \phi(z) = \log(1 + e^{-z}) \) respectively. For example, \( y_j > y_k \) means that \( H^j \) ranks higher (is more plausible) than \( H^k \) with regards to the query \( (O_1, O_2) \).
We conduct our experiments on the ART [1] dataset. ART is the first large-scale benchmark dataset for abductive reasoning in narrative texts. It consists of ~20K pairs of observations with over 200K explanatory hypotheses, where observations are drawn from a collection of manually curated stories, and the hypotheses are collected by crowd-sourcing. Besides, the candidate hypotheses for each narrative context in the test sets are selected through an adversarial filtering algorithm that uses BERT\_\text{LARGE} as the adversary.

For our $L^2R^2$ approach, the data need to be reorganized into a ranking form. Concretely, we merge original instances $(O_1, O_2, H^i, H^j)_{i \neq j}$ sharing the same observation pair $(O_1, O_2)$ into a new instance $(O_1, O_2, H, H^j)$, where $H = \{H^j\}_{j=1}^{N}$ is a set of candidate hypotheses for a given observation pair. In the ART training set, there are an average of 13.41 hypotheses for each observation pair $(O_1, O_2)$, of which 4.05 are plausible. We further employ a heuristic labeling strategy to construct ground truth plausibility scores $y = \{y_j\}_{j=1}^{N}$ for $H$. Consider $j$-th hypothesis $H^j$ for $(O_1, O_2)$, the ground truth plausibility score $y_j$ of $H^j$ is labeled with $\frac{\#(H^j \text{ occurs as plausible})}{\#(H^j \text{ occurs})}$.

To demonstrate the effectiveness of our approach, we develop 18 $L^2R^2$ models based on three scoring functions, i.e. ESIM, BERT\_\text{LARGE} and RoBERTa\_\text{LARGE}, with six ranking loss functions, including Logistic for the loss (Eq 2) used in RankNet, Hinge for that (Eq 2) used in Ranking SVM, LambdaRank for that (Eq 3) used in LambdaRank, KLD for that (Eq 4) used in ListNet, Likelihood for that (Eq 5) used in ListMLE, and ApproxDNCG for that (Eq 6) used in ApproxDNCG.

Table 1 shows the experimental results of $L^2R^2$ models and baselines on the development set. Our best model was evaluated officially on the test set, which achieved the state-of-the-art accuracy (Table 2).

We summarize our observations as follows. (1) All 16 versions of our $L^2R^2$ approaches improve the performance on the abductive reasoning task, which means that the ranking perspective is better than classification. (2) Pair-wise models perform better than classification models, and most list-wise models perform better than pair-wise models. The former boost can be attributed to full version list-wise is due to the global reasoning over the entire candidate set. (3) BERT\_\text{LARGE} based ranking models have the largest gains about 8.2% improvement over the corresponding baseline. It is because BERT\_\text{LARGE} was taken as the adversary for dataset construction, the substantial improvement illustrates that our $L^2R^2$ approach is more robust to adversarial inputs. (4) The loss functions optimizing NDCG metric, i.e. LambdaRank and ApproxDNCG, have poorer performances than others, mainly due to the gap between NDCG metric during training and accuracy metric during testing.
the right part (probability > 0.5) can be viewed as accuracy values. As shown in the figure, the classification model distinguishes the pairs of candidate hypotheses with a great disparity, either close to the probability 0 or 1, whereas the $L2R^2$ model has the ability to judge the borderline instances whose two candidates are competitive to each other. Look at the sampled borderline instance in the bottom of Figure 2, where both hypotheses are likely to happen but $H^1$ is slightly more plausible, the $L2R^2$ model makes the right choice, which outputs two competitive probabilities for $H^1$ and $H^2$, 0.5891 vs 0.4109; whereas the classification model not only fails to distinguish which one is better but also outputs probabilities 0.0024 and 0.9976 in a significantly large gap. That is to say, the ranking view in $L2R^2$ approach is a more reasonable way to model the abductive reasoning task.

5 CONCLUSION

In the αNLI task, all the hypotheses have their own chance to happen, so it is naturally treated as a ranking problem. From the ranking perspective, $L2R^2$ is proposed for the αNLI task under the learning-to-rank framework, which contains a scoring function and a loss function. The experiments on the ART dataset show that reformulating the αNLI task as ranking has improvements, also reaches the state-of-the-art performance on the public leaderboard.

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