Interviewer-Candidate Role Play: Towards Developing Real-World NLP Systems

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Abstract

Standard NLP tasks do not incorporate several common real-world scenarios such as seeking clarifications about the question, taking advantage of clues, abstaining in order to avoid incorrect answers, etc. This difference in task formulation hinders the adoption of NLP systems in real-world settings. In this work, we take a step towards bridging this gap and present a multi-stage task that simulates a typical human-human questioner-responder interaction such as an interview. Specifically, the system is provided with question simplifications, knowledge statements, examples, etc. at various stages to improve its prediction when it is not sufficiently confident. We instantiate the proposed task in Natural Language Inference setting where a system is evaluated on both in-domain and out-of-domain (OOD) inputs. We conduct comprehensive experiments and find that the multi-stage formulation of our task leads to OOD generalization performance improvement up to 2.29% in Stage 1, 1.91% in Stage 2, 54.88% in Stage 3, and 72.02% in Stage 4 over the standard unguided prediction. However, our task leaves a significant challenge for NLP researchers to further improve OOD performance at each stage. 1

1 Introduction

Despite impressive progress made in Natural Language Processing (NLP), we are far from employing these systems reliably in real-world tasks. This can be partially attributed to the misalignment between formulations of real-world and standard NLP tasks. Specifically, real-world tasks present several scenarios that are often not included in the standard task formulations such as (1) seeking clarifications about the question (2) taking advantage of clues provided at inference time (3) learning from a few examples similar to the given question (4) abstaining in order to avoid incorrect predictions, etc.

In order to bridge this alignment gap, prior work in NLP has investigated few tasks that are closer to the real-world settings such as Selective Prediction (Kamath et al., 2020; Jones et al., 2020; Varshney et al., 2020), Few-Shot Learning (Brown et al., 2020; Schick and Schütze, 2021b; Ye et al., 2021; Tam et al., 2021), Prompting (Shin et al., 2020; Ye et al., 2021; Tam et al., 2021), and others. However, these tasks have been limited in their ability to capture the full spectrum of real-world scenarios. Our proposed multi-stage task addresses this limitation by providing the system with various forms of assistance at different stages, thereby allowing it to make more informed predictions.

1 Code and datasets for our task are available at https://github.com/nrjvarshney/interviewer-candidate-role-play
Jiang et al., 2020; Le Scao and Rush, 2021; Mishra et al., 2021), etc. Selective Prediction enables a system to maintain high accuracy by abstaining on instances where it is likely to be incorrect. Few-Shot Learning challenges a system to learn from a limited number of training examples. Prompts provide task/instance related guidance in order to improve model’s predictions. Though these works are a step in the right direction, they have several limitations. First, all these tasks give only a single opportunity to the system to either make a correct prediction or abstain. Whereas, in a typical human-human interaction, the questioner often gives hints, clarifications, examples, etc. in cases where the responder is not confident of their answer. Second, evaluation on these tasks is limited to specific aspects of system performance. This motivates research into designing a realistic task that simulates a questioner-responder interaction and provides a unified evaluation of multiple aspects.

An interview is a prototypical example of questioner-responder interaction. In an interview, when the candidate is not confident in their answer, the interviewer first tries to simplify the question in order to help them understand it better. If the simplification doesn’t help then they usually give some hints. Next, they typically provide some similar examples as further assistance to improve their answer. Finally, the interviewer may give a worksheet that has a number of similar unsolved questions and allow some more time for the candidate to strengthen their concepts and reattempt the question.

In this work, we present a multi-stage task that simulates the above-mentioned interviewer-candidate interaction as illustrated in Figure 1. Prior work has shown that model’s confidence of prediction is often positively correlated with correctness similar to humans (Hendrycks and Gimpel, 2017; Lakshminarayanan et al., 2017) i.e a prediction is more likely to be correct if the confidence is high and more likely to be incorrect if the confidence is low. Hence, we assist the system with input simplifications, clues, examples, etc. at various stages when it is not sufficiently confident in its prediction (Section 3). We organize our task into four sequential stages as shown in Figure 2. Initially, the model makes a prediction on the given test instance. If the prediction confidence is below a certain threshold then it enters the first stage where a few semantic preserving simplifications of the test instance are provided. The system is expected to utilize this help and better its prediction. If it enters Stage 2 then it is provided with some knowledge statements about the test instance. Similarly, in the third stage, a few similar labeled examples are provided. Finally, a number of unlabeled examples are given as further assistance in the fourth stage. This task not only simulates a real-world scenario but also integrates a number of paradigms such as Selective Prediction, Prompting, Few-Shot Learning, and Unsupervised Learning.

We instantiate the proposed task in Natural Language Inference (NLI) setting (Section 4) and evaluate on both in-domain and out-of-domain inputs. We conduct comprehensive experiments on several NLI datasets and show that it improves OOD generalization performance up to 2.29% in Stage 1, 1.91% in Stage 2, 54.88% in Stage 3, and 72.02% in Stage 4 over the standard unguided prediction.

In summary, our contributions are as follows:
(1) Addressing limitations of the standard NLP tasks, we propose a novel multi-stage task that is closer to the real-world setting and simulates an interviewer-candidate interaction.
(2) To the best of our knowledge, we are the first to study post-abstention scenarios where a model is assisted with guidance in various forms to answer the originally abstained questions.
(3) Our task improves OOD generalization performance up to 2.29% in Stage 1, 1.91% in Stage 2, 54.88% in Stage 3, and 72.02% in Stage 4 on the evaluation metric of the proposed task. There exists a noteworthy headroom for performance improvement on our task, which hopefully will motivate further work in this direction of developing NLP systems that align well with the real-world tasks.

2 Related Work

2.1 Selective Prediction

Selective Prediction task expects a system to answer when it likely to be correct and abstain otherwise. There exists a large body of work on selective prediction in machine learning (Chow, 1957; El-Yaniv et al., 2010; Geifman and El-Yaniv, 2017). Typically, the prediction confidence is used to decide when to answer and when to ab-
stain. In NLP, selective prediction has mostly been studied in connection with Calibration (Platt et al., 1999) i.e. aligning a model’s output probability with the true probability of its predictions. Desai and Durrett (2020) study calibration of recently introduced pre-trained transformer models. Kamath et al. (2020) train a calibrator leveraging softmax probabilities and instance-specific features such as input lengths for Question Answering (QA) models. Varshney et al. (2020) propose to transform calibration from classification to a regression problem incorporating difficulty scores of the instances. Zhang et al. (2021) incorporate input example embedding from a pre-trained language model as additional features for the calibrator. Unlike prior work, we also focus on post-abstention scenarios where a system is provided guidance in various forms to answer the originally abstained questions.

2.2 Few-shot Learning
Standard supervised learning approaches require a huge amount of labeled training data. Inspired by human learning from just a few examples, few-shot learning presents a challenge of learning from a limited number of labeled training examples (Brown et al., 2020; Schick and Schütze, 2021b; Ye et al., 2021; Tam et al., 2021). Several works have shown that models can achieve comparable performance just by using a few representative samples (Wang et al., 2018; Nachum et al., 2018; Mishra and Sachdeva, 2020; Sucholutsky and Schonlau, 2021). Stage 3 in our task presents a few-shot learning challenge where a few labeled examples similar to the test instance are provided.

2.3 Knowledge Addition
Incorporating knowledge in models has been a long-standing research area in NLP. Researchers leverage large knowledge banks such as COMET-ATOMIC (Hwang et al., 2020), ConceptNet (Speer et al., 2017), etc. to solve commonsense reasoning tasks (Mitra et al., 2019; Chang et al., 2020; Shen et al., 2020; Mishra et al., 2020) like CommonsenseQA (Talmor et al., 2019), QUOREF (Dasigi et al., 2019), etc. Recently, prompting where additional task-related information is provided gained attention especially for regimes where only a small labeled dataset is available for training (Shin et al., 2020; Schick and Schütze, 2021a; Le Scao and Rush, 2021; Mishra et al., 2021). In our task, we provide instance-specific knowledge in Stage 2 when the system’s confidence in its prediction is below a certain threshold.

2.4 Unsupervised Learning
Unsupervised Learning pertains to learning from unlabeled data (Lewis et al., 2019). This field is gaining interest as obtaining labeled data is both time consuming and expensive. In contrast, unlabeled data can be collected cheaply. For downstream tasks, it has mostly been explored for Question Answering task (Chung et al., 2018; Yang et al., 2017; Dhingra et al., 2018; Wang and Jiang, 2019; Alberti et al., 2019) where it is modeled as a data augmentation or a domain adaptation problem. In this work, we provide unlabeled examples to the system in the final stage of our task.

3 The Proposed Task
In this section, we detail our proposed multi-stage task, its mathematical formulation, and evaluation metric.

Task Description: Prior work has shown that the model’s confidence is often positively corre-
lated with its correctness (Hendryckx and Gimpel, 2017; Lakshminarayanan et al., 2017) i.e. its prediction is more likely to be correct if the confidence is high and more likely to be incorrect if the confidence is low. Following this, we design our task in four sequential stages where a system goes from one stage to the next if it is not sufficiently confident in its prediction. Figure 2 illustrates the flow of the task. Each stage provides instance-specific guidance in various forms to assist the model in improving its prediction. If the prediction confidence in a stage exceeds a certain threshold then it attempts the test instance and skips the subsequent stages.

The stages are organized based on the steps that a typical interviewer follows in an interaction with a candidate (Section 1). Initially, the model makes a prediction on the given input and the overall system outputs the prediction if the confidence is above a certain threshold and enters Stage 1 otherwise. In Stage 1, it is provided with several semantic-preserving simplifications of the test instance. The system is expected to leverage these input simplifications and improve its prediction on the given test instance. Prior work has shown that even state-of-the-art models are sensitive to the input and simplifying the input can significantly boost model’s performance (Jiang et al., 2020; Elazar et al., 2021; Anantha et al., 2021). In Stage 2, it is given some knowledge statements relevant to the test instance. A few similar labeled examples are provided in Stage 3. In the final stage, it is further given a number of similar unlabeled examples. If the system fails to surpass the confidence threshold even after the final stage then it abstains from answering on that test instance in order to avoid incorrect prediction.

Mathematical Formulation: Algorithm 1 shows the general structure of the proposed task. The system continues to make the prediction on the given test instance leveraging the provided guidance until its confidence exceeds a certain threshold. Hendryckx and Gimpel (2017) showed that $MaxProb$ (maximum softmax probability) is a simple yet strong estimate of prediction confidence. Formally, $MaxProb$ estimates confidence on input $i$ as:

$$conf_{MaxProb} = \max_{y' \in Y(i)} \text{Model}(y'|i)$$

where $Y(i)$ denotes the possible output classes.

Algorithm 1: Task Structure

Given:

1. $i$: Test Instance,
2. $th$: Confidence Threshold,
3. $M_0$: Trained Model,
4. $T_s$: Stage-specific Guidance Function

Initialization: stage: $s \leftarrow 0$

while $s \leq 4$ do

1. $M_s \leftarrow$ Update $M_{s-1}$ using $T_s(i)$ if $s > 0$
2. $pred_s, conf_s = M_s(i)$
3. if $conf_s > th$ then
4. return $pred_s$
5. $s++ = 1$

end

return “Abstain”

 Calibration using a held-out dataset can further align the model’s output probabilities (Lee et al., 2017; Kamath et al., 2020) and give better confidence estimates. The function $T_s$ provides guidance to the system in Stage $s$ for an instance $i$ and is defined as:

$$T_s(i) = \begin{cases} 
\emptyset, & \text{if } s = 0 \\
\text{Simplified Inputs}, & \text{if } s = 1 \\
\text{Knowledge Stmts.}, & \text{if } s = 2 \\
\text{Similar Labeled Ex.}, & \text{if } s = 3 \\
\text{Similar Unlabeled Ex.} & \text{if } s = 4 
\end{cases}$$

Evaluation Metric: In Selective Prediction, “Coverage” is defined as the fraction of examples answered by the system while accuracy on covered examples is the fraction answered correctly. Furthermore, risk pertains to the error on the covered examples. Selection of confidence threshold above which the system answers is application dependent i.e for tolerant applications like movie recommendation, a low threshold can be selected but for intolerant applications like medical diagnosis, a high threshold is selected to minimize risk. Hence, instead of evaluating a system at a particular threshold value, coverage and its associated risk is computed for every threshold value $th$ in order to estimate its overall performance. As $th$ decreases, coverage will increase, but the risk will usually also increase. We plot risk versus coverage for all values of $th$ and calculate the area under this curve (AUC). AUC represents the overall performance of a method as it combines performance across all $th$ values. Lower AUC is preferred as it
represents lower average risk across all thresholds. We compute AUC for each stage as described below:

Let the model’s initial prediction on instance \( i \) be \( pred_{i0} \) with a confidence of \( con_{f_{i0}} \) and prediction in stage \( s = 1..4 \) be \( pred_{is} \) with a confidence of \( con_{f_{is}} \). Note that the system gets to make a prediction in a stage only if the confidence in the previous stage was below the threshold \( th \). For every \( th \) and stage \( s \), we compute two values \( c_{is} \) and \( p_{is} \) as:

\[
c_{is} = \begin{cases} 
1 & \text{if } con_{f_{is}} > th \\
0 & \text{otherwise}
\end{cases}
\]

\[
p_{is} = \begin{cases} 
1 & \text{if } con_{f_{is}} > th \\
0 & \text{otherwise}
\end{cases}
\]

We use \( c_{is} \) and \( p_{is} \) to compute Coverage \( C \) and Accuracy \( A \) on covered examples in stage \( s \) as:

\[
C_s = \frac{\sum\limits_{i=1}^{n} 1(c_{is} \geq th)}{n}
\]

\[
A_s = \frac{\frac{1}{n} \sum\limits_{i=1}^{n} (1(c_{is} \geq th) \cdot v_{is})}{C_s}
\]

where, \( 1 \) is the indicator function, \( n \) is size of test dataset and parameter \( v_{is} \) is 1 when prediction \( p_{is} \) is correct and 0 otherwise.

We then plot risk-coverage curves and compute AUC to evaluate a system’s performance.

### 4 Task Instantiation

While our framework is general, we instantiate the proposed task in Natural Language Inference (NLI) that pertains to the task of identifying the relationship between a “premise” and a “hypothesis” sentence. This relationship can be classified as either Entailment (hypothesis must be true if the premise is true), Contradiction (hypothesis can never be true if the premise is true), or Neutral (hypothesis can be both true and false as the premise does not provide enough information to make a decision). Table 1 shows examples of the NLI task.

We include the standard NLI datasets in our setup and consider SNLI (Bowman et al., 2015) as in-domain dataset with Multi-NLI (Williams et al., 2018) and Dialogue NLI (Welleck et al., 2019) as Out-of-Domain (OOD) datasets. We include the OOD datasets in our setup as the inputs often diverge from the model’s training data in a real-world task. Figure 3 illustrates the method we followed to create various stages in our task instantiation. We detail the four stages of the proposed task for NLI below:

**Stage 1:** The first stage requires the input to be simplified in case of abstention. We compile simplified versions of the premise-hypothesis tuples in an automated way using the paraphrasing tool introduced in (Zhang et al., 2020). We conduct a small user study in order to find the best strategy of employing this tool to compile semantic preserving variations of the original input. We provide three sets of examples where we paraphrase only premise, only hypothesis, and both premise and hypothesis for the three labels (Entailment, Contradiction, and Neutral) separately. We also provide the original PH tuple to the participants and ask them to annotate whether the transformation is label preserving. We find that for Entailment and Contradiction PH tuples, paraphrasing the hypothesis is label preserving in most cases, whereas it is paraphrasing the premise for Neutral. Using these findings, we compile 10 semantic preserving variations of the test instances and provide them to the system in case of abstention in the first stage. Table 2 shows examples of the transformed PH tuples provided to the system in Stage 1.

**Stage 2:** In Stage 2, some knowledge statements relevant to the test instance are provided. We collect these knowledge statements from ConceptNet (Speer et al., 2017) by querying for nouns and verbs present in the sentence and ranking based on the similarity. Table 3 shows examples of knowledge statements fetched for SNLI test instances in Stage 2.

| Premise (P), Hypothesis (H) | Label (L) |
|-----------------------------|-----------|
| P: A man is being filmed in the middle of a soccer field. | Entailment |
| H: A male is being recorded on a sports field. | Contradiction |
| P: A woman is talking on the phone while standing next to a dog. | Neutral |
| H: The woman is sleeping in her room. | |
| P: A girl is talking on a cellphone. | Neutral |
| H: The girl is calling her mother. | |

Table 1: Illustrative examples of the NLI task for Entailment, Contradiction, and Neutral label.
Figure 3: Steps involved at every stage during instantiation of the proposed task for NLI.

| Label     | Original Premise (P), Hypothesis (H)                                      | Transformed Premise (P), Hypothesis (H)                                      |
|-----------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Entailment| **P**: A young family enjoys feeling ocean waves lap at their feet.       | **P**: A young family enjoys feeling ocean waves lap at their feet.         |
|           | **H**: A family is at the beach.                                         | **H**: A family is near the water.                                         |
| Entailment| **P**: A woman with a green headscarf, blue shirt and a very big grin.    | **P**: A woman with a green headscarf, blue shirt and a very big grin.      |
|           | **H**: The woman is very happy.                                           | **H**: The woman is in a good mood.                                        |
| Neutral   | **P**: People jump over a mountain crevasse on a rope.                    | **P**: People are jumping over a crevasse.                                  |
|           | **H**: Some people look visually afraid to jump.                          | **H**: Some people look visually afraid to jump.                            |
| Neutral   | **P**: A dog jumping for a Frisbee in the snow.                          | **P**: The dog is playing in the snow.                                      |
|           | **H**: A pet is enjoying a game of fetch with his owner.                  | **H**: A pet is enjoying a game of fetch with his owner.                    |
| Contradiction | **P**: Three firefighter come out of subway station.                | **P**: Three firefighter come out of subway station.                        |
|           | **H**: Three firefighters playing cards inside a fire station.            | **H**: Three firefighters are inside a fire station.                        |
| Contradiction | **P**: An older women tending to a garden.              | **P**: An older women tending to a garden.                                  |
|           | **H**: The lady is cooking dinner.                                        | **H**: The lady is making a meal.                                          |

Table 2: Illustrative examples corresponding to each label for Stage 1.

Stage 3: In Stage 3, we provide a few labeled examples similar to the test instance in case of abstention. We use POS tagger of spacy library (Honnibal et al., 2020) and find examples with matching subjects and nouns. For each instance, we find similar examples from its corresponding training dataset. Note that we sample equal number of examples for each label to avoid label imbalance. We experiment varying the number of similar examples in this stage from 8 to 128. Table 4 shows examples found for an SNLI test instance from the SNLI training dataset in Stage 3.

Stage 4: In Stage 4, we provide a number of unlabeled examples compiled from the corresponding training dataset of the test instance. We experiment varying the number of unlabeled examples in this stage from 5000 to 20000. We expect this stage to be particularly beneficial for the OOD inputs as this provides exposure to instances that have not been observed during training performed prior to Stage 1.

5 Experiments and Results

In this section, we provide experimental details and analyse performance of our baseline approach.

5.1 Approach

We train a 3-way classification model on the training dataset and use MaxProb i.e maximum soft-
P: Children bathe in water from large drums.  
H: The kids are wet.  

Knowledge: Water is related to wet
Water is a fluid

P: Boys in what appears to be a library or school room.  
H: Boys are in a place of learning.  

Knowledge: You can use a library to obtain and read books.  
A library is for finding information.

P: Kids work at computers with a teacher’s help.  
H: The kids are learning.  

Knowledge: A teacher wants students to learn.  
Teacher is a type of educator.

P: A couple walk hand in hand down a street.  
H: A couple is sitting on a bench.  

Knowledge: If you want to walk then you should stand.  
Walk is related to movement.

P: A dog jumping for a Frisbee in the snow.  
H: A cat washes his face and whiskers with his front paw.  

Knowledge: Cat is not dog.  
Paw is a type of animal foot.

Table 3: Examples showing top 2 knowledge statements provided in Stage 2.

| Label     | Premise                                                                 | Hypothesis                                                                 |
|-----------|-------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Entailment| A tattooed skateboarder is doing a trick.                               | A tattooed skateboarder is pulling a stunt.                               |
| Entailment| The man is performing a trick on a bicycle high in the air.              | The man can ride a bike.                                                   |
| Neutral   | A tattooed skateboarder is doing a trick.                               | A skateboarder is performing for a crowd.                                  |
| Neutral   | A man on a bike tries to do a trick on the railing of an outdoor fountain.| The man has on elbow pads and a helmet.                                   |
| Contradiction| A man is pulling off a trick on his rollerblades.                  | A man is sitting down on the floor.                                        |
| Contradiction| A boy doing a trick in the air on his bicycle.                       | A boy is playing a clarinet.                                               |

Table 4: Illustrative examples corresponding to each label for Stage 3 for the original test instance:  
P: A skateboarding youth does a trick on a rail.,  
H: A young person on a skateboard.

Figure 4: Our baseline approach for each stage of the proposed task.

We use max probability across the three classes as the confidence measure. Initially, we make inference on the given test instance and proceed to Stage 1 if the confidence is below the threshold. For the first stage, we further make inference on the provided simplifications of the test instance and find the most frequent prediction among those. Then, we use ensembling techniques to find the final prediction i.e we compare the prediction on the original input with this most frequent prediction and if that prediction matches then we take the maximum prediction confidence among the variants where the system predicts the most frequent label otherwise we take the average of those prediction confidences. For the second stage, we concatenate the knowledge statement(s) with the premise and make inference on the concatenated input. For the third stage, we further fine-tune the model on the provided labeled instances and reattempt the original test instance using the fine-tuned model. For the final stage, we pseudo-label the provided unlabeled examples using the finetuned model obtained in Stage 3, fine-tune the model using those pseudo-labeled examples, and make inference on the test instance again. Figure 4 illustrate our baseline approach for each stage of the proposed task.

Table 6 shows the performance of the SNLI-trained model on all the evaluation datasets before Stage 1. We refer this stage as Stage 0 in our analysis. As expected, the in-domain accuracy is high and AUC of risk-coverage curve is low. Whereas, the out-of-domain accuracy is low and AUC is high.
5.2 Experimental Details

Since NLI is a 3-way classification task, we use BERT-BASE model (Devlin et al., 2019) with a linear layer on top of [CLS] token representation for training the model. We use batch sizes of 32 and a learning rate ranging in $10^{-5}$. All experiments are done in Nvidia V100 16GB GPUs. We train the model using 10k examples of the SNLI training dataset and evaluate on SNLI, MNLI (matched and mismatched), and DNLI datasets.

Table 5: Table showing percentage improvement at various stages for all datasets. * indicates that this has been evaluated for 200 samples only due to limited computational budget.

| Stage | SNLI | MNLI mat. | MNLI mis. | DNLI |
|-------|------|------------|------------|------|
| S1    | 0.89 | -1.29      | 0.71       | 2.29 |
| S2    | -7.62| -2.01      | 0.37       | 1.91 |
| S3    | -7.88| 10.54      | 9.5        | 54.88|
| S4*   | -    | -          | -          | 72.02|

Table 6: Table showing metric values obtained by the SNLI trained model on all the evaluation datasets before Stage 1 i.e without providing any extra information about the test instances. AUC corresponds to Area under risk-coverage curve. ↑ indicates higher is better while ↓ indicates lower is better.

| Metric | SNLI | MNLI mat. | MNLI mis. | DNLI |
|--------|------|------------|------------|------|
| Accuracy↑ | 80.43 | 59.12      | 59.74      | 42.73|
| AUC ↓  | 7.87 | 27.89      | 26.73      | 57.2 |

5.3 MaxProb as a confidence Measure

We plot $MaxProb$ vs $Accuracy$ achieved by the SNLI trained model for all the datasets in Figure 6. It shows that $MaxProb$ is positively correlated with correctness i.e with increase in $MaxProb$, the accuracy also increases. This justifies the use of $MaxProb$ as a confidence measure for our task.

5.4 Performance Prior to Stage 1

5.5 Performance Analysis

Figure 5 shows the risk-coverage curves for all the evaluation datasets obtained in various stages of
our task. We find that Stage 3 leads to a significant improvement for OOD datasets. In contrast, there is a marginal drop in performance for in-domain dataset (SNLI). This is expected as the model is already trained on the training dataset of the in-domain dataset and fine-tuning on a few examples in Stage 3 leads to overfitting and hence drop in performance. Furthermore, we find that their is not a significant improvement in performance in Stage 1 and Stage 2. This leaves scope for better ways to leverage the input simplifications and knowledge statements in Stage 1 and 2 respectively.

6 Conclusion

We introduced a multi-stage task in order to bridge the gap between real-world and standard NLP task formulations. Inspired by human-human interaction such as an interview, we designed our task by incorporating various forms of guidance to help a system improve its prediction and learn the underlying concept to achieve generalization. We instantiated the proposed task in Natural Language Inference setting and demonstrated that each of the stages improve OOD generalization performance of systems. However, there still exists significant room to improve OOD generalization at each stage (especially Stage 1 and 2). We hope this work will bring more attention to developing NLP systems that align more closely with the real-world tasks.

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