It's better to say "I can't answer" than answering incorrectly: Towards Safety critical NLP systems

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Abstract

In order to make AI systems more reliable and their adoption in safety critical applications possible, it is essential to impart the capability to abstain from answering when their prediction is likely to be incorrect and seek human intervention. Recently proposed "selective answering" techniques model calibration as a binary classification task. We argue that, not all incorrectly answered questions are incorrect to the same extent and the same is true for correctly answered questions. Hence, treating all correct predictions equally and all incorrect predictions equally constraints calibration. In this work, we propose a methodology that incorporates the degree of correctness, shifting away from classification labels as it directly tries to predict the probability of model's prediction being correct. We show the efficacy of the proposed method on existing Natural Language Inference (NLI) datasets by training on SNLI and evaluating on MNLI mismatched and matched datasets. Our approach improves area under the curve (AUC) of risk-coverage plot by 10.22% and 8.06% over maxProb with respect to the maximum possible improvement on MNLI mismatched and matched set respectively. In order to evaluate our method on Out of Distribution (OOD) datasets, we propose a novel setup involving questions with a variety of reasoning skills. Our setup includes a test set for each of the five reasoning skills: numerical, logical, qualitative, abductive and commonsense. We select confidence threshold for each of the approaches where the in-domain accuracy (SNLI) is 99%. Our results show that, the proposed method outperforms existing approaches by abstaining on 2.6% more OOD questions at respective confidence thresholds.

Introduction

In the recent years, deep neural networks have made remarkable progress on a variety of supervised learning tasks ranging from language to vision (Devlin et al. 2018; Tan and Le 2019). Most of these models are trained based on the closedworld assumption that the test data distribution will be similar to the training data distribution. However, when employed in real-world tasks, this assumption doesn't hold true (Torralba and Efros 2011; Quionero-Candela et al. 2009). Their performance drops drastically on such inputs (Eykholt

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et al. 2018; Jia and Liang 2017). Furthermore, these models make high confidence predictions on such inputs making their detection difficult (Nguyen and O'Connor 2015; Nguyen, Yosinski, and Clune 2015).

While, this is acceptable for tolerant applications like movie recommendations, high risk associated with wrong predictions hinders the adoption of such models in real-world safety critical applications like medical diagnosis and self-driving cars. (Amodei et al. 2016; Hendrycks and Gimpel 2016). The objective behind selective answering is to teach neural network models the ability to abstain from answering whenever they are not sufficiently confident. This capability enables the model to maintain high accuracy on the questions they decide to answer and seek opportunity for human intervention in case of abstention, allowing wide adoption of AI systems possible.

Most recently, selective answering in NLP was studied for Question Answering setting in (Kamath, Jia, and Liang 2020), which trains a binary classification calibrator model to identify inputs on which the model is likely to fail. They annotate a heldout dataset such that correctly answered questions are labeled as positive samples and incorrectly answered questions as negative. This approach uses softmax probabilities and sentence lengths as features for training the calibrator.

In this work, we explore the setting of selective answering for a classification task. The motivation behind this work is the fact that not all incorrect predictions are incorrect to the same extent and not all correct predictions are correct to the same extent as the model is not equally confident on all its predictions. For example, a dog classifier model gets its prediction wrong on two samples, one is of a cat and other is of a car. Though, the model is incorrect on both the samples, it is clearly more incorrect on car as compared to the cat. Hence, assigning the same annotation label to both samples limits the learning of calibrator. On the other hand, assigning gold annotation based on the degree of correctness provides more flexibility to the calibrator to look for fine-grained features distinguishing various annotation scores. Keeping this in mind, we propose a novel method that shifts away from the categorical labels and directly targets the probability of the model's prediction being correct. Specifically, we transform the calibrator training from a classification problem to a regression problem where the regression score gives an estimate of the extent to which the models prediction is correct. We propose a number of ways to compute gold scores for training calibrator on the regression task and compare performance of the proposed method with other approaches in the selective answering literature. Table 1 illustrates the difference between the proposed annotation strategy and the annotation strategy used in existing approaches.

We also propose a novel setup involving questions with a variety of reasoning skills to evaluate our method in OOD setting. Our setup includes a test set for each of the five reasoning skills: numerical, logical, qualitative, abductive and commonsense in an NLI-like setting. Table 2 shows examples of all the test sets. A model not trained on such reasoning skills should abstain in order to avoid incorrect answering.

In summary, this paper makes the following contributions:

- We propose a novel approach for selective answering that treats calibrator training as a regression problem and directly predicts the probability of the correctness of model's prediction. Our approach improves area under the curve (AUC) of risk-coverage plot by 10.22% and 8.06% over maxProb with respect to the maximum possible improvement on MNLI mismatched and matched set respectively.
- We also propose a test set for each of the five aforementioned reasoning skills which serve as OOD data. We show that using MaxProb as the confidence measure performs poorly since the model just achieves 50% accuracy on these binary classification test sets while being overconfident.
- We select confidence threshold for each of the approaches where the in-domain accuracy (SNLI) is 99%. Our results show that, the proposed method outperforms existing approaches by abstaining on 2.6% more OOD questions at respective confidence thresholds.

Problem Formulation

In selective answering setting, a model chooses to abstain on questions it is not sufficiently confident. Coverage is defined as the percentage of questions answered by the model while accuracy is the percentage of correctly answered questions. Risk is opposite of accuracy i.e the percentage of incorrectly answered questions. Coverage and Accuracy are mathematically defined as follows.

Let the prediction confidence of a model on evaluating a sample i of dataset D be c_i , th be the confidence threshold above which the model chooses to answer, p be model's prediction and g be the gold label. Size of dataset D is n. Then, Accuracy A and Coverage C are calculated as:

$$v = \begin{cases} 1, & \text{if } p = g \\ 0, & \text{otherwise} \end{cases}$$

$$step(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$C = \sum_{i=1}^{n} \frac{\text{step}(c_i - th)}{n}$$

$$A = \frac{\frac{1}{n} \sum_{i=1}^{n} \operatorname{step}(c_i - th) * v_i}{C}$$

Approaches

In this section, we first give a broad overview of existing approaches in the selective answering literature and then present our approach for the same task.

• Maximum softmax probability

(Hendrycks and Gimpel 2016) introduced a simple yet strong baseline for selective answering that directly uses the maximum softmax probability across all labels as the confidence and abstains when this confidence is below a defined threshold. It has been shown that maxProb is a good indication of correctness of model's prediction which means that a higher maxProb indicates higher likelihood of the prediction being correct.

$$softmax_j = \frac{e^{z_j}}{\sum_{i=1}^K e^{z_i}} \tag{1}$$

Train a binary classification Calibrator model

In this approach, we holdout a small portion of the training set and train the model on the remaining dataset. The heldout examples are then annotated using the trained model such that correctly answered questions are labeled as positive samples and incorrectly answered questions as negative. Then a binary classification model is trained on this annotated heldout dataset. Selective QA (Kamath, Jia, and Liang 2020) uses softmax probabilites, sentence lengths as features to train a random forest classification model as a calibrator. The probability of positive label assigned by this calibrator model is taken as the confidence.

• Calibrator with multiple rejection classes

One of the limitations of the binary classification calibrator model is that it may not be able to fit all the negative samples in a single class as there could be a lot of variety in the samples. (Mohseni et al. 2020) proposed a strategy to add multiple rejection classes, converting the binary classification problem to a (1 + n) classification problem where n is the number of rejection classes. The heldout dataset is annotated in the same way as in the binary classification calibrator model but the training procedure changes slightly. Here, the gold labels for training are computed on the fly. When the prediction is one of the rejection classes and the annotation is negative then the predicted label is chosen as the gold label. Also, when the prediction is the positive class and annotation is negative then one of the rejection classes is randomly selected as the gold label. In another variant of this approach, instead of selecting a random rejection class, we select the rejection class with the highest probability among all rejection classes. A similar setup can be used for positive samples i.e multiple selection classes.

• Train a regression Calibrator model

In this method, instead of training a classification model for calibration, we train a regression model. The intuition behind this is the fact that *not all incorrect predictions* are incorrect to the same extent and the same is true for

| Premise | Hypothesis | Classification Annotation | Proposed Annotation |
|---|---|------------------------------|------------------------|
| A construction worker assembles a scaffold. | The scaffold was assembled by the worker. | 1 | 0.983 |
| A man outside cracking an egg over a bowl as a woman looks on | The couple is cooking with eggs. | 1 | 0.737 |
| A large group of young adults are crammed into an area for entertainment. | People at a concert. | 1 | 0.505 |

Table 1: Our proposed annotation strategy based on the degree of correctness in contrast to the categorical label used in existing approaches.

correct predictions as the model is not equally confident on all its predictions. In this setup, we do not annotate the samples in heldout dataset as positive or negative, instead we assign a score that reflects the probability of correctness of the model's prediction. We use maximum softmax probability and prediction to compute the gold socre. We propose a number of strategies to annotate the heldout dataset for this regression task. Table 1 illustrates the difference between the proposed annotation approach and the classification annotation. This approach is inspired from Uncertain NLI (Chen et al. 2019), that proposes a refinement of NLI task and targets direct prediction of human subjective probability assessments for classes. Let p be the model prediction and p be the gold annotation. The regression score p is defined as:

Approach 1:

$$r = \begin{cases} 0.5 + \frac{maxProb}{2}, & \text{if } p = g\\ 0.5 - \frac{maxProb}{2}, & \text{otherwise} \end{cases}$$

Approach 2:

$$r = \begin{cases} maxProb, & \text{if } p = g\\ 0.5 - \frac{maxProb}{2}, & \text{otherwise} \end{cases}$$

We also experiment with several variants of these approaches incorporating predicted label in computing the regression score. Specifically, we use maxProb and predicted label to compute the gold score.

Experiments and Results

This section describes the datasets used for experiments, experimental details, and compares the performance of the proposed approach with existing approaches in selective answering literature.

Datasets

SNLI (Bowman et al. 2015) and **MNLI** (Williams, Nangia, and Bowman 2017) are large crowdsourced corpora of NLI data. Sentences in MNLI are derived from ten distinct genres of written and spoken English as opposed to a single genre in SNLI – image captions.

Reasoning skill based OOD datasets

We also compile a number of test sets, each requiring a different reasoning skill that is not present in the training dataset. All the test datasets pose a 2-way classification task. We eliminate the neutral samples from the NLI dataset and use it as the training dataset for this binary classification task. Table 2 shows examples of all the OOD test sets. We highlight the distinctive properties of the datasets and the compilation procedure below.

- Numerical Reasoning

Questions in this category are Maths word problems that require addition and subtraction skills. We compile such questions from an online learning platform ¹. These questions are different from existing numerical reasoning datasets as they are in NLI-like format (each question has a premise and a hypothesis but is a 2-way classification task) and reflect real world scenarios as opposed to synthetically generated questions.

- Qualitative Reasoning

This category includes questions that require reasoning with qualitative relationships. We perform preprocessing on the QuaREL dataset (Tafjord et al. 2019) which has questions in multiple choice format and convert it to the NLI-like format. Preprocessing steps on this dataset include replacing the blanks/question words with the answer options, separating the question into premise and hypothesis and removing the non-coherent questions as the last step.

- Commonsense Reasoning

We compile pronoun resolution questions which require commonsense reasoning from the Winogrande dataset[(Sakaguchi et al. 2019).] following similar preprocessing steps. This dataset is similar to the WNLI dataset but has more variety and is harder (Sakaguchi et al. 2019).

- Abductive Reasoning

Abductive reasoning concerns with selecting the most plausible explanation. We compile such questions from aNLI corpus (Bhagavatula et al. 2019).

- Logical Reasoning

Questions in this category require reasoning with logical operators AND, OR, and NOT. We manually create

¹k5learning.com

| Reasoning | Premise | Hypothesis | Answer | Test Size |
|--------------------------|---|---|---------------|-----------|
| Numerical Reasoning | In order to start constructing the house, Charlie and his father needed to gather some wood from the forest. If they initially have 15 extra planks of wood in the house and Charlie and his father got 10 planks of wood each. | They would have 35 pieces of wood in total. | Entailment | 338 |
| | The wolves, though accustomed to cold weather, also wanted to move away from the incoming winter. If there are 43 packs of wolves living in the forest and 31 packs went away | There were 10 wolf packs left in the forest. | Contradiction | |
| Qualitative Reasoning | Carlos is rolling his baseball around on different surfaces. When Carlos rolls his baseball on a grass field , the ball rolls easily . When he tries rolling the ball on the rocky parking lot , the ball doesn't roll very far . | The rocky parking lot had more resistance than the grass field. | Entailment | 424 |
| | Bryce challenged Gary , who is much weaker than Bryce, to see who could throw a stone the farthest . | Bryce is more likely to not have thrown it as far. | Contradiction | |
| Commonsense Reasoning | John had to bow to walk through the door but have to crawl to enter the tent. | The tent is shorter. | Entailment | 403 |
| | Lawrence had lost a lot of weight on their diet but Hunter wasn't nearly as successful. | Lawrence was now heavy. | Contradiction | |
| Logical Reasoning | Jennifer and Nora are buying gifts for Tony's birthday party. Jennifer bought a pen and a toy car while Nora bought a cycle. Upon reaching, Tony declared that people who have brought toy car are only allowed to join his party. | Nora will not be allowed to join the party | Entailment | 200 |
| | Our school has decided to award students with an A grade in both Maths and Science. My friend Ron and I got A grade in Science. Abigail also performed well and got B in Science. Everybody in the class got A in Maths. | Abigail will be awarded for her performance. | Contradiction | |
| Abductive Reasoning | Ron started his new job as a landscaper to- day. Ron ignores his bosses's orders and called him an idiot. | Ron is immediately fired for insubordination. | Entailment | 400 |
| | Ron started his new job as a landscaper to- day. Ron's boss called him an idiot. | Ron is immediately fired for insubordination. | Contradiction | |

Table 2: Example premise hypothesis pairs from our test datasets highlighting the parts relevant to their reasoning skills.

such questions. Table 2 shows examples of all the five OOD test sets.

• Experimental Details

We hold out a small percentage of SNLI training dataset and use the remaining to train a classification model. We use bert-base-uncased model and a linear layer on top of CLS representation for all our experiments. For the OOD setting i.e 2-way classification problem, we remove the neutral samples from SNLI and MNLI datasets. The remaining OOD datasets are already in the two class format. For classification based calibration approach, we annotate all correctly answered questions as positive samples and all incorrectly answered questions as negative. For regression based calibration approaches, we experiment with multiple annotation strategies for computing gold scores. We use random forest classifier and random forest regressor implementation of Scikit-learn. (Pedregosa et al. 2011) for a set of calibration approaches.

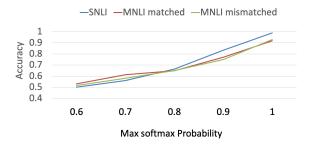


Figure 1: Variation of MaxSoftmax Probability with confidence for SNLI and MNLI datasets.

Results

Maximum softmax probability

This method directly uses the maximum softmax probability across all labels as the estimate of model's confidence. Figure 1 shows how the accuracy varies with confidence for SNLI and MNLI datasets. The following observations can be made from this plot:

- As the confidence increases, the accuracy of the model also increases for both the datasets. This implies that maxProb is a good indication of the likelihood of model's prediction being correct.
- At almost all the points, the accuracy is closer to the confidence value for SNLI dataset but significantly lower for MNLI dataset. Average maxProb of a model trained on SNLI on its dev set is 97.11% which is very close to its overall accuracy of 96.47%. While the average maxProb of the same model on MNLI matched dataset is 89.99% which is significantly higher than its accuracy of 83.99% on this dataset. Average confidence much higher than the accuracy is a clear symptom of models overconfidence on the MNLI dataset.

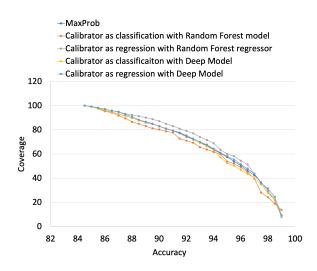


Figure 2: Accuracy coverage curve for MNLI mismatched.

Classification based Calibrator approaches

We leverage maxProb, prediction and other auxiliary features like semantic textual similarity as input and train a binary classification model. We experiment with two models in this subsection, one that trains a random forest model, and other that trains a deep neural network. Table 3 shows the AUC value of the risk-coverage plot for the SNLI trained model on MNLI dev matched and mismatched datasets. Our regresion based approach achieves significalty lower AUC value than other approaches for both the datasets while maintaining similar AUC on the in-distribution dataset. Figure 2 and 3 show the accuracy coverage plot for MNLI dev mismatched and matched datasets. Our method has better coverage at almost all accuracy points than other approaches.

• OOD experiments In this section, we first show that the SNLI trained model can't reason over any of the OOD datasets. Then, we compare various approaches based on the percentage of questions abstained from the OOD test set. Table 4 shows the performance of SNLI trained model on all the OOD test set individually. Since, this is a binary classification task and the model achieving 50 % accuracy is a clear sign of model's incompetency on these datasets. Hence, a model that abstains on maximum number of questions is preferable. AUC value can not be compared here as the accuracy never increases beyond 50%. Hence, we select confidence threshold for each of the approaches where the in-domain accuracy (SNLI) is 99%. Table 5 shows the percentage of questions the abstained from answering on the complete OOD dataset. Our results show that, the proposed method outperforms existing approaches by abstaining on 2.6% more OOD questions at respective confidence thresholds. A high percentage implies that the model is relatively less confident on OOD questions which is a desired characteristic.

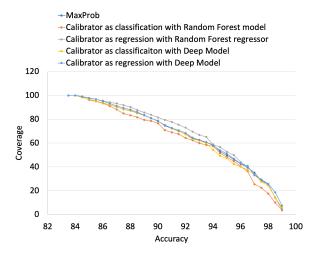


Figure 3: Accuracy coverage curve for MNLI matched.

Comparison between reasoning skills pertaining to the OOD set We distinguish different OOD datasets by comparing the percentage of questions abstained at a range of confidence thresholds. Figure 4 shows that Qualitative reasoning data samples are easier to abstain on as compared to other types of reasoning datasets as the model has lower confidence on its samples. Order of abstaining at each threshold is Qualitative followed by Logical, Numerical, Commonsense and Abductive data samples.

| Approach | AUC matched | AUC mismatched |
|-----------------------------------|----------------|-------------------|
| MaxProb | 5.25 | 6.07 |
| Calibrator as RF classification | 5.59 | 6.49 |
| Our approach | 4.84 | 5.69 |
| Calibrator as Deep classification | 5.37 | 6.15 |
| Calibrator as Deep regression | 5.15 | 5.91 |

Table 3: AUC of risk-coverage plot for a SNLI trained model on MNLI datasets. Lower AUC is better.

Related Works

Selective Answering Selective Answering where a model can either answer or abstain has been studied for several different applications (Geifman and El-Yaniv 2019). Selective Answering under domain shift which has been recently studied for Extractive Question Answering (Kamath, Jia, and Liang 2020) in NLP, has also been studied in health-care (Feng et al. 2019) and in chemistry (Roy, Ambure, and Kar 2018). We study selective answering in NLI setting and show that posing it as a regression problem performs better than existing approaches that model it as a classification problem.

| Dataset | Accuracy |
|-------------|----------|
| Numerical | 0.47 |
| Qualitative | 0.50 |
| Abductive | 0.53 |
| Commonsense | 0.49 |
| Logical | 0.50 |

Table 4: Performance of an SNLI trained model on OOD datasets.

| Approach | MaxProb | Classification | Regression |
|-------------|---------|----------------|------------|
| % Abstained | 61.5 | 63.9 | 66.4 |

Table 5: Percentage of questions in the OOD datasets abstained by various approaches. We select the confidence where accuracy on SNLI dataset is 99% as threshold.

OOD datasets Encountering OOD sample is inevitable in real world tasks either because training set does not characterize the entire distribution or the distribution evolves with respect to time (Torralba and Efros 2011: Ouionero-Candela et al. 2009). Recently, several OOD datasets have been proposed based on writing style, topic, and vocabulary (Hendrycks et al. 2020). Our focus in this paper is to develop OOD datasets involving questions that require different reasoning skills than the ones present in the training set. A growing number of studies have shown that many popular models overfit to spurious biases instead of learning generalizable features like human. Biases prevent model from generalization and cause inflation in model performance (Sakaguchi et al. 2019; Mishra et al. 2020a). Generalizing to Out of Distribution datasets is a challenge for Machine Learning systems (Eykholt et al. 2018; Bras et al. 2020; Mishra et al. 2020b), making abstaining important.

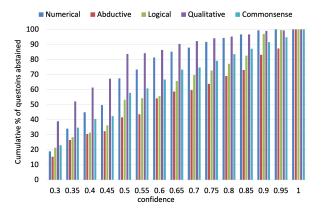


Figure 4: Confidence Vs Cumulative percentage of questions abstained on different OOD datasets.

Conclusion

We propose a novel regression based approach to train a calibrator in selective answering setting. Our approach improves area under the curve (AUC) of risk-coverage plot by 10.22% and 8.06% over maxProb with respect to the maximum possible improvement on MNLI mismatched and matched set respectively. We also propose a novel OOD setup involving questions with five types of reasoning skills: numerical, logical, qualitative, abductive and commonsense. A model not trained on such reasoning skills should abstain on as many questions as possible to avoid incorrect answering. We select confidence threshold for each of the approaches where the in-domain accuracy (SNLI) is 99%. Our results show that, the proposed method outperforms existing approaches by abstaining on 2.6% more OOD questions at respective confidence thresholds.

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