A Survey on Measuring and Mitigating Reasoning Shortcuts in Machine Reading Comprehension

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Abstract

The issue of shortcut learning is widely known in NLP and has been an important research focus in recent years. Unintended correlations in the data enable models to easily solve tasks that were meant to exhibit advanced language understanding and reasoning capabilities. In this survey paper, we focus on the field of machine reading comprehension (MRC), an important task for showcasing high-level language understanding that also suffers from a range of shortcuts. We summarize the available techniques for measuring and mitigating shortcuts and conclude with suggestions for further progress in shortcut research. Importantly, we highlight two concerns for shortcut mitigation in MRC: (1) the lack of public challenge sets, a necessary component for effective and reusable evaluation, and (2) the lack of certain mitigation techniques that are prominent in other areas.

1 Introduction

Machine reading comprehension (MRC) is a task that requires the model to answer a given question by using the provided paragraphs. To answer correctly, models need to connect and extract information across one or multiple paragraphs of text, exhibiting reading and reasoning skills; therefore, the MRC task is considered important for evaluating natural language understanding (NLU). Many large-scale MRC datasets have been proposed, such as SQuAD (Rajpurkar et al., 2016), RACE (Lai et al., 2017), HotpotQA (Yang et al., 2018), DROP (Dua et al., 2019), MuSiQue (Trivedi et al., 2022), and STREET (Ribeiro et al., 2023).

Transformer-based models (Devlin et al., 2019; Liu et al., 2019c; Yang et al., 2019; Clark et al., 2020; Lan et al., 2020, inter alia) have defeated humans on the SQuAD leaderboard. Although these results are impressive, these models are ‘brittle’ when they are evaluated on adversarial examples or out-of-distribution (OOD) test data. For example, via adversarial evaluation, Jia and Liang (2017) demonstrate that current models do not understand natural language precisely. Sugawara et al. (2018) show that many datasets contain a large number of ‘easy’ questions that can be answered by only looking at the first few words of the question. Figure 1 presents an example from SQuAD, where the model can answer the question by using word-matching (green) or the first word in the question (orange).

Inspired by these findings, lots of studies have been proposed to detect, measure, and reduce reasoning shortcuts in MRC. This raises the need for a survey paper. There are many existing survey papers for MRC, such as papers that focus on datasets (Dzendzik et al., 2021; Rogers et al., 2023) or systems/methods (Liu et al., 2019b; Baradaran et al., 2022). To our knowledge, there is no existing survey paper specifically dedicated to reasoning shortcuts in MRC. Although there are some survey papers on reasoning shortcuts (Geirhos et al., 2020; Schlegel et al., 2020a; Wang et al., 2022b; Du et al., 2023), they predominantly focus on general tasks.

Figure 1: Example of reasoning shortcuts from SQuAD. The question can be answered by using word-matching (green) or the first word in the question (orange).
in NLP or in larger domains such as computer vision. For example, Geirhos et al. (2020) focus on shortcut learning in deep neural networks, including computer vision, while Schlegel et al. (2020a), Wang et al. (2022b), and Du et al. (2023) cover a broader range of tasks in NLP, such as machine translation and natural language inference (NLI).

Different from existing survey papers, we go deeper into the MRC task, and highlight the shortcut detection and mitigation shortcomings that are unique to this task. Specifically, we try to summarize and classify most existing studies to provide a broad-picture view for researchers on measuring and mitigating shortcuts in MRC (Section 3 and Section 4). We also discuss several directions for future work (Section 5). Importantly, we highlight two main concerns for shortcut mitigation in MRC: the lack of public challenge sets and the lack of certain mitigation techniques that are prominent in other areas. Figure 2 summarizes the techniques for measuring and mitigating shortcuts we survey in this paper, as well as proposed future directions.

2 Background

2.1 Machine Reading Comprehension Task

MRC is a sub-field within NLU where the text prompts given to the model are longer in nature, thus requiring the model’s reading comprehension capability. Based on the answer format, four types of MRC datasets are available: span extraction, multiple-choice (MC), cloze style, and free-form answer (Chen, 2018). In addition, to evaluate the multi-step reasoning ability of the models across paragraphs, Welbl et al. (2018) introduce the multi-hop MRC task. It requires a model to answer a given question by performing reasoning over multiple paragraphs. Recently, conversational MRC tasks such as Choi et al. (2018) and Reddy et al. (2019) have also been introduced. For a comprehensive list of available datasets, we refer the reader to Dzendzik et al. (2021), Sugawara et al. (2021), Bai and Wang (2022), and Rogers et al. (2023).

2.2 Definitions and Terminologies

**Reasoning Shortcut** We define shortcuts as statistical correlations in the data that allow a machine learning model to achieve high performance on a task without acquiring all the intended knowledge. When these shortcuts happen in a task that was supposed to require a reasoning step, we denominate it reasoning shortcut. The most important side-effect of shortcut learning is under-performance on adversarial or OOD data.

**Adversarial Example** Following previous studies (Geirhos et al., 2020; Schlegel et al., 2020a; Zhang et al., 2020), we define adversarial examples as those that are designed to mislead machine learning models but not humans. Usually, the perceived difficulty for a human remains unchanged, while models fail due to their shortcut behavior.

**Challenge Set** An evaluation dataset that highlights a particularly difficult aspect of a task, such as overcoming a prominent shortcut. These datasets are important to allow comparison between methods, and assess the progress made in shortcut mitigations.

**Robustness and Generalization** We define a model as robust if its performance remains rela-
tively unaltered under adversarial attacks. Similarly, a model has the ability to generalize if it can perform well on OOD test data.

3 Measuring Shortcuts

Measuring the presence of shortcuts is an important first step necessary to understand the behavior of models and the biases present in the training data. In this work, we divide the existing methods into four main groups from Sections 3.1 to 3.4.

3.1 Adversarial Data Evaluation

Adversarial samples are a clear and convenient way to highlight shortcut behavior because they are easy to construct and pose no additional difficulty for humans to solve. Adversarial methods either add or edit an original example to create a more challenging example. Based on the change of the gold label, we divide this method into two main groups: (1) label-preserved (the answer is unchanged) and (2) label-changed (the answer is changed). We summarize the methods we cover in Table 1.

Label-Preserved We divide this group into the following four types.

Context-modification: Jia and Liang (2017) is the first work that proposed adversarial examples for evaluating reading comprehension systems. They insert distractor sentences into the original context of SQuAD (AddSent); their experimental results demonstrate that the current models fail to answer the modified examples. After that, Wang and Bansal (2018) extend the AddSent method by adding the distractor sentence into various locations in the context (AddSentDiverse). In addition to showing that the models are fragile on AddSentDiverse, they also showcase how their method improves robustness. In the same direction, Tran et al. (2023) introduce a negation attack for SQuAD 2.0 to make models produce unanswerable responses to answerable questions. They found that the performance of models trained on SQuAD 2.0 drops significantly on the negation attack. Wallace et al. (2019) propose a universal adversarial attack by using gradient-guided search for many tasks in NLP, including MRC. Their triggers can attack 72% of ‘why’ questions in SQuAD, making them produce the same answers. They also reveal that the models are based heavily on the words around the answer in the paragraph and question types when producing an answer.

For the multi-hop MRC task, instead of adding distractor sentences, Jiang and Bansal (2019) add a distractor paragraph. They demonstrate that many examples in the HotpotQA dataset contain reasoning shortcuts, where the models can answer the question by using word matching.

Question-modification: Ribeiro et al. (2018) introduce a set of rules that modify some characters in the question but still keep the semantics. These are called semantically equivalent adversarial rules (SEARs). Their experimental results show that models are weak to these changes; the model’s predictions are changed after applying these rules. After that, Rychalska et al. (2018) modify the questions by changing some important words using the LIME (Locally Interpretable Model Agnostic Explanations) framework (Ribeiro et al., 2016). They show that performance decreases when some words in the questions are replaced with their synonyms. Later in this direction, Gan and Ng (2019) introduce two approaches to paraphrase the questions: (1) make them similar to the original questions to test model over-sensitivity, and (2) use context words near an incorrect answer candidate. They show that their models drop in performance on both types of paraphrased questions.

Option-modification: Lin et al. (2021) modify options in the multiple-choice dataset RACE while keeping the passage and the question. Specifically, they replace one wrong option among the four candidates with an irrelevant option which is chosen from a set of options via experiments. Their results reveal that the models exploited statistical biases in the datasets when answering the questions.

Mix-modification: Si et al. (2021) introduce four types of adversarial attacks and create a new benchmark for evaluating robustness in MRC. Their dataset, AdvRACE, is created by modifying RACE. Their experimental results show that the models are vulnerable under all of these attacks; meanwhile, their dataset, AdvRACE can be served as test data for evaluating robustness. Al-Negheimish et al. (2021) evaluate top-performing models in the DROP leaderboard on a variety of modified versions of the DROP dataset. They find that the models do not reason about the question and the content of the passage, instead exploiting spurious patterns in the dataset to obtain the answers.

Label-Changed For the case when the dataset modifications include a change in the answer, Ribeiro et al. (2019) automatically generate new
Table 1: Existing adversarial methods. For each method, we present the name, the level at which the method performs modifications (e.g., word-level), the creation method, the original dataset, and the naturalness of the modified examples. Naturalness represents whether the modified example is natural and can occur in the real world. Dataset∗ represents a subset of the dataset that is used.

| Name | Add/Edit Level | Creation Method | Original Dataset | Naturalness |
|------|----------------|-----------------|------------------|-------------|
| AddSent (Jia and Liang, 2017) | sentence | semi-auto | SQuAD | ✓ |
| AddSentDiverse (Wang and Bansal, 2018) | sentence | semi-auto | SQuAD | ✓ |
| Negation (Tran et al., 2023) | sentence | auto | SQuAD 2.0 | ✓ |
| Universal (Wallace et al., 2019) | sentence | auto | SQuAD | ✓ |
| AddDoc (Jiang and Bansal, 2019) | paragraph | auto | HotpotQA | ✓ |
| Label-Preserved | | | | |
| SEARs (Ribeiro et al., 2018) | question | auto | SQuAD | ✓ |
| Word-Replace (Rychalska et al., 2018) | question | semi-auto | SQuAD | ✓ |
| Ques-Paraphrase (Gan and Ng, 2019) | question | semi-auto | SQuAD | ✓ |
| Modify-Option (Lin et al., 2021) | option | auto | RACE | ✓ |
| Mix-Attack (Si et al., 2021) | char/sent | auto | RACE | ✓ |
| (Al-Negheimish et al., 2021) | ques/pass | auto | DROP* | ✓ |
| Changed | | | | |
| Consistency (Ribeiro et al., 2019) | question | auto | SQuAD | ✓ |
| Contrast Sets (Gardner et al., 2020) | word | experts | DROP, Quoref, ... | ✓ |
| SAM (Schlegel et al., 2021) | word | auto | SQuAD, HotpotQA, DROP, NewsQA | ✓ |
| Break, Perturb, Build (Geva et al., 2022) | question | auto | DROP, HotpotQA, IIRC | ✓ |

From the above-mentioned methods, we have several adversarial or challenge datasets, such as Adversarial SQuAD and AdvRACE. Additionally, some others are created by humans or a human-and-model in the loop process. Specifically, Khashabi et al. (2020a) apply human-driven natural perturbations to create a natural perturbation dataset (Natural-Perturbed-QA) in which the answer can be changed or unchanged when compared with the original example. Bartolo et al. (2020) use a human-and-model-in-the-loop method to create the AdversarialQA dataset. Similar to Bartolo et al. (2020), Kiela et al. (2021) introduce the Dynabench framework, which supports human-and-model-in-the-loop dataset creation. They apply their framework for four NLP tasks, including the MRC task. Different from all the mentioned approaches, Miller et al. (2020) introduce four new test sets for SQuAD, with three of them aiming to measure robustness to natural distribution shifts. They find that models are less robust on two of these three datasets, while human results remain the same. All adverserial datasets are summarized in Appendix A.1.

3.2 Artifact-Based Models

Artifact-based models are trained on insufficient or incomplete data, such as question-only, passage-only, or single-paragraph-only (in multi-hop tasks). If these models perform well, it can be inferred that
the missing information was not necessary, and shortcuts were used within the provided data.

Kaushik and Lipton (2018) perform various experiments on 5 MRC datasets by using two artifact-based models: question-only and passage-only. Their results reveal that the models can achieve higher scores when they are trained in this way. For example, in task 18 of the bAbI dataset, the question-only approach obtains 91%, while the best performance of a standard model is 93%. These results indicate that the models are not solving the task in the manner expected, and instead abuse shortcuts. After that, Si et al. (2019) use the same methods as Kaushik and Lipton (2018); they also add another experiment by shuffling the words in the context. They suggest that there exist artifacts and statistical cues in five MC datasets.

In multi-hop MRC, where at least two paragraphs are required to answer the question, Min et al. (2019a) and Chen and Durrett (2019) design a sentence-factored model and a single-paragraph BERT-based model respectively. The introduced models are not trained in the full context; therefore, they should not have the ability to answer the questions. However, their results show that these models can answer a large portion of examples; this indicates that these models do not perform multi-hop reasoning in the QA process. With the same idea, Trivedi et al. (2020) introduce the DiRe (Disconnected Reasoning) condition by removing the connection of the two supporting facts to measure reasoning shortcuts. They conclude that there had not been much progress in multi-hop reasoning.

Different from the above works, Sugawara et al. (2018) use the first few words in the question instead of using the full question. It was revealed that the BiDAF model (Seo et al., 2017) can infer the answer by using entity type matching. Sen and Saffari (2020) expand the idea in Sugawara et al. (2018) by using BERT and find that again, the model can answer the questions without using most or all of the words in the question.

There is one special case in this group where a shortcut is detected by using a subset of the dataset. Specifically, Ko et al. (2020) demonstrate the presence of the position bias in the SQuAD dataset by training the models on a subset of SQuAD in which the answer is in the first sentence of the context. Model performance drops significantly when evaluated on the SQuAD development set.

3.3 Intermediate Reasoning Task Evaluation

The underlying reasoning process from question to answer is important information to verify whether the models know how to answer the question in a step-by-step manner. One special requirement for this method is that it is only applicable to complex questions, such as multi-hop questions. The reasoning steps from question to answer of complex questions can be used to design new sub-tasks or to evaluate the reasoning abilities of the model.

In general, there are two main types of questions in the multi-hop MRC task: bridge and comparison questions. Tang et al. (2021) simply evaluate the underlying reasoning process via a set of sub-questions for bridge questions. It reveals that the existing multi-hop models do not have the ability to answer the sub-questions well, and many of them are answered incorrectly while their corresponding multi-hop questions are correctly predicted. After that, Ho et al. (2022) evaluate the underlying reasoning process for comparison questions by introducing the HieraDate dataset with three probing sub-questions: extraction, reasoning, and robustness. They find that even when the model is fine-tuned on the reasoning sub-questions, it does not have the ability to subtract two dates, although it can subtract two numbers.

Inoue et al. (2020) and Ho et al. (2020) propose a new task for predicting or generating the reasoning chain; it is called derivation prediction in R^4C and evidence generation in 2WikiMultiHopQA (2Wiki; Ho et al., 2020). Wolfson et al. (2020) propose the ‘Break It Down’ dataset that contains an ordered list of steps in the process from question to answer. However, these steps are only used for training, not for evaluation. After that, Geva et al. (2021) introduce the StrategyQA dataset with sub-questions to explain the answers. Recently, Trivedi et al. (2022) propose the MuSiQue dataset, which is constructed via single-hop question composition. Most of these existing multi-hop datasets contain only a small number of reasoning steps, which are easy for the models. To solve this issue, Ribeiro et al. (2023) introduce the STREET dataset with more reasoning steps in the QA process. STREET requires a model not only to predict an answer for the question but also to generate a step-by-step structured explanation to explain the answer. Their results reveal that few-shot prompting GPT-3 and fine-tuned T5 do not possess sufficient skills to generate the structured reasoning steps.
We summarize all the studies mentioned above in Appendix A.2. As shown in Appendix A.2, currently, there are many forms (e.g., sub-questions and triples) used to represent the reasoning steps from the question to the answer. However, it is still not clear what the different effectiveness of each form is for measuring and mitigating shortcuts.

There are some other related studies to this approach, such as building more explainable models (Min et al., 2019b; Fu et al., 2021) by using question decomposition (Perez et al., 2020).

### 3.4 Language Understanding Skills Evaluation

For humans to answer the question in the MRC task correctly, it requires several skills such as entity linking or coreference resolution. In this section, we explore approaches that evaluate models on these basic skills. Models that answer the task correctly but fail at the required skills for the task can be said to be abusing shortcuts.

Ribeiro et al. (2020) introduce CheckList, a list of basic linguistic skills to test the models comprehensively. Includes several skills, such as temporal reasoning, negation, coreference resolution and semantic role labeling. Their results show that models do not have the abilities to handle these skills. As an example, given the context “Aaron is an editor. Mark is an actor.” and the question “Who is not an actor?”, the model incorrectly predicts “Mark”. At the same time, Dunietz et al. (2020) introduce a template of understanding, which is “a set of question templates”, to systematically test the comprehension abilities of the models regarding the content. Through a pilot experiment, they show that the XLNet (Yang et al., 2019) model performs worse on their designed questions.

Wu et al. (2021) introduce seven MRC skills that are related to discourse relations, such as negative causality reasoning and explicit conditional reasoning. Their results show that the three datasets (SQuAD, SQuAD 2.0, and SWAG (Zellers et al., 2018)) are insufficient for evaluating the understanding of discourse relations. Prior to this, Sugawara et al. (2020) analyze 10 datasets with 12 requisite skills. They also conclude that most existing MRC datasets might be insufficient for evaluating the discourse relations understanding.

We argue that evaluating the models on more basic NLP skills is an effective way to ensure that the models follow what humans do in the QA process. Future studies for carefully designing a set of language skills corresponding to each evaluation test data would be a need.

### 3.5 Summary & Discussion

In addition to the studies belonging to these groups, there are several methods that detect reasoning shortcuts by manually analyzing the datasets (Pugaliya et al., 2019; Schlegel et al., 2020b; Lewis et al., 2021). For example, via analysis, Lewis et al. (2021) show that there is a significant overlap between the train and test sets. Via experiments, they show that the model performance is worse on test examples that do not overlap with the training set.

The four introduced methods can be divided into two types: external and internal. Adversarial data evaluation and artifact-based models are the external methods; meanwhile, intermediate reasoning task evaluation and language understanding skills evaluation are the internal methods. The external methods do not focus on the reasoning steps from question to answer. In contrast, the internal methods focus on evaluating the reasoning steps in the QA process or evaluating related basic language understanding skills that are necessary for humans in the QA process. Both methods can detect the existence of shortcuts in the QA process of the current MRC models. It seems that the internal methods are more explainable and more similar to humans in the QA process than the external methods.

In summary, there are four types of shortcuts that the existing studies have detected: 
*entity type*, 
text overlap (it includes question-passage overlap and train-test overlap), 
*statistical bias*, and 
*position bias*. However, there may still be many other types of shortcuts that we have not discovered yet.

### 4 Mitigating Shortcuts

Most shortcut measuring approaches detailed in the previous section can be leveraged for mitigation purposes. Thus, we follow a similar order: training on several kinds of adversarial data, followed by leveraging artifact models and data subsets, then utilizing the intermediate reasoning tasks, and finally a brief mention of other approaches.

#### 4.1 Training on Adversarial Data

**Adversarial Datasets** Adversarial data was described in 3.1 as a vital approach to highlight unwanted model behaviors. However, it can also be used as an effective mitigation approach. As a
matter of fact, most studies that collect or generate adversarial data also use it as training data to analyze the robustness improvements. For example, both AddSent (Jia and Liang, 2017) and AddSentDiverse (Wang and Bansal, 2018) have trained models on their newly generated data. While AddSent showed only ‘limited utility’, AddSentDiverse achieved ‘significant robustness improvements’. The more elaborate AddDoc, which appends whole documents as an additional source, shows ‘statistically significant improvements’ when training on the generated data.

While the above methods use automatically generated data, it is also common to refer to human crowdsourcing to generate adversarial samples. Bartolo et al. (2021) propose to improve the quality of such adversarially collected data with automatic procedures, achieving even stronger results. Naturally, manual annotation usually yields more diverse data at a higher cost, but suffers from the well-known human annotation artifacts. Arguably, any adversarial dataset can be used for training, and should in a majority of cases contribute towards robustness. Liu et al. (2019a) illustrate this clearly: including just a few samples of adversarial data in the training process greatly improves scores, a clear indication of their debiasing potential.

UnifiedQA (Khashabi et al., 2020b) was recently introduced as a new state-of-the-art model for question answering, its strong-point being that it was trained on a large variety of datasets at once. Yet, limitations on generalizability are still being observed. In Le Berre et al. (2022), an unsupervised question generation process is developed that, similarly to other adversarial data generation methods, contains distractor sentences. This additional data helps UnifiedQA improve its out-of-domain generalization. This research direction shows that, even at extreme data and model sizes, generalization remains an issue and adversarial data generation can continue to help improve performance.

**Unanswerable Data**  Unanswerable questions are samples in the dataset that require a new ‘unanswerable’ label, and the model should correctly identify the questions that have no answer. The main goal is to avoid over-confidence, which contributes to the reduction of shortcut abuse.

Trivedi et al. (2020) introduce a method to transform datasets to include ‘disconnected reasoning’ evaluation in HotpotQA. Essential paragraphs required for a complete reasoning chain are grammatically removed, and the new data can be used to train a model to predict when the question is answerable, which in turn reduces shortcut-learning behavior. Lee et al. (2021) obtain pseudo-evidentiality labels for HotpotQA, such that the training set contained both questions with enough evidence and questions without. On the latter, the model is discouraged from achieving high confidence by modifying the training objective. Tran et al. (2023) compare models trained on answerable samples only (SQuAD) and models trained on both answerable and unanswerable samples (SQuAD 2.0). By introducing a technique called ‘force to answer’, they show that models trained on SQuAD 2.0 are more robust than those trained on SQuAD for answerable questions. Additionally, models trained on SQuAD 2.0 also demonstrate greater robustness on additional OOD datasets.

**Data Perturbations**  Data perturbations or augmentations have been standard practice in computer vision for a long time, and only significantly entered the NLP in more recent years. Feng et al. (2021) outline the main approaches that exist to date. As an important subfield, perturbations can be made to the embedding space instead of the input token space. Liu et al. (2020) perform this technique on the SQuAD dataset, with this being the only notable mention for MRC. Tangentially, while not an MRC application, we see potential in the approach taken by Wang et al. (2022a), where individual biased words are masked out, leading to debiasing benefits.

### 4.2 Altering the Training Process

The approaches in this section utilize some additional information to either modify the loss function, or filter out / select certain samples in the training data.

**Debiasing Losses**  For this technique, we require a purposefully biased model whose predictions will be used to estimate the level of bias in each sample. These models can be created as described in Section 3.2. The bias level can be leveraged during train time, modifying the loss function to discourage bias learning.

Product-of-expert (Hinton, 2002) combines the logits of the biased model with those of the target model. The target model is thus forced to take the lead in learning non-biased behavior, as the bias is already being provided. A successor to this strategy, Learned Mixin (Clark et al., 2019),
has a learnable parameter controlling the balance between the logits of both models. On the other hand, Sample Reweighting (Schuster et al., 2019) reduces the contribution of biased samples towards the loss, while Confidence Regularization (Utama et al., 2020a) aims to encourage the model to produce higher-entropy answers for biased questions by smoothing the labels based on the bias level.

In MRC, we have seen a few major applications of these methods. Clark et al. (2019) compare Product-of-Expert against Learned Mixin on the SQuAD dataset, while Wu et al. (2020) apply Confidence Regularization leveraging multiple biases simultaneously by incorporating the biased predictions of several models into the loss function. It is one of the more comprehensive debiasing works in MRC, with five datasets being used to evaluate the approach: SQuAD, HotpotQA, TriviaQA (Joshi et al., 2017), NewsQA (Trischler et al., 2017) and Natural Questions (Kwiatkowski et al., 2019).

The case of removing unknown shortcuts or biases is treated as a separate challenge. In this scenario, we cannot build artifact-based models; instead, we use the concept of weak models. Sanh et al. (2021) propose using under-parameterized models, under the assumption that these models learn mostly shortcuts. Their method is evaluated on SQuAD. Similarly, Utama et al. (2020b) proposed utilizing an under-trained model. Ghaddar et al. (2021) improve the technique even further by integrating the bias model (a simple attention-based classification layer) into the main model, and training both simultaneously. This brings the benefit of avoiding the separate weak model training stage. Generally speaking, there is a lack of work regarding the removal of unknown shortcuts in the field of MRC, and we expect this area to experience more attention in the coming years.

Valuable Subsets We include in this category methods that select a subset of the data for retraining or additional training, with the goal of improving robustness. We mention these methods due to their importance in other NLP tasks, but their application in MRC is yet to be seen. The existing methods for this technique are presented in Appendix B.1.

4.3 Utilizing Intermediate Reasoning Tasks

The idea behind this approach is to determine whether utilizing the intermediate tasks along the path from question to answer can improve the robustness of the models. Currently, there are two well-defined tasks in the QA process. The first one is extractive rationale prediction (Lei et al., 2016; Chen et al., 2022). The extractive rationale is referred to as a highlight in Wiegreffe and Marasović (2021). This information is also similar to the ‘sentence-level supporting facts (SFs)’ in the multi-hop MRC task. This task is often formulated as a binary classification task, where the objective is to predict sentences or words that appear in the context and can be used to answer the questions. The second task is reasoning chain prediction. This task is similar to the task in Inoue et al. (2020) and Ho et al. (2020) (refer to Section 3.3 for details).

Chen et al. (2022) propose three types of attacks and conduct experiments on 5 datasets, including two MRC tasks (SQuAD and MultiRC (Khashabi et al., 2018)), to verify whether rationalization can improve the robustness of the models. Their results reveal that explicitly training the models with the rationale prediction task does not guarantee the robustness of the models on attacks. Ho et al. (2023) utilize both sentence-level SFs task and entity-level reasoning task in the multi-hop MRC task for their training. They find that the model, trained with intermediate tasks, reduces position bias in the 2Wiki dataset but not in a subset of HotpotQA. They attribute this result to varying levels of position bias and differences in the percentage of comparison and bridge questions across the datasets. In summary, these results are quite sensitive to the datasets. Currently, there are no comprehensive analyses that fully exploit the effectiveness of intermediate tasks to prevent reasoning shortcuts and biases.

4.4 Other Approaches

InfoBERT (Wang et al., 2021) was recently proposed as a way to control the amount of information that is learned during the fine-tuning stage. The goal is to use the mutual-information measure to filter out noise and obtain more robust representations. Promising results have been obtained in several tasks including SQuAD.

4.5 Summary & Discussion

We have covered methods of varying kinds to mitigate or reduce the effect of shortcuts in our models. A table with the list of studies and the challenge set used can be found in Table 2. Adversarial data and bias labels with artifact models are more difficult to apply, since they require a deeper knowledge about the kinds of shortcuts that are present, or in-
Table 2: Major shortcut mitigation works in MRC and their corresponding evaluation (challenge) sets.

| Name                                                                 | Type/Sub-type | Evaluation Dataset               |
|----------------------------------------------------------------------|---------------|----------------------------------|
| AddSentDiverse (Wang and Bansal, 2018)                               | Adversarial   | Adversarial SQuAD                |
| AddDoc (Jiang and Bansal, 2019)                                      |               | Add4Docs, Add8Docs               |
| Synthetic Adversarial Generation Pipeline (Bartolo et al., 2021)     | Adversarial   | AdversarialQA                    |
|Disconnected Reasoning (Trivedi et al., 2020)                        | Unanswerable  | Custom                           |
| Pseudo-evidentiality in HotpotQA (Lee et al., 2021)                 |               | Custom                           |
| Force to Answer (Tran et al., 2023)                                 | Perturbations | Adversarial SQuAD                |
| Embedding Space Perturbations (Liu et al., 2020)                    | Bias Labels   | Non-Adv OOD Tasks                |
| Learned-Mixin (Clark et al., 2019)                                  |               | Adversarial SQuAD                |
| Multi-bias Confidence Regularization (Wu et al., 2020)              |               | Adversarial SQuAD                |
| Underparameterized Weak Models (Sanh et al., 2021)                  |               |                                  |
| Rationalization (Chen et al., 2022)                                 | Intermediate  | Custom                           |
| Reasoning Steps (Ho et al., 2023)                                   |               | Custom                           |
| InfoBERT (Wang et al., 2021)                                        | Regularization| Adversarial SQuAD                |

volve expensive annotation and verification work. The other methods, including bias labels with weak models, can be applied with more ease.

SQuAD receives the most attention, as most papers showcase their mitigation techniques against Adversarial SQuAD. We highlight the lack of challenge sets for more MRC datasets in Section 5, and encourage further work on mitigation methods that have not seen an application outside of SQuAD.

5 Future Directions

Evaluating on More Basic NLP Tasks When humans can answer the question correctly, humans also can answer several related basic tests that are required for the QA process correctly. Ribeiro et al. (2020) introduce the CheckList — a list of linguistic skills for model evaluation. However, their list is not complete (e.g., only in MC questions form), and it is automatically generated without using internal knowledge. To develop safer and more controllable models, we should carefully design a list of basic NLP tasks for comprehensive evaluation.

Building More Community Challenge Sets Adversarial SQuAD has been the most used challenge set for studies proposing mitigation techniques in MRC, as is reflected in Table 2. Most others either use a custom dataset, or propose one that has not been widely adopted yet. For example, Lee et al. (2021) create a challenge set version of HotpotQA by excluding samples where models ignored evidentiality requirements. We argue that more challenge sets are needed, especially utilizing other MRC datasets as a base. Adopting a wider range of testbeds will allow future mitigation techniques to be more thoroughly evaluated, and more importantly, compared with each other.

Adopting More Mitigation Methods We would like to encourage the community to explore the wider range of mitigation methods available. For example, finding a more valuable data subset based on minority samples, or training a weak model for unknown-bias debiasing.

Connecting Intermediate Reasoning Tasks and Chain-of-Thought Wei et al. (2022) introduce chain-of-thought (COT) prompting, demonstrating its ability to enhance the performance of large language models (LLMs) on complex reasoning tasks by generating intermediate reasoning steps. However, it is still unclear whether COT can improve the robustness of LLMs or not. We believe that exploring the relationships between COT and reasoning shortcuts in the multi-hop MRC would be interesting (e.g., whether COT can overcome the reasoning shortcut issues?).

Checking the Validity and Naturalness of Adversarial Examples Morris et al. (2020) evaluate two type of attacks and show that the obtained adversarial examples “often do not preserve semantics” and contain grammatical errors. Dyrmishi et al. (2023) survey 378 people about the perceptibility of the adversarial examples. They reveal that a large portion of the adversarial examples do not pass human quality standards. It is noted that these
two studies were only conducted for text classification and entailment tasks. We suggest thoroughly examining the validity and naturalness of adversarial examples in the MRC task to determine if model failures are genuine or if the issue stems from the quality of the adversarial examples.

6 Conclusion

We have covered the shortcut identification and mitigation landscape in MRC. The presence of shortcuts can be made clear through a variety of methods, and most researchers are aware of this issue. Mitigation methods are varied and have some degree of success, but a lot more work is needed before we can achieve models mostly free of shortcut biases. Efforts should be made to improve MRC shortcut debiasing techniques by incorporating those found in other fields such as computer vision and NLI, as well as finding methods with lower human and/or computation costs.

Limitations

With the rapid growth of the research community and the limited length of the paper, we cannot guarantee that we cover all existing methods in the ‘Measuring Shortcuts’ and ‘Mitigating Shortcuts’ sections. Instead, we summarize and classify the most prominent studies across different approaches and methodologies for each section.

We also do not have a section discussing why MRC models learn shortcuts. We refer readers to Lai et al. (2021) and Du et al. (2023). In summary, the reasons explaining why MRC models learn shortcuts can come from various factors, such as the size and training objective of the LMs, as well as the existing shortcuts in the training set.

Recently, many research papers related to LLMs (Zhao et al., 2023) are being published every day. Various types of promptings (Qiao et al., 2023) are being introduced to leverage the abilities of LLMs. Most of the studies we cover in this survey, which focus on measuring shortcuts and mitigating shortcuts, are related to pre-trained language models rather than LLMs. We will leave the study of reasoning shortcuts and the robustness of LLMs for future work.

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Type | Datasets
--- | ---
Label-preserved | Adversarial SQuAD (Jia and Liang, 2017), Add4Docs & Add8Docs (Jiang and Bansal, 2019), AdvRACE (Si et al., 2021)
Label-changed | Contrast Sets (Gardner et al., 2020), SAM (Schlegel et al., 2021)
Mix | Natural-Perturbed-QA (Khashabi et al., 2020a)
Adversarial annotation | AdversarialQA (Bartolo et al., 2020), Dynabench (Kiela et al., 2021)
Natural distribution shift | Natural-shift-QA (Miller et al., 2020)
Unanswerable questions | Not-answerable questions (Nakanishi et al., 2018), SQuADRun (Rajpurkar et al., 2018), MuSiQue (Trivedi et al., 2022)

Table 3: Existing adversarial datasets and their corresponding types. Mix denotes the datasets that include both label-preserved and label-changed samples. Unanswerable questions indicate the datasets that contain unanswerable questions. It is noted that for the two types, Label-preserved and Label-changed, each method in Table 1 would create a new dataset. For brevity, we only mention some popular adversarial datasets in these two types.

| Paper | Form | Purpose | Task | Github | Dataset | Note |
| --- | --- | --- | --- | --- | --- | --- |
| Inoue et al. (2020) | Triple | Evaluation & Training | Derivation generation | URL | R4C | based on HotpotQA |
| Ho et al. (2020) | Triple | Evaluation & Training | Evidence generation | URL | 2WikiMultiHopQA | |
| Wolfson et al. (2020) | QDMR | Training | - | URL | Break it down | based on ten datasets (e.g., HotpotQA & DROP) |
| Tang et al. (2021) | Sub-question | Evaluation | QA about sub-questions | URL | 1000 samples | based on HotpotQA |
| Geva et al. (2021) | Sub-question | Evaluation & Training | QA about sub-questions | URL | StrategyQA | implicit questions |
| Ho et al. (2022) | Sub-question | Evaluation & Training | QA about sub-questions | URL | HieraDate | only for comparison about Date information |
| Trivedi et al. (2022) | Sub-question | Evaluation & Training | QA about sub-questions | URL | MuSiQue | |
| Dalvi et al. (2021) | Entailment Tree | Evaluation & Training | tree generation | URL | EntailmentBank | based on ARC and WorldTree V2 |
| Ribeiro et al. (2023) | Graph | Evaluation & Training | Graph generation | URL | STREET | based on ARC, SCONE, GSM8K, AQUA-RAT, and AR-LSAT |

Table 4: All studies and datasets that are mentioned in Section 3.3: Intermediate Task Evaluation.
is re-trained on those samples that had a low loss during the first training pass. Again, performing additional training steps on these subsets has a positive impact on robustness.

Finally, Bras et al. (2020) use the notion of predictability to filter out samples with a negative bias influence. Their adversarial algorithm identifies these samples, and their filtered results show promising debiasing performance.