arXiv:2201.05017v3 [cs.CL] 14 Feb 2022

Towards Automated Error Analysis: Learning to Characterize Errors

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Abstract

Characterizing the patterns of errors that a system makes helps researchers focus future development on increasing its accuracy and robustness. We propose a novel form of "meta learning" that automatically learns interpretable rules that characterize the types of errors that a system makes, and demonstrate these rules' ability to help understand and improve two NLP systems. Our approach works by collecting error cases on validation data, extracting meta-features describing these samples, and finally learning rules that characterize errors using these features. We apply our approach to VilBERT, for Visual Question Answering, and RoBERTa, for Common Sense Question Answering. Our system learns interpretable rules that provide insights into systemic errors these systems make on the given tasks. Using these insights, we are also able to "close the loop" and modestly improve performance of these systems.

1 Introduction

Although deep-learning systems have made remarkable progress in recent years, systems still make a significant number of errors on complex and diverse tasks. An important step in engineering highly-accurate, robust systems is error analysis, which has been defined as the process of examining development set examples misclassified by the algorithm and understanding the underlying causes of those missclassifications. This process helps engineers prioritize critical problems and prompts them in the direction of handling the problems (Solegaonkar 2019).

Unfortunately, such analysis usually needs manual inspection and reasoning, which is an onerous, timeconsuming and hit-or-miss process. Pure manual analysis may lead to a biased conclusion, as common features appearing in both successful and failed classifications could be misunderstood as the root cause of failure (Rondeau and Hazen 2018). While other works have proposed improved approaches to error analysis (e.g. Wu et al. 2019; Kahng et al. 2017; Chung et al. 2020), some are not scalable to large-scale datasets, hindering their practical application, while others require a deep understanding of the errors even before conducting their proposed method. In contrast, our pipeline (1) makes weak prior assumptions about the attributes of failures, (2) is scalable to large-scale datasets, (3) groups errors with interpretable and globally unbiased rules, enabling fast manual inspection and analysis. Developers can benefit from such a systematic view and develop patches addressing different problems disclosed by different sets of rules.

Specifically, we propose using machine learning to help automate error analysis by inducing interpretable rules that characterize the errors that a system makes. First, our approach runs a predictive model on a set of held-out validation data and records which examples the system classifies correctly or incorrectly. Next, we characterize each example using a set of "meta-features" that describe the problem (e.g. for question answering, a meta-feature could be: question starts with "How many"). Finally, we learn interpretable rules from this data which predict failure using these metafeatures (Figure 1). For example, one rule could be: "If the question starts with 'How many' and the answer is greater than 2, then it is probably wrong." In fact, this is an example of a rule learned by a prototype of our approach when analyzing the errors made by a Visual Question Answering (VQA) system that does not include a specific mechanism for counting problems.

Developers can then browse the errors grouped by the rules and gain insight from the errors and their description. This can guide them to engineer improvements to the system that increase its accuracy and robustness. They can also help developers and users build a "mental model" of the system that enables them to better predict its performance and gauge when and when not to trust it.

To demonstrate the effectiveness of our approach, we present results applying our approach to ViLBERT (Lu et al. 2019) for Visual Question Answering v2.0 (VQA) (Goyal et al. 2018), and RoBERTa (Liu et al. 2019) for CommonsenseQA (CSQA) (Talmor et al. 2019). We induce humaninterpretable rules providing insights into systemic errors these systems make on these tasks. We then show how to "close the loop" and modify the systems to improve their performance using some of these insights.

2 Automatic Error Characterization

This section describes the pipeline for our approach to automatic error characterization. It first runs a pre-trained system on development data not used during training and collects the predictions that it makes. Next, these examples are described using a set of extracted meta-features that character-

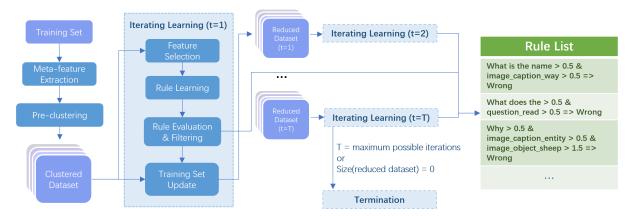


Figure 1: Pipeline Overview

ize properties of the problems. Finally, we run a rule learner that uses these meta-features to characterize the model's mistakes. Figure 1 provides a visualization of this pipeline.

2.1 Meta-feature Extraction

Meta-feature engineering is a domain-specific process requiring understanding of the problem as well as the properties that affect model behavior. For our two QA tasks, language tokens in the questions and the gold answers are the most important meta-features. For images in VQA, we added meta-features representing objects in images detected by YOLOv3 (Redmon and Farhadi 2018) as well as generated image captions (Luo et al. 2018), which may encode extra properties and relations for the objects in the image.

All the text tokens are then lemmatized and part-of-speech tagged, providing additional meta-features. We lookup all nouns and verbs in WordNet (Miller 1995) and add their hypernyms up to 4 levels as additional meta-features. Hypernyms help group similar features across examples and allow more abstract characterizations of error cases. Finally, stopwords are removed and all meta-features are represented by a sparse vector, where each entry represents the occurrence frequency of one meta-feature in an example. Figure 2 gives an overview of this process for VQA.

2.2 Pre-clustering

Characterizing a large dataset is difficult for existing rule learners due to issues scaling to large numbers of examples and features. Hence, motivated by discriminative clustering (Bansal, Farhadi, and Parikh 2014), we first cluster the dataset into several smaller sub-datasets and run the rule learner on each cluster separately. This pre-clustering step speeds up the rule extraction process and helps arrange the resulting rules in a semantically meaningful way.

Following the prior work (Bansal, Farhadi, and Parikh 2014), we run k-means on the error cases (i.e. positive examples) and build 2 clusters for CSQA. Both of them are combined with all negative examples, creating 2 smaller overlapping sub-datasets for rule learning. Similarly, we run k-means on VQA error cases and found that words that typically represent question types (e.g. "why") are all close to

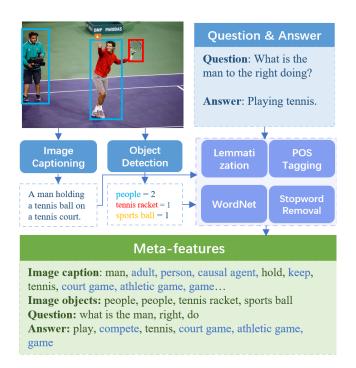


Figure 2: Meta-feature extraction process. Hypernyms in meta-features are marked in blue.

cluster centers. To obtain finer-grained clusters that better divide the tremendous amounts of data, we proceeded with this observation and categorize the dataset into 65 clusters by question types which are given in the official annotations for this data.

2.3 Rule Learning

Finally, we automatically induce a model that predicts success or failure on an example given its meta-features. For this task we used a rule learner which provides us interpretable insight into the errors made by the target model. Our system utilizes SkopeRules, a Python based machine learning library that "aims to learn logical and interpretable rules" (Gardin et al. 2017). While other interpretable classi-

fiers such as simple linear models could also have been used, we present the rationale for choosing rule learning in Section 3.3, where we compare our approach to other learned models trained to predict errors.

Feature Selection In practice, the raw extracted metafeature dataset is high dimensional, sparsely populated, and noisy. This prevents the rule learner from generating effective rules, justifying the necessity of dimensionality reduction. Following Yang and Pedersen (1997), we used a chisquare feature selection method as it is an efficient way to reduce the number of features. We performed grid search on the possible number of dimensions and selected 100 metafeatures as the best value.

Iterative Learning In order to make the rule learner more efficient and effective, we run it multiple times with a high precision threshold (60%) for the rules it produces, redoing feature selection at each iteration to allow new rule sets to potentially focus on a new set of important features. At the beginning of each iteration, chi-square is used to select features and SkopeRules is run on the current training set to generate a set of high-precision rules for identifying error cases. We then remove the cases covered by these rules and repeat this process until no more error cases can be characterized with high precision, or until a maximum number of iterations is reached, which is 50 in our configuration.

Rule Evaluation and Filtering To ensure learned rules accurately predict errors and do not just overfit the development set, we created a 90/10 training/test split from the original development set for the rule learning process. Rules are then learned from the training subset and evaluated on the test subset. Any rule that is not at least 60% accurate on the test split is removed from the final rule set.

3 Experimental Results

We ran our pipeline on ViLBERT pretrained on VQA, and RoBERTA finetuned on CSQA. We collected 404 and 81 rules covering 14.1% and 60.8% of error examples for two tasks respectively. Examining the rules learned from our approach, we were able to gain deeper insights into both tasks. Below we highlight and discuss some of the error patterns that we have detected.

3.1 VILBERT on VQA

OCR Problems The major category of errors that we identified involves reading text from images, therefore requiring Optical Character Recognition (OCR). Sample rules together with a covered problem instance are shown in Figure 3. For example, when a question, starting with "what", asks about a "letter," ViLBERT has an 82.7% chance of getting it wrong. Similarly, questions involving URLs and dates have low accuracy. Sign-reading problems are another typical OCR-type problem in VQA; as shown by the third example involving road signs. Some challenging OCR problems also exist in VQA, as shown by the fourth example, which requires reasoning about texts' positioning. Since the lack of OCR ability is the most significant problem uncovered by

our system, we propose a mixed architecture to alleviate it in Section 4.

Referring Expression Problems Several rules indicate that examples that require describing the position of an object are likely to cause failure, even if the answer is reasonable. Due to VQA's open-ended nature, VQA accuracy, the standard VQA evaluation metric shown below, frequently incorrectly scores answers to such questions:

VQA Accuarcy =
$$\min\left(\frac{n}{3}, 1\right)$$

where n is the number of gold answers exactly matched by the generated answer. While there are 10 gold answers as candidates, in practice, many of the 10 gold answers are identical and thus provide low tolerance to reasonable answer variants.

The examples in Figure 4 illustrate this problem for "where"-type questions, where the answers are reasonable but counted as wrong. This illustrates a problem with the scoring method rather than with the model. One proposed solution is Alternative Answer Sets (Luo et al. 2021), an improved metric relying on WordNet to recognize synonyms of a gold answer. This might solve the first and third problem in Figure 4, but it would not solve the other ones. In general, this requires determining whether two *referring expressions* denote the same object in an image, a difficult language-vision problem (Qiao, Deng, and Wu 2020).

Time-reading Problems There are some rules found that cover "what time" questions. The rules in Figure 5 illustrates the challenge with these problems. Apart from the knowledge of various number representations, the underlying clock-reading rules are also difficult for the model to infer during training.

Counting Problems VilBERT performs well on some counting problems; however, it fails on cluttered scenes with many objects as illustrated in Figure 6.

3.2 RoBERTa on Commonsense QA

We obtained several rules for RoBERTa on CSQA, that highlighted specific types of common sense knowledge which the model is lacking. For instance, the rules learn that RoBERTa is unable to answer questions related to "American states", suggesting that more prior knowledge about this topic would be helpful. More examples of concepts that seem to be the source of errors are shown in Figure 7.

3.3 Comparing Learning Approaches

In order to evaluate the accuracy of the learned rules we use to predict error cases from meta-features, we compared our approach to other learned classifiers. We compared Skope-Rules to decision trees, logistic regression, discriminative clustering (Bansal, Farhadi, and Parikh 2014) and a 2-layer MLP neural network. Decision trees, logistic regression and 2-layer MLP neural network follow the implementation in scikit-learn (Pedregosa et al. 2011). The maximum depth of the decision tree was set to 10. For the MLP network, the number of neurons of the first and the second hidden layers were 256 and 128 respectively. We re-implemented the

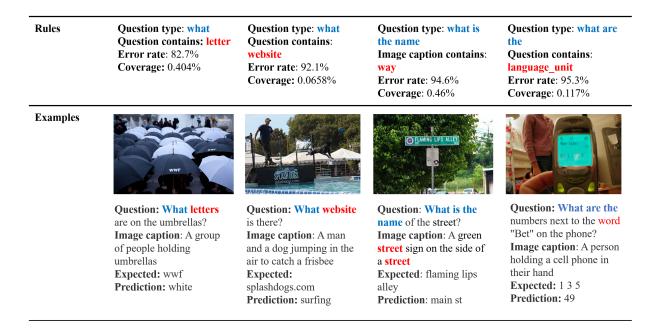


Figure 3: OCR problem examples. Words (or their hypernyms) mentioned by the rule are marked in red. Question types are marked in blue.

discriminative clustering method and chose the number of clusters to be 3.

Following the similar procedure in Section 2.3, these classifiers were trained and evaluated on new training/test sets created from the original development set of VQA and CSQA. We averaged the classifiers' precision and recall weighted by size of datasets, and plotted an average precision-recall curve for predicting errors shown in Figure 8. The results show that our SkopeRules system is competitive with other models in terms of accurately predicting error cases, at least for the high precision end of the curve.¹ It is unable to achieve high recall; however, for aiding error analysis and interpreting the weaknesses of a model, we believe precisely modeling a subset of errors is more useful than achieving high recall with low precision.

Although decision trees and discriminative clustering (Bansal, Farhadi, and Parikh 2014) are interpretable, the results show that they do not provide very high precision. While the weights on individual meta-features computed by logistic regression are also quite interpretable, we found that these globally computed feature importances without context do not provide as much insight. Conversely, Skope-Rules considers combinations of meta-features under various cases, providing more interpretable insights than other competing methods.

Overall, we believe that learned rules provide the best trade-off between producing a high-precision model of error cases while also furnishing an interpretable characterization that provides the type of insight that one is typically seeking during error analysis.

4 Improving Model Accuracy

The ultimate goal of error analysis is use the insight gained about a model's weaknesses to "close the loop" and develop an improved model. Here we present our results on using the understanding gained from examining the rules learned by our approach to increase model accuracy.

4.1 VILBERT for VQA

Not only do several learned rules indicate that ViLBERT has problems with reading text, we can use these rules to automatically identify cases where applying OCR might prevent the model from making a mistake. Therefore, we tried to utilize a state-of-the-art OCR-VQA system, M4C (Hu et al. 2020), to improve ViLBERT. Specifically designed for OCR-VQA, M4C generates answers conditioning on additional text extracted by an OCR system. We used Mask TextSpotter v3 (Liao et al. 2020) as the OCR system. To ensure M4C fits the right distribution, we trained M4C on the official training set of VQA, then finetuned M4C on training examples whose images have text. During testing, we picked the 40 most accurate OCR rules (by F-score) to identify OCR questions, and redirect these questions to M4C. The final prediction of our system is a mixture of ViLBERT and M4C, depending on whether the rules indicate the question requires OCR.

The results are in Table 1 and show this ensemble is better than either of the individual systems. The improvement is modest due to the difficulty of OCR problems and relatively low global coverage of them in the dataset (only 3.86% of the testing questions are identified as OCR problems). However it illustrates how the learned rules can help direct system improvement.

¹The curve of SkopeRules is truncated due to its high precision cut-off value in the training phase.

Rule Question type: where are the Question contains: clothing Error rate: 100% Coverage: 0.0207%

Question type: where is the Question contains: edible fruit Error rate: 80% Coverage: 0.03%

Examples **Question: Where are the Question: Where are the** Question: Where is the Question: Where is the boys in soccer uniforms? zip ties? apple? lemon? Image caption: Two Image caption: A person Image caption: a plate of Image caption: a man young boys playing a sitting on the floor with a sitting at a desk with a food with a banana and a game of soccer on a field kite laptop computer fork Expected: soccer field Expected: left Expected: on desk Expected: on right Prediction: field Prediction: bottom Prediction: table Prediction: on plate

Figure 4: Referring expression problem examples

Data Split	dev		test-c	lev			test-sta	ndard	
Question Type	Overall	Yes/No	Number	Other	Overall	Yes/No	Number	Other	Overall
M4C	53.17	68.71	38.12	47.09	54.98	68.81	37.81	47.49	55.28
ViLBERT	68.75	86.12	51.69	59.28	69.47	86.48	50.7	59.32	69.64
Mix	69.44	86.12	52.84	59.35	69.64	86.48	51.79	59.46	69.82

Table 1: Performance on VQA v2.0

Rules	Question type: what time Objects on Images: clock Error rate: 90.7% Coverage: 1.73%	Question type: what time Question contains: say Error rate: 95.7% Coverage: 0.041%	Rules	Question type: how many people are Image caption contains: group Objects on Images: number of cups ≥ 8 , number of people ≥ 7	Question type: how many Image caption contains: arrangement, bunch Objects on Images: number of bottles > 4
Examples		TTTT I		Error rate: 81.2% Coverage: 0.024%	Error rate: 88.9% Coverage: 0.015%
			Examples		
	Question: What time is it? Image caption: a clock on a wall next to a window Expected: 5:40 Prediction: 3:20	Question: What time does the clock say on the stove? Image caption: a stove top oven sitting in a kitchen Expected: 10:32			
		Prediction: 4:30		Question: How many people are gathered around?	Question: How many jars are there?
Fig	gure 5: Time-reading p	problem examples		Image caption: A group of women sitting around a table	Image caption: A group of jars of food on a table
				Expected: 6 Prediction: 10	Expected: 8 Prediction: 12

4.2 RoBERTa for CSQA

The error-analysis rules learned for RoBERTa on CSQA point to a number of general conceptual areas where the model exhibits weaknesses. One approach to improving the model based on this insight is to train the model on additional relevant data to correct for these deficiencies. We observed that while Wikipedia is a part of the pretraining dataset, RoBERTa can still "forget" critical knowledge during large scale pretraining given the overwhelming coverage of Wikipedia. Hence, we introduce a dataset refinement approach to ensure that RoBERTa has used the given pre-training data efficiently and effectively for optimizing

Figure 6: Counting problem examples

CSQA performance. We ranked discovered rules by their Fscores and picked 11 most interpretable rules for demonstration, which themselves consist of a keyword list as a summary of RoBERTa's "knowledge gap." Next, we filtered Wikipedia data by retaining sentences containing these keywords or one of their hyponyms, as well as their neighboring sentences. Afterward, RoBERTa was first finetuned on this filtered Wikipedia data and then finetuned again on Commonsense QA, obtaining 78.7% accuracy on the develop-

Rules	Answer contains: <mark>American State</mark> Error rate: 70% Coverage: 4.24%	Answer contains: kitchen Error rate: 100% Coverage: 1.41%	Question contains: chordate, where Error rate: 100% Coverage: 1.06%
Examples	Question: Where are the most	Question: From where would	Question: Where does a wild
	famous BBQ steakhouses in	you normally take a cup when	bird usually live?
	America?	you're about to get a drink?	Gold: countryside
	Gold: Texas	Gold: kitchen cabinet	Prediction: sky
	Prediction: Kansas city	Prediction: water fountain	Negative Answers: cage, sky,
	Negative Answers: building,	Negative Answers: dishwasher,	desert, windowsill
	Kansas city, Maine, falling down	water fountain, sand box, toilet	
			Question: Where is a bird likely
	Question: The tourist entered		to make its home?
	Mammoth cave, what state were		Gold: forest
	they in?		Prediction: nest
	Gold: Kentucky		Negative Answers: nest, roof,
	Prediction: West Virginia		leaves, sky
	Negative Answers: West Virginia,		-
	Rocky Hills, Scotland, Canyon		

Figure 7: Rules for RoBERTa on CSQA, green examples are correctly answered by our "refocused" RoBERTa.

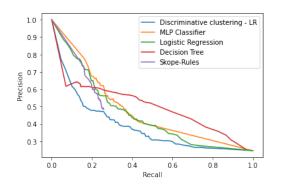


Figure 8: Precision-Recall curve of different classifiers

ment set.

As shown on Table 2, our "refocused" RoBERTa obtained a 0.35 percentage point improvement on the CSQA test set, which is nearly the best among RoBERTa's single model variants. We also show the best performance that the single RoBERTa model could achieve, which is trained with G-DAUG-Combo data augmentation technique (Yang et al. 2020)². Compared to this method, we did not augment the dataset with complex synthetic data but only refocused training on critical aspects of the original training data and still obtained 70% of the additional improvement gained by the best-performing model. The refocused model corrects several of the original errors shown in Figure 7, illustrating the effectiveness of our approach.

Model	Accuracy
RoBERTa + G-DAUG-Combo	72.6
Ours	72.45
RoBERTa (Baseline)	72.1

Table 2: Single RoBERTa's performance on CSQA test split, collected from the public leaderboard compared to our "refocused" model.

5 Related Work

5.1 Black-box Explanation

In the Explainable Artificial Intelligence (XAI) literature, the decisions made by a black-box model could be explained example-wise, i.e. in local explanations (Ribeiro, Singh, and Guestrin 2016; Lundberg and Lee 2017). Another way to explain a black-box model is disclosing its underlying decision logic in a structural and organized way, which form global explanations (Johansson and Niklasson 2009; Ribeiro, Singh, and Guestrin 2018; Krishnan and Wu 2017). Among these techniques, there has been a body of work on "rule extraction" from complex machine learning models that uses rule induction methods to produce a surrogate model that can predict the output of the trained blackbox model (Shavlik and Craven 1999; Sushil, Šuster, and Daelemans 2018; Manjunatha, Saini, and Davis 2019; Ramon et al. 2020). Unlike these prior works that extract rules mimicking the I/O behavior of a model, our approach suggest a new way to understand black-box models, which attempts to predict when their output is wrong and directly support error analysis. This provides a different form of "global explanation" that specifically characterizes the limitations of a model rather than just trying to predict its exact behavior.

²The actual best performing RoBERTa on the leaderboard is finetuned on Open Mind Common Sense (OMCS) corpus and has an accuracy of 73.3%. However, since Commonsense QA is generated from ConceptNet, which is a part of OMCS, finetuning RoBERTa on OMCS may lead to unexpected data exposure and unfair comparison.

5.2 Bias and Error Analysis

As Machine Learning techniques have gained traction in the society, revealing their potential biases and errors are also becoming vitally important. Some works have already investigated the weaknesses of VQA models (Kafle and Kanan 2017; Agrawal, Batra, and Parikh 2016), but the methods are highly specific to the task and irreproducible, whereas our method is task-agnostic given generic meta-features. Manjunatha, Saini, and Davis (2019) used a rule learner to imitate existing VQA models and explore their biases. However, rule learning is not an ideal approximator to the complex model, resulting in very limited insights. Similar to our work, Rondeau and Hazen (2018) designed meta-features associated with hypothesized challenges and trained a logistic regression classifier that predicts the difficulty of questions to evaluate hypotheses systematically. Errudite (Wu et al. 2019) helps users explore and test hypotheses to identify the underlying cause of failure. Both of them, however, require strong prior hypotheses about errors before users can design tests and gain in-depth insights from the results. In contrast, our approach only needs weak hypotheses on potentially influential properties in the meta-feature extraction process, which would be systematically and unbiasedly validated in batches, directing users to true patterns of errors and significantly facilitating the error analysis process. Bansal, Farhadi, and Parikh (2014) use a discriminative clustering approach to characterize classes of errors made by an image classifier. Unlike the declarative rules learned by our approach, the discovered clusters can be difficult to interpret. We also extract a broader range of interpretable metafeatures to characterize instances beyond the discretized image features employed in this approach, allowing a richer characterization of error classes. Moreover, none of aforementioned works has shown the practical value of error analysis, while we build better systems guided by interpretable insights and proved the quality of them.

5.3 Meta Features

The term "meta-feature" in meta-learning is used to refer to features that characterize dataset complexity (Filchenkov and Pendryak 2015; Jomaa, Schmidt-Thieme, and Grabocka 2021; Xia et al. 2020). On the other hand, concurrent works in XAI use a different interpretation of the term. "Superpixels" in image classification explanation are sometimes used as meta-features (Wei et al. 2018). In the context of natural language classification, meta-features are created by either data-driven (Ramon et al. 2020) or domain-based approaches (Alvarez-Melis and Jaakkola 2018; Chen et al. 2016) addressing the sparsity of textual features. Our approach utilizes domain-based meta-features, which categorize features into high-level and semantically similar groups even across modalities while maintaining their interpretability. These meta-features have broadened the coverage of rules and facilitated the error analysis process.

6 Conclusion & Future Work

In this paper, we presented a novel pipeline that helps automate the error analysis process by learning interpretable rules that characterize the type of mistakes that a system makes. We then demonstrated its effectiveness by applying this pipeline to two different tasks. Presented in the form of well-organized rules, deficiencies and weaknesses in the model, datasets, and even the evaluation metrics were disclosed to researchers, shedding light on potential directions for improvement. We demonstrated the ability to "close the loop" and use the insight gained from some of the induced rules to make modest improvements to these systems. These simple but effective approaches have the potential to be applied in production environment shortening the iterative update cycle of models.

As discussed in Section 3, our analysis revealed several other problems for these tasks that remain open and could be addressed in future development. Besides, there are a number of aspects also deserving of future study before the achievement of full automated error analysis. For example, although the requirement for manual customization to tasks is already quite limited in our error analysis approach, meta-feature extraction is still a critical step that is responsible for disclosing underlying interrelationships among error examples and determining their human understandability. Therefore, apart from using hand-crafted meta-features only, data-driven meta-features could also be explored, though it remains challenging how to ensure that data-driven metafeatures are still understandable by human developers.

In addition, incorporating such automated error analysis into an overall automated machine learning (AutoML) process is another promising direction for future work. Most of the AutoML literature (Kandasamy et al. 2018; White, Nolen, and Savani 2020; Lu et al. 2021) heavily relies on a single metric to evaluate the model's performance, whereas such an individual metric is usually uninformative of errors and biases in the model, limiting the development process. Our pipeline enriches the information available about weaknesses of the current model and could potentially aid a process that helps automatically "close the loop" and improve the speed and effectiveness of the evolution of continually improved models.

7 Acknowledgment

This research was supported by the DARPA XAI program under a grant from AFRL. We would like to thank Bill Ferguson and his colleagues at Raytheon for inspiring our work on global explanations.

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8 Appendix

8.1 Other Error Characterizations Detected on VQA

Commonsense Knowledge "How" questions with "know" word are likely commonsense questions that the model could not answer. While ViLBERT often answers such questions with nonsensical words, we observed some cases that reasonable answers could not get points in evaluation, as shown in the second example in Figure 9. Similar situation also happens in "why"-type questions, where the content of questions and answers are totally unrestricted and impose challenges on both the model and the current evaluation metric.

Fictional Characters ViLBERT fails on "what" questions with words whose hypernym is "creativity". These questions ask the model to identify or reason the cartoon characters on the image. The first two examples in Figure 10 indicate that difficulty lies in learning the mapping between abstract 2D scratches to natural 3D objects as their details usually vary significantly, and ViLBERT did not demonstrate such ability. The third example even needs the model to speculate the future acting as a character, whereas no hint could be found in the training set, suggesting that insufficient training data on certain domain is another critical factor to ViLBERT's failure.

Sensation Problems One interesting rule shown in Figure 11 detects an odd set of problems involving human sensory judgement (e.g. taste, smell). The gold answers for these problems are also dubious or cover only a subset of reasonable answers. We believe most of these problems are just poor choices for VQA, indicating a problem with the data rather than the model.

8.2 Rules Used for Improvement

Here we present raw rules used to guide the models' improvement in the main paper for CSQA (table 3) and VQA (table 4).

Rule
answer_american_state > 0.5
question_educational_institution > 0.5 and
$question_to > 0.5$
answer_natural_phenomenon > 0.5
answer_mishap > 0.5
answer_kitchen > 0.5
answer_cupboard > 0.5
question_rational_motive > 0.5
answer_geographical_area > 0.5 and
question_location > 0.5
question_television > 0.5
answer_juvenile > 0.5
$question_astonishment > 0.5$

Table 3: Rule picked for RoBERTa. Words in these rules are directly used to filter the Wikipedia dataset.

Rule	Question type: how Question	n contains: know Error rate: 80%	Coverage: 0.045%
Examples			
	Question: How does the person know it is safe to cross in this specific area? Image caption: A person walking across a street with a blue umbrella Expected: crosswalk Prediction: umbrella	Question: How do we know the guy on the right is done skateboarding at the moment? Image caption: a man walking a dog in a park with a park bench Expected: he stopped Prediction: walk	Question: How do we know this picture is being taken from the road? Image caption: A stop sign in front of a field Expected: stop sign Prediction: wires

Figure 9: Commonsense problem examples

Rule	Question type: what Quest	on contains: creativity Error rate: 83	3.6% Coverage: 0.105%
Examples			
	Question: What cartoon character does this hydrant most remind you of? Image caption: A yellow fire hydrant on the side of a street Expected: spongebob Prediction: mickey mouse	Question: What cartoon character is the pizza supposed to look like? Image caption: A pizza sitting in a box Expected: mickey mouse Prediction: no	Question: What Warner Bros cartoon character would be thrilled to see this? Image caption: A carrot and a spoon on a blue table Expected: bugs bunny Prediction: no

Figure 10: Ficitional problem examples

Rule	Question type: what does the	Question contains: sensation E	rror rate: 100% Coverage: 0.011%
Examples			
	Question: What does the beverage in the glass taste like? Image caption: A pizza sitting on a table with a glass of wine Expected: wine Prediction: red	Question: What does the coffee taste like? Image caption: A laptop computer sitting on top of a desk Expected: coffee Prediction: good	Question: What does the city smell like? Image caption: A group of people riding motorcycles down a street Expected: exhaust Prediction: clean

Figure 11: Sensation problem examples

Question Type	Rule
what	image_caption_evidence > 0.5
what does the	question_say > 0.5
what is the	question_magnitude > 0.5
what does the	question_evidence > 0.5
what	question_social_group > 0.5
what	question_say > 0.5
what number is	image_object_person > 2.5
what number is	image_caption_matter > 0.5
what	question_document > 0.5
what is the name	image_caption_way > 0.5
what	question_language_unit > 0.5
what number is	question_instrumentality > 0.5
what is the name	image_caption_evidence > 0.5
what number is	image_object_person > 5.5
what number is	question_contestant > 0.5
what are the	question_number > 0.5
what number is	image_caption_state > 0.5
what number is	image_caption_facility > 0.5
what number is	image_caption_facility > 0.5
what is the	question_motor_vehicle > 0.5
what number is	image_caption_two > 0.5
what is the	question_stopword > 0.5 and question_use > 1.0
what number is	image_caption_consumer_goods > 0.5
what number is	image_caption_measure > 0.5
what does the	image_caption_back > 0.5
what	question_act > 0.5 and question_year > 1.0
which	question_relation > 0.5
what are the	question_letter > 1.0
what number is	image_caption_rid > 0.5
what kind of	question_product > 0.5
what is the	image_object_clock > 1.5 and question_time > 1.0
what is the	question_company > 1.0
what does the	image_caption_proctor > 0.5
where are the	image_caption_radiation > 0.5
what is	question_truck > 1.0
what is	image_caption_travel > 0.5 and question_announce > 0.5
what is the	image_caption_vascular_plant > 0.5 and question_bus > 1.0
what is in the	image_object_hot_dog > 0.5
what is in the	image_caption_unpleasant_person > 0.5
what is this	image_object_boat > 1.5

Table 4: OCR Rules used for ViLBERT's improvement