RETINAQA : A Knowledge Base Question Answering Model Robust to both Answerable and Unanswerable Questions.

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Abstract

State-of-the-art KBQA models assume answerability of questions. Recent research has shown that while these can be adapted to detect unanswerability with suitable training and thresholding, this comes at the expense of accuracy for answerable questions, and no single model is able to handle all categories of unanswerability. We propose a new model for KBQA named RetinaQA that is robust against unanswerability. It complements KB-traversal based logical form retrieval with sketch-filling based logical form construction. This helps with questions that have valid logical forms but no data paths in the KB leading to an answer. Additionally, it uses discrimination instead of generation to better identify questions that do not have valid logical forms. We demonstrate that RetinaQA significantly outperforms adaptations of state-of-the-art KBQA models across answerable and unanswerable questions, while showing robustness across unanswerability categories. Remarkably, it also establishes a new state-of-the art for answerable KBQA by surpassing existing models.

1 Introduction

Question answering over knowledge bases (KBQA) (Saxena et al., 2022; Zhang et al., 2022; Mitra et al., 2022; Wang et al., 2022; Das et al., 2022; Cao et al., 2022; Ye et al., 2022; Chen et al., 2021; Das et al., 2021; Shu et al., 2022; Gu et al., 2023), requires answering natural language questions over a structured knowledge base most commonly via producing formal queries or logical forms that are then executed over the knowledge base to retrieve the answers. While specialized models for handling unanswerability have been proposed for other question answering tasks (Rajpurkar et al., 2018; Choi et al., 2018; Reddy et al., 2019; Sulem et al., 2022; Raina and Gales, 2022), all existing models for KBQA assume answerability of questions over the given KB. This is an unrealistic assumption, since user queries are typically agnostic of the underlying KB, which are often incomplete.

Recently, Patidar et al. (2023) published a benchmark dataset called GrailQAbility (Patidar et al., 2023), adapting the GrailQA dataset (Gu et al., 2021) to incorporate different categories of unanswerable questions, and also proposed the task of detecting unanswerabilty while answering KB questions. This work also demonstrated that state-of-the-art KBQA models naturally perform poorly for unanswerable questions. This performance improves with extrinsic adaptation for unaswerability, such as adding unanswerable questions during training, and thresholding. However, such adaptation significantly hurts performance for answerable questions. Additionally, different state-of-the-art models struggle with different categories of unaswerability, such as (a) questions for which schema elements (i.e. relations or entity types) are missing in the KB and which therefore do not have valid logical forms, and (b) questions for which data elements (i.e. entities or facts) are missing in the KB and which therefore have logical forms that are valid but return empty answers.

Our analysis of state-of-the-art KBQA models provides a few key insights about KBQA architectures that are robust against different categories of unanswerability. First, good model calibration is crucial for separating questions that are answerable (having a valid logical form) and those that are unanswerable due to missing schema elements (not having a valid logical form). Secondly, while KB traversal-based retrieval is useful for identifying candidate logical forms for answerable questions, this fails when relevant data elements are missing in the KB, but a valid logical form exists. Detecting this type of unanswerability requires traversal-free logical form construction.

Based on these insights, we propose a new multi-staged **RET**r**I**eve, ge**N**erate and r**A**nk model for KBQA which is robust against unanswerabil-

ity named RetinaQA. For better calibration, instead of generating logical forms as the final stage, RetinaQA discriminates between candidate logical forms. To construct candidate logical forms, RetinaQA complements KB-traversal based retrieval with sketch-filling based construction, which generates KB-independent sketches and then grounds these by directly retrieving schema elements relevant for the question. This enables identification of logical forms for questions with missing data elements and therefore no connected KB path.

RetinaQA brings together and adapts ideas from different KBQA architectures for robust KBQA over answerable and unanswerable questions. While traversal based retrieval (Ye et al., 2022; Chen et al., 2021; Shu et al., 2022) and sketch-filling (Cao et al., 2022; Ravishankar et al., 2022; Li et al., 2023) have been separately used for in-domain and transfer settings for KBQA, we recognize the simultaneous need for both styles for handling unanswerability and unify these in a single architecture. Also, while step-by-step discrimination has been recently proposed for KBQA (Gu et al., 2023), this is the first model that discriminates between fully-formed logical forms in the final stage.

Using experiments over GrailQAbility, we demonstrate that RetinaQA significantly outperforms adaptations of multiple state-of-the-art KBQA models that assume answerability, not only across different categories of unanswerable questions, but also for answerable questions. Interestingly, we demonstrate that the RetinaQA architecture performs strongly for fully answerable KBQA benchmarks as well, and establishes a new state-of-the-art performance on the GrailQA dataset.

2 Related Work

The predominant approach for KBQA is to construct logical forms based on the question which are then executed to retrieve answers (Cao et al., 2022; Ye et al., 2022; Chen et al., 2021; Das et al., 2021). State-of-the-art models involve a KB traversal-based retrieval stage that retrieves k-hop data paths from linked entities in the question (Ye et al., 2022; Shu et al., 2022). Some models instead (Chen et al., 2021) or additionally (Shu et al., 2022) retrieve schema elements (namely entity types and relations) based on the question. These are used to generate the target logical form. *These architectures are completely dependent on KB-traversal for creating input context for logical form generation.* In contrast to this generative style, Pangu (Gu et al., 2023) uses language models to incrementally evaluate and discriminate between partial logical forms. Some retrieval-based methods (Saxena et al., 2020, 2022) also perform ranking of answer paths to select answer nodes, however these methods are optimized to increase the similarity score between a relation (partial answer path) and question. *While we perform contrastive-learning based one-shot discrimination on fully-formed logical form candidates as the final stage.*

In addition to iid settings, transfer (Cao et al., 2022; Ravishankar et al., 2022) and few-shot (Li et al., 2023) settings has also been studied for KBQA. Here, test questions involve unseen KB relations and entity types. These approaches use the notion of generalizable sketches (also called drafts or skeletons) that capture the syntax of the target language. Such sketches are first generated and then filled in with KB-specific arguments to construct complete programs, which are then scored and ranked. *Notably, these transfer architectures do not involve any traversal based component to retrieve logical forms.*

Unanswerability and specialized models for detecting unanswerable questions have been studied for different question answering tasks (Rajpurkar et al., 2018; Choi et al., 2018; Reddy et al., 2019; Sulem et al., 2022; Raina and Gales, 2022). *However, no specialized models have been proposed for detecting unanswerable questions in KBQA.* All existing KBQA models assume that questions have valid logical forms with non-empty answers. Even in the transfer setting for KBQA (Cao et al., 2022; Ravishankar et al., 2022), questions are still assumed to be answerable in the target domain though the logical forms may involve schema elements unseen during training. Recent work (Patidar et al., 2023) has published the GrailQAbility benchmark by modifying the popular GrailQA dataset (Gu et al., 2021) to incorporate various categories of unanswerable questions. This work also demonstrates the shortcomings of loose adaptions of existing KBQA models that assume answerability for the detecting unanswerable questions.

3 Problem and Solution

We first briefly define the KBQA with unanswerability task and then describe the architecture of our proposed model RetinaQA.

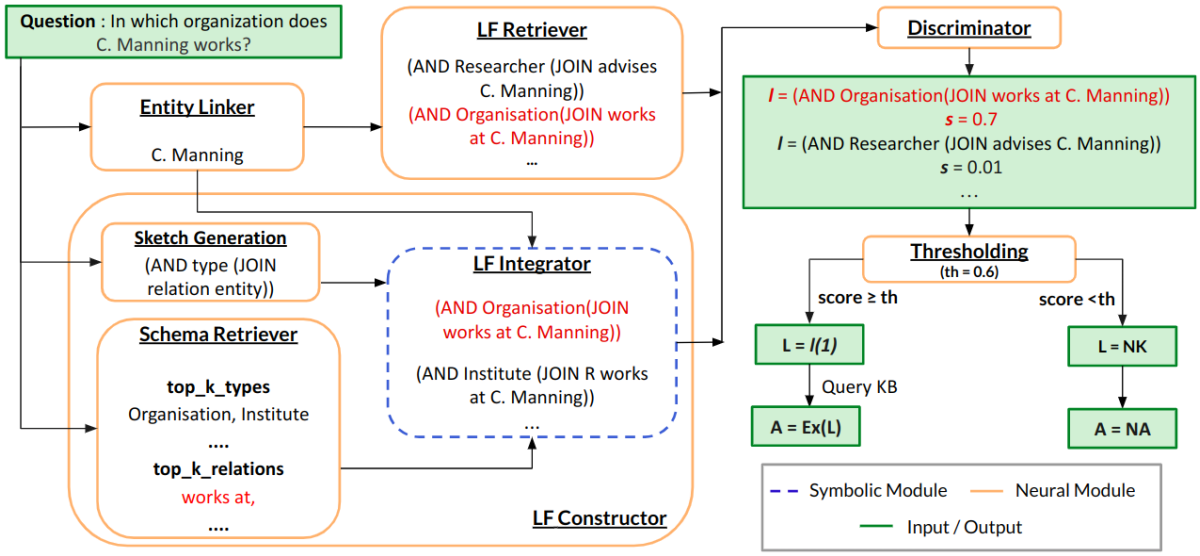

Figure 1: RetinaQA Architecture showing different components illustrated with an example question. Symbols l and s represent candidate logical form and its score as Discriminator output, L the output logical form, A the final answer, $l(1)$ the top ranked logical form, Ex(l) the answer obtained by executing logical form l. NK and NA are special symbols indicating No Knowledge (for logical form) and No Answer. The logical form in red under LF Retriever would not be found if data element *(C. Manning, works at, Stanford)* is missing in the KB, and additionally that in red under LF Integrator would not be found if relation *works at* is missing in KB schema and therefore not retrieved by the Schema Retriever. The candidate logical form in red under Discriminator would not be found if both of these are missing.

3.1 KBQA with Unanswerability

A Knowledge Base G consists of a schema S with data D stored under it. The schema consists of entity types T and binary relations R defined over pairs of types. Together we refer to these as schema elements. The data D consists of entities E as instances of types T, and facts $F \subseteq E \times R \times E$. Together, we refer to these as data elements. We follow the definition of (Patidar et al., 2023) for defining the task of Knowledge Base Question Answering (KBQA) with unanswerability. A natural language question q is said to be answerable for a KB G if it has a corresponding logical form l which when executed over G returns a non-empty answer A. In contrast, a question q is unanswerable for G, if it either (a) does not have a corresponding logical form that is valid for G, or (b) it has a valid logical form l for G, but which on executing returns an empty answer. The first case indicates that G is missing some schema element necessary for capturing the semantics for q. The second case indicates that the schema S is sufficient for q, but G is missing some necessary data elements for answering it. In the KBQA with unanswerability task, given a question q, if it is answerable, the model needs to output the corresponding logical form l and the non-empty answer A entailed by it, and if it is unanswerable, the model either needs to output NK (meaning No Knowledge) for the logical form, or a valid logical form l with NA (meaning No Answer) as the answer. While different formalisms have been proposed for logical forms, we use *s-expressions* (Gu et al., 2021). These have set-based semantics, functions with arguments and return values as sets.

3.2 The RetinaQA Model

Fig. 1 shows the architecture of RetinaQA. At a high level, RetinaQA has two stages - **logical form enumeration**, followed by **logical form ranking**. For logical form enumeration, RetinaQA follows two complementary approaches and then takes the union. The first is **KB-traversal based retrieval**. Starting from linked entities in the question, RetinaQA traverses *data-level KB paths* and transforms these to logical forms. The second is **sketch-filling based construction**, which is critical when the KB has missing data elements for the question. Here, RetinaQA first *generates* **logical form sketches** corresponding to the question, and then *enumerates* semantically valid groundings for these by *retrieving* relevant KB schema elements for filling in the sketch arguments. Note that this approach

utilizes only the KB schema and avoids data. Once candidate logical forms are so identified, RetinaQA uses *discriminative* scoring to rank these logical forms with respect to the question. We next explain each of these components in more detail.

Entity Linker: The pipeline starts with linking mentioned entities in the question with KB entities E. This is required for both logical form retrieval and logical form construction. We use an off-the-shelf entity linker (Ye et al., 2022) previously used in the KBQA literature (Shu et al., 2022; Gu et al., 2023). More details are in the Appendix A.1. If the mentioned entities are missing in the KB, the entity linker returns an empty set.

Logical Form Retriever: As the first approach for enumerating logical forms, RetinaQA uses KB data path traversal (Ye et al., 2022). RetinaQA traverses 2-hop paths starting from the linked entities and transforms these to logical forms in s-expression. These logical forms are then scored according to their similarity with the question and the top-10 logical forms are selected for the next stage, as illustrated under LF Retriever in Fig. 1. Following (Ye et al., 2022), we score a logical form l and question q as:

$$s(l, q) = \textsc{Linear}(\textsc{BertCls}([l; q])) \quad (1)$$

and optimize a contrastive objective for ranking:

$$\mathcal{L}_{ret} = -\frac{\exp(s(l^*, q))}{\exp(s(l^*, q)) + \sum_{l \in L \wedge l \neq l^*} \exp(s(l, q))} \quad (2)$$

where l^* is the gold-standard logical form for q and L is the set of logical forms similar to l^*. Note that the transformation to logical forms from KB-paths only covers certain operators (such as *count*), but not some others (such as *argmin*, *argmax*), so that this enumeration approach is not guaranteed to cover all logical forms. As illustrated in Fig. 1, this approach cannot retrieve the logical form in red when the relevant data path in the KB is broken, as by the absence of the data element *(C. Manning, works at, Stanford)* in our example.

Logical Form Constructor: The second approach used by RetinaQA for logical form enumeration is sketch-filling. Drawing inspiration from the transfer approaches for KBQA (Cao et al., 2022; Ravishankar et al., 2022; Li et al., 2023), RetinaQA uses logical form sketches, which capture KB-independent syntax of s-expressions with functions, operators and literals, and replace KB-specific elements, specifically entities, entity types and relations, with arguments. RetinaQA first generates sketches using a **sketch generator**, and in parallel retrieves relevant schema elements as candidates for arguments using a **schema retriever**, and finally fills in arguments for each candidate sketch using the retrieved argument candidates in all possible valid ways using a **logical form integrator**. Since this style bypasses data-path based KB-retrieval, this can construct valid logical forms when these exist, even when some relevant data element for the question is missing in the KB, for example when the data element *(C. Manning, works at, Stanford)* is missing in the KB but the relation *works at* is present in the KB schema.

Sketch Generator: The sketch generator takes the question q as input and outputs a sketch s, optimizing a cross-entropy-based objective:

$$L_{sketch} = -\sum_{t=1}^{n} \log(p(s_t | s_{<t}, q))$$

Specifically, we fine-tune T5 (Raffel et al., 2020) as the Seq2Seq model. We also perform constraint decoding during inference to ensure syntactic correctness of the generated sketch. This step is unaffected by any KB incompleteness.

Schema Retriever: To retrieve candidate arguments for generated sketches, we follow the schema retriever pipeline of TIARA (Shu et al., 2022). It is a cross encoder and uses the form of Eqn.1 to score a schema element x and the question q, and uses an objective same as sentence-pair classification task (Devlin et al., 2019) for optimization. We train two retriever models, one for relations and one for types, and use the top-10 types and top-10 relations as candidate arguments for each question. As illustrated in Fig. 1, this step is affected when relevant relations, such as *works at*, or entity types are missing from the KB schema.

Logical Form Integrator: This component grounds each generated candidate sketch using the retrieved candidate arguments and also the linked entities to construct complete logical form candidates. Each candidate sketch is grounded using every possible combination of arguments. A symbolic checker ensures type-level validity of the grounded logical forms for the KB G. This also avoids a combinatorial blow-up and restricts the space of logical form candidates. This component does not involve any trainable parameters.

Logical Form Discriminator: Finally, this component considers the union of logical form candidates from the retriever and constructor components and scores and ranks these. A T5 encoder-decoder model is trained to compute scores. Following Zhuang et al. (2022), we feed a (question, logical form) pair to the encoder and use decoding probability for a special token as ranking score.[1] This component uses a contrastive learning based optimization objective similar to Eqn.2. We perform random negative sampling, typically covering all negative candidates, since the the set of negative candidates is very small. For a test question, the candidate logical forms are ranked according to the predicted discriminator scores. If the score of top-ranked candidate is below a threshold (tuned on validation set), it is classified as unanswerable i.e. l =NK. Otherwise, the top ranked candidate is predicted as the logical form. This helps in identifying questions for which valid logical forms do not exist due to missing schema elements. For example, in Fig. 1, if the logical form in red is missing from the candidate list, the discriminator assigns a low score to the rank 1 logical form candidate, and NK is output after thresholding. Our experiments suggest that this also helps in separating correct and incorrect logical forms for answerable questions.

4 Experiments

We address the following research questions: (1) How does RetinaQA compare against baselines on both answerable and unanswerable questions in two different train-settings: one that have only answerable questions and the other that have both answerable and unanswerable questions? (2) How does RetinaQA perform for different categories of unanswerable questions? (3) What are the individual contributions of various model components towards the performance of RetinaQA in (1) and (2) above? (4) How does RetinaQA compare against baselines on only-answerable questions?

4.1 Experimental Setup

Datasets: For research questions (1), (2) and (3) above we use the GrailQAbility dataset, which is the only KBQA dataset that contains both answerable and unanswerable questions. For research question (4), we use the two most popular KBQA datasets with only answerable questions, namely GrailQA and WebQSP. **GrailQA** is a popular KBQA dataset that contains only answerable questions. The background KB is Freebase. It contains questions at various levels of generalization: iid (seen schema elements), compositional (unseen combination of seen schema elements) and zero-shot (unseen schema elements). **WebQSP** also has only answerable questions with Freebase as the KB, but unlike GrailQA, where the questions are synthetically constructed, contains real user queries annotated with logical forms. It only has IID test questions. **GrailQAbility** is a recent dataset that adapts GrailQA to additionally incorporate unanswerable questions. The unanswerable questions are constructed by systematically dropping data and schema elements from the KB. More details are added in the appendix A.4.

Evaluation Metrics: We primarily focus on evaluating the logical form using the Exact Match (EM) metric, which verifies whether the predicted logical form is same as the gold logical form (which is NK for unanswerable questions with missing schema element). We also evaluate the answers using the F1 score, which compares the predicted answers with the gold answers. For unanswerable questions, similar to prior work (Patidar et al., 2023), we report two F1 scores – the strict score compares the list of answers based on the given incomplete KB. and lenient score - it does not penalize a model for returning ideal answers i.e. it accepts answers wrt to both KBs - the ideal/complete KB and new/incomplete KB. In a way, it evaluates the model's ability to infer missing paths and predict the correct answer

Baselines: We compare RetinaQA against existing state-of-the-art KBQA models, as per the GrailQA leaderboard and code availability. These are TIARA (Shu et al., 2022), RnG (Ye et al., 2022), and Pangu (Gu et al., 2023). Of these, the first two are shown to the best performing models on GrailQAbility, and Pangu is a SoTA model for GrailQA[2] and WebQSP (Gu et al., 2023). For fair comparison, all models use the same entity linker (Ye et al., 2022) and T5-base as base LLM. For GrailQAbility, we adapt all models appropriately for unanswerability. Specifically, we perform thresholding (denoted as "+T") on entity disambiguation and logical form generation to output NK. The thresholds are tuned on the dev set. Additionally, we train the models using both answerable

[1] We use $< extra\_id\_6 >$ token of T5 for tuning ranking score.

[2] https://dki-lab.github.io/GrailQA/

Train	Model	Overall			Answerable			Unanswerable		
		F1(L)	F1(R)	EM	F1(L)	F1(R)	EM	F1(L)	F1(R)	EM
A	RnG	67.80	65.60	51.60	78.10	78.10	74.20	46.90	40.10	5.70
	RnG+T	67.60	65.80	57.00	71.40	71.30	68.50	59.90	54.50	33.60
	Tiara	75.05	72.84	53.69	80.03	80.00	75.63	64.95	58.31	9.20
	Tiara + T	73.26	71.62	55.23	74.08	74.05	70.56	71.60	66.68	24.15
	Pangu	63.09	60.06	54.55	78.72	78.7	74.00	31.40	22.25	15.13
	Pangu + T	79.14	77.89	66.53	75.52	75.51	72.37	86.48	82.70	54.68
	RetinaQA	76.83	75.24	64.54	**81.22**	**81.2**	**77.41**	67.93	63.16	38.45
	RetinaQA+ T	**83.30**	**82.18**	**73.76**	81.19	81.17	75.01	**87.59**	**84.22**	**71.20**
A+U	RnG	80.50	79.40	68.20	75.90	75.90	72.60	89.70	86.40	59.40
	RnG+T	77.80	77.10	67.80	70.90	70.80	68.10	92.00	89.80	67.20
	Tiara	78.29	77.43	66.29	71.33	71.32	68.29	92.4	89.82	62.24
	Tiara + T	77.67	76.94	66.87	69.89	69.88	66.98	93.43	91.24	66.65
	Pangu	63.59	60.42	53.79	79.45	79.42	73.49	31.42	21.89	13.85
	Pangu +T	78.29	76.91	66.14	75.25	75.22	71.62	80.46	80.32	55.03
	RetinaQA	77.31	75.71	64.79	**80.98**	**80.97**	**76.95**	69.87	65.04	40.14
	RetinaQA+ T	**83.30**	**82.69**	**77.45**	77.91	77.91	75.16	**94.21**	**92.38**	**82.10**
A+U	RetinaQA - LFR + T	77.36	76.37	65.37	73.40	73.39	70.90	85.38	82.43	54.17
	RetinaQA - LFI + T	74.89	73.53	53.89	70.89	70.85	68.07	83.01	78.95	25.13
	RetinaQA - (SG ∪ SR) + T	64.68	62.58	52.46	72.99	72.95	68.13	47.84	41.54	20.70

Table 1: Performance of different models on the GrailQAbility dataset: overall and for answerable and unanswerable questions. A indicates training with answerable questions, A+U with answerable and unanswerable questions, +T indicates thresholding. Ablations of RetinaQA are named as RetinaQA - X, where we denote logical form retriever as LFR, logical form integrator as LFI and sketch generator and schema retriever together as (SG ∪ SR).

Train	Model	Schema Element Missing						Data Element Missing			
		Type		Relation		Mention Entity		Other Entity		Fact	
		F1(R)	EM	F1(R)	EM	F1(R)	EM	F1(R)	EM	F1(R)	EM
A	RnG+T	55.50	49.50	57.10	46.60	44.70	40.30	56.00	11.50	58.60	13.90
	Tiara + T	66.27	21.70	70.21	28.06	61.01	23.43	68.91	22.97	68.29	23.63
	Pangu + T	**87.97**	**87.50**	**80.07**	**79.63**	90.57	**90.41**	83.19	0.00	76.48	1.07
	RetinaQA+ T	86.32	80.31	79.41	62.08	**90.72**	77.83	**85.71**	**68.07**	**84.68**	**71.14**
A+U	RnG+T	93.40	86.80	89.70	**85.50**	92.10	89.60	87.10	30.80	86.00	32.50
	Tiara + T	91.63	83.84	**90.90**	72.37	**94.50**	71.38	91.60	50.42	90.38	52.85
	Pangu+T	90.80	**90.68**	78.66	78.44	90.41	**90.25**	74.51	0.00	69.71	0.95
	RetinaQA+ T	**94.22**	90.21	88.52	81.91	94.34	86.64	**93.84**	**75.91**	**94.30**	**76.13**

Table 2: Performance of different models for the unanswerable questions in GrailQAbility, grouped by categories of KB incompleteness. Note that missing mention entities result in invalid logical form, while other missing entities lead to valid logical form with no answer.

and unanswerable questions (denoted as A+U training vs A training). Further implementation details are in the Appendix A.2.

4.2 Results for KBQA with Unanswerability

Table 1 reports aggregate performance on GrailQAbility. With A+U Training, RetinaQA+T outperforms all models overall and is about 9 pct points ahead of the closest competitor (Pangu+T) in term of EM. For unanswerable questions, RetinaQA achieves a 16 pct points improvement, while being consistently better for answerable questions. Unsurprisingly, thresholding helps all models for unanswerable questions and hurts slightly for answerable ones. This drop is relatively small for Pangu and RetinaQA, suggesting that they are better calibrated due to their discriminative training.

Table 2 drills down on performance for different categories of unanswerability. First, we observe that for the baselines, performance varies significantly across different categories. Pangu is good for missing schema elements but the worst for missing data elements. TIARA is the best baseline for missing data elements but is not as good for missing schema elements. The reasons for such behaviors are described in the Appendix(Sec. A.3.1). We observe that RetinaQA performs the best by a large margin for questions with missing data elements, and comparably with Pangu for missing schema elements, making it the overall model of choice across different categories of unanswerability. We also note that RetinaQA with thresholding results in minimal or no loss for questions with missing data (which have valid logical forms), and in huge

gains for questions with missing schema elements.

As a testimony to its robustness, in the A Training setting, RetinaQA achieves comparable performance for answerable and unanswerable questions, with a gap of only 4 pct points for EM. This gap is 18 to 45 pct points for other models. Other trends are very similar to the A+U setting. Additionally, we see that RetinaQA largely outperforms existing models across different generalization settings for answerable (Table 3) and unanswerable questions (Table 6 in appendix). For answerable questions, RetinaQA beats previous the best results for IID and compositional generalization, but for zero-shot generalization, RetinaQA has a slightly worse performance than Pangu. This is mainly because of the traversal dependence trade-off, as we explain further in Section 4.4.

4.3 Results for Answerable-only KBQA

Since RetinaQA performs the best for answerable questions as well in GrailQAbility, we also evaluate it for traditional KBQA benchmarks with only answerable questions. Since all questions are answerable in this setting, we apply Execution Guided Check (EGC) as the final step for all models including RetinaQA. With EGC, models output the highest-ranked logical form which when executed over the KB returns a non-empty answer. In Table 4, we report results on GrailQA. We find that overall RetinaQA beats previous state of the art by around 1.2 pct points for F1 and 1.8 pct points for EM, establishing a new state-of-the-art for this dataset. We also see that, as for answerable questions in GrailQAbility, here too RetinaQA performs the best for IID and compositional generalization, and performs almost at par with Pangu for zero-shot generalization.

Further analysis shows that RetinaQA performs well across questions of various complexities. It is the best model for 1, 2, and 4-hop questions, while it is outperformed by TIARA for 3-hop questions Table 13. More details are in Appendix A.3.2.

In Table 5, we record results for WebQSP.Here, RetinaQA outperforms Pangu by 0.3 pct points but ranks below TIARA by 0.5 pct points, further establishing the usefulness of its architecture for answerable-only KBQA as well.

4.4 Ablation Study

Here we assess the contributions of the different components in RetinaQA. First, we remove (one at a time) the three key components: the logical form integrator (LFI), the logical form retriever (LFR), and the coupled sketch generator (SG) and schema retriever (SR). The last three rows of Table 1 shows that at the aggregate level all components contribute towards RetinaQA's performance on GrailQAbility to different extents for answerable and unanswerable questions.

Next, we drill down into specific question categories. First, we study the *recall* of the correct logical form within the candidate set for unanswerable questions with missing data elements. If we remove SR and SG, the resulting RetinaQA ablation only retrieves candidate logical forms via traversal. We find that removing SR and SG results in a massive 65 pct point drop in recall. In contrast, removing LFR does not hurt much (see Table 11 in appendix). This agrees with our intuition that when relevant data is missing, traversal necessarily retrieves irrelevant logical forms.

Next, we study the impact of traversal-dependent logical form retrieval on the recall of the right logical form for answerable questions. Removing LFR (and also SR+SG) results in a substantial drop in recall (Table 12 in appendix). Also, LFR has significantly impact for the zero-shot generalization subset of answerable questions. For question forms unseen during training, KB-traversal is the only reliable approach for retrieving logical forms.

Finally, we evaluate the impact of LFI and EGC in reducing the space of logical form candidates for the discriminator, by pruning out invalid logical forms, in the answerable setting in GrailQA. By switching off LFI and EGC separately, we see about 4 pct points and 2 pct point performance drops respectively. However, on switching off both together, a 17 pct point drop is observed (Table 10 in appendix). This suggests that these components can compensate for each other, but at least one of them is needed for good performance.

Additional ablations over questions of different complexities show that SG and SR contribute more to the performance of 3-hop and 4-hop questions. See Sec. A.3.2 for more details.

4.5 Error Analysis

We now briefly report a summary of error analysis for RetinaQA on GrailQAbility. More details are in Sec. A.3.3. We use the the best version RetinaQA+T (A+U). There are three main error categories: (1) *thresholding error*, where, due to thresholding, RetinaQA incorrectly predicts NK for

Train	Model	IID			Compositional			Zero-Shot		
		F1(L)	F1(R)	EM	F1(L)	F1(R)	EM	F1(L)	F1(R)	EM
A	RnG	85.50	85.40	83.20	65.90	65.90	60.20	72.70	72.70	67.30
	Tiara	86.53	86.47	84.52	72.02	72.02	64.93	74.24	74.24	67.60
	Pangu	82.00	81.97	79.09	71.63	71.63	65.95	**77.02**	**77.02**	**70.18**
	RetinaQA	**87.94**	**87.90**	**85.85**	**73.92**	**73.92**	**67.48**	74.84	74.84	69.68
A+U	RnG	85.40	85.30	83.30	65.80	65.80	60.80	66.90	66.90	62.60
	Tiara	82.38	82.36	80.57	65.16	65.16	59.84	58.50	58.50	54.65
	Pangu	81.08	81.01	76.85	**77.43**	**77.43**	**69.52**	**78.01**	**78.01**	**70.42**
	RetinaQA	**89.00**	**88.98**	**87.06**	71.69	71.69	65.55	73.59	73.59	67.51

Table 3: Performance of different models for answerable questions in the GrailQAbility dataset, for IID, compositional, and zero-shot test scenarios. Names have the same meanings as in Table 1.

Model	Overall		IID		Compositional		Zero-Shot	
	F1	EM	F1	EM	F1	EM	F1	EM
RnG	85.50	83.20	85.50	83.20	65.90	60.20	72.70	67.30
Tiara	81.90	75.30	**91.20**	88.40	74.80	66.40	80.70	73.30
Pangu	82.16	75.90	86.38	81.73	76.12	68.82	**82.82**	**76.29**
RetinaQA	**83.33**	**77.84**	**91.22**	**88.58**	**77.49**	**70.48**	82.32	76.20

Table 4: Performance of different models on GrailQA (validation set) (which has only answerable questions) for IID, compositional, and zero-shot test scenarios. Note that we beat previous SOTA on GrailQA.

Model	F1
Tiara	**75.80**
Pangu	75.00
RetinaQA	75.30

Table 5: Performance of different models on WebQSP (test set) containing only IID answerable questions. We use the WebQSP evaluation script that only reports F1.

a question with a valid logical form; (2) *reranking error*, where the discriminator makes a mistake in scoring, though the candidates contain the correct logical form, and (3) *recall error*, where the correct logical form is not in the set of discriminator candidates. This may be due to errors in entity linking, logical form retrieval or logical form construction.

On the subset of answerable questions, thresholding and reranking errors occur in around 37.67%, and 30% of questions, respectively. The most frequent error is recall error (70%). Among these, entity linking errors occur 80% of the time. Unsurprisingly, the majority of the errors of all categories occur for the zero-shot generalization questions. Detailed statistics are in Table 8. For unanswerable questions with missing data elements, (around 90%) of errors are recall errors, out of which about 72% are attributable to the entity linker, 45% to thresholding and 5% to reranking. See Table 9 for more details. Finally, for the subset of unanswerable questions with missing schema elements, 14% have errors, all due to thresholding. 90% of these occur for zero-shot generalisation.

5 Conclusions

We have presented RetinaQA, the first specialized KBQA model that shows robust performance for both both answerable and unanswerable questions. For this, RetinaQA unifies key aspects of KBQA models previously used separately for answerable-only iid and transfer settings so that candidate logical forms are identified using data-traversal based retrieval, as well as schema-based generation via sketch-filling that bridges over data gaps that break traversal. RetinaQA also discriminates between fully formed candidate logical forms at the final stage instead of generating these. This enables it to better differentiate between valid and invalid logical forms. We show that RetinaQA is the first model that demonstrates stable performance across adaptation strategies, across answerable and different categories of unanswerable questions, and across different generalization settings for answerable and unanswerable questions. By comparing against state-of-the-art KBQA models adapted extrinsically for answerability, we show that RetinaQA performs significantly better for unanswerable questions and almost at par for answerable ones. RetinaQA also retains this stability for answerable-only KBQA benchmarks, achieving a new state-of-the-art performance on the answerable-only GrailQA dataset. We will make our code-base [3] public for further research.

[3] https://anonymous.4open.science/r/RETINAQA-122B

6 Limitations

A sketch, while free of references to the KB, still specifies the length of the path to be traversed in the KB. The subsequent grounding step is limited by this and cannot adapt the path length after retrieving schema elements from the KB. RetinaQA inherits this limitation from existing sketch generation approaches (Cao et al., 2022; Ravishankar et al., 2022). We hope to improve this in future work.

For unanswerable questions without valid logical forms for the given KB, RetinaQA only outputs l =NK. However, this does not explain the gap in the schema, which, if bridged, would have make this question answerable. The situation is similar for unanswerable questions with valid logical forms but missing data elements. This is also an important area of future work.

7 Risks

Our work does not have any obvious risks.

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A Appendix

Train	Model	IID		Zero-Shot	
		F1(R)	EM	F1(R)	EM
A+U	RnG	91.90	73.30	81.70	47.10
	RnG+T	94.30	75.90	85.90	59.50
	Tiara	93.76	75.22	86.35	50.84
	Tiara + T	95.10	77.77	87.86	56.88
	Pangu	21.40	12.17	22.32	15.32
	Pangu +T	80.51	57.52	80.15	52.85
	RetinaQA	64.59	36.43	65.44	43.40
	RetinaQA+ T	**97.01**	**89.94**	**88.31**	**75.22**

Table 6: Performance of different models for unanswerable IID and zero-shot test scenarios in GrailQAbility. Names have the same meanings as in Table 1.

Train	Model	Full Z-Shot		Partial Z-Shot	
		F1(R)	EM	F1(R)	EM
A+U	RnG	87.20	75.90	78.00	40.00
	RnG+T	89.70	86.70	**83.10**	71.00
	Tiara	90.15	68.97	80.25	40.45
	Tiara + T	**90.64**	78.82	82.64	54.14
	Pangu	24.63	20.69	21.18	15.76
	PAngu +T	89.66	**89.66**	79.94	**79.46**
	RetinaQA	57.64	25.12	43.47	11.31
	RetinaQA+ T	88.67	77.83	80.89	70.54

Table 7: Performance of different models for partial zero-shot and full-zero test scenarios in GrailQAbility. Names have the same meanings as in Table 1.

A.1 Entity Linker

We use an off-the-shelf entity linker (Ye et al., 2022) previously used in the KBQA literature (Shu et al., 2022; Gu et al., 2023), which uses a standard

Components	Overall	IID	Compositional	Zero-shot
#questions	6808	3386	981	2441
#errors	1691	445	347	899
thresholding_error	637	161	113	363
reranking_error	508	49	134	325
coverage_error	1183	396	213	574
entity_linking_error	949	343	136	470
schema_retriever_error	460	61	77	322
sketch_parser_error	420	43	154	22

Table 8: Component wise errors of RetinaQA+ T (A+U) for answerable questions

Components	Overall	IID	Zero-shot
#questions	1196	530	666
#errors	287	127	160
thresholding_error	131	59	72
reranking_error	16	5	11
coverage_error	271	122	149
entity_linking_error	195	77	118
schema_retriever_error	56	29	27
sketch_parser_error	49	27	22

Table 9: Component wise errors of RetinaQA+ T (A+U) for data element missing unanswerable questions

3-staged pipeline - Mention Detection, Candidate Generation, and Entity Disambiguation. Mention Detector first identifies span of text from question which corresponds to name of an entity. For each mention a set of candidates entities are generated using alias mapping of FACC1 (Gabrilovich et al., 2013). Final stage is a neural disambiguator which rank candidates given the question and context of entities.

A.2 Implementation Details

To perform experiments for GrailQAbility, we first update the original Freebase KG using codebase[4]. To test baselines for GrailQAbility, we use the existing codebases[5] [6] [7] and make changes in code to adapt for answer-ability detection. All of the baselines assumes answerability and employs Execution Guide Check i.e. if a logical form returns an empty answer upon execution then they select next best logical form. We have removed this constraint while performing experiments for GrailQAbility. Also for A+U training we have made code changes so that models can be trained to predict logical form as NK unanswerable questions. We implement our model using Pytorch (Paszke et al., 2019) and Hugging Face[8]. All the experiments of RetinaQA are performed using an NVIDIA A100 GPU with 80 GB RAM. Above mentioned configurations are the maximum ones, since we have different components and all do not require same compute configurations. For Sketch Generation we fine tune Seq2Seq t5-base model for 10 epochs (fixed). We use learning rate of 3e-5 and batch size of 8. We use beam search during decoding with $beamsize = 10$. We also check syntactic correctness while selecting top ranked sketch. Training time for sketch parser is around 3 hours. LF Integrator is a parameter free module and does not require any training. Since, LF Integrator converts logical forms into query-graphs and validates type-level constraints, it is a costly operation. So we employ parallel processing(with cache) for this stage i.e. we use 4-6 CPUs (each with 2 cores) to create pool of valid logical forms. It takes around 5 hours to generate candidates for all train, dev and test data. Finally we train Discriminator which fine-tune t5-base Seq2Seq model. We train Discriminator with learning rate 1e-4 and batch size 4 for 10 epochs. For discriminator training we use AdmaW (Loshchilov and Hutter, 2019) optimizer and linear scheduler with warm up ratio of 0.01. We use 64 negative samples per question for contrastive training. Generally discriminator model converges in 2 epochs of training so we use patience of 2 i.e. if best model does not change for consequent 2 epochs then we assume model has converged and will stop training. It takes around 7-8 hours to train a discriminator. Inference time for discriminator is few minutes.

For A+U training components like Entity Linker, Schema Retriever, LF Retriever are trained only on question where logical form is known. While training for questions with l ="NK" is performed only at last step.

All the results presented for single run (however

[4] https://github.com/dair-iitd/GrailQAbility

[5] https://github.com/dki-lab/Pangu

[6] https://github.com/microsoft/KC/tree/main/papers/TIARA

[7] https://github.com/salesforce/rng-kbqa

[8] https://huggingface.co/

Model	Overall		IID		Compositional		Zero-Shot	
	F1	EM	F1	EM	F1	EM	F1	EM
RetinaQA'	83.33	77.84	91.22	88.58	77.49	70.48	82.32	76.2
RetinaQA' - EGC	80.62	75.68	89.81	87.7	74.78	68.1	79.03	73.58
RetinaQA' - LFI	78.65	73.1	88.1	84.81	75	67.31	76.04	70.4
RetinaQA' - LFR	71.8	68.33	87.33	85.56	69	63.47	66.19	62.83
RetinaQA' - (SG ∪ SR)	73.2	66.78	77.06	72.13	60.63	54.43	76.73	69.56
RetinaQA' - LFI - EGC	63.29	59.99	79.84	77.84	59.33	54.03	57.73	54.68

Table 10: Ablation experiment on GrailQA dev set. EGC refers to Execution Guided Check and LFI refers to Logical Form Integrator, RetinaQA' = RetinaQA + EGC

Model	Overall	IID	Zero-shot
RetinaQA	77.34	76.98	77.63
RetinaQA- LFR	77.17	76.79	77.48
RetinaQA- SP - SR	12.29	10	14.11

Table 11: Ablation experiment of Logical Form Coverage(%) on GrailQAbility test set. LFR refers to Logical Form Retriever, SP refers to Sketch Parser and SR refers to Schema Retriever.

the reproducibility of results is already verified). We release our code-base[9] for the community.

A.3 In Depth Analysis

A.3.1 Trade-off Analysis

Sec 4.4 describes how individual components strengthens performance for different types of answerabilties and unanswerabilties. This section discusses an important trade-off i.e. **Traversal dependent Retrieval Vs Traversal independent Retrieval** : Traversal based Retrieval methods perform step by step enumeration over KB to retrieve next possible set of candidates(which is retrieval at data level). While Traversal independent Retrieval based method generate candidates based on semantic similarity with the question(which is at schema level). So for Data Element Missing unanswerability where data paths are missing, Traversal based methods will never find correct path during enumeration and hence will not be able to reach to a correct logical form. While Traversal independent method can generate correct logical form. Hence Traversal independent methods performs well for data element missing.
At the same time the search space for Traversal independent methods is much larger as it lacks KB grounding information. So for zero-shot generalisation where schema elements are unseen Traversal dependent tends to get confused between similar schema elements.

[9] https://anonymous.4open.science/r/RETINAQA-122B

A.3.2 Complexity Analysis

Tab. 13 records the performance of RetinaQA for queries of different complexities represented by number of relations in s-expression (or number of hops in answer path). We can see that for 1-hop and 2-hop questions RetinaQA is better than both baselines, while for 3-hop questions RetinaQA is not the best but is better than Pangu. Further by comparing ablations i.e. without Logical Form Retriever and without (Sketch Generation and Schema Retriever) we can see that Sketch Generation and Schema Retriever contribute more to the performance of 3-hop and 4-hop questions.

A.3.3 Error Analysis

We now briefly report a summary of error analysis for RetinaQA on GrailQAbility. For this, we use the A+U training with thresholding version which is the most robust. All errors can be classified into three categories: (1) *thresholding error*, where, due to thresholding, RetinaQA incorrectly predicts NK for a question with a valid logical form; (2) *reranking error*, where even though the correct logical form is present in the pool of candidates, the discriminator makes a mistake in scoring; and, (3) *recall error*, where the correct logical form is not in the set of candidates considered by the discriminator due to errors in the earlier stages. This may include errors in entity linking, logical form retrieval or logical form construction (via sketch generation and schema retrieval).

On the subset of answerable questions, thresholding and reranking errors occur in around 37.67%, and 30% of questions, respectively. The most frequent error is recall error (70%). Among these, entity linking errors occur 80% of the time. Unsurprisingly, the majority of the errors of all categories occur for the zero-shot generalization questions. Detailed statistics are in Table 8.

For unanswerable questions, we first look at those with missing data elements. We find that

Model	Overall	IID	Compositional	Zero-shot
RetinaQA	82.62	88.3	78.29	76.49
RetinaQA- LFR	74.24	85.91	67.38	60.79
RetinaQA- SP - SR	71.94	74.22	65.24	71.49

Table 12: Ablation experiment of Logical Form Coverage(%) on GrailQAbility test set for Answerable questions. LFR refers to Logical Form Retriever, SP refers to Sketch Parser and SR refers to Schema Retriever.

#relation	1	2	3	4
Pangu	82.8	63.5	24.7	0.0
Tiara	81.2	64.7	**29.3**	**50.0**
RetinaQA	**83.7**	**68.5**	26.9	**50.0**
RetinaQA - LFR	76.3	50.9	25.1	50.0
RetinaQA - SG_SR	72.9	56.9	12.0	0.0

Table 13: Performance for different types of questions on the GrailQA validation set in terms of EM. #relation denotes the number of relations in the s-expression.

the vast majority of errors (around 90%) are recall errors, out of which about 72% are attributable to the entity linker. This occurs when mentioned entities in the question are missing in the KB, but entity linker outputs spurious entities. Thresholding error accounts for 45% of errors, while reranking errors only occurs in 5% of questions. This suggests that the discriminator is calibrated well for relative ranking of logical forms, but still errs in assigning correct absolute scores to logical forms. See Table 9 for more details.

Finally, we look at the subset of unanswerable questions with missing schema elements. Since for these, the gold logical form is NK, thresholding error can be only source of error. This occurs only 14% of time, out of which 90% errors occur for zero-shot generalisation. This indicates that model is largely good in this setting, but makes some mistakes in absolute scoring of logical forms with schema elements not seen during training.

A.4 GrailQAbility - Dataset Creation

We summarise the dataset creation algorithm of GrailQAbility (Patidar et al., 2023) here. In a nutshell, the authors start with a standard KBQA dataset containing only answerable questions for a given KB. Then they introduce unanswerability in steps, by deleting schema elements (entity types and relations) and data elements (entities and facts) from the given KB. They mark questions that become unanswerable as a result of each deletion with appropriate unanswerability labels. So starting from a larger set of all answerable questions, the authors create two subsets of data - one set of answerable questions and another set of unanswerable questions (which are unanswerable due to missing structures in graph/KB).