Abstract

QDMR is a meaning representation for complex questions, which decomposes questions into a sequence of atomic steps. While state-of-the-art QDMR parsers use the common sequence-to-sequence (seq2seq) approach, a QDMR structure fundamentally describes labeled relations between spans in the input question, and thus dependency-based approaches seem appropriate for this task. In this work, we present a QDMR parser that is based on dependency graphs (DGs), where nodes in the graph are words and edges describe logical relations that correspond to the different computation steps. We propose (a) a non-autoregressive graph parser, where all graph edges are computed simultaneously, and (b) a seq2seq parser that uses gold graph as auxiliary supervision. We find that a graph parser leads to a moderate reduction in performance (0.47 → 0.44), but to a 16x speed-up in inference time due to the non-autoregressive nature of the parser, and to improved sample complexity compared to a seq2seq model. Second, a seq2seq model trained with auxiliary graph supervision has better generalization to new domains compared to a seq2seq model, and also performs better on questions with long sequences of computation steps.

1 Introduction

Training neural networks to reason over multiple parts of their inputs across modalities such as text, tables, and images, has been a focal point of interest in recent years (Antol et al., 2015; Pasupat and Liang, 2015; Johnson et al., 2017; Suhr et al., 2019; Welbl et al., 2018; Talmor and Berant, 2018; Yang et al., 2018; Hudson and Manning, 2019; Dua et al., 2019; Chen et al., 2020; Hannan et al., 2020; Talmor et al., 2021). The most common way to check whether a model is capable of complex reasoning, is to pose in natural language a complex question, which requires performing multiple steps of computation over the input.

To address the need for better understanding of complex questions, Wolfson et al. (2020) recently proposed QDMR, a meaning representation where complex questions are represented through a sequence of simpler atomic executable steps (see Fig. 1), and the final answer is the answer to the final step. QDMR has been shown to be useful for multi-hop question answering (QA) (Wolfson et al., 2020) and also for improving interpretability in visual QA (Subramanian et al., 2020).

State-of-the-art QDMR parsers use the typical sequence-to-sequence (seq2seq) approach. However, it is natural to think of QDMR as a dependency graph over the input question tokens. Consider the example in Fig. 1. The first QDMR
step selects the span “Indiana Jones”. Then, the
next step uses a PROJECT operation to find the
“movies” of Indiana Jones, and then next step uses
another PROJECT operation to find the date when
the movies were “released”. Such relations can
naturally be represented as labeled edges over
the relevant question tokens, as shown in Fig. 1, bottom.

In this work, we propose to use the dependency
graph view of QDMR to improve QDMR parsing. We describe a conversion procedure that auto-
matically maps QDMR structures into dependency
graphs, using a structured intermediate logical form
representation (Fig 1, middle). Once we have graph
supervision for every example, we train a depen-
dency graph parser, in the spirit of Dozat and Mann-
ing (2018), where we predict a labeled relation
for every pair of question tokens, representing
the logical relation between the tokens. Unlike seq2seq
models, this is a non-autoregressive parser, which
decodes the entire output structure in a single step.

A second method to exploit the graph supervi-
sion is to train a seq2seq model, but have an aux-
iliary loss term where the graph is decoded from
the encoder representations. Towards that end, we
propose a Latent-RAT encoder, which uses relation-
aware transformer (Shaw et al., 2018) to explicitly
represent the relation between every pair of input
tokens. Relation-aware transformer has been shown
to be useful for encoding graph structures in the
context of semantic parsing (Wang et al., 2020).

Last, we propose a new evaluation metric, LF-
EM, for QDMR parsing, which is based on the
aforementioned intermediate logical form, and
show it correlates better with human judgements
compared to existing metrics.

We find that our graph parser leads to a small
reduction in LF-EM compared to seq2seq models
(0.47 → 0.44), but is 16x faster due to its non-
autoregressive nature. Moreover, our graph parser
has better sample complexity and outperforms the
seq2seq model when trained on 10% of the data or
less. When training a seq2seq model along with
the auxiliary graph supervision, we find that the
parser obtains similar performance when trained
on the entire dataset (0.471 LF-EM), but substan-
tially improves performance when generalizing to
new domains. Moreover, The Latent-RAT parser
performs better on examples with a large number
of computation steps.

Our code is available at https://github.

Figure 2: Overview. For training (top), we create gold
DGs from gold QDMRs (§4) through a conversion into
LFs (§3.1). At test time (bottom), we convert model
predictions, either QDMRs or DGs, into LFs (§3.1, §4),
and evaluate by comparing them to the gold LFs. A-
terisk (*) denotes gold representations.

2 Overview

The core of this work is to examine the utility of a
dependency graph (DG) representation for QDMR. We propose conversion procedures that enable train-
ing and evaluating with DGs (see Fig. 2). First, we
convert gold QDMR structures into logical forms
(LF), where each computation step in QDMR is
represented with a formal operator, properties and
arguments (§3.1). Then, we obtain gold DGs by
projecting the logical forms onto the question to-
kens (§4). Once we have question-DG pairs, we
can train a graph parser. At test time, QDMRs and
DGs are converted into LFs for evaluation. We
propose a new evaluation metric over LFs (§3.2),
and show it is more robust to semantic-preserving
changes compared to prior metrics.

Our proposed parsers are in §5. On top of
standard seq2seq models, we describe (a) a graph
parser, and (b) a multi-task model, where the en-
coder of the seq2seq model is also trained to predict
the DG.

3 QDMR Logical Forms

QDMR (Wolfson et al., 2020) is a text-based mean-
ing representation focused on representing the
meaning of complex questions. It is based on a
decomposition of questions into a sequence of sim-
pler executable steps (Fig. 1), where each step
corresponds to a SQL-inspired operator (Table 6
in Appendix §A.1). We briefly review QDMR and
then define a logical form (LF) representation based
on these operations. We use the LFs both for map-
“Which group from the census is smaller: Pacific islander or African American?”

1. return census groups
2. return #1 that is Pacific islander
3. return #1 that is African American
4. return size of #2
5. return size of #3
6. which is lowest of #4, #5

\[ V_q = \{ \ldots \text{group}, \text{groups}, \ldots \text{small}, \text{smaller}, \text{smallest}, \ldots \} \]

\[ V_{\text{ref}} = \{ \#1, \#2, \#3, \#4 \} \]

\[ V_{\text{const}} = V_q \cup V_{\text{store}} \cup V_{\text{aux}} \]

\[ V_{\text{op}} = \{ \text{difference, sum, lowest, highest, for each, } \ldots \} \]

\[ V_{\text{store}} = \{ \text{a, is, are, of, that, the, with, was, did, to } \ldots \} \]

\[ V_{\text{aux}} = \{ \text{is, nor, the, with, was, did, to } \ldots \} \]
Logical Form Normalization

Remove unnecessary tokens

return the size of #1
PROJECT[subject, prop; the size of]  ➔
return #1 size
PROJECT[subject; condition; size]

Replace with representative

return country
SELECT[sub-country]

Merge steps

return blue objects
SELECT[sub-objects; blue]

Figure 4: An illustration of LF normalization. Normalization is done on the LF \( Z \), and we present QDMR steps for ease of reading.

Presentation is given by representing each step as described in §3:

\[
\text{OPERATOR} \left[ \text{property} (\text{arg}=\ldots; \ldots) \right]
\]

We apply the following steps (Fig. 4):

**Remove and normalize tokens** Each LF step includes a list of tokens in its arguments. In this normalization step, we remove lexical items, such as “max”, which are used to detect the operator and property (Table 7 in §A.1), as those are already represented outside the arguments. In addition, we remove words from a stop word list (\( V_{\text{aux}} \), see Fig. 3). Finally, we use a synonym list to represent words in such a list with a single representative (\( \text{countries}\rightarrow\text{country} \)).

**Merge steps** QDMR annotations sometime vary in their granularity. For example, one example might contain ‘return metal objects’, while another might have ‘return objects; return #1 that are metal’.

This is especially common in FILTER and PROJECT steps. We merge chains of FILTER steps, as well as FILTER or PROJECT steps that follow a SELECT step. See details in §A.2.

**Reorder steps** QDMR describes a directed acyclic graph of computation steps, and there are multiply ways to order the steps (Fig. 4). We recursively compute the \( \text{layer}(s) = \max \{\text{layer}(s^{ef}), \ldots\} + 1 \), where the maximization is over all steps \( s \) refers to. We then re-order steps by layer and then lexicographically.

We manually evaluate the metrics normalized EM and LF-EM on 50 random development set examples using predictions from the CopyNet-BERT model (see §6). We find that both (binary) metrics have perfect precision: they only assign credit when indeed the QDMR reflects the correct question decomposition, as judged by the authors. However, LF-EM covers more examples, where the LF-EM on this sample is 52.0, while normalized EM is 40.0. Thus, LF-EM provides a tighter lower bound on the performance of a QDMR parser and is a better metric for QDMR parsing.

4 From LFs to Dependency Graphs

Given a QDMR decomposition \( S = (q; s^1, \ldots, s^m) \), we construct a dependency graph \( G = (N, E) \), where the nodes \( N \) correspond to question tokens, and the edges \( E \) describe the logical operations, resulting in a graph with the same meaning as \( S \).

The LF→DG procedure is shown in Fig. 5 and consists of the following steps:

- **Token alignment**: align each token in the question to a token in a QDMR step.
- **Spans Dependency Graph (SDG) extraction**: construct a graph where each node corresponds to a list of tokens in a QDMR step, and edges describe the dependencies between the steps.
- **Dependency Graph (DG) extraction**: convert the SDG to a DG over the question tokens. Here, we add span edges for tokens that are in the same step, and deal with some representation issues (see §4.3).

Because we convert predicted DGs to LFs for evaluation, the LF→DG conversion must be invertible. We now describe the details of the LF→DG conversion. Our conversion succeeds in 97.12% of the BREAK dataset (Wolfson et al., 2020).

4.1 Token Alignment

We denote the question tokens by \( q = (q_1 \ldots q_n) \) and the \( i \)th QDMR step tokens by \( \forall i \in [1..m], s^i = (s^i_1 \ldots s^i_{n_i}) \). An alignment is defined by \( M = \{(q_i, s^i_k) \mid q_i \approx s^i_k; i \in [1..n], k \in [1..m], j \in [1..n], j \} \), where by \( t \approx t' \) we mean \( t, t' \) are either identical or equivalent. Roughly speaking, these equivalences are based on BREAK annotation lexicon (Fig. 3) - in particular, the inflections of the question tokens \( V_q \) (e.g., “object” and “objects”), and equivalence classes on top of the constant lexicon \( V_{\text{const}} \) (e.g., “biggest” and “longest”). See Table 8 in Appendix §A.2 for more details.
To find the best alignment $M$, we formulate an optimization problem in the form of an Integer Linear Program (ILP) and use a standard ILP solver. The full details are given as a part of our open source implementation. The objective function uses several heuristics to assign a high score to an alignment that has the following properties (Fig. 6):

- **Minimalism**: Aligning each question token to at most one QDMR step token and vice versa is preferable.

- **Exact Match**: Aligning a question token to a QDMR token that is identical is preferable.

- **Sequential Preference**: Aligning long sequences from the question to a single step is preferable (when a step has a reference token (\#1), we take into account the tokens in the referenced step, see Fig. 6, top right).

- **Steps Coverage**: Covering more steps is preferable.

### 4.2 Spans Dependencies Extraction

Given the QDMR, LF, and alignment $M$, we construct the Span Dependency Graph (SDG). Each QDMR step is a node labeled by a list of tokens (spans). The list of tokens is computed with the alignment $M$, where given a QDMR step $s^k$, the list contains all question tokens $q_i$, such that $(q_i, s^k_j) \in M$, where $s^k_j$ is a word in $s^k$. The list is ordered according to the position in the question.

Edges in the SDG are computed using reference tokens. If step $s_i$ has a reference token to step $s_j$, we add an edge $(s_i, s_j)$ (we abuse notation and refer to SDG nodes and QDMR steps with the same notation). Each edge has a tag, which is a triple consisting of the operator $o_i$ of the source node $s_i$, the property $\rho_j$ of the source node, and the named argument $\eta_{ref}^j$ that contains the reference token. For readability we denote the tag triplet $tag(i,j) = \langle o_i, \rho_j, \eta_{ref}^j \rangle$ by $o_i^j \eta_{ref}^j[\rho]^j$. Figure 5 shows an extracted SDG.
4.3 SDG → DG

We construct a DG by projecting the SDG on the question tokens. This is done by: (a) For each SDG node and its list of tokens, add edges between the tokens from left-to-right with a new span tag (black edges in Fig 5); (b) use the rightmost word in every span as its representative for the edges between different spans.

However, this transformation is non-trivial for two reasons. First, some SDG nodes do not align to any question token. Second, some question tokens align to multiple SDG nodes, which does not allow the DG to be converted back to an SDG unambiguously for evaluation. We now explain how we resolve such representation issues, mostly based on adding more tokens to the input question.

Domain-specific concepts QDMR annotators were allowed to use a small number of tokens that are pragmatically assumed to exist in the domain \( \mathcal{V}_{\text{store}} \) in Fig. 3. For example, when annotating ATIS questions (Hemphill et al., 1990), the word “flight” is allowed to be used in the QDMR structure even if it does not appear in the question, since this is a flight-reservation domain. We concatenate all the words in \( \mathcal{V}_{\text{store}} \) to the end of each question after a special separator token, which allows token alignment (§4.1) to map such QDMR steps to a question word (Fig. 7, top).

Empty SDG nodes some steps only contain tokens that are not in the question (e.g., “Number of #2” in Fig. 7 bottom), and thus their list of tokens in the SDG node is empty. In this case, we cannot ground the SDG node in the question. Therefore we add a constant number of dummy tokens, [DUM], which are used to ground such SDG nodes.

Single tokens to multiple SDG nodes A single question token can be aligned to multiple SDG nodes. Recall the tokens of each SDG nodes are connected with a chain of span edges. This leads to cases where two chains that pass through the same question token cannot be distinguished when converting the DG back to an SDG for evaluation. We solve this by concatenating a constant number of special [DUP] tokens that conceptually duplicate another token by referring to it with a new duplicate tag. Now, each span chain uses a different copy of the shared token by referring to the [DUP] instead of the original one.

5 Models

Once we have methods to convert QDMRs to DGs and LFs, and DGs to LFs, we can evaluate the advantages and disadvantages of standard autoregressive decoders compared to graph-based parsers. We describe three models: (a) An autoregressive parser, (b) a graph parser, (c) an autoregressive parser that is trained jointly with a graph parser in a multi-task setup. For a fair comparison, all models have the same BERT-based encoder (Devlin et al., 2019).

CopyNet-BERT (baseline) This autoregressive QDMR parser is based on the CopyNet baseline from Wolfson et al. (2020), except we replace the BiLSTM encoder with a transformer initialized with BERT. The model encodes the question \( q \) and then decodes the QDMR \( S \) step-by-step and token-by-token.

The QDMR decoder is an LSTM (Hochreiter and Schmidhuber, 1997) augmented with a copy mechanism (Gu et al., 2016), where at each time step the model either decodes a token from the vocabulary or a token from the input. Since the input is tokenized with word pieces, we average word pieces that belong to a single word to get word representations, which enables word copy-
Training is done with standard maximum likelihood.

**Biaffine Graph Parser (BiaffineGP)** The biaffine graph parser takes as input the question \( q \) augmented with the special tokens described in §4.3 and predicts the DG by classifying for every pair of tokens whether there is an edge between them and the label of the edge. The model is based on the biaffine dependency parser of Dozat and Manning (2018), except here we predict a DAG and not a tree, so each node can have more than one outgoing edge.

Let \( H = (h_1, \ldots, h_{|H|}) \) be the sequence of representations output by the BERT encoder. The biaffine parser uses four 1-hidden layer feed-forward networks over each contextualized token representation \( h_i \):

\[
\begin{align*}
    h_{edge-head}^i &= FF_{edge-head}(h_i), \\
    h_{edge-dep}^i &= FF_{edge-dep}(h_i), \\
    h_{label-head}^i &= FF_{label-head}(h_i), \\
    h_{label-dep}^i &= FF_{label-dep}(h_i).
\end{align*}
\]

The probability of an edge from token \( i \) to token \( j \) is given by \( \sigma(h_{edge-dep}^i W_{edge} h_{edge-head}^j) \), where \( W_{edge} \) is a parameter matrix. Similarly, the score of an edge labeled by the tag \( t \) from token \( i \) to token \( j \) is given by \( s_{ij}^t = h_{i}^t W_{t} h_{j}^t \), where \( W_t \) is the parameter matrix for this tag. We then compute a distribution over the set of tags \( T \) with softmax(\( s_{1ij}, \ldots, s_{|T|ij} \)).

Training is done with maximum likelihood both on the edge probabilities and label probabilities. Inference is done by taking all edges with edge probability \( > 0.5 \) and then labeling those edges according to the most probable tag.

There is no guarantee that the biaffine parser will output a valid DG. For example, if an SDG node has an outgoing edge labeled with filter-sub and another labeled with project-sub, we cannot tell if the operator is FILTER or PROJECT. This makes parsing fail, which occurs in 1.83% of the cases. To create a SDG, we first use the span edges to contract SDG nodes with lists of tokens, and then add edges between SDG nodes by projecting the edges between tokens to edges between the SDG nodes. To prevent cases where parsing fails, we can optionally apply an ILP that takes the predicted probabilities as input, and outputs a valid DG. The exact details are given in our open source implementation.

**Multi-task Latent-RAT Encoder** In this model, our goal is to improve the sequence-to-sequence parser by providing more information to the encoder using the DG supervision. Our model will take the question \( q \) (with special tokens as before) as input, and predict both the graph \( G \) directly and the QDMR structure \( S \) with a decoder. We would like the information on relations between tokens to be part of the transformer encoder, unlike the biaffine parser that uses separate feed-forward networks for that, so that the decoder can take advantage of this information. To accomplish that, we use RAT transformer layers (Shaw et al., 2018; Wang et al., 2020), which explicitly represent relations between tokens, and have been shown to be useful for encoding graphs over input tokens in the context of semantic parsing.

RAT layers inject information on the relation between tokens inside the transformer self-attention mechanism (Vaswani et al., 2017). Specifically, the similarity score \( e_{ij} \) computed using queries and keys is given by:

\[
e_{ij} \propto h_i W_Q (h_j W_K + r_{ij} W_K) T,
\]

where \( W_Q, W_K \) are the query and key parameter
matrices and the only change is the term $r_{ij}^{K}$, which represents the relation between the tokens $i$ and $j$. Similarly, the relation between tokens is also considered when summing over self-attention values:

$$\sum_{j=1}^{H} \alpha_{ij}(x_{j}W_{V} + r_{ij}^{V}),$$

where $W_{V}$ is the value parameter matrix, $\alpha_{ij}$ is the attention distribution and the only change is the term $r_{ij}^{V}$.

Unlike prior work where the terms $r_{ij}^{K}, r_{ij}^{V}$ were learned parameters, here we want these vectors to (a) be a function of the contextualized representation and (b) be informative for classifying the dependency label in the gold graph. By learning latent representations from which the gold graph can be decoded, we will provide useful information for the sequence-to-sequence decoder. Specifically, given a RAT layer with representations $h_{i}, h_{j}$ for tokens $i$ and $j$, we represent relations and compute a loss in the following way (see Figure 8):

$$r_{ij}^{K} = FF_{K}(h_{i} - h_{j}),$$
$$S_{K}^{R} = R_{K}^{V}W^{out} + b^{K} \in \mathbb{R}^{n \times n \times |T|},$$
$$Loss_{K}^{R} = CE(S_{K}^{R}).$$

$FF_{K}$ is a 1-hidden layer feed-forward network, $R_{K}^{V}$ is a concatenation of all $r_{ij}^{K}$ for all pairs of tokens, $W^{out} \in \mathbb{R}^{d_{\text{transformer}} \times |T|}$ is a projection matrix that provides a score for all possible labels (including the NONE label).

We compute an analogous loss $Loss_{K}^{V}$ for $r_{ij}^{V}$ and the final graph loss is $Loss_{K}^{R} + Loss_{K}^{V}$ over all RAT layers. To summarize, by performing multi-task training with this graph loss we push the transformer to learn representations $r_{ij}$ that are informative of the gold graph, and can then be used by the decoder to output better QDMR structures.

6 Experiments

We now describe our empirical evaluation of the models described above.

6.1 Experimental Setup

We build our models in AllenNLP (Gardner et al., 2018), and use BERT-base (Devlin et al., 2019) to produce contextualized token representations in all models. We train with the Adam optimizer (Kingma and Ba, 2015). Our Latent-RAT model include 4 RAT layers, each with 8 heads. Full details on hyperparameters and training procedure in Appendix §A.3.

We examine the performance of our models in three setups:

- **Standard**: We use the official BREAK dataset.
- **Sample Complexity (SC)**: We examine the performance of models with decreasing amounts of training data. The goal is to test which model has better sample complexity.
- **Domain Generalization (DomGen)**: We train on 7 out of 8 sub-domains in BREAK and test on the remaining domain, for each target domain. The goal is to test which model generalizes better to new domains.

As an evaluation metric, we use LF-EM and also the official BREAK metric, normalized EM, when reporting test results on BREAK.

6.2 Results

**Standard setup** Table 2 compares the performance of the different models (§5) to each other and to the top entries on the BREAK leaderboard. As expected, initializing CopyNet with BERT dramatically improves test performance (0.388→0.47). The Latent-RAT sequence-to-sequence model achieves similar performance (0.471), and the biaffine graph parser, BiaffineGP, is slightly behind with an LF-EM of 0.44 (but has faster inference, as we show below). Adding an ILP layer on top of BiaffineGP to eliminate constraint violations improves performance to 0.454.

While our proposed models do not significantly improve performance in the LF-EM setup, we will see next that they improve domain generalization and sample complexity. Moreover, since BiaffineGP is a non-autoregressive model that predicts all output edges simultaneously, it dramatically reduces inference time.

Last, the top entry on the BREAK leaderboard uses BART (Lewis et al., 2020), a pre-trained seq2seq model (we use a pre-trained encoder only), which leads to a state-of-the-art LF-EM of 0.496.

**Domain generalization** Table 3 shows LF-EM on each of BREAK’s sub-domains when training on the entire dataset (top), when training on all domains but the target domain (middle), and the relative drop compared to the standard setup (bottom).

The performance of BiaffineGP and Latent-RAT is higher compared to CopyNET+BERT in the...
Table 2: Normalized EM and LF-EM on the development and test sets of BREAK.

| Model               | NormEM | LF-EM   |
|---------------------|--------|---------|
|                     | dev    | test    | dev    | test    |
| CopyNet             | -      | 0.294   | -      | 0.388   |
| BART (leaderboard #1) | -      | 0.389   | -      | 0.496   |
| CopyNet+BERT        | 0.373  | 0.375   | 0.474  | 0.47    |
| BiaffineGP          | -      | -       | 0.441  | 0.44    |
| BiaffineGP$_{d_{LP}}$ | -      | -       | 0.453  | 0.454   |
| Latent-RAT          | 0.356  | 0.363   | 0.469  | 0.471   |

DomGen setup. In particular, the performance of Latent-RAT is the best in 7 out of 8 sub-domains, and the performance of BiaffineGP is the best in the last domain. Moreover, Latent-RAT outperforms CopyNet+BERT in all sub-domains. We also observe that the performance drop is lower for BiaffineGP and Latent-RAT compared to CopyNet+BERT. Overall, this shows that using graphs as a source of supervision leads to better domain generalization.

**Sample Complexity** Table 4 shows model performance as a function of the size of the training data. While the LF-EM of BiaffineGP is lower given the full training set (Table 2), when the size of the training data is small it substantially outperforms other models, improving performance by 3-4 LF-EM points given 1%-10% of the data. With 20%-50% of the data Latent-RAT and CopyNet+BERT have comparable performance.

**Inference time for the graph parser** The graph parser, BiaffineGP, is a non-autoregressive model that predicts all output edges simultaneously, as opposed to a sequence-to-sequence model that decodes a single token at each step. We measure the average runtime of the forward pass for both BiaffineGP and CopyNet+BERT and find that BiaffineGP has an average runtime of 0.08 seconds, compared to 1.306 seconds of CopyNet+BERT – a 16x speed-up.

**6.3 Analysis**

**Model agreement** Figure 9 shows model agreement between CopyNet+BERT, BiaffineGP, and Latent-RAT on the development set. Roughly 60% of the examples are predicted correctly by one of the models, indicating that ensembling the three models could result in further performance improvement.

The agreement of Latent-RAT with CopyNet+BERT (5.5%) and BiaffineGP (4.27%) is greater than the overlap between CopyNet+BERT and BiaffineGP, perhaps since it is a hybrid of a seq2seq and graph parser. Moreover, in 3.83% of the examples, Latent-RAT is the only model with a correct prediction.

**Length analysis** We compared the average LF-EM of models for each possible number of steps in the QDMR structure (Fig. 10). We observe that CopyNet+BERT outperforms Latent-RAT when the number of steps is small, but once the number of steps is $\geq 5$, Latent-RAT outperforms CopyNet+BERT, showing it is handles complex decompositions better, and in agreement with the tendency of sequence-to-sequence models to struggle with long output sequences.

**Error analysis** We randomly sampled 30 errors from each model and manually analyzed them. Table 5 describes the error classes for each model, and Appendix A.4 provides examples for these classes. Each example can have more than one error category.

For all models, the largest error category is actually cases where the prediction is correct but not
Table 3: Domain Generalization. LF-EM on the development set per sub-domain when training on the entire training set (top), and when training on all domains except the target one (middle). The bottom section is the performance drop from the full setup to the DomGen setup.

| Model         | ATIS   | CLEVR  | COMQA  | CWQ    | DROP   | GEO    | NLVR2  | SPIDER |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|
| CopyNet+BERT  | 0.58   | 0.564  | 0.562  | 0.36   | 0.473  | 0.66   | 0.344  | 0.369  |
| BiaffineGP    | 0.591  | 0.489  | 0.595  | 0.322  | 0.445  | 0.62   | 0.293  | 0.41   |
| Latent-RAT    | 0.589  | 0.524  | 0.598  | 0.316  | 0.479  | 0.64   | 0.353  | 0.376  |
| CopyNet+BERT  | 0.282  | 0.351  | 0.423  | 0.173  | 0.131  | 0.52   | 0.039  | 0.189  |
| BiaffineGP    | 0.302  | 0.339  | 0.483  | 0.168  | 0.146  | 0.52   | 0.04   | 0.197  |
| Latent-RAT    | 0.335  | 0.356  | 0.435  | 0.189  | 0.149  | 0.58   | 0.063  | 0.201  |

Table 4: Development set LF-EM as a function of the size of the training set.

| Model         | 1%     | 5%     | 10%    | 20%    | 50%    |
|---------------|--------|--------|--------|--------|--------|
| CopyNet+BERT  | 0.112  | 0.261  | 0.323  | 0.38   | 0.426  |
| BiaffineGP    | 0.159  | 0.296  | 0.351  | 0.382  | 0.411  |
| Latent-RAT    | 0.003  | 0.227  | 0.326  | 0.383  | 0.432  |

Table 5: Error classes and their frequency over a sample of 30 random errors. Model names were shortened from CopyNet+BERT, BiaffineGP and Latent-RAT.

- **Out of Vocabulary**: seq2seq models sometimes predict tokens that are not related to the question nor the decomposition. For example, "rodents" in a question about flowers.

7 Conclusion

In this work, we propose to represent QDMR structures with a dependency graph over the input tokens, and propose a graph parser and a seq2seq model that uses graph supervision as an auxiliary loss. We show that a graph parser is 16x faster than a seq2seq model, and that it exhibits better sample complexity. Moreover, using graphs as auxiliary supervision improves out-of-domain generalization and leads to better performance on questions that represent a long sequence of computational steps. Last, we propose a new evaluation metric for QDMR parsing and show it better corresponds to human intuitions.

In future work, we will examine ensemble models that take into account the complementary nature of graph parsers and seq2seq parser to further improve performance on QDMR parsing.
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A Appendices

A.1 QDMR LF

Table 6 shows the different operators, their properties and examples of LFs. Table 7 shows terms that are used to identify the QDMR step operator’s properties. We use the same lexicon from BREAK (Wolfson et al., 2020) for detecting operators, extended with some specifications for numeric properties such as equals_0.

A.2 LF-Based Evaluation (LF-EM)

In §3.2 we described a LF-based evaluation metric. Given a logical form of a QDMR, Z, the metric transforms it to a normalized form $Z_{\text{norm}}$ in the following way: (1) Normalize the steps by removing unnecessary tokens and replace equivalents; (2) Merge steps with their referrer; and (3) Reorder the steps in a consistent order. Now we describe these steps more formally.

**Normalize Steps** Let $z = \langle o, \rho, A \rangle$ be a logical form of step $s$, where $A = \{ (\eta^a, \tau^a) | \eta^a \in PROP_o, \tau^a \subseteq s |_{a=1} \}$ is the named-arguments set. Note here $\tau$ is a set of tokens instead of subsequence of $s$. A normalization transformation is a function $T_{o,\rho} : s \rightarrow \{\emptyset\} \cup V_o \cup V_{\text{store}}$ mapping each token to an equivalent token out of the allowed vocabulary or to $\emptyset$ for removal. We denote by $T_{o,\rho}(A) := \{ (\eta, \{T_{o,\rho}(\tau_1), \ldots, T_{o,\rho}(\tau_{|\tau|})\}) | (\eta, \tau) \in A \}$, i.e., applying a transformation on the named-arguments set is defined by applying it on each of the arguments tokens. The final normalized form of $l$ is given by applying multiple transformations on the arguments, $z_{\text{norm}} = \langle o, \rho, T_{o,\rho}^{\text{rep}} \circ T_{o,\rho}^{\text{aux}} \circ T_{o,\rho}^{\text{prop}}(A) \rangle$. 
| Operator       | PROP | ARG         | Example                                                                 |
|---------------|------|-------------|-------------------------------------------------------------------------|
| SELECT        | ∅    | sub         | return cubes SELECT[(sub=cubes)]                                        |
| FILTER        | ∅    | sub, condition | return #1 from Toronto FILTER[(sub=#1, cond=from Toronto)]             |
| PROJECT       | ∅    | sub, projection | return the head coach of #1 PROJECT[(sub=#1, projection=head coach of)] |
| AGGREGATE     | max, min, count, sum, avg | arg | return maximal number of #1 AGGREGATE[max][arg=#1]                      |
| GROUP         | max, min, count, sum, avg | key, value | return the number of #2 for each #1 GROUP[count](key=#1, value=#2)      |
| SUPERLATIVE   | max, min | sub, attribute | return #2 where #3 is the lowest SUPERLATIVE[min](sub=#2, attribute=#3) |
| COMPARATIVE   | equals, equals-[0/1/2], more, more-than-[0/1/2], less, less-than-[0/1/2] | sub, attribute, condition | return #1 where #2 is more than 100 COMPARATIVE[more](sub=#1, condition=100) attribute=#2, |
| COMPARISON    | max, min, count, sum, avg, true, false | arg | return which is higher of #1, #2 COMPARISON[max][arg=#1, arg=#2]        |
| UNION         | ∅    | sub         | return #1, #2 UNION[(sub=#1, sub=#2)]                                  |
| INTERSECTION  | ∅    | intersect, projection | return parties in both #2 and #3 INTERSECTION%(intersect=#2, projection=parties) intersect=#3, |
| DISCARD       | ∅    | sub, exclude | return #1 besides #2 DISCARD%(sub=#1, exclude=#2)                       |
| SORT          | ∅    | sub, order | return #1 ordered by name SORT%(sub=#1, order=)                        |
| BOOLEAN       | equals, equals-[0/1/2], more-than-[0/1/2], less-than-[0/1/2], and-true, or-true, or-false, if-exists | sub, condition | return if #1 is the same as #2 BOOLEAN[equals](sub=#1, condition=#2)     |
| ARITHMETIC    | sum, diff, multiply, div | arg, left, right | return the difference of #3 and #4 ARITHMETIC[diff](left=#3, right=#4)   |

Table 6: LF operators, properties and arguments. Each QDMR step can be mapped to one of the above operators, where its LF consists of its operator, properties and arguments. The example column shows an example for such LF.
Table 7: Property lexicon. Tokens for detecting the properties of a QDMR step, for creating its logical form.

\[
\begin{array}{|c|c|c|}
\hline
\text{Operator} & \text{PROP} & \text{Lexical entries} \\
\hline
\text{AGGREGATE}, \text{COMPARISON}, \text{GROUP} & \text{max} & \text{max, most, more, last, biggest, biggest, larger, longest} \\
\hline
\text{AGGREGATE}, \text{COMPARISON}, \text{GROUP} & \text{min} & \text{min, least, least, first, fewer, smaller, smallest, lower, lowest, shortest, shorter, earlier} \\
\hline
\text{AGGREGATE}, \text{ARITHMETIC}, \text{GROUP} & \text{count} & \text{count, number of, total number of} \\
\hline
\text{AGGREGATE}, \text{ARITHMETIC}, \text{GROUP} & \text{sum} & \text{sum, total} \\
\hline
\text{AGGREGATE}, \text{COMPARISON}, \text{GROUP} & \text{avg} & \text{avg, average, mean} \\
\hline
\text{ARITHMETIC} & \text{diff} & \text{difference, decline} \\
\hline
\text{ARITHMETIC} & \text{multiply} & \text{multiplication, multiply} \\
\hline
\text{ARITHMETIC} & \text{div} & \text{division, divide} \\
\hline
\text{BOOLEAN}, \text{COMPARATIVE} & \text{equals} & \text{equal, equals, same as} \\
\hline
\text{BOOLEAN} & \text{if-exists} & \text{any, there} \\
\hline
\text{COMPARATIVE} & \text{more} & \text{more, at least, higher than, larger than, bigger than} \\
\hline
\text{COMPARATIVE} & \text{less} & \text{less, at most, smaller than, lower than} \\
\hline
\text{SUPERLATIVE} & \text{max} & \text{most, biggest, largest, highest, longest} \\
\hline
\text{SUPERLATIVE} & \text{min} & \text{least, fewest, smallest, lowest, shortest, earliest} \\
\hline
\end{array}
\]

Table 8 shows some examples for these classes.

| Type       | Equivalence Class |
|------------|-------------------|
| Modifications | cubed, cubes, ... |
|             | old, oldness, ... |
|             | taller, tall, ... |
|             | working, work, ... |
| Operational | biggest, longest, highest, ... |
| Synonyms   | elevation, height |
|            | 0, zero |
|            | ... |

Table 8: BREAK Equivalence Classes. (1) Modifications - the same modifications of the question tokens that were used for creating BREAK annotation lexicon (e.g. plural/singular form, nounify adjectives, lemmatize adjectives, lemmatize verbs); (2) Operational equivalence induced from properties lexicon; (3) Manually-defined Synonyms lexicon. We mostly retrieve the final equivalence classes by merging classes that share some tokens.

\[
\begin{align*}
&\rho : \text{V}_{\text{aux}} \rightarrow \text{V}_{\text{aux}}, \text{PROP} \\
&\text{T}_{\text{aux}} \text{ removes uninformative tokens, such as prepositions. These V}_{\text{aux}} \text{ were added in the first place to allow continuous fluent sentences to be written.} \\
&\text{T}_{\rho} \text{ maps a token to its representative token. Recall BREAK samples where annotated based on an allowed vocabulary, which is built on top of the question tokens variations and some additional ones. We define equivalence classes of break equivalent tokens and set a representative for each class. Table 8 shows some examples for these classes.} \\
\end{align*}
\]

**Merge Steps** The level of elaboration varies between annotators, leading to implicit steps, i.e., steps that are contained in other steps. This is especially common in FILTER and PROJECT steps. Therefore we offer a merging mechanism for group-

\[
\begin{align*}
&\langle o^{\text{src}}, \eta^{\text{src}}, o^{\text{dst}}, o^{\text{out}}, f^o, f_\eta \rangle \text{ where } o^{\text{src}}, \eta^{\text{src}} \text{ are the referrer step operator and argument name with the observed reference, } o^{\text{dst}} \text{ is the referred step operator, } o^{\text{out}} \text{ is the merged step operator and } f^o : \text{PROP}_{o^{\text{src}}} \times \text{PROP}_{o^{\text{dst}}} \rightarrow \text{PROP}_{o^{\text{out}}}, f_\eta : \text{ARG}_{o^{\text{src}}} \text{PROP}_{o^{\text{src}}} \cup \text{ARG}_{o^{\text{dst}}} \text{PROP}_{o^{\text{dst}}} \rightarrow \text{ARG}_{o^{\text{out}}} \text{ are mappings for the merged step properties and named arguments. The values for the arguments, } \tau, \text{ are induced by merging the values of the arguments names that are mapped to the merged argument name.} \\
&\text{In particular, we use the following merging rules:} \\
\end{align*}
\]

\[
\begin{align*}
&\bullet \text{ project-sub } \rightarrow \text{ select } = \text{project} \text{ Collapse select step that is referred by a project step as its subject.} \\
&\langle o^{\text{src}}, \eta^{\text{src}}, o^{\text{dst}}, o^{\text{out}}, f^o, f_\eta \rangle = \langle \text{project, subj, select, project} \rangle \\
&f^o(\rho^{\text{src}}, \rho^{\text{dst}}) = \rho^{\text{src}} \\
&f_\eta(a) = \begin{cases} a, & \text{if } a \in \text{ARG}_{\text{src}} \\
&\text{subj}, & \text{if } a \in \text{ARG}_{\text{dst}} \\
\end{cases} \\
\end{align*}
\]

\[
\begin{align*}
&\bullet \text{ filter-sub } \rightarrow \text{ select } = \text{filter} \text{ Collapse select step that is referred by a filter step as its subject.} \\
&\bullet \text{ filter-sub } \rightarrow \text{ filter } = \text{filter} \text{ Collapse filter step that is referred by another}
\end{align*}
\]
filter step as its subject. This rule deals with filter chains, when a sequence of filters referred by each other with sub argument, any order of them has the same meaning.

Reorder Execution Graph In some cases there are multiple possible sequential orderings for the same execution graph, for example for parallel execution branches (Fig. 4). We reorder the graph by first splitting the steps into layers where each layer may refer to previous layers only, and then order within a layer lexicographically. Formally, let $REF(z^i) \in [m] \setminus \{i\}$ be the references of step $z^i$. We define the degree (layer) of $z^i$ by:

$$d(z^i) := \begin{cases} 0, & \text{if } REF(s) = \emptyset \\ \max_{j \in REF(z^i)} d(z^j) + 1, & \text{otherwise} \end{cases}$$

Since QDMR execution graph is a DAG, $d(\cdot)$ is well defined. Let $\Delta_d = \{i \mid d(z^i) = d\}$ for $d \in [0..m]$. $rnk_{d(z^i)}(z^i)$ is the alphabet rank of $z^i$ in $\Delta_d(z^i)$, where $z^i$ textual representation is of the form $o^i[p^i_1, \ldots, p^i_\rho]([\eta^i_1 = \tau^i_1, \ldots, \eta^i_{|A^i|} = \tau^i_{|A^i|})].$

The properties $p^i_1, \ldots, p^i_\rho$ are sorted, and so the arguments $\eta^i_1 = \tau^i_1, \ldots, \eta^i_{|A^i|} = \tau^i_{|A^i|}$ first by the names $\eta$ and second by the values $\tau$. The textual representation of an argument value $\tau$ consists of alphabet ordered token, references first. Finally, the total rank of a step is given by $\langle d(z^i), rnk_{d(z^i)}(z^i) \rangle$, i.e primary order by degree and secondary order by in-layer rank.

A.3 Experiments Parameters

CopyNet-BERT The LSTM decoder has hidden size 768. We use a batch size of 32 and train for up to 25 epochs ($\sim$35k steps) with beam search of size 5.

Biaffine Graph Parser The POS embeddings are of size 100. The four FFNs consist of 3-layers with hidden size 300 and use ELU activation function. We use dropout of rate 0.6 on the contextualized encodings, and of rate 0.3 on the FF representations. We use a batch size of 32 and train for up to 80 epochs ($\sim$111k steps).

Latent RAT We stack 4 relation-aware self-attention layers on top of the contextualized encodings, each with 8 heads and dropout with rate 0.1. The FFNs for relation representation uses 3-layers with hidden size of 96, ReLU activation function and dropout rate of 0.1. We tie the layers, and multiply the graph loss by 100. The rest is identical to the CopyNet-BERT configuration.

Optimization We used the Adam optimizer (Kingma and Ba, 2015) with the hyperparameters. The learning rate changes during training according to slanted triangular schema, in which it linearly increases from 0 to lr for the first $warmup\_steps = 0.06 \cdot max\_steps$, and afterwards linearly decreases back to 0. We use learning rate of $1 \cdot 10^{-3}$, and a separate learning rate of $5 \cdot 10^{-5}$ for the BERT-based encoder.
A.4 Error Analysis Examples

Some examples for each error class from §6.3. The gold decompositions are given on left, and the predictions are on the right.

**Equivalent Solution**

How many yards longer was the longest field goal over the second longest?

1. select(sub=field goals)
2. project(projection=yards of #REF; sub=#1)
3. aggregate(max(arg=longest; #2))
4. aggregate(max(arg=second longest; #2))
5. arithmetic(difference)(left=#3; right=#4)

If there are exactly two fluffy dogs and no reflections.

1. select(sub=dogs)
2. filter(condition=that are fluffy; sub=#1)
3. aggregate(count(arg=#2))
4. boolean(equals_2)(condition=equal to two; sub=#3)
5. select(sub=reflections)
6. aggregate(count)(arg=#5)
7. boolean(equals_0)(condition=equal to zero; sub=#6)
8. boolean(logical_and;true)(sub=#4; #7)

**Elaboration Level**

What TV program with more than 19 episodes did Joey Lawrence play on?

1. select(sub=Joey Lawrence)
2. project(projection=TV programs of #REF; sub=#1)
3. filter(condition=with more than 19 episodes; sub=#2)

**Redundancy**

How many TD passes were under 10 yards?

1. select(sub=TD passes)
2. project(projection=yards of #REF; sub=#1)
3. comparative(less_than;attribute=#2)
   - condition=lower than 10 yards; sub=#1
4. aggregate(count)(arg=#3)

**Wrong Gold**

How many objects are either yellow or shiny?

1. select(sub=objects)
2. filter(condition=that are yellow; sub=#1)
3. filter(condition=that are shiny; sub=#1)
4. aggregate(count)(arg=#2)
5. aggregate(count)(arg=#3)
6. arithmetic(sum)(arg=#4; #5)
Missing Information

What shape of the only object that won’t roll if pushed?

1. select(sub=objects)
2. filter(condition=that won’t roll if pushed; sub=#1)
3. project(projection=shape of #REF; sub=#2)

Additional Steps

What is the smallest shape and also yellow?

1. select(sub=shapes)
2. project(projection=sizei of #REF; sub=#1)
3. superlative(min;attribute=#2; sub=#1)
4. filter(condition=that are yellow; sub=#3)

If at least five orange dogs without collars sit upright in a row, gazing intently, in one image, and the other image includes dogs in collars arranged more or less in a row.

1. select(sub=one image)
2. project(projection=dogs in #REF; sub=#1)
3. filter(condition=that are orange; sub=#2)
4. select(sub=collars)
5. filter(condition=#4; without; sub=#3)
6. filter(condition=that sit upright; sub=#5)
7. filter(condition=are in a row; sub=#6)
8. filter(condition=are gazing intently; sub=#7)
9. aggregate(count;[arg=#8])
10. boolean(condition=at least five; sub=#9)
11. select(sub=the other image)
12. project(projection=dogs in #REF; sub=#10)
13. filter(condition=#4; in a row; sub=#12)
14. boolean(condition=mores or less in a row; sub=#13)
15. boolean(logical_and_true)(sub=#10,#14)

Wrong Global Structure

How many was the difference between Sobieski’s force and the Turks and Tatars?

1. select(sub=Sobieski)
2. project(projection=the force of #REF; sub=#1)
3. project(projection=sizei of #REF; sub=#2)
4. select(sub=the Turks and Tatars)
5. project(projection=the force of #REF; sub=#4)
6. project(projection=sizei of #REF; sub=#5)
7. arithmetic(difference)(left=#6; right=#3)
Wrong Step Structure

How many years after Knopf was founded was it officially incorporated?

1. select(sub=Knopf was founded)
2. select(sub=Knopf was officially incorporated)
3. project(projection=year of #REF; sub=#1)
4. project(projection=year of #REF; sub=#2)
5. arithmetic(difference)(left=#4; right=#3)

Out of Vocabulary

What country is currently led by an acting prime minister and is a part of NATO?

1. select(sub=NATO)
2. project(projection=countries of #REF; sub=#1)
3. filter(condition=that are currently led by an acting prime minister; sub=#2)
4. select(sub=company)
5. filter(condition=that is currently led by an acting prime minister; sub=#1)
6. filter(condition=that is part of NATO; sub=#2)