Conversational Machine Comprehension: a Literature Review

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Abstract

Conversational Machine Comprehension (CMC) is a research track in conversational AI which expects the machine to understand an open-domain text and thereafter engage in a multi-turn conversation to answer questions related to the text. While most of the research in Machine Reading Comprehension (MRC) revolves around single-turn question answering, multi-turn CMC has recently gained prominence, thanks to the advancement in natural language understanding via neural language models like BERT and the introduction of large-scale conversational datasets like CoQA and QuAC. The rise in interest has, however, led to a flurry of concurrent publications, each with a different yet structurally similar modeling approach and an inconsistent view of the surrounding literature. With the volume of model submissions to conversational datasets increasing every year, there exists a need to consolidate the scattered knowledge in this domain to streamline future research. This literature review, therefore, is a first-of-its-kind attempt at providing a holistic overview of CMC, with an emphasis on the common trends across recently published models, specifically in their approach to tackling conversational history. It focuses on synthesizing a generic framework for CMC models, rather than describing the models individually. The review is intended to serve as a compendium for future researchers in this domain.

1 Introduction

Developing open-domain, intelligent dialog systems that can satisfactorily interact like humans, perform complex tasks and/or answer on a range of topics has been one of the most ambitious and difficult goals in Artificial Intelligence (AI). The study of such systems, called Conversational AI (ConvAI), is at the confluence of Natural language Processing (NLP), Information Retrieval (IR), and Machine Learning (ML), attracting significant research from both academia and industry. The recent developments in Deep Learning (DL) (Du and Black, 2019; Hatua et al., 2019) and Reinforcement Learning (RL) (Lipton et al., 2016; Peng et al., 2018) have further boosted research in the domain, making it one of the most sought after research topics in AI.

ConvAI has three major areas of research, based on the nature of problems a dialog system is expected to solve (Gao et al., 2018). Question Answering involves providing answers to user queries through conversation, using the knowledge drawn from various data sources like a snippet from a text, a collection of web documents, or an entire knowledge base. Task completion expects the conversational agent to accomplish task/s for the user using the information acquired through conversation. Finally, Social Chat makes the agent emulate humans and converse seamlessly and appropriately with users, as in the Turing test. Each of these fields has its own set of challenges to tackle.

Challenges in Question Answering (QA) can vary depending on the source of knowledge, the answer extraction strategy employed, and the domain of the question. Machine Reading Comprehension (MRC) is one such challenge in QA, that requires the conversational QA (ConvQA) agent to understand a given open-domain text and thereafter answer question/s in conversation about it. These questions are often not paraphrased and may co-reference previous queries. The required solution may be a span of given text or free-form. When the machine comprehension dialog involves multiple co-referenced questions such that a latter question may be a logical successor of the former, the challenge is termed as Conversational Machine Comprehension (CMC).

Although much of the history and research in
MRC revolves around single-turn QA, in reality, it is the multi-turn CMC that holds relevance, because humans seek information conversationally, by asking follow-up questions for additional information based on what they have already learned. Still, the inherent complexity involved in dealing with text comprehension and reasoning over context had kept CMC as a far-fetched goal. However, the recent success in achieving at-par-with-human performance on single-turn MRC models due to the advancement in natural language understanding and modeling, and the introduction of large-scale conversational datasets CoQA (Reddy et al., 2018) and QuAC (Choi et al., 2018) have made information-seeking dialogs possible.

As a consequence, CMC has seen a significant surge in research in recent years. In less than 2 years since the introduction of these datasets, there have been 38 submissions\(^1\) to CoQA leaderboard\(^2\) and 22 submissions\(^1\) to QuAC leaderboard\(^3\). Many of these models are unpublished, indicating active ongoing research on these datasets. Besides, the current state-of-the-art in QuAC lags behind human performance F1 benchmark by a margin of 6.7\(^1\), suggesting scope for improvement. Almost simultaneously, there have been breakthroughs in NLP (Devlin et al., 2018; Radford et al., 2018; Liu et al., 2019) which the researchers have tried to leverage in their upcoming models (Qu et al., 2019b; Yeh and Chen, 2019; Chen et al., 2019). Since many models are being published concurrently, there have been inconsistencies in their methodology and justification, for example, recently published CMC model FlowDelta (Yeh and Chen, 2019) did not compare or justify its BERT fine-tune based approach against BERT+History Embedding approach of History Answer Embedding (HAE) model (Qu et al., 2019a) published almost a year earlier which used BERT in the same form. This prevailing scenario has blurred the bigger picture and made it difficult for researchers to intending novel research in this field. Moreover, as of this date, there is no singular summarized view on CMC models, expect the individual literature studies of these publications which can be highly localized and inconsistent with the global view. Thus, the current mayhem motivates the need for organizing the scattered knowledge across these publications into a consolidated overview, so that future research in this field may be streamlined.

This literature review, therefore, provides a bird-eye overview of the domain of Conversational Machine Comprehension. We commence with a summary of the traditional single-turn MRC models that preceded conversational models and laid the foundation for their development. Thereafter, the reader is acquainted with the challenges that make CMC unique and the large-scale conversational datasets that spurred the field. To develop a general understanding of the CMC approaches, we shift the focus from understanding individual models to observing the common trends that mark these models, synthesizing a generic framework for a CMC model in the process. The review would finally end with a discussion on the current trends in the domain and the suggested advancements in the future. For interested readers, we also briefly walk through the history of Machine Comprehension in the appendix A.

2 Related Work

There have been several published literature reviews on MRC in recent years. (Gao et al., 2018) provides an extensive review of Conversational AI with a detailed account of the neural approaches being employed in each of its dialog systems (QA, Task completion, and social chat). While it briefly discusses the problem of CMC and its datasets, it does not comment upon the recent advancements and prevalent approaches in this domain. (Zhang et al., 2019a) provides a summary of all the recent single-turn MRC datasets and approaches, however, it only talks briefly on CoQA and does not touch upon any approaches for CMC. (Qiu et al., 2019) too summarizes the classic models of single-turn MRC, but with a focus on deriving a common architecture and suggesting improvements based on the analysis. CMC is mentioned as an emerging research direction in this paper. The latest review, (Baradaran et al., 2020), is an overview of MRC with statistical analysis of the various types of problems and datasets existing in this domain and an account of its most cited approaches. CMC is mentioned as an MRC challenge but is not detailed.

What, therefore makes this review different from its predecessors is its relative focus on Conversational (multi-turn) Machine Comprehension, which

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1Recorded as of March 22, 2020. Please note that many of these submissions are either ensemble versions of single models, or hyper-parameter variants of their pre-published models or are simply unpublished. Therefore, unique published models’ count is 13 in CoQA and 7 in QuAC.

2https://stanfordnlp.github.io/coqa/

3http://quac.ai/
has only been briefly touched upon in the previous surveys. CMC has its own set of challenges different from single-turn and has active ongoing research with no established conventions. This calls for considering CMC as a separate research direction from the rest of MRC and review its rapid developments in terms of its general trends. While this paper briefly revisits single-turn models, it is only to facilitate the explanation of CMC models.

3 Traditional Machine Comprehension - Single-Turn Predecessor

Although QA systems have existed since the 1960s (Green et al., 1961; Klein and Simmons, 1963; Plath, 1977), MRC has only grown as an independent research direction in the last 2 decades, specifically since the first MRC task introduced by DeepRead (Hirschman et al., 1999). The evolution of MRC systems, detailed in appendix A, demonstrates the challenges faced by researchers in dealing with the initial static, rule-based MRC systems. Neural language models (Bengio et al., 2003; Graves, 2013; Vaswani et al., 2017; Devlin et al., 2018) relatively eased the task by handling the low-level semantic information which was previously handcrafted. To fully utilize the potential of these data-intensive models, new large-scale, open-domain datasets like MCTest (Richardson et al., 2013) and the “the Imagenet for MRC”, SQuAD (Rajpurkar et al., 2016) consists of 100K+ questions from a variety of answer types while version 2.0 (Rajpurkar et al., 2018) lays emphasis on unanswerable questions with over 50K additional questions.

- CNN/Daily Mail (Hermann et al., 2015): Released by Google DeepMind and the University of Oxford, this is the first large-scale MRC dataset constructed synthetically. Created by collecting 93K articles from the CNN and 220K articles from the Daily Mail and converting their bulleted summaries into document-query-answer triples.
- NewsQA: NewsQA (Trischler et al., 2016) is based on 12,744 news articles from CNN news with 119K question-answer pairs generated by crowd workers. Compared to SQuAD, a larger proportion of questions in NewsQA require a higher level of reasoning skills.
- WIKIHOP+MEDHOP (Welbl et al., 2018) are first of their kind-multi-hop reasoning datasets, that evaluate the system’s ability to be able to collect, reason and combine evidence across different documents to answer the given question. Wikihop generates multi-hop questions from Wikipedia corpus while MedHop on a biomedical corpus.

Datasets with descriptive answers: These datasets require descriptive answers which are usually free-form (abstractive) and may or may not require evidence. They may be useful in situations where the questions are implicit and may require the use of common sense or world knowledge. It is relatively difficult to evaluate the system performance on these datasets precisely and objectively, however, models performing well on these datasets can be precursors to conversational QA systems.

- MS MARCO: (Nguyen et al., 2016) is a large scale real-world MRC dataset released by Microsoft, sampled from real anonymized queries issued through Bing or Cortana. The questions are either unanswerable or have answers given by crowd workers in the form of complete sentences using the search results provided by the engine. MS MARCO requires
systems to generate an answer (if there is one) from multiple disconnected passages. Therefore, it is far more challenging and requires more sophisticated comprehension skills than other datasets like SQuAD.

- **Narrative QA**: (Kociský et al., 2017) is another dataset released by DeepMind and the University of Oxford, now with descriptive answers, that tests a system’s ability to capture the underlying narrative elements to answer questions which cannot be answered by simple pattern recognition. Question-answer pairs are created by crowd workers using stories and plot summaries from books and movie scripts, without seeing the entire corpus, thus preventing localized context.

**Datasets with Multi-choice options:** These datasets provide multiple-choice questions on the text and expect the system to choose the correct option/s. The advantages of these datasets are objective evaluation and restricted scope, as they only require correlating options with the questions instead of matching all sentences (as in extractive datasets). For example, Microsoft’s high-quality dataset, *MCTest* (Richardson et al., 2013), consists of 500 children stories and 2000 multi-choice questions that are easy and comprehensible and do not require world knowledge to answer. However, the dataset size is too small to train a proper neural model. *MCScript* (Ostermann et al., 2018), on the other hand, focuses on questions that need reasoning using commonsense knowledge, by providing multi-choice implicit questions created by crowd workers on peoples daily activities. The dataset is large enough for training.

3.2 Techniques

Several end-to-end neural methods, employing different types of attention mechanisms (Bahdanau et al., 2014; Luong et al., 2015), have become the default choice for solving the MRC task. Some of these models are summarized:

- **Match-LSTM+Pointer Network** (Wang and Jiang, 2016): was the first end-to-end neural architecture proposed for SQuAD. This model combines the match-LSTM (Wang and Jiang, 2015), which gets a unidirectional query-aware representation of passage, and the Pointer Network (Vinyals et al., 2015), which constructs an answer with its every token coming from the input text.

- **Bidirectional Attention Flow (BiDAF)**: (Seo et al., 2016): uses bi-directional attention flow, namely, a passage-to-query attention and a query-to-passage attention, to get a query-aware passage representation, which is then modeled together via Bi-LSTM (Hochreiter and Schmidhuber, 1997) and DenseNet (Huang et al., 2016) to generate span.

- **Gated-Attention Reader**: (Dhingra et al., 2016) uses bidirectional Gated Recurrent Unit (bi-GRU) (Cho et al., 2014) to get contextualized representations from embeddings for both passage and query. Then, at each stage, a multiplicative interaction between the query and the hidden state from the previous stage is employed in its attention mechanism to generate contextualized embeddings. It is generally applied for multi-hop reasoning based QA over multiple documents.

- **Dynamic Coattention Networks (DCN)** (Xiong et al., 2016): introduces co-attention mechanism in the encoder to combine co-dependent representations of query and document, and a dynamic iteration in the decoder to avoid being trapped in local incorrect maxima. The DCN decoder takes in the output of the co-attention encoder and generates the final predictions.

- **FastQA**: (Weissenborn et al., 2017) achieved competitive performance with a simple architecture against its complex QA counterparts that employ a complex interaction layer to catch the interactivity between the query and the context. It makes use of a context/type matching heuristic to find computable features on the word level to instill the interaction. Due to its simplicity, it can serve as a strong neural baseline for future models.

- **ReasoNet**: (Shen et al., 2016) makes use of RL to dynamically determine the number of reading and reasoning turns, based on the complexity of queries and passages. The intuition comes from the fact that the difficulty of different questions can vary in the same dataset (Chen et al., 2016), and humans usually revisit important parts of passage and question while answering.
QANet: (Yu et al., 2018) was the first non-sequential neural model published on SQuAD leaderboard\(^4\) that only used convolution and self-attention in its encoding layers. It achieved state-of-the-art accuracy during its release, with up to 13x speedup in training, compared to its sequential counterparts. The model was a precursor to the Transformers (Vaswani et al., 2017) which had the same encoder structure with the only difference of using FCNN instead of CNN for interaction.

Pre-trained Language models: Since the release of BERT (Devlin et al., 2018), numerous pre-trained language models (LM) have emerged, like the lighter ALBERT (Lan et al., 2019), semantically-aware BERT (Zhang et al., 2019b), autoregressive pre-training based LM – XLNet (Yang et al., 2019), GPT (Radford et al., 2018), two-stage reader and verifier – RetroReader (Zhang et al., 2020), and the robustly optimized pre-training based LM (Liu et al., 2019). These LMs have delivered state-of-the-art results on accuracy on most MRC datasets, outperforming their predecessor sequential models both in performance and time. All these LMs use deep bi-directional transformer-based encoder representations to produce contextualized embeddings for every passage token, which are then passed through an FC layer to obtain the required answer span.

To put formally, the task of CMC is defined as:

Given a passage \(P\), the conversation history in the form of question-answer pairs \(\{Q_1, A_1, Q_2, A_2, \ldots, Q_{i-1}, A_{i-1}\}\) and a question \(Q_i\), the model needs to predict the answer \(A_i\). The answer \(A_i\) can either be a text span \((s_i, e_i)\) (Choi et al., 2018) or a free-form text \(\{a_{i,1}, a_{i,2}, \ldots, a_{i,j}\}\) with evidence \(R_i\) (Reddy et al., 2018).

Single-turn MRC models cannot directly cater to CMC, as the latter is much more challenging to address. Some of the challenges are:

- The encoding module needs to be extended to encode not only \(P\) and \(A_i\) but also the conversational history.
- General observation about information-seeking dialog in humans is that the starting dialog-turns tend to focus on the beginning chunks of the passage and shift focus to the later chunks as the conversation progresses (Choi et al., 2018). The model is thus expected to capture these focal shifts during a conversation and reason pragmatically, instead of only matching lexically or via paraphrasing.
- Multi-turn conversations are generally incremental and coreferential. These conversational dialogs are either drilling down (the current question is a request for more information about the topic), shifting topic (the current question is not immediately relevant to something previously discussed), returning topic (the current question is asking about a topic again after it had previously been shifted away from), clarification of topic, or definition of an entity (Yatskar, 2018). The model should, therefore, be able to take context from history which may or may not be immediate.

5 Multi-Turn Conversational Datasets

One of the major causes for a surge in CMC research has been the emergence of large-scale multi-turn conversational datasets – CoQA (Reddy et al., 2018) and QuAC (Choi et al., 2018). There have been other multi-turn conversational datasets. ShARC (Saeidi et al., 2018), for example, requires interpretation of a regulatory text for answering co-referenced questions, through the application of background knowledge and the formulation of free-form clarification questions (the model can cross-question). However, these datasets do not follow the definition of CMC as given in section 4, and are hence ignored.

5.1 CoQA

Conversational QA (CoQA) dataset consists of 126k questions sourced from 8k conversations.

Dataset preparation: conversations are prepared over passages are collected across 7 different domains, each with its source dataset. These domains are – Children’s stories derived from MCTest (Richardson et al., 2013), news articles derived from CNN (Hermann et al., 2015), literature articles derived from Project Gutenberg\(^5\), high school

\(^4\)https://rajpurkar.github.io/SQuAD-explorer/

\(^5\)https://www.gutenberg.org/
The Virginia governor’s race, billed as the marquee battle of an otherwise anticlimactic 2013 election cycle, is shaping up to be a foregone conclusion. Democrat Terry McAuliffe, the longtime political fixer and moneymen, hasn’t trailed in a poll since May. Barring a political miracle, Republican Ken Cuccinelli will be delivering a concession speech on Tuesday evening in Richmond. In recent ...

Q₁: What are the candidates running for?
A₁: Governor
R₁: The Virginia governor’s race

Q₂: Where?
A₂: Virginia
R₂: The Virginia governor’s race

Q₃: Who is the democratic candidate?
A₃: Terry McAuliffe
R₃: Democrat Terry McAuliffe

Q₄: Who is his opponent?
A₄: Ken Cuccinelli
R₄: Republican Ken Cuccinelli

Q₅: Which of them is winning?
A₅: Terry McAuliffe
R₅: Democrat Terry McAuliffe, the longtime political fixer and moneymen, hasn’t trailed in a poll since May

Figure 1: A QA dialog example in the CoQA dataset. Every dialog is based on a context and each turn of the dialog contains a question (Qᵢ), an answer (Aᵢ) and a rationale (Rᵢ) that supports the answer. The phrase pairs colored with the same color (e.g., ‘running’ and ‘Where’ are colored blue) depicts co-referencing between dialog turns. Source: (Reddy et al., 2018)

English exams from RACE (Lai et al., 2017), science articles from A12 science questions (Welbl et al., 2017), Reddit articles from Writing Prompts (Fan et al., 2018), and articles from Wikipedia. Amongst these 7 domains, Reddit and Science articles are used for out-of-domain evaluation (only for evaluation, not training), while the other five aid in-domain evaluation (both training and evaluation). The dialog is prepared in a two annotator setting with one questioning and another answering, both referring to the entire context.

Questions: Questions are factoid but require sufficient co-referencing and pragmatic reasoning (Bell, 1999).

Answers: Answers are free-form, with their corresponding rationale highlighted in the passage. However, (Yatskar, 2018) identified that the answers are slightly modified versions of the rationale, and therefore optimizing an extractive model to predict the answer span with maximum F1 overlap to the gold answer can achieve up to 97.8 F1.

Dialog features: Its dialogs mostly involve drilling-down for details (about 60% of all questions) but lack other dialog features like topic-shift, clarification, or definition.

Evaluation: Macro-average F1 score of word overlap is used as evaluation metric. Computed separately for in-domain and out-of-domain as well.

Figure 2: A QA dialogue example in the QuAC dataset. Student asks questions and teacher responds in the form of text spans from the given section, and dialogue acts. Dialog acts include (1) continuation (whether the student should ↪, could ↪→, or should not ↪→, ask a follow-up); (2) affirmation (Yes / No), and, (3) No answer, when appropriate. Source: (Choi et al., 2018)

5.2 QuAC

Question Answering in Context (QuAC) contains 100K questions obtained from 14K information-seeking dialogs.

Dataset preparation: Dialogs are prepared over sections from Wikipedia articles about people from different genres like culture, wildlife, politics, geography, health, and entertainment. The dataset is prepared using an asymmetric setting, with a student exposed only to the title of the article and a summary while the teacher exposed to the entire section of the article on which the dialog is to be based. The student, therefore, tries to seek information about the hidden questions based on the limited information it gets from the dialog, and the teacher answers by providing short excerpts from the section (or ‘No Answer’ if not possible).

Questions: Questions are descriptive, highly-
contextual, and open-ended due to the asymmetric nature of the dataset that prevents paraphrasing. They require sufficient co-referencing and pragmatic reasoning.

**Dialog features**: Besides drilling down, dialogs switch to new topics more frequently than CoQA, while still lacking definition or clarification dialogs. (Gao et al., 2018) defined the steps for performing them. They require sufficient co-referencing and pragmatic reasoning. Besides extractive span, the response also includes additional signals called dialog acts like continuation (follow up, maybe follow up, or don’t follow up), affirmation (yes, no, or neither) and answerability (answerable or no answer), which provides additional useful dialog flow information to train on, as used in (Qu et al., 2019b; Ju et al., 2019). Further, analyzing answer token length in table 1 shows that QuAC answers are longer which can be attributed to its asymmetric nature which motivates seeker to ask open-ended questions to gauge hidden text.

**Evaluation**: Besides the macro-averaged F1 score on the entire set, QuAC also evaluates Human Equivalence Quotient (HEQ) to judge system performance relative to an average human, by finding the percentage of instances for which the systems F1 matches or exceeds human F1. HEQ-Q and HEQ-D are thus HEQ scores with the instances as questions and dialogs respectively.

### 6 Generic Framework of a CMC Model

(Gao et al., 2018) defined the steps for performing reading comprehension in a typical neural MRC model as (1) encoding the questions and context into a set of embeddings in a neural space; (2) reasoning in the neural space to identify the answer vector and (3) decoding the answer vector into a natural language output. (Huang et al., 2018) adapted these steps in CMC by adding conversational history modeling. (Qu et al., 2019c) proposed a ConvQA model with separate modules for history selection and modeling. Based on these prior works, we propose a generic framework for a CMC model.

A typical CMC model is provided with context $C$, current question $Q_i$ and the conversation history $H_i = \{[Q_k, A_k]\}_{k=1}^{i-1}$, and needs to generate an output set $O_i$. Figure 3 illustrates this CMC framework. There are four major components, based on their contribution to the overall CMC flow.

| Characteristic (average) | CoQA | QuAC |
|-------------------------|------|------|
| **Dataset source** | Passages collected from 7 diverse domains e.g. children stories from MCTest, news articles from CNN, Wikipedia articles, etc. | Sections from Wikipedia articles filtered in the “people” category associated with subcategories like culture, animal, geography, etc. |
| **Conversation setting** | Questioner-Answerer setting where both have access to the entire context. | Teacher-Student setting where the teacher has access to the full context for answering, while the student has only the title and summary of the article. |
| **Question type** | Factoid. | open-ended, highly contextual |
| **Answer type** | Free-form with an extractive rationale. | Extractive span which can be yes/no or ‘No Answer’. It also provides dialog acts. |
| **Total number of dialogs** | 18K | 14K |
| **Total number of questions** | 126K | 100K |
| **Context, Ques and Ans token lengths** | 271, 5.5, 2.7 | 401, 6.5, 14.6 |
| **Turns per dialog** | 15.2 | 7.2 |
| **Unanswerable questions** | Very low and often erroneously marked. | Significant quantity of type ‘missing info’ |
| **Evaluation metrics** | F1 scores for in-domain, out-of-domain and overall | F1, Human Equivalence Quotient (HEQ) scores at question and dialog levels. |

Table 1: A comparison of the multi-turn conversational datasets- CoQA (Reddy et al., 2018) and QuAC (Choi et al., 2018) based on different characteristics as defined in their respective papers and (Yatskar, 2018).

#### 6.1 History Selection module

With complicated dialog behaviors like topic shift or return (Yatskar, 2018), simply selecting immediate turns may not work well. A history selection module, therefore, chooses a subset $H'_i$ of the history turns $H_i$ based on a policy (dynamic or static) that is expected to be more helpful than others. If the history selection module is based on a dynamic learned policy (e.g. (Qu et al., 2019b)), then feedback from the other modules can guide its update.

#### 6.2 Encoder

The lexical tokens of the context passage $C$, selected conversational turns $H'_i$, and the current question $Q_i$ need to be transformed into input embeddings as required by the reasoning module. Encoder facilitates this transition. Although the steps used by the encoder may vary with every approach and reasoning inputs, at a high level, encoding generally involves transformation and combination of context-independent word embeddings called *lexical embeddings* e.g. GloVE (Pennington et al., 2014), *intra-sequence contextual embeddings* like ELMo (Peters et al., 2018), BERT (Devlin et al., 2018) or RNN, *question-aware embeddings*, and *additional feature embeddings* like POS tags (Zhu...
et al., 2018), history embedding (Qu et al., 2019c) or conversation count. Conversational history \( H' \) is generally integrated with this module into any or all of the contextual input embeddings. This process is called **History modeling** and is the most significant aspect of a CMC encoder.

### 6.3 Contextual Integration layer

Contextual information accumulated in the passage, query, and/or history embeddings individually must be fused to generate query-aware and history-aware contextualized output embeddings. This process may involve a single layer (*single-step reasoning*) or repetition across multiple layers (*multi-step reasoning*). Input for this module generally consists of two (or more) sequence sets, for every history turn or aggregated across all turns, which are then fused in each layer and often inter-weaved (Huang et al., 2017) with attention.

### 6.4 Output Predictor

The model output may be in the form of text span, signals like dialog acts (Choi et al., 2018) or free-form (abstractive) answer (Reddy et al., 2018). Contextual embeddings generated by the reasoning module have all the latent information about the question, context passage, and conversational history. If the embeddings are not aligned per context token, alignment measures like attention can be used. To get the token-level output, a fully-connected network followed by a softmax layer is generally used for per-token probability (abstractive) or start/end probability (extractive). Besides, a linear neural network may be used to find the aggregated result of the sequence.

### 7 Common Trends across CMC models

Instead of describing each CMC model separately, it makes sense to analyze them, categorized under the approaches they employ in their components (section 6) or other model characteristics. This will help develop a high-level understanding of the CMC models, without getting lost in details. Please note that most CMC models are extensions of the single-turn models defined in 3.2, and thus the latter may often be referred to facilitate explanation.

#### 7.1 Trends in History Selection

Almost all of the current CMC models select conversational history based on a heuristic of considering \( k \) immediate turns, often decided by performance e.g. BiDAF++ (Choi et al., 2018; Yatskar, 2018), SDNet (Zhu et al., 2018), BiDAF++ w/ 2-ctx (Ohsugi et al., 2019) use last two turns as including the third turn degrades performance. History Attention Mechanism (HAM) based model (Qu et al., 2019b) is the only CMC model to use a dynamic history selection policy by attending over contextualized representations of all the previous history turns at word-level or sequence-level and combining with current turn’s representation as shown in Figure 4.

#### 7.2 Trends in History Modeling

How conversational history is integrated or used in the encoding process of contextual input embeddings can be used to classify CMC models. Different trends observed in this respect are described below. Some models may use a combination of these approaches.
Figure 4: HAM uses a dynamic attention-based history selection policy. Contextualized representations are generated by the model’s encoder (BERT with PosHAE here) for every history turn at word and sequence levels. Sequence-level embeddings are used to compute attention weights via scaled-dot product, and aggregate representations are generated by a weighted combination of embeddings of each turn in the proportion of their attention weights. Thus, attention weights help in determining the degree of selection (relevance) of each history turn. Source: (Qu et al., 2019b)

A. Appending selected history questions and/or answers (in raw form or text span indices) to the current question before encoding. QA tokens across turns should be distinguishable or separated when appending. Models DrQA+PGNet (Reddy et al., 2018), SDNet (Zhu et al., 2018) and RoBERTa + AT + KD (Ju et al., 2019) append all history QA pairs separated by tokens like symbols \[Q\] or \[A\] such that new \[Q_k^* = \{[Q], Q_1, [A], A_1, ..., [Q], Q_{k-1}, [A], A_{k-1}, [Q], Q_k\}\]. On the other hand, Quac baseline model BiDAF++ w/ 2-ctx (Ohsugi et al., 2019) and GraphFlow (Chen et al., 2019) append only the history questions to the current question and encode relative dialog-turn number within each question embedding to differentiate. (Choi et al., 2018) validates that this dialog-turn encoding strategy performs better in practice.

B. Encoding context tokens with history answer marker embeddings (HAE) before passing on for reasoning. These embeddings indicate if the context token is present in any conversational history answer or not, e.g. BiDAF++ w/ 2-ctx (Choi et al., 2018), GraphFlow (Chen et al., 2019), BERT+HAE (Qu et al., 2019a) and HAM (Qu et al., 2019b). HAM encodes a dialog-turn encoded variant of HAE called Positional HAE. It maintains a lookup table of history embeddings for every relative position from the current conversation, and embeds the corresponding embedding if the token is found in that history answer, e.g. for the current question \(q_k\) and history answer \(a_{k-2}\), if the token is found, then embedding at index 2 is encoded, else embedding at index 0 is encoded. The setting is illustrated in figure 8.

C. Integrating intermediate representations generated in the reasoning modules of selected history conversation turns to grasp the deep latent semantics of the history, rather than acting on raw inputs. This approach is also called the FLOW based approach. The models that follow this approach are FlowQA (Huang et al., 2018), FlowDelta (Yeh and Chen, 2019), and GraphFlow (Chen et al., 2019). GraphFlow encodes conversational histories into context graphs which are used by reasoning module for contextual analysis.

7.3 Trends in Contextual Encoding

The encoder can employ different models to infuse contextual information into static lexical embeddings of history, question, and context. Following are some commonly seen contextual models.

A. Bidirectional LSTM (Hochreiter and Schmidhuber, 1997): (Reddy et al., 2018) uses document reader model of DrQA (Chen et al., 2017) which internally uses biLSTM to propagate context while (Choi et al., 2018) uses modified BiDAF (Seo et al., 2016) which uses biLSTM to generate contextualized tokens before passing to attention flow layer.

B. ELMo (Peters et al., 2018) is a deep bidirectional sequential language model pre-trained on a large text corpus. These models were state-of-the-art for contextualized embeddings before BERT. FlowQA (Huang et al., 2018) and FlowDelta (Yeh and Chen, 2019) use ELMo to obtain contextualized embeddings before passing to Integration Flow layer.

C. BERT (Devlin et al., 2018) is a deep bidirectional transformer (Vaswani et al., 2017) based language model that can be used for both feature representation (with frozen weights) and base modeling for downstream tasks (via fine-tuning). Amongst CMC models, SDNet (Zhu et al., 2018) and GraphFlow (Chen et al., 2019) use the average of output vectors from all transformer layers of a frozen BERT model as contextualized embedding for their encoders. When used as a fine-tuned model with both question and context as input, it can perform both encoding and reasoning to generate final contextualized embeddings (discussed in section 7.4).
7.4 Trends in Contextual Reasoning

While every CMC model has its unique flavor in integrating encoded representations of the query, history, and text contextually, some recurrent themes in reasoning can still be drawn. It is important to note that some of these themes will reflect state-of-the-art techniques around their release, which may now be obsolete. However, having their knowledge would prevent the re-exploration of those ideas. Following are the commonly observed themes:

7.4.1 Attention based Reasoning with Sequence Models

This was a common theme across MRC models until transformers (Vaswani et al., 2017) were introduced and got rid of sequence modeling. Consequently, initial baseline models were based on this approach.

- CoQA baseline (Reddy et al., 2018) first involves DrQA (Chen et al., 2017), which performs biLSTM based contextual integration over encoded tokens for extractive span, and later PGNet, that uses attention-based neural machine translation (Bahdanau et al., 2014) for abstractive answer reasoning.

- QuAC baseline (Choi et al., 2018) combines self-attention with BiDAF (Seo et al., 2016) that performs reasoning via multi-layered bidirectional attention flow layer followed by multi-layered biLSTM.

- SDNet (Zhu et al., 2018) applies both inter-attention and self-attention in multiple layers, interleaved with bi-LSTM, to comprehend conversation context.

7.4.2 FLOW based approaches

Analogous to recurrent models like RNN which propagate contextual information through the sequence, FLOW is a sequence of latent representations that propagates reasoning in direction of the dialog progression by feeding intermediate latent representations, generated during reasoning in previous conversations, into contextual reasoning for the current question. This helps to leverage the reasoning effort of previous conversations as compared to using shallow history, like directly appending history question-answers, where important contextual information in conversations may be lost due to the overwhelming input. There are two major flow-based approaches based on the manifestation of propagated latent representation.

1. Integration-Flow (IF): This mechanism uses contextualized embeddings as the propagated latent representation. Used in FlowQA (Huang et al., 2018) which also introduced the idea of FLOW, it involves sequential processing along context tokens (context integration) in parallel of the question turns, followed by sequential processing in direction of the question turns (Flow), in parallel of context tokens. The process is illustrated in Figure 5. FlowQA employs multiple IF layers interleaved with self and cross attentions to reason over encoded embeddings (see Figure 6). Recently released FlowDelta (Yeh and Chen, 2019) is an improvement on the IF approach that uses the same FlowQA architecture but achieves better results. Instead of passing the latent representation directly as in FlowQA, FlowDelta passes the information gain (the difference between the latent representation of previous 2 layers) with the intuition that information gain would allow the model to focus on more informative cues in context.

2. Integration-GraphFlow (IG): GraphFlow (Chen et al., 2019) authors claim that the IF mechanism does not mimic human reasoning, as it first performs reasoning in parallel for each question, and then refines the reasoning results across different turns. They, therefore, use dynamically constructed, question-aware context graphs for each turn as the propagated latent representation. Processing through this flow (called GraphFlow) is facilitated by ap-
Applying GNNs (Li et al., 2016) on the current context graph and previous context. To capture local interactions among consecutive words in context before feeding to a GNN, a BiLSTM is applied for contextual Integration. GraphFlow architecture alternates this mechanism with co-attention over the question and GNN output as in Figure 7.

Figure 7: Architecture of the Reasoning Layer of GraphFlow. Context graph-based flow sequence is processed using GNNs and alternated with bi-LSTM and co-attention mechanisms. Source: (Chen et al., 2019)

### 7.4.3 Contextual Integration using Pre-trained Language Models

Large-scale pre-trained LMs like BERT, GPT (Radford et al., 2018) and RoBERTa, has become the current state-of-the-art approach for contextual reasoning in CMC models, with leaderboards of both datasets stacked with these models or their variants. The approach is based on the fine-tune BERT-based MRC modeling outlined in (Devlin et al., 2018), in which question and context are packed together (with marker embeddings to distinguish) in an input sequence to BERT that outputs contextualized question-aware embeddings for each input token. Besides remarkable results, relying on pre-trained models for reasoning is advantageous in two aspects:

1. It simplifies the architecture by fusing encoding and reasoning modules into a single module.
2. It provides a ready-to-tune architecture that abstracts out complex contextual interactions between query and context while providing sufficient flexibility to control interactivity via augmentation of input embeddings i.e. concatenation of special embeddings to input tokens that signal the model to incorporate a desirable characteristic in contextualization.

However, incorporating history into these models is a key challenge in this approach as most of these models e.g. BERT accepts only 2 segments in the input sequence. Based on recent research in CMC, two trends in solving the history integration issue can be identified.

1. **Modify the input embeddings for a single-turn MRC model** to incorporate history. This is either be done by appending the entire conversation to the question e.g. (Ju et al., 2019) that uses RoBERTa (Liu et al., 2019) as the base model and truncates query if it exceeds the limit or adds special embeddings that signal conversational history to the model e.g.
HAE (Qu et al., 2019a) embeds history answer embeddings with each context token if it is present in any of the history turns (detailed in section 7.2, part B). This approach does not effectively use the model to capture interactions between every dialog-turn and context.

2. Use separate model for each conversational turn to capture one-to-one interaction between history and context, and merge the per-turn contextualized embeddings into aggregated history-aware embeddings. Two models follow this trend. (Ohsugi et al., 2019) uses BERT models to capture contextual interaction for every question (history and current) and answer (2N+1 sequences for N turns) and concatenates all sequences together. Finally, it runs Bi-GRU (Cho et al., 2014) over the aggregated sequence to capture inter-turn interactions before sending for prediction. On the other hand, HAM (Qu et al., 2019b) ignores the history questions and uses the current question as a query with positional History Answer Embeddings (refer 7.2-History Modelling), thus generating one output sequence per turn. Fig 8 shows HAM encoder. The final sequence is generated by token-level attention based aggregation across all per-turn contextualized sequences.

7.5 Trends in Training Methodology

Due to the multi-output nature of both CoQA and QuAC (see section 5), multi-task training is quite common amongst CMC models e.g. HAM (Qu et al., 2019b) uses multi-task learning over QuAC to also predict dialog prediction and continuation acts, while GraphFlow (Chen et al., 2019) uses multi-task learning over CoQA to also predict question type. Besides, recently published (Ju et al., 2019) achieved state-of-the-art results using RoBERTa, by applying multiple training techniques together over CoQA. These are rationale tagging multi-task (predict if the token exists in CoQA evidence), Adversarial Training (Goodfellow et al., 2014), and Knowledge Distillation (Furlanello et al., 2018).

8 Discussion

How does the research progress in CMC, a constrained setup, benefit the more into-the-wild domain of Conversational Search? As stated in (Qu et al., 2019a), Conversational QA (and thus CMC) is a simplified setting of Conversational Search (ConvSearch), an information-seeking, System Ask, User Respond paradigm (Zhang et al., 2018b), that does not focus on asking proactively. CMC, specifically, tries to address the challenges of NLU, via contextual encoding and reasoning, and handling conversational history, via history selection and modeling. In that aspect, CMC is concrete enough setting for IR researchers to understand the change of information needs and interactivity between conversational cycles.

Can Commonsense Reasoning improve CMC? Commonsense Reasoning (CR) is based on the set of background information or world knowledge that an individual is intended to know or assume, and may be missing from context. On the other hand, Pragmatic reasoning, which the current CMC models cater to, is based on the derivation of explicit and implicit meanings within the context. The current MRC systems are nearing human performance on most datasets, however, they still perform poorly on single-turn CR based questions (Zhang et al., 2018a). While there is recently increasing interest in CR in the single-turn MRC setting (Huang et al., 2019; Ostermann et al., 2018; Lin et al., 2017), CMC remains relatively untouched. This may probably be due to the lack of foreknowledge-requiring unanswerable questions (e.g. in SQuAD 2.0 (Rajpurkar et al., 2018)) in current CMC datasets (Yatskar, 2018), suggesting a need for more complex CMC datasets that incorporate CR. However, humans annotators may often apply common-sense reasoning involuntarily while answering questions or comprehending, thus leaving room for incorporating CR in models. There seems to be no recent work that invalidate, experimentally, the role of CR in CMC. QuAC, for example, is drawn from articles on personalities, and current models still lag behind the human benchmark. It may be worth experimenting if adding domain knowledge or attributes about personality, like location and gender, help improve answering these questions.

Why did the paper focus on common trends across each component rather than a single overarching classification of CMC models? The decision to study the common trends in modeling, rather than a single overarching classification, helped provide a multi-faceted view of CMC that
can generalize on future models, and identify possible open-ended research questions, like

• Based on our discussion of trends in history selection (section 7.1), HAM (Qu et al., 2019b) has proved to be both effective and intuitive, in selecting relevant history turns. The application of this history selection approach on previous models (that considered immediate K turns) can be experimented.

• Based on our discussion of trends in training methodology (section 7.5), State-of-the-art results of RoBERTa-based CMC model (Ju et al., 2019), that used knowledge distillation and adversarial training to optimize the CoQA baseline (Reddy et al., 2018), indicate that training approach and model architecture can also play a big role in improving system performance. Experimenting more-complex CMC modeling approaches like (Qu et al., 2019b; Yeh and Chen, 2019) using advanced models and training techniques can help up the whole game.

9 Conclusion

In this paper, we provide a holistic overview of Conversational Machine Comprehension, which has turned into a hot-bed of research in recent years, owing to advancements in neural language modeling and introduction of large-scale conversational datasets. Readers are acquainted with the need to consolidate scattered knowledge across CMC literature and how the existing reviews fall short in capturing the intricacies of this rapidly changing domain. We briefly touch upon the single-turn MRC datasets and models as they lay the requisite groundwork for most approaches in CMC. We discuss the challenges that make CMC different from MRC and compare the multi-turn conversational datasets – CoQA and QuAC– based on different CMC characteristics. To develop a high-level understanding of all the existing approaches to tackle CMC, we synthesize a general model framework and analyze the common trends across all the published models in CMC, loosely based on the components outlined in the framework. Finally, we discuss some open questions that emerged during our research and which, in our view, can be explored further.

It is hoped that this review would serve as a compendium for researchers in this domain and help streamline research in CMC.

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A Evolution of Machine Reading Comprehension

To understand the evolution of CMC, it is important to view it in association with the growth of the Question Answering domain.

A.1 Advent of QA- Precursor to MRC

The first discussion about Question Answering Systems can be found in the survey (Simmons, 1965) where the author reviewed fifteen different experimental systems developed in five years. This was the nascent stage for QA as these systems were domain-specific, lacked effectiveness and generality, and were highly restrained. Some of these systems were as follows (categorized as in (Hirschman and Gaizauskas, 2001)):

- **Front end to structured databases**: These systems provide an interactive interface that derives response from structures in the knowledge base. Examples are rule-based systems like Oracle (1960) which parse and perform structural matching on a coded database, or List based systems like BASEBALL (Green et al., 1961) which parses questions using linguistic knowledge into the canonical form which can then be used to query a knowledge base.

- **Text based IR styled systems**: These systems tried to answer a text from the unstructured corpus and therefore were more 'into the wild' as there was no fixed vocabulary or syntax which the question or data could fractionate to. These employed the IR techniques of indexing and TF-IDF to develop similarity, for example, Protosyntex (Klein and Simmons, 1963) can be called as first of its kind Part of Speech Tagger that used these labels for semantic analysis and IR techniques for QA matching.

- **Logical inference systems**: These systems employ logical reasoning or predicate calculus as an underlying approach for answering questions. All other aspects like parsing, presentation, and knowledge retrieval remain the same. For example, (Raphael, 1964) talks about Darlington Logic programs that translate a subset of English into various forms of the propositional and predicate calculi and then test the validity of arguments using them.

Even though these systems lacked generality, scalability, and reliability, what makes these systems important milestones in QA are the variety of ideas they introduce, e.g. semantic and syntactic analysis, and the general QA principles that they all exhibit like the strong organization of data storage and conversion to canonical forms.

Over time, new systems started emerging that improvised on the query processing component of QA (or in a way Natural Language Understanding) while still aligning to the idea of being front-end to databases. REQUEST (Plath, 1977), for example, tried to make query languages completely natural and independent of any formal language disguised as a pseudo-natural language (called ‘System Interaction by the authors’). On the other hand, PLANES is an aircraft maintenance database (Waltz, 1978) that uses augmented transition network subnets (non-neural) for recognizing phrases with special meaning such as plane type, date and period, concept case frames for semantic analysis to aid translation into query language and context registers for keeping history. These systems, therefore, reflected a gradual shift of focus towards increasing research in NLU while backend database remaining a constant. This would serve as a precursor to MRC which decouples analysis from knowledge management by making the system concentrate on a given passage as its only context.

Another major issue with the early QA systems was the lack of proper large scale evaluation which had stifled the research for an open-domain system. Perhaps the first major boost to open-domain QA research started with the introduction of the Question Answering track in the Text Retrieval Conferences, beginning with TREC-8 in 1999 (Voorhees, 1999). Participants were given 200 fact-based, short-answer questions, and a set of TREC documents as context with an answer guaranteed to be present in context. Participants returned a ranked list of five (document-id, answer-string) pairs per question believed to have the answer, which was then evaluated by human assessors and the final score was computed as reciprocal of the rank at which the first correct response was returned (0 if none were correct), averaged across all questions. TREC surged massive research in this domain and reflected on the need for surfacing more such large scale open-source evaluation sets. This led to the use of reading comprehension sets used at schools for QA (Hirschman et al., 1999) due to the high vol-
volume of an available corpus, thus raising scientific interest in MRC.

A.2 MRC- Early days

Although DeepRead (Hirschman et al., 1999) may be called the first MRC evaluation task, the survey by the same author (Hirschman and Gaizauskas, 2001) attributes the early works of Reading(Story) comprehension to Wendy Lehnert’s QUALM (Lehnert, 1977) that followed the approach of analyzing both question and story text into a conceptual dependency representation, contrary to the then-common notion of QA as essentially an IR process. Nevertheless, it was DeepRead that revived interest in this area, which was held back due to lack of an agreed way to evaluate systems. DeepRead claimed that reading comprehension tests could be a better solution to language understanding tasks than other QA evaluation datasets like TREC, because:

- The systems to be evaluated in TREC were each closely tied to a particular task e.g. document retrieval or Information Extraction. Instead, DeepRead proposed using full-fledged, open-domain, text-based QA as a task.

- Test materials, collected from student books, were already available and there was no need for special efforts to produce them.

- The context corpus provided in TREC evaluation systems was largely due to which “participating systems focused increasingly more narrowly on those few parameters that were measured in the evaluation, to the detriment of more general properties.” (Schwitter et al., 2000). Reading comprehensions are relatively smaller test data and therefore would prevent developers from resorting to shallow models to gain scores.

- Human performance measures provide an evaluation benchmark for assessing the capabilities of a given system, as compared to precision, recall, F-1, etc. which are often un-intuitive.

DeepRead introduced three metrics to evaluate MRC systems. First, Precision and recall on stemmed content(non-stop) words comparing the system’s response to test publisher’s answer key. Second, HumSent, calculated by comparing the response (match or no match-binary) against a set of sentences annotated by a human from the text as candidate answers to the question. The final score as an average of all scores. Finally, AutSent, similar to HumSent in evaluation, except that human annotation was replaced by an automatic selection of candidate sentences having higher recall with the published answer key. These evaluations required minimal human intervention, were automatic, and comparable with human benchmarks, thus paving the way for a surge in MRC research. So much so that in May 2000, ANLP-NAACL conducted the first workshop on “Reading Comprehension Tests as Evaluation for Computer-Based Language Understanding Systems” at Seattle. Three of the prominent papers in the field of MRC were presented in this workshop.

First, Quarc (Riloff and Thelen, 2000), which was an MRC system built on hand-crafted heuristic rules that scans the story and question and look for semantic and lexical clues to find the most appropriate sentence from the story that answers the question. Although the system used simple word-level semantic class tagging, it demonstrated the use of DeepRead evaluation as an effective model for MRC challenges, therefore promoting future research.

On the other hand, the second paper (Schwitter et al., 2000) critiqued the evaluation method of DeepRead as a full-fledged NLU task to be too difficult and resource-intensive for the then state-of-the-art QA system, covering a far too wide range of topics that require unrestricted vocabulary and lexical information than possible to accommodate and expecting machines to be able to understand the intrinsically framed questions designed specifically for humans thereby require world knowledge, difficult for the machines back then. As an alternative, the paper proposed using Answer Extraction i.e. retrieve the specific sentence(s) in the text that contain(s) the explicit answer to the query. This constrained the former evaluation by using explicit questions which do not require world knowledge, restricting text to only a narrow domain and only extracting complete sentence instead of generating solution. Although DeepRead’s evaluation is closer to our current evaluations (free-form answers), the paper is significant as it not only helped converge research focus to the then important linguistic problems like ambiguities, anaphoric references, and synonymy/hyponymy but would also cater to the urgent need for Information Extraction systems over
AQUAREAS (Ng et al., 2000) was a full-fledged machine learning approach to MRC, clearly an improvement over the third paper of the conference (Wang et al., 2000). In their approach, for each sentence in the text, the question-sentence pair was encoded as feature vector comprising of various syntactic and semantic rules used by their previous works, e.g. word match score relative to other sentences, a rule for a sentence containing entity booleans, search for coreference information, keyword match, and ascertaining whether its sentence is an answer or not. Five classifiers were trained over the training set for each question type (WHO, WHAT, WHY, WHEN, WHERE). The authors found that the accuracy of this system was comparable to other handcrafted rule-based systems. This was a remarkable experiment and shifted the research trend in MRC towards ML until the neural boom came along.

To get a detailed and comprehensive view of this era of MRC and the history of QA, the survey (Hirschman and Gaizauskas, 2001) is highly recommended.

A.3 Word Embeddings and the Neural Revolution

One of the fundamental limitations with all the prior models that prevented their universality or scalability, was their representation of vocabulary as a set of discrete elements. This made learning semantics a static process, with rules manually handcrafted by developers, and prevented it from enjoying the benefits offered by the dynamism of machine learning. Besides, the use of bag-of-words in neural networks was not efficient due to the curse of dimensionality associated with computations on high-dimensional vocabulary matrices. This made continuous representations of words in a low dimensional space essential and gave birth to the idea of ‘Word Embeddings’. Although vector space modeling for distributional semantics had been prevalent since the 1990s, e.g. Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA), the term ‘word embeddings’ was originally coined in the paper (Bengio et al., 2003) where the authors had trained word embeddings in a neural language model together with the models parameters.

Pre-trained embeddings further emerged as a solution to the problem of under-fitting with small scale datasets and helped language models leverage linguistic information from a wider unannotated corpus via unsupervised learning. Collobert and Weston were arguably the first to demonstrate the power of pre-trained word embeddings in their paper (Collobert and Weston, 2008), in which they establish word embeddings as a highly effective tool when used in downstream tasks, while also announcing a neural network architecture that many of today’s approaches were built upon. Later, word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) brought pre-trained word embeddings among the mainstream.

Another severe limitation to the prior MRC models was the close coupling of the high-level text comprehensibility with low-level linguistic decoding, thereby requiring the model to not just understand the meaning of the text for answering questions, but also perform semantic and lexical analysis of the sentences to be able to understand them. This was mitigated by the introduction of neural language models (Bengio et al., 2003) whose feed-forward NN was later replaced with recurrent neural networks (Mikolov et al., 2010) and long short-term memory networks (Graves, 2013) for language modeling. Neural language models abridge the token representation of sentence words into low-dimensional hidden states encapsulating the semantic context, thereby aiding the downstream tasks like MRC to only focus on a high-level understanding of the text. However, being sequential, RNNs faced the issue of localization of context in case of long sequences. This gave birth to the idea of forming a soft context over all previous states in sequence, called Attention (Bahdanau et al., 2014), which is one of the most revolutionary concepts in NLP. Researchers soon realized that self-attention, followed by convolution (transformers), can get rid of non-vectorizable sequence models altogether (Vaswani et al., 2017), and thus paved way for the current state-of-the-art BERT models (Devlin et al., 2018), built entirely of those transformer representations.

Introduction of neural methods to NLP further helped in moving away from KB based QA systems (see survey (Gao et al., 2018) for detail on KB-QA systems) that relied on storing and retrieving important world knowledge and contextual patterns from KB to be able to answer questions. Deep neural methods with large parameters were able to learn the requisite patterns and correlations from a
freely available corpus without the need for humans to explicitly add those contexts.

Therefore, the introduction of word embeddings and the neural revolution infused new life to MRC by giving it the foundation to grow further complexity and thus transformed the research direction from static, restricted systems to the dynamic form we see today.