A Survey on Machine Reading Comprehension Systems

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Abstract— Machine reading comprehension is a challenging task and hot topic in natural language processing. Its goal is to develop systems to answer the questions regarding a given context. In this paper, we present a comprehensive survey on different aspects of machine reading comprehension systems, including their approaches, structures, input/outputs, and research novelties. We illustrate the recent trends in this field based on 124 reviewed papers from 2016 to 2018. Our investigations demonstrate that the focus of research has changed in recent years from answer extraction to answer generation, from single to multi-document reading comprehension, and from learning from scratch to using pre-trained embeddings. We also discuss the popular datasets and the evaluation metrics in this field. The paper ends with investigating the most cited papers and their contributions.

Index Terms— Natural language processing, question answering, machine reading comprehension, deep learning, literature review

1 INTRODUCTION

Machine reading comprehension (MRC) task is a useful benchmark to evaluate natural language understanding of machines and has been a challenging task in natural language processing (NLP) field with considerable researches in recent years. For measuring the machine comprehension of a piece of natural language text, a set of questions about the text is given to the machine, and its responses are evaluated against the gold standard. Also, MRC systems have important applications in different areas such as conversational agents [1, 2] and customer service support [3].

Even though in some studies, MRC is referred to as question answering (QA), they are different in the following ways:

- The main objective of QA systems is to answer the input questions, while in an MRC system, as its name indicates, the main goal is to understand natural languages by machines.

- The only input to QA systems is the question, while the inputs to MRC systems are the question and the corresponding context that should be used to answer the question. For this reason, sometimes MRC is referred to as QA from text [4-6].

- The information sources that are used to answer questions in MRC systems are natural language texts; while in QA systems, the structured and semi-structured data sources such as knowledge-bases can be used besides the non-structured data like texts.

In recent years, with the success of machine learning techniques, especially the neural networks, and the usage of recurrent neural networks to process sequential data such as texts, MRC has become an active area in the field of NLP. The goal of this paper is to categorize these studies, provide related statistics, and show the trends in this field. Some recent surveys focused on QA systems [7, 8]. Another paper presented a partial survey on some MRC systems but did not provide a comprehensive classification of different aspects and different statistics in this field [9]. We analyze and categorize MRC studies from different aspects and present statistics on the amount of research attention to these aspects. Specifically, the contributions of this paper are the followings:

- Investigating recently published MRC papers from different perspectives including problem-solving approaches, system input/outputs, contributions of these studies, and evaluation metrics.

- Providing statistics for each category over different years and highlighting the trends in this field.

- Reviewing available datasets and classifying them based on important factors.

- Investigating the most cited papers from different aspects.

Due to a large number of papers in this field, we limit our study to the papers published in recent years, i.e., from 2016 to 2018. Table 1 shows the number of reviewed papers over different years.

The rest of this paper is organized as follows. Section 2 reviews the main problem-solving approaches for the MRC task. Section 3 provides an analysis of the type of input/outputs of MRC systems. The review of the papers based on the basic phases of an MRC system is presented in Section 4. The recent datasets and evaluation measures are reviewed in Sections 5 and 6, respectively. In Section 7, the MRC studies are categorized based on their contributions and novelties. The most cited papers are investigated in Section 8. Finally, the paper is concluded in Section 9.
Table 1: Number of reviewed papers over different years.

| Year | Number of Papers |
|------|------------------|
| 2016 | 25               |
| 2017 | 38               |
| 2018 | 61               |
| Total| 124              |

2 Problem-solving approaches

The approaches used for developing MRC systems can be grouped into three categories: rule-based methods, classical machine learning-based methods, and deep learning-based methods.

The traditional rule-based methods use the rules handcrafted by linguistic experts. These methods suffer from the problem of the incompleteness of the rules. Also, this approach is domain specific where for any new domain, a new set of rules should be handcrafted. As an example, Riloff and Thelen [10] present a rule-based MRC system called Quarc, which reads a short story and answers the input question by extracting the most relevant sentences. Quarc uses a separate set of rules for each question type (WHO, WHAT, WHEN, WHERE, and WHY).

In this system, several NLP tools are used for parsing, part of speech tagging, morphological analysis, entity recognition, and semantic class tagging. As another example, Akour et al. [11] introduce the QArabPro system, which is a system for answering reading comprehension questions in the Arabic language. It is also developed using a set of rules for each type of question and uses multiple NLP components, including question classification, query reformulation, stemming, and root extraction.

The second approach is based on the classical machine learning. These methods rely on a set of human-defined features and train a model for mapping input features to the output. Note that in classical machine learning-based methods, even though the hand-crafted rules are not necessary, feature engineering is a critical necessity.

For example, Ng et al. [12] have developed a machine learning-based MRC system and introduced some of features to be extracted from a context sentence like “the number of matching words/verb-types between the question and the sentence”, “the number of matching words/verb-types between the question and the previous/next sentence”, “co-reference information”, and binary features like “sentence-contain-person”, “sentence-contain-time”, “sentence-contain-location”, “sentence-is-title” and so on.

The third approach uses deep learning methods to learn features from raw input data automatically. These methods require a large amount of training data to create high-accuracy models. Because of the growth of available data and computational power in recent years, deep learning methods have gained state-of-the-art results in many tasks. In the MRC task, most of the recent researches fall into this category. Two main deep learning architectures used by MRC researchers are the Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN).

RNNs are often used for modeling sequential data by iterating through the sequence elements and maintaining a state containing information relative to what has been seen so far. Two common types of RNNs are Long Short-Term Memory (LSTM) [13] and Gated Recurrent Unit (GRU) [14]. In MRC systems, like other NLP tasks, these architectures are used to represent text data in different parts of their pipelines, such as for representing the questions and passages. Bidirectional versions of LSTM [15-20] and GRU [21-28] are also very popular in this task. LSTM and GRU are also used in higher levels of the MRC system architecture like in the modeling layer [18, 19, 29-31].

CNN is a type of deep learning model that is universally used in computer vision applications. It utilizes layers with convolution filters that are applied to local spots of their inputs [32]. Originally introduced for computer vision, CNN models have subsequently been shown to be effective for NLP and have achieved excellent results in various NLP tasks [33]. In MRC systems, CNN is used in the embedding phase (especially, character embedding) [18, 34, 35] as well as in the reasoning phase for modeling interactions between the question and passage like in the QANet [36]. QANet uses CNN and self-attention blocks instead of the RNN, which results in faster answer span detection on the SQuAD dataset [37]. About 56%, 40% and 4% of reviewed studies have used the LSTM, GRU, and CNN for their context representation, respectively.

3 Input/output-based analysis

3.1 MRC Systems Input

The inputs to an MRC system are question and passage texts. The passage is often referred to as context. Moreover, in some systems, the candidate answer list is part of the input.

3.1.1 Question

Input questions can be grouped into three categories: factoid questions, non-factoid questions, and yes/no questions.

Factoid questions are questions that can be answered with simple facts expressed in short text answers like a personal name, temporal expression, or location. For example, the answer to the question “Who founded Virgin Airlines?” is a personal name; or questions "What is the average age of the onset of autism?" and "Where is Apple Computer based?" have number and location as an answer, respectively [38]. In other words, the answers to factoid questions are one or more entities or a short expression. Because of its simplicity compared to other types, most researches in MRC literature have focused on this type of questions [15, 18, 19, 21, 39, 40].

Non-factoid questions, on the other hand, have longer answers compared to the factoid questions. As an example, the explanatory questions are put into this category. In our reviewed papers, 19% of works focus on non-factoid questions. Because of their difficulty, the systems dealing with non-factoid
questions have often lower accuracies [29, 41-44]. Yes/No questions, as indicated by their name, have yes or no as answers. According to our investigations, the papers which deal with this type of question consider other types of questions as well [31, 45, 46].

Refer to Table 2 for the statistics of input/output types in MRC systems. It is clear from the table that the popularity of non-factoid and yes/no questions are increased. Note that since some papers focus on multiple question types, the sum of percentages is greater than 100% in this table.

3.1.2 Context
The input context can be a single passage or multiple passages. It is obvious that as the context gets longer, finding the answer becomes harder and more time-consuming. Until now, most of the papers have focused on a single passage [18, 19, 29, 47-50]. But multiple passages MRC systems are becoming more popular [39, 45, 51, 52]. According to Table 2, only 4% of the reviewed papers have focused on multiple passages in 2016, but this ratio has reached 8% and 35% in 2017 and 2018, respectively.

3.2 MRC Systems Output
The output of MRC systems can be classified into two categories: abstractive (generative) output and extractive (selective) output.

In the abstractive mode, the answer is not necessarily an exact span in the context and is generated according to the question and context. This output type is especially suitable for non-factoid questions [29, 30, 41, 42, 53].

In the extractive mode, the answer is a specific span of the context [18, 19, 48, 54-56]. This output type is appropriate for factoid questions; however, it is possible that the answer to a factoid question may be generative or the answer to a non-factoid question may be extractive. For example, the answer to a non-factoid question may be a whole sentence which is extracted from the context.

There has generally been more focus on extractive MRC systems, but according to Table 2, the popularity of abstractive MRC systems has been increased over recent years. From another point of view, MRC outputs can be categorized as quiz style, cloze style, and detail style.

In the quiz style mode, the answer is one of the multiple candidate answers that must be selected according to the context. In the cloze style mode, the question includes a blank that must be filled as an answer according to the context. In the detail style mode, there is no candidate or blank, so the answer must be extracted or generated according to the context. As shown in Table 2, most studies (68%) in the reviewed papers have focused on the detail style mode.

In general, about 67% of researches in the reviewed papers have focused on factoid questions, single passage, and extractive answers due to their less complexity and existence of rich datasets. For a more detailed categorization of papers based on their input/outputs, refer to Table A1.

### Table 2: Statistics of input/output types in MRC systems.

| Year | Question Type | Context Type | Exact Span | Selective | Quiz | Cloze | Detail |
|------|---------------|--------------|------------|----------|------|-------|--------|
| 2016 | 100%          | 4%           | 0%         | 96%      | 4%   | 4%    | 24%    |
| 2017 | 100%          | 23%          | 0%         | 92%      | 8%   | 84%   | 19%    |
| 2018 | 100%          | 25%          | 10%        | 73%      | 35%  | 83%   | 16%    |
| All  | 100%          | 19%          | 5%         | 84%      | 19%  | 88%   | 14%    |

4 MRC Phases
Most of the recent deep learning-based MRC systems have the following phases: embedding phase, reasoning phase, and prediction phase. Many of the researches focus on developing new structures for these phases, especially the reasoning phase.

4.1 Embedding phase
In this phase, input characters, words, or sentences are represented by real-valued dense vectors in a meaningful space. The goal of this phase is to provide question and context embedding. Different levels of embedding are used in MRC systems. Character-level and word-level embeddings can capture the properties of words, and higher level representations can represent syntactic and semantic information of input text. Table 3 shows the statistics of various embedding methods used in the reviewed papers. Since there is not any paper that uses the character embedding as the only embedding method, there is no character embedding column in this table.

### Table 3: Statistics of different embedding methods used by reviewed papers.

| Year | Word Embedding | Hybrid (Word-Char Embedding) | Sentence Embedding | Contextual Embedding |
|------|----------------|-----------------------------|-------------------|----------------------|
|      | 86%            | 14%                         | 14%               | 50%                  |
| 2016 |                |                             |                   | GRU                  |
|      | 54%            | 46%                         | 4%                | 37%                  |
| 2017 |                |                             |                   | LSTM                 |
|      | 45%            | 54%                         | 6%                | 36%                  |
| 2018 |                |                             |                   | CNN                  |
|      | 56%            | 44%                         | 7%                | 40%                  |

4.1.1 Character embedding
Some papers use character embedding as part of their embedding phase. This type of embedding is useful to overcome unknown and rare words problems [18, 19, 57]. To generate the input representation, deep neural network models are commonly used. Inspired by Kim’s work [33], some papers have used CNN models to embed the input characters [18, 34, 50, 58, 59]. Some other papers have used character level information captured from the final state of an RNN model like LSTM (or BiLSTM) and GRU (or BiGRU) [16, 19, 47, 51, 60,
61]. As another approach which uses both CNN and LSTM to embed input characters, LSTM-char CNN [62] is also used in MRC literature [63]. We classify these papers in two categories, CNN and RNN, and so the sum of percentages is greater than 100% in Figure 1.

Figure 1 shows the percentage of different character embedding methods over different years. Other methods include skip-gram, n-grams, and more recent methods like ELMo [64]. The overall trend shows a relative decrease in the usage of RNN-based methods and a relative increase in the usage of CNN-based methods.

![Character embedding methods](image)

**Figure 1:** The percentage of different character embedding methods over different years.

### 4.1.2 Word embedding

There are three main approaches to obtain word representations: 1. One-hot encoding, learning word embedding jointly with the main task and using pre-trained word embeddings (fixed or fine-tuned). Note that some works use multiple methods, so the sum of percentages in the tables may be greater than 100%.

One-hot encoding is the most basic way to turn a token into a vector. These are binary, sparse, and very high dimensional vectors; therefore, this approach has been less popular than other approaches in recent papers [25, 65, 66].

Another popular way to represent words is word embedding, which delivers dense real-valued representations. In the presence of a large amount of training data, it is advised to learn the word embeddings from scratch jointly with the main task [67].

Some studies have shown that initializing word embeddings with pre-trained values results in better accuracies than random initialization [22, 68]. This approach is especially useful in the low-data scenarios [22, 67]. GloVe embedding [69] is a common pre-trained word representation used in MRC systems [15, 27, 51, 55, 58, 61, 68, 70, 71]. Word2Vec [72] is another popular word embedding used in this task [20, 73, 74]. Also, due to the success of ELMo embedding [64] in the contextual representation of words, some recent studies have used it as the pre-trained word embedding [16, 75-77]. ELMo is used either besides other embeddings [16, 76, 78] or alone [77]. In general, GloVe is the most popular pre-trained word embedding method in MRC systems with an 82% usage ratio. Compare this with word2vec, which is used only in 16% of the reviewed papers.

These pre-trained word embeddings are fine-tuned [20, 21, 27, 50, 54, 73] or left as fixed embeddings [18, 19, 25, 58, 79, 80]. Fine-tuning some keywords such as “what”, “how”, “which”, and “many” could be crucial for QA systems, while most of the pre-trained word embeddings can be kept fixed [15].

Finally, it is worth noting that some papers use hand-designed word features such as named entity (NE) tag and part-of-speech (POS) tag along with embedding of words [25, 39]. Table 4 and Figure 2 show the statistics of these approaches through different years in the reviewed papers.

![Word embedding methods](image)

**Figure 2:** The percentage of different word embedding methods over different years.

**Table 4:** Statistics of different word representation methods in the reviewed papers.

| Year | One-hot encoding | Learned word embedding | Fixed pretrained | Fine-tuned |
|------|------------------|------------------------|-----------------|-----------|
| 2016 | 14%              | 33%                    | 48%             | 19%       |
| 2017 | 4%               | 11%                    | 37%             | 48%       |
| 2018 | 4%               | 8%                     | 63%             | 33%       |
| All  | 6%               | 14%                    | 52%             | 34%       |

### 4.1.3 Hybrid word-character embedding

The combination of word embedding and character embedding is used in some reviewed papers [18, 47, 50, 58]. Hybrid embedding tries to use the strengths of both word and character embeddings. A simple approach is to concatenate the word and character embeddings. As an example, Wang et al. [19] used GloVe as the word embedding and the output of the LSTM model as the character embedding.
This approach suffers from a potential problem. Word embedding has better performance for frequent words, while it can have negative effects for representing rare words. The reverse is true for character embedding [47]. To solve this problem, some researchers introduced a gating mechanism which regulates the flow of information. Yang et al. [47] used a fine-grained gating mechanism for dynamic concatenation of word and characters embedding. This mechanism uses a gate vector, which is a linear multiplication of word features (POS and NE), to control the flow of information of word and character embeddings. Seo et al. [18] used highway networks [81] for embedding concatenation. These networks use the gating mechanism learned by the LSTM network.

According to Table 3, the use of hybrid embedding is increased in recent years, from 14% to 54%.

4.1.4 Sentence embedding
Sentence embedding is a high-level representation in which the entire sentence is encoded in a single vector. It is often used along with other embeddings [71]. However, sentence embedding is not so popular in MRC systems, because the answer is often a sentence part, not the whole sentence.

4.1.5 Contextual embedding
Contextual embedding represents each word considering its context (surrounding words) to generate more meaningful vectors. In MRC systems, a sequence modeling method, usually an RNN, is used for this purpose. For example, Chen et al. [15] used a multi-layer BiLSTM model on top of the word embedding layer contextualized embedding. In Sordoni et al. study [26], forward and backward GRU hidden states are combined to generate contextual representations of query and document words. Bajgar et al. [82] used the combination of all GRU hidden states as a representation of document words while the final hidden state of GRU is used for query words. For a complete list of papers by different embedding methods, refer to Table A2.

4.2 Reasoning phase
The goal of this phase is to match the input query (question) with the input document (context). In other words, this phase determines the related parts of the context for answering the question by calculating the relevance between question and context parts. Recently, Phrase Indexed Question Answering (PIQA) model [78] enforces complete independence between document encoder and question encoder and does not include any cross attention between question and document. In this model, each document is processed beforehand, and its phrase index vectors are generated. Then, at inference time, the answer is obtained by retrieving the nearest indexed phrase vector to the query vector.

The attention mechanism [83], originally introduced for machine translation, is often used for this phase. The attention mechanism used in MRC systems can be explored in three perspectives: direction, dimension, and number of steps. For the statistics, refer to Table 5.

4.2.1 Direction
Some researches only use the context-to-query (C2Q) attention vector [39, 65, 79, 84, 85] called one-directional attention mechanism. It signifies which query words are relevant to each context word [18, 86].

In bi-directional attention mechanism, query-to-context (Q2C) attention weights are also calculated [18, 21, 55, 56, 70, 86] along with C2Q. It signifies which context words have the closest similarity to one of the query words and are hence critical for answering the question [18, 86]. As shown in Table 5, the ratio of bi-directional attention usage is increased in recent years.

4.2.2 Dimension
There are two attention dimensions in the reviewed papers: one-dimensional and two-dimensional attentions. In one-dimensional attention, the whole question is represented by one embedding vector, which is usually the last hidden state of the contextual embedding [22, 27, 79, 80, 87]. It does not pay more attention to important question words. On the contrary, in two-dimensional attention, every word in the query has its own embedding vector [15, 18, 21, 25, 26, 48, 86].

According to Table 5, 76% of all reviewed papers use two-dimensional attention. Also, the use of two-dimensional attention has been increased over recent years.

4.2.3 Number of steps
According to the number of reasoning steps, three types of MRC systems can be seen [42]: single-step reasoning, multi-step reasoning with a fixed number of steps, and dynamic multi-step reasoning.

In the single step reasoning, question and passage matching is done in a single step. However, the obtained representation can be processed through multiple layers to extract or generate the answer [18, 21, 27]. In multi-step reasoning, question and passage matching is done in multiple steps, where the number of steps is static [16, 26, 48] or dynamic [42, 80, 88] [22]. Dynamic multi-step reasoning uses a termination module to decide whether the inferred information is sufficient for answering or more reasoning steps are still needed. Therefore, the number of reasoning steps in this model depends on the complexity of the passage and question. It’s obvious that in multi-step reasoning, the model complexity is increased by the number of reasoning steps.

According to Table 5, about 75% of reviewed papers use single step reasoning, but the popularity of multi-step reasoning is increased over recent years. For a detailed list of the used reasoning methods in different papers refer to Table A3.
5 MRC DATASETS

Rich datasets are the first prerequisite for having accurate machine learning models. Especially, deep neural network models require high volumes of training data to achieve good results. For this reason, in recent years, many researchers have focused on collecting big datasets. For example, Stanford Question Answering Dataset (SQuAD) [37], which is a popular MRC dataset used in many studies, includes over 100,000 training samples.

MRC datasets can be categorized according to their volume, domain, question type, answer type, context type, data collection method, and language.

In terms of domain, MRC datasets can be classified into two categories: open domain and close domain. Open domain datasets contain diverse subjects, while close domain datasets focus on specific areas such as the medical domain. For example, the SQuAD [37] dataset, which contains Wikipedia articles, is an open domain dataset and Quasar-s [17] is a close domain dataset with computer programming as its subject.

There are two data collection approaches in MRC datasets, automatic approach, and crowdsourcing approach. The former generates questions/answers without direct human interventions. For instance, datasets that contain cloze-style questions, such as Children’s Book Test dataset [93], are generated by removing important entities from text. Also, in some datasets, questions are automatically extracted from the search engine’s user logs [94] or real reading comprehension tests [95].

On the other hand, in the crowdsourcing approach, humans generate questions, answers, or select related paragraphs. Of course, a dataset can be generated by a combination of these two approaches. For instance, in MS MARCO [94], questions have been generated automatically, while these questions have answered and evaluated by crowdsourcing.

Table 7 shows a detailed list of the datasets proposed from 2016 to 2018. The number of datasets presented in 2016, 2017, and 2018 is 8, 6, and 14, respectively.

6 MRC EVALUATION MEASURES

Based on the system output type, different evaluation metrics are introduced. We classify these measures into two categories: extractive metrics and generative metrics.

6.1 Extractive metrics

These metrics are used for the extractive outputs. Table 8 shows the statistics of these measures in the reviewed papers.

- **F1 score**: The harmonic mean of precision and recall is a common extractive metric for evaluating MRC systems. It takes into account the system output and the ground-truth answer as bag-of-tokens (words). Precision is calculated as the number of correctly predicted tokens divided by the number of all predicted tokens. The recall is also the number of correctly predicted tokens divided by the number of ground-truth tokens. The F1 score is then calculated as:
| Dataset                  | Open/Closed Domain | Language | Question Type | Context Type | Answer Type | #Question | #Context | Collect Data | Question Classification | Link Address                           |
|--------------------------|--------------------|----------|---------------|--------------|-------------|-----------|----------|--------------|-------------------------|----------------------------------------|
| MS MARCO [94]            | Open               | English  | Factoid       | Multi-document | Abstractive | 100K      | 1M Passage +200K Document | Q: Automatic | A/Crowdsourced         | Yes                                   | http://www.msmarco.org                 |
| Newsqa [96]              | Open               | English  | Factoid       | Single paragraph | Extractive (Detail) | 100K      | 10K Articles | Crowdsourced | No                      | https://dataset.s.maluuba.com/NewsQA    |
| BookTest (NE, CN) [82]   | Open               | English  | Factoid       | Single paragraph | Extractive (Cloze Style) | 14M       | 13.5K Books | Automatic    | No                      | https://ibm.box.com/v/booktest-v1       |
| People Daily News dataset [65] | Open         | Chinese  | Factoid       | Single paragraph | Extractive (Cloze Style) | 876K      | 60k Articles | Automatic    | No                      | http://hfl.iflytek.com/chinese-rc/      |
| Children's Fairy Tale (CFT) [65] | Open       | Chinese  | Factoid       | Single paragraph | Extractive (Cloze Style) | 3.5K       | 60 k Passages | Automatic    | No                      | http://hfl.iflytek.com/chinese-rc/      |
| SQuAD [37]               | Open               | English  | Factoid       | Single paragraph | Extractive (Detail) | 100K      | 536 Articles | Crowdsourced | No                      | https://stanford.edu/sqaud             |
| MC-AFP [90]              | Open               | English  | Factoid       | Single paragraph | Extractive (Quiz Style) | 2M        | -         | Automatic    | No                      | https://github.com/google/mc-faqp       |
| Who did what [97]        | Open               | English  | Factoid       | Single paragraph | Extractive (Quiz Style) | 330K      | 200 k Passages | Automatic    | No                      | https://tticnlp.github.io/who_did_what/  |
| [98]                     | Open               | English  | Factoid       | Single paragraph | Extractive (Cloze Style) | 13K       | 4K Passages | P: Crowdsourced | Q&A: Automatic | http://hfl.iflytek.com/emorynlp/character-mining |
| CiCi [73]                | Close (medical)    | English  | Factoid       | Single paragraph | Extractive (Cloze Style) | 105K      | 12K Passages | Automatic    | No                      | https://github.com/clips/cicr           |
| DRCD [99]                | Open               | Chinese  | Factoid       | Single paragraph | Extractive (Detail) | 30K       | 10K Paragraphs from 2K articles | Crowdsourced | Yes                     | https://github.com/DRCSolutionService/DRCD |
| DuoRC [100]              | Open               | English  | Factoid and non-Factoid | Multi-paragraph | Abstractive | 186K      | 7.5K Passages | Crowdsourced | No                      | https://duorc.github.io/                |
| QBLINK [101]             | Open               | English  | Factoid       | Multi-paragraph | Extractive (Detail) | 56K       | Context is extracted before reading. | Automatic    | No                      | https://sites.google.com/view/qanta/projects/qblink |
| SQuAD-T [102]            | Open               | English  | Factoid       | Single Paragraph | Extractive (Detail) | 100K      | 536 Articles | Crowdsourced | No                      | https://github.com/Chuanqi1992/SQuAD-T  |
| SQuAD 2.0 [103]          | Open               | English  | Factoid       | Single paragraph | Extractive (Detail) | 150K      | 505 Articles | Crowdsourced | No                      | https://rajpurkar.github.io/SQuAD-explorer |
The final F1 score is then obtained by averaging over all question-answer pairs.  

- **Exact Match (EM).** This is the percentage of answers that exactly match with the correct answers. If there are multiple answers to a question in a dataset, a match with at least one of the answers is considered as an exact match. Some QA systems such as multiple-choice QA systems [42] or sentence selection QA systems [56] call this measure as accuracy (ACC) instead of EM.

- **Mean Average Precision (MAP).** This measure is used when the system returns several answers along with their ratings. The MAP for a set of question-answer pairs is the mean of Average Precision scores (AveP) for each one.

\[
F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}
\]  

(1)
where Q is the number of queries. AveP is an evaluation measure used in information retrieval systems. It evaluates a ranked list of documents in response to a given query. In MRC literature, the ranked list of answers for a given query is evaluated. AveP is computed as the average of precisions over the interval from recall=0 to recall=1 in the precision-recall curve [114].

- **Mean Reciprocal Rank (MRR).** This is a common evaluation metric for factoid QA systems introduced in TREC QA track 1999. MRR evaluates a ranked list of answers based on the inverse of the rank of the correct answer. For example, if the rank of the correct answer in the output list of a system is 4, the reciprocal rank score for that question would be 1/4. This measure is then averaged for all questions in the test set [38].

- **Precision@K.** This measure is also borrowed from information retrieval literature. It is the number of correct answers in the first k returned answers without considering the position of these correct ones [115].

- **Hit@K or Top-K.** Hit@K, which is equivalent to the Top-K accuracy, counts the number of samples where their first k returned answers include the correct answer.

### 6.2 Generative metrics

The metrics used for evaluating the performance of generative MRC systems are the same metrics used for machine translation and summarization evaluation. Table 9 shows the statistics of these measures in the reviewed papers.

- **Recall-Oriented Understudy for Gisting Evaluation (ROUGE).** This measure compares a system-generated answer with the human-generated one [116]. It is defined as the recall of the system based on the n-grams, i.e., the number of correctly generated n-grams divided by the total number of n-grams in the human-generated answer.

- **BiLingual Evaluation Understudy (BLEU).** This metric first introduced for evaluating the output of machine translation task. It is defined as the precision of the system based on the n-grams, i.e., the number of correctly generated n-grams divided by the total number of n-grams in the system-generated answer [117].

- **Metric for Evaluation of Translation with Explicit Ordering (METEOR).** This measure is designed to fix some weaknesses of the popular BLEU measure. METEOR is based on an alignment between the system output and reference output. It also introduces a penalty to have longer matches between two strings [118].

- **Consensus-based Image Description Evaluation (CIDEr).** This measure is initially introduced for evaluating the image description generation task [119]. It is based on the n-gram matching of the system output and reference output in the stem or root forms. According to this measure, the n-grams that are not in the reference output should not be in the system output. Also, the common n-grams in the dataset are less informative and have lower weights.

Figure 3 shows the ratio of the used extractive/generative measures in the reviewed papers. According to this figure, the usage of generative metrics is increased from 5% in 2016 to 22% in 2018. The obvious reason for this is the trend toward developing abstractive MRC systems. For more details, refer to Table A5.

### Table 8: Statistics of Extractive Evaluation Measures Used in Reviewed Papers

| YEAR | EM | F1 | MAP | MRR | P@1 | R@1 | ACC | Hit@Top-K |
|------|----|----|-----|-----|-----|-----|-----|-----------|
| 2016 | 38%| 38%| 5%  | 5%  | 0%  | 0%  | 67%| 0%        |
| 2017 | 52%| 59%| 7%  | 7%  | 3%  | 0%  | 34%| 3%        |
| 2018 | 57%| 66%| 4%  | 2%  | 7%  | 7%  | 36%| 0%        |
| All  | 51%| 57%| 5%  | 4%  | 4%  | 3%  | 42%| 1%        |

### Table 9: Statistics of Generative Evaluation Measures Used in Reviewed Papers

| YEAR | ROUGE_L | BLEU | METEOR | CIDEr |
|------|---------|------|--------|-------|
| 2016 | 5%      | 5%   | 0%     | 5%    |
| 2017 | 7%      | 3%   | 0%     | 0%    |
| 2018 | 22%     | 18%  | 7%     | 2%    |
| All  | 14%     | 10%  | 3%     | 3%    |

### 7 Research Contribution

The contribution of MRC researches can be grouped into four categories: developing new model structures, creating new datasets, combining with other tasks and improvement, and introducing new evaluation measures. Table 10 shows the statistics of these categories. Note that some studies have more than one contribution type, so the sums of greater than 100 in this table. For example, Ma et al. [98] introduced a new dataset
from the “Friends” sitcom transcripts and developed a new model architecture as well. For more details, refer to Table A6.

7.1 Developing new model structures
Many MRC papers have focused on developing new model structures to address the weaknesses of previous models. Most of them developed new internal structures [16, 18, 20, 22, 25, 39, 65, 70, 80, 86, 87]. Some others changed the system inputs. For example, in Pan et al. study [34], in addition to word embedding, NER and POS embeddings have also been used as the input to the model. Also, some papers introduced a new way of entering the input into the system. For example, Hewlett et al. [2] proposed breaking the context into overlapping windows and entering each window as an input to the system.

7.2 Creating new datasets
One of the main reasons for advancing the MRC researches in recent years is the introduction of rich datasets. Many researches have focused on creating new datasets with new features in recent years [17, 37, 73, 94-96, 104, 106]. The main trend is to develop multi-document datasets, abstractive style outputs, and more complex questions that require more advanced reasoning.

7.3 Combining with other tasks
Simultaneous learning of multiple tasks (multi-task learning) [120] and exploiting the learned knowledge from one task in another task (transfer learning) [121] have been promising directions for obtaining better results, especially in the data-poor setting. As an example, Wang et al. [61] trained their MRC task with a question generation task and achieved better results. Besides these approaches, some papers exploit other task solutions as sub-modules in their MRC system. As an example, Yin et al. [71] used a question classifier and a natural language inference (NLI) system as two sub-modules in their MRC system.

7.4 Introducing new evaluation measures
Reliable assessment of an MRC system is still a challenging topic. While some systems go beyond human performance in specific datasets such as SQuAD by the current measures [37], further investigations show that these systems fail to achieve a thorough and true understanding of human language [75, 122, 123]. In these papers, the passage is successfully edited to mislead the model. These papers can be seen as a measure to evaluate the true comprehension of systems. Also, some papers have evaluated the required comprehension and reasoning capabilities for solving the MRC problem in available datasets [27, 124].

### Table 10: Statistics of different research contributions to MRC task in the reviewed papers.

| Year | Model Structure | Dataset | Other Tasks | Evaluation Measure |
|------|-----------------|---------|-------------|--------------------|
| 2016 | 77%             | 27%     | 11.5%       | 4%                 |
| 2017 | 56%             | 14%     | 25%         | 5%                 |
| 2018 | 72%             | 28%     | 17%         | 6%                 |
| All  | 68%             | 23%     | 18%         | 5%                 |

8 Hot MRC papers
Table 11 shows the top 10 papers in each year (2016-2018) based on the number of citations in the Google Scholar service. According to this table, hot papers are often those papers that introduce a new successful model structure or a new dataset.

### Table 11: Hot papers based on the number of citations in the Google Scholar service.

| Title                                                        | Publication Venue | Year | Contribution       |
|--------------------------------------------------------------|-------------------|------|--------------------|
| Squad: 100,000+ questions for machine comprehension of text   | EMLP              | 2016 | Dataset            |
| Bidirectional attention flow for machine comprehension         | arXiv             | 2016 | Model structure (BiDAF) |
| Dynamic coattention networks for question answering           | arXiv             | 2016 | Model structure (DCN) |
| Machine comprehension using match-LSTM and answer pointer     | arXiv             | 2016 | Model structure (Match-LSTM and Answer Pointer) |
| A thorough examination of the CNN/Daily Mail reading comprehension task | ACL               | 2016 | Evaluation dataset |
| Text understanding with the attention sum reader network      | ACL               | 2016 | Model Structure (AS) |
| MS MARCO: A human generated machine reading comprehension dataset | arXiv             | 2016 | Dataset            |
| Multi-perspective context matching for machine comprehension  | arXiv             | 2016 | Model structure    |
| NewsQA: A machine comprehension dataset                        | arXiv             | 2016 | Dataset            |
| Words or characters? Fine-grained gating for reading comprehension | arXiv             | 2016 | Model structure    |
9 Conclusion

Machine reading comprehension, as a hot research topic in NLP, focuses on reading the document(s) and answering questions about it. The ideal goal of an MRC system is to gain a comprehensive understanding of text documents to be able to reason and answer related questions. In this paper, we presented an overview of different aspects of recent MRC researches, including approaches, internal architecture, input/output type, research contributions, and evaluation measures. We reviewed 124 papers from 2016 to 2018 to investigate recent researches and find new trends.

Based on the question type, MRC papers are categorized to factoid, non-factoid, and yes/no questions. The input context is also categorized to single or multiple passages. According to statistics, a trend toward non-factoid questions and multiple passages is obvious in recent years.

The output types are categorized to extractive and abstractive outputs. From another point of view, the output types are classified as quiz, cloze, and detail styles. The statistics show that even though the extractive outputs have been more popular, the abstractive outputs are becoming more popular in recent years.

We also reviewed the developed datasets along with their features, including data volume, domain, question type, answer type, context type, collection method, and data language. A large number of datasets are developed in 2018 which are in general more challenging than previous datasets.

Regarding research contributions, some papers develop new model structures, some introduce new datasets, some combine MRC task with other tasks, and others introduce new evaluation measures. Among these, the majority of papers develop new...
model structures or introduce new datasets. Finally, most cited papers are presented which show the most popular datasets and models in the MRC literature.

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# AUXILIARY TABLES

## Table A1. Reviewed Papers Categorized Based on Their Input/Output

| Question | FACTOID | NON-FACTOID | YES/NO | CONTEXT | SINGLE PARAGRAPH | MULTI-PARAGRAPH | EXTRACTIVE | ABSTRACTIVE | QUIZ | CLOZE | DETAIL |
|----------|---------|-------------|--------|---------|------------------|-----------------|------------|------------|------|-------|--------|
| INPUT    | [15], [48], [21], [79], [29], [30], [16], [80], [49], [54], [34], [39], [41], [42], [50], [55], [40], [58], [61], [51], [85], [2], [125], [126], [127], [52], [128], [129], [130], [53], [86], [22], [43], [131], [63], [132], [45], [59], [76], [77], [23], [133], [78], [134], [123], [31], [46], [135], [136], [137], [24], [138], [47], [18], [25], [19], [26], [84], [27], [20], [96], [70], [68], [65], [71], [44], [139], [140], [87], [66], [89], [141], [90], [142], [98], [74], [35], [28], [143], [144], [124], [145], [146], [147], [60], [102], [148], [149], [36], [88], [150], [75], [92], [151] |
| NON-FACTOID | 56, [29], [30], [41], [42], [2], [129], [43], [132], [45], [77], [133], [31], [46], [137], [24], [138], [44], [145] |
| YES/NO      | [45], [31], [137], [46], [24] |
| CONTEXT     | 15, [48], [56], [79], [29], [30], [16], [80], [49], [54], [34], [39], [42], [50], [55], [40], [58], [61], [85], [2], [125], [127], [52], [128], [129], [130], [86], [22], [43], [131], [63], [132], [59], [76], [77], [23], [133], [78], [136], [24], [138], [47], [18], [25], [19], [26], [84], [27], [20], [96], [70], [68], [65], [71], [44], [139], [140], [87], [66], [89], [141], [90], [142], [98], [74], [35], [28], [143], [144], [124], [145], [146], [60], [102], [149], [36], [88], [150], [75], [92] |
| MULTI-PARAGRAPH | 21, [41], [51], [126], [129], [53], [45], [133], [123], [31], [46], [135], [137], [94], [145], [147], [148], [36], [92], [151] |
| EXTRACTIVE  | 48, [48], [21], [56], [79], [16], [80], [49], [54], [34], [39], [50], [55], [40], [58], [61], [51], [85], [125], [126], [127], [52], [128], [129], [130], [86], [22], [133], [63], [45], [59], [76], [23], [133], [134], [137], [138], [123], [31], [135], [136], [137], [138], [47], [18], [25], [19], [26], [84], [27], [20], [96], [70], [68], [65], [71], [44], [139], [140], [87], [66], [141], [90], [142], [98], [74], [35], [28], [143], [144], [124], [145], [146], [147], [60], [102], [149], [36], [88], [150], [75], [92], [151] |
| ABSTRACTIVE | 29, [30], [41], [42], [2], [53], [43], [132], [77], [46], [24], [89], [35], [147] |
| QUIZ       | 42, [40], [129], [53], [43], [132], [46], [24], [47], [71], [44], [90], [142], [74], [143], [124], [145] |
| CLOZE      | [152], [86], [22], [23], [138], [47], [18], [26], [27], [20], [68], [65], [140], [87], [66], [141], [98], [28], [124], [149], [88] |
| DETAIL     | 15, [48], [79], [16], [80], [49], [54], [34], [39], [50], [55], [58], [61], [85], [125], [127], [52], [128], [130], [131], [63], [50], [76], [78], [134], [136], [21], [51], [126], [129], [123], [135], [56], [29], [30], [2], [77], [41], [45], [31], [137], [133], [138], [47], [18], [25], [19], [84], [96], [70], [44], [139], [66], [89], [35], [144], [124], [145], [146], [147], [60], [102], [148], [36], [150], [75], [92], [151] |

## Table A2. Reviewed Papers Categorized Based on Their Embedding Phase

| CHARACTER EMBEDDING | CNN | RNN | OTHER |
|---------------------|-----|-----|-------|
|                     | [21], [56], [79], [34], [80], [50], [55], [58], [85], [128], [131], [63], [59], [134], [78], [123], [18], [35], [124], [75] |
|                     | [16], [49], [41], [42], [61], [23], [63], [76], [138], [47], [19], [28], [146], [60], [102] |
|                     | [127], [31], [136], [137], [144], [36] |

| WORD EMBEDDING | ONE HOT | LEARNED | FIXED PRE-TRAIN | FINE-TUNE |
|----------------|---------|----------|-----------------|----------|
|                | [25], [53], [65], [89], [145], [150] |
|                | [30], [53], [86], [45], [77], [47], [26], [68], [65], [140], [87], [90], [147], [60] |
|                | [15], [48], [21], [56], [79], [29], [16], [80], [49], [34], [41], [42], [50], [55], [39], [58], [51], [2], [129], [126], [131], [63], [132], [59], [76], [77], [134], [79], [123], [135], [136], [137], [24], [18], [25], [19], [84], [96], [70], [71], [44], [139], [142], [98], [74], [144], [124], [145], [146], [102], [149], [36], [150], [75], [151] |
|                | [15], [48], [54], [39], [50], [61], [85], [125], [127], [52], [128], [152], [130], [22], [43], [132], [23], [133], [31], [46], [138], [27], [20], [68], [141], [35], [28], [143], [124], [148], [88], [92] |
| HYBRID | - | [21], [56], [79], [34], [55], [16], [80], [49], [41], [42], [50], [58], [61], [85], [127], [128], [22], [131], [63], [59],[76], [134], [78], [123], [31], [136], [137], [138], [22], [47], [18], [19], [35], [28], [144], [124], [146], [60], [102], [36], [150], [75] |
| SENTENCE EMBEDDING | - | [71], [66], [89], [142], [74], [144], [151] |
| CONTEXT EMBEDDING | GRU | [48],[21], [30],[80], [49], [41], [50], [2], [53], [86], [22], [63], [132], [23], [134], [123], [138], [25], [26], [27], [96], [68], [65], [140], [87], [90], [142], [35], [28], [143], [124], [145], [146], [102], [149], [88] |
| LSTM | [15], [56], [79], [34], [55], [29], [16], [54], [39], [42], [58], [61], [51], [129], [85], [125], [127], [52], [128], [130], [43], [131], [45], [59], [76], [77], [133], [78], [31], [46], [135], [136], [137], [24], [47], [18], [19], [84], [20], [70], [44], [139], [141], [98], [124], [147], [60], [148], [150], [75], [92] |
| CNN | [71], [98], [146], [36] |

**Table A3. Reviewed papers categorized based on their reasoning phase**

| DIRECTION | ONE-DIRECTION | TWIN-DIRECTION | DIMENSION |
|-----------|---------------|----------------|-----------|
| ONE-DIRECTION | [15], [48], [79], [29], [80], [49], [39], [41], [42], [51], [85], [2], [52], [128], [129], [152], [22], [43], [131], [63], [132], [135], [24], [84], [27], [20], [65], [71], [44], [140], [87], [89], [90], [74], [28], [143], [144], [124], [146], [147], [102], [148], [149], [88], [92], [151], [66] |
| TWIN-DIRECTION | [21], [56], [55], [125], [126], [91], [86], [45], [46], [133], [134], [78], [137], [16], [34], [53], [50], [58], [127], [59], [76], [77], [31], [136], [138], [47], [18], [25], [26], [70], [139], [35], [124], [145], [36], [150], [75] |

**Table A4. Reviewed papers categorized based on their prediction phase**

| EXTRACTION MODE | BOUNDARY IDENTIFICATION | CANDIDATE RANKING |
|-----------------|-------------------------|------------------|
| ONE-DIRECTION | [15], [48], [21], [79], [16], [50], [55], [40], [58], [61], [51], [85], [125], [126], [127], [52], [128], [129], [130], [86], [22], [131], [45], [59], [76], [23], [134], [78], [111], [31], [135], [136], [137], [138], [80], [49], [54], [34], [39], [47], [18], [19], [26], [84], [96], [70], [65], [140], [87], [141], [28], [144], [124], [145], [146], [102], [149], [36], [150], [151] |
| CANDIDATE RANKING | [56], [30], [80], [125], [91], [152], [63], [133], [25], [27], [20], [68], [71], [44], [139], [66], [90], [98], [74], [143], [145], [60], [148], [88], [92] |

**GENERATION MODE**

| ANSWER GENERATION | CANDIDATE RANKING |
|-------------------|------------------|
| [29], [77], [41], [89], [35], [100], [147] |
| [42], [53], [43], [132], [46], [24] |
### Table A5. Reviewed Papers Categorized Based on Their Evaluation Metrics

| Extractive Metric | EM       | F1       | MAP      | MRR      | P@1      | R@1      | ACC      | Hit@k/Top@k |
|-------------------|----------|----------|----------|----------|----------|----------|----------|-------------|
|                   | [15], [48], [21], [104], [79], [16], [80], [49], [54], [34], [39], [55], [58], [61], [51], [85], [125], [126], [52], [128], [129], [130], [131], [59], [76], [134], [78], [123], [136], [138], [63], [133], [47], [18], [25], [19], [84], [96], [70], [139], [144], [146], [147], [60], [148], [36], [150], [151] | [15], [48], [21], [104], [79], [16], [80], [49], [54], [34], [39], [105], [55], [58], [61], [51], [85], [2], [125], [126], [52], [128], [129], [130], [131], [59], [76], [134], [78], [123], [136], [138], [63], [133], [47], [18], [25], [19], [84], [96], [70], [139], [144], [146], [147], [60], [102], [148], [36], [150], [75], [151] | [56], [91], [44], [144], [92] | [56], [91], [44], [92] | [56], [60], [102], [92] | [135], [60], [102] | [30], [95], [42], [152], [86], [22], [43], [132], [23], [24], [63], [105], [91], [47], [18], [26], [27], [20], [68], [65], [71], [140], [87], [66], [89], [141], [90], [142], [98], [74], [28], [143], [144], [124], [145], [102], [149], [88] | [53] |

| Generative Metric | ROUGE_L  | BLEU     | METEOR   | CIDER    |
|-------------------|----------|----------|----------|----------|
|                   | [79], [133], [29], [45], [41], [31], [137], [77], [94], [35], [124], [145], [147] | [79], [133], [41], [31], [137], [77], [96], [35], [145], [147] | [77], [35], [145] | [77], [96] |

### Table A6. Reviewed Papers Categorized Based on Their Novelties

| Model Structure   | Input/Output | Internal | Dataset | Knowledge Transfer | Evaluation Measure |
|-------------------|--------------|----------|---------|-------------------|-------------------|
|                   | [30], [54], [34], [41], [55], [2], [126], [128], [129], [135] | [15], [21], [79], [29], [16], [80], [49], [95], [41], [39], [42], [58], [85], [127], [52], [152], [86], [22], [43], [131], [63], [132], [45], [59], [77], [133], [134], [78], [136], [137], [24], [46], [153], [47], [18], [25], [19], [26], [84], [20], [96], [70], [68], [65], [71], [44], [139], [87], [66], [89], [141], [90], [142], [98], [74], [35], [28], [143], [144], [145], [146], [147], [102], [148], [149], [36], [88], [151] | [104], [95], [105], [17], [106], [107], [108], [109], [110], [111], [112], [113], [94], [96], [82], [65], [37], [90], [97], [98], [73], [99], [100], [101], [102], [103] | [15], [48], [56], [29], [61], [125], [91], [152], [130], [76], [23], [137], [123], [138], [135], [71], [44], [140], [60], [150], [92] | [122], [154], [27], [124], [102], [75] |