Teaching Machine Comprehension with Compositional Explanations

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Abstract

Advances in extractive machine reading comprehension (MRC) rely heavily on the collection of large scale human-annotated training data (in the form of "*question-paragraph-answer span*"). A single question-answer example provides limited supervision, while an explanation in natural language describing human's deduction process may generalize to many other questions that share similar solution patterns. In this paper, we focus on "teaching" machines on reading comprehension with (a small number of) natural language explanations. We propose a data augmentation framework that exploits the compositional nature of explanations to rapidly create pseudo-labeled data for training downstream MRC models. Structured variables and rules are extracted from each explanation and formulated into *neural module teacher*, which employs softened neural modules and combinatorial search to handle linguistic variations and overcome sparse coverage. The proposed work is particularly effective when limited annotation effort is available, and achieved a practicable F1 score of 59.80% with supervision from 52 explanations on the SQuAD dataset[2].

1. Introduction

Recent advances in sequence-to-sequence learning and pre-trained language models (Devlin et al., 2019; Joshi et al., 2019; Lan et al., 2019) yields strong (human-level) performance on several reading comprehension datasets. However, these state-of-the-art results, as well as results in other sequence learning tasks, strongly rely on large-scale annotated corpora, which is often time-consuming and costly to collect. This often leads to a large gap between methods in the research setting and practical settings, as large amounts of annotated data rarely exist for a new task or a low-resource domain. To reduce this dependency on annotation efforts, we seek to improve the efficiency in obtaining and applying

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[2]Our code and data can be found at https://github.com/INK-USC/nl-explanation

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Reference Instance
Q: When was Queen Victoria's *funeral* **held**?
C: Her *funeral* was **held** on Saturday, 2 February, in St George's Chapel, Windsor Castle, and after two days of lying-in-state ...
A: Saturday, 2 February
NL Explanation
X is "funeral". Y is "held". In the question X is within 4 words after "when was" and Y is directly after X. "on" is directly before the answer. Y is within 2 words before the answer. X is within 3 words left of Y. The question starts with "when", so the answer should be a date.
Strictly-matched Instance
Q: When was *independence* **declared**?
C: ... *Independence* was unilaterally **declared** on 24 September 1973.
A: 24 September 1973

Reference Instance
Q: Where is *hydrogen* **highly soluble**?
C: ... *Hydrogen* is **highly soluble** in many rare earth and transition metals and is soluble in both nanocrystalline and amorphous metals. ...
A: many rare earth and transition metals
NL Explanation
X is "hydrogen". Y is "highly soluble". Y is directly after X and X is directly after "where is" in the question. X is within 5 words before Y. Y is within 2 words before the answer. "in" is directly before the answer. "is" is between X and Y.
Softly-matched Instance
Q: Where is *the divinity herself* **purified**?
C: ... Afterwards the car, the vestments, and, if you like to believe it, *the divinity herself*, are **purified** in a secret lake. ...
A: a secret lake *(confidence = 72.48%)*
Note
In the reference instance, Y (highly soluble) is supposed to be an adjective phrase. In the new instance, FILL module suggested "purified" to be a promising candidate for variable Y.

Table 1. Examples of natural language explanations, strictly-matched instance and softly-matched instance.

human supervision.

A human's ability to answer a question is not solely dependent on the *quantity* of questions they have seen solutions for; instead, we also attempt to learn methods of deduction from each question-answer example. When we encounter a new question, we reference what we have already seen, then select and apply the appropriate deduction method. In contrast, datasets we collect for training machine learning models fail to emphasize this pivotal step of abstracting deduction rules, and hence these methods lack a human's "one-shot" learning ability.

In light of this, we explore to build annotation-efficient, down-to-earth machine reading comprehension (MRC) systems *afresh* by incorporating high-level abstractions in
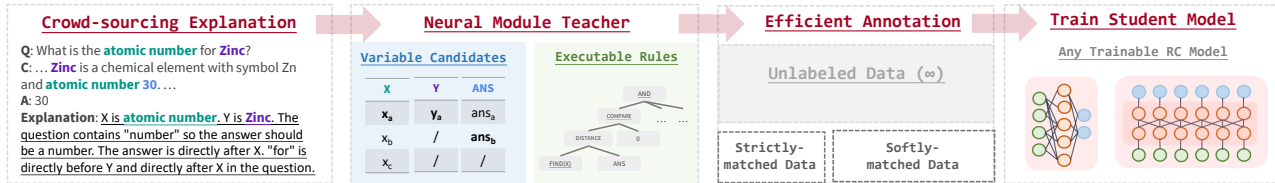
Figure 1. **Overview of proposed work.** Variables and rules (Sec. 3.2) are parsed from crowd-sourced natural language explanations and formulated into neural module teachers (Sec. 3.3). These neural module teachers act as programs to annotate largely-available unlabeled data in data programming paradigm. Annotated instances are later sent to train a downstream reading comprehension model (Sec. 4.2).

forms of natural language (NL) explanations (Table 1) and applying them in data programming manner (Ratner et al., 2019). We specifically focus on extractive MRC task, which is to identify an answer span from a given paragraph. NL explanations have long been leveraged as auxiliary supervision in various NLP tasks (Srivastava et al., 2017; Li et al., 2018; Rajani et al., 2019). Within this scope, annotation efficiency is emphasized in several recent work (Hancock et al., 2018; Wang et al., 2020), where NL explanations are processed into *programs* for data programming. However, previous works are limited to classification tasks. In comparison to these simple and static programs for classification (*i.e.*, labeling functions), programs for extractive MRC are more challenging to construct due to the following reasons: (1) no explicit anchor words (*e.g.*, subject and object as in relation extraction); (2) no pre-defined, finite set of labels; and (3) sparser coverage for each explanation.

To deal with these challenges, we propose Neural Module Teacher (NMTeacher) – *programs* constructed from NL explanations that are (1) capable of taking sequential steps and combinatorial search; (2) dynamically composed of modules as described in the NL explanation; and (3) capable of fuzzy matching and grounding by softening the constraints in the program. Fig. 1 illustrates the overview of our framework. One collected explanation will first go through a Combinatory Categorial Grammar (CCG) parser (Zettlemoyer & Collins, 2012) and is formulated into structured *variables* and *rules* (Sec. 3.2). A neural module teacher makes use of these structured results and functions as a weak model for the specific type of question described in the explanation (Sec. 3.3). All neural module teachers act together and separate the unlabeled corpus into strictly-matched instances and softly-matched instances, which are later sent to train a downstream student MRC model (Sec. 4.2). It is important to note that while the inspiration for this work is tied to the particular task of reading comprehension, we believe a modified version of our work can be utilized for a wide range of machine learning tasks.

We evaluated our approach on two datasets in extractive MRC setting: SQuAD v1.1 (Rajpurkar et al., 2016) and Natural Questions (Kwiatkowski et al., 2019). Experimental results show the strength of the proposed approach in ex-

tremely low-resource scenarios. With high-level supervision from 52 NL explanations, we manage to achieve 46.55% in exact match and 59.60% in the F1 score on the SQuAD dataset. Moreover, our analysis shows that explanations continue to improve model performance when a medium-sized human-annotated dataset is already available.

2. Problem Formulation

We are interested in rapid data augmentation for learning machine reading comprehension *in the low-resource regime*. Our goal is to train an extractive machine reading comprehension (MRC) model $\mathbb{F}$, which takes as input a tuple (q, c) of question and context, and extract an answer span $a = (s, t)$ within the context c. s is the start index and t is the end index of the span in c. A low-resource situation is assumed where a tiny set $\mathcal{S}_o$ (< 100 instances) of (q, c, a) triples is available at the beginning.

Notations and Problem Definition. To achieve this goal, we first collect natural language explanations e_i for each known (q_i, c_i, a_i) instance in $\mathcal{S}_o$. One neural module teacher $\mathbb{G}_i$ will be constructed from each explanation e_i, enabling it to answer questions similar to (q_i, c_i, a_i). All neural module teachers acting together can be viewed as an ensemble teacher $\mathbb{G}$. We then apply $\mathbb{G}$ to largely-available (q, c) pairs, getting $\mathcal{S}_a = \{(q, c, a)\}$, a strictly-labeled dataset that $\mathbb{G}$ can directly answer. The remaining unmatched instances are denoted as $\mathcal{S}_u = \{(q, c)\}$. After softening the constraints in each $\mathbb{G}_i$, we may get a noisily-labeled dataset $\mathcal{S}_p = \{(q, c, a, z)\}$ from $\mathcal{S}_u$, where z is a confidence score given by $\mathbb{G}$. The overview is depicted in Fig. 1.

$\mathcal{S}_a$ and $\mathcal{S}_p$ provide more sufficient supervision than $\mathcal{S}_o$. We then use them to train a downstream MRC model $\mathbb{F}$. Note that our approach is model-agnostic as $\mathbb{F}$ can take any form as long as it is trainable. To further demonstrate that the neural module teacher is widely-applicable, we also consider training $\mathbb{F}$ with medium-size human-annotated data $\mathcal{S}_r$, showing that supervision from $\mathcal{S}_a$ and $\mathcal{S}_p$ is complementary in this situation.

In the following, we will refer to the $(q_i, c_i, a_i) \in \mathcal{S}_o$ part in (q_i, c_i, a_i, e_i) as the "reference instance" for explanation e_i,

Name	Description	Example
FILL $s_{ref}, p_{ref}, s \to p$	Select the span p in a given sentence s that plays the same syntactic role of span p_{ref} in sentence s_{ref}.	s_{ref} = How is packet switching characterized? p_{ref} = [2,3] (packet switching) s = How is hunting regulated? $\to p$ = [2,2] (hunting)
FIND $q_{ref}, p_{ref}, s \to p$	Find the span p in a context sentence s that refers to the span p_{ref} in the question q_{ref}	q_{ref} = How is a promoter sequence recognized? p_{ref} = [2,4] (a promoter sequence) s = The promoter is recognized and bound by ... $\to p$ = [1,1] (promoter)
COMPARE $d_0, d_1 \to p$	Softly evaluate $d_1 \le d_0$	$d_0 = 0, d_1 = 1 \to p = 0.75$ $d_0 = 4, d_1 = 2 \to p = 1$
LOGICAND $p_1, p_2 \to p$	Perform soft logic AND to two scalar probabilities p_1, p_2	$p_1 = 0.9, p_2 = 0.85 \to p = 0.75$ $p_1 = 1, p_2 = 1 \to p = 1$

Table 2. **Summary of atomic modules used in rule evaluation.** Rules from compositional explanations may internally call these modules to fulfill complex functionalities. For example, LEFT(X, Y) is transformed to COMPARE(DISTANCE(FIND(X), FIND(Y)), 0)

as we will frequently check this (q_i, c_i, a_i) "for reference" when we apply $\mathbb{G}_i$ to new, unseen instances.

3. Neural Module Teacher

A neural module teacher (NMTeacher) acts as a *program* that answers a question following the deduction process described in a natural language explanation. In this section, we first introduce the basic modules used for rule execution in Sec 3.1. We then discuss how variables and rules are obtained from natural language explanations by semantic parsing in Sec 3.2. Finally, in Sec 3.3, we present how a neural module teacher is composed, *i.e.*, how rules are used together with search algorithm to derive answers for reading comprehension tasks.

3.1. Atomic Modules

We introduce the four atomic modules used in neural module teacher: FILL, FIND, COMPARE and LOGIC. Higher-level functionalities, such as LEFT, LESSTHAN, may internally call these four modules to fulfill their compositional task (Sec. 3.2). Each atomic module has its own strict and softened version, so that a strictly-matched set $\mathcal{S}_a$ and a softened-matched set $\mathcal{S}_p$ can be obtained separately (Sec. 4.2). A summary of module input/output format and usage is presented in Table 2.

FILL. The motivation behind FILL module is that when humans encounter a new question, we relate to those questions we've already learned by matching the syntactical structure and keywords. For example, when we try to answer *"How is hunting regulated?"* given that we've previously learned *"How is packet switching characterized?"*, we intuitively link "packet switching" to "hunting", and "characterized" to "regulated". Additionally, if two questions have similar syntactical structures, their answers usually share similarities as well. In the two example questions

Figure 2. **A Concrete Example for Fill and Find Module.** "atomic number" from the reference instance is generalized to "telephone number" in a new question with Fill module . This span is further mapped to "phone" within the context with Find module.

above, the contexts are *"packet switching is characterized by a fee per unit of information transmitted"* and *"hunting is regulated by state law"* respectively, and the underlined answers play similar syntactical roles. Based on these observations, we build FILL module to identify such phrases in a new sentence given some reference to follow; that is, given as input two sentences s_{ref} and s, and one span p_{ref} in reference sentence s_{ref}, FILL will predict most plausible matches p in s.

The strict version of FILL module looks at pre-processing results such as (a) named entities, (b) dependency, or (c) constituency. It will output every span in s that has the same role of p_{ref} in s_{ref} considering these three criteria. Note that we expect FILL module to propose as many promising candidates as possible, even though some of them may be wrong and noisy, since the rule execution and validation process later on is error-tolerant.

The softened version of FILL is a neural network so that when no span is found in the strict version, FILL may still propose promising candidates for s, just like the example in Table 1 where "highly soluable", an adjective phrase is linked to "purified", a verb phrase, in a new unseen question.

The implementation of the FILL module is a ranking model based on similarities between phrase representations. We first calculate the phrase representation of p_{ref} in s_{ref} as e'. We then rank all constituents p in sentence s with the cosine similarity between its representation e and e', and return the top k constituents along with their score as the output of FILL module. Suppose we're given a sentence s as a sequence of tokens $[x_1, x_2, ..., x_m]$ and a span p with left and right boundaries $[l, r]$, to compute representation for this phrase, we first encode the sentence with BERT-base (Devlin et al., 2019) and get representations $[\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_m]$ for each token,

$$[\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_m] = \text{BERT}(s), \quad i = 1...N. \quad (1)$$

We then apply pooling over all tokens in the span to get the phrase representation $\mathbf{e}$[1]. We explored two pooling methods: mean pooling and attentive pooling,

$$\text{Mean:} \quad \mathbf{e} = \sum_{j=l}^{r} \frac{\mathbf{h}_j}{r - l}; \quad (2)$$

$$\text{Attentive:} \quad a_j = \frac{\exp(\mathbf{u}^T \tanh(\mathbf{B}\mathbf{h}_j))}{\sum_{j'=lb}^{rb} \exp(\mathbf{u}^T \tanh(\mathbf{B}\mathbf{h}_{j'}))}; \quad (3)$$

$$\mathbf{e} = \sum_{j=lb}^{rb} a_j \mathbf{h}_j, \quad (4)$$

where $\mathbf{B}$ and $\mathbf{u}$ are trainable parameters in the attention layer. e' is calculated in a similar way with s_{ref} and p_{ref}. The similarity score between e and e' can be calculated using cosine similarity or adding a bilinear layer, *i.e.*,

$$\text{Cosine:} \quad \text{Sim}(\mathbf{e}, \mathbf{e}') = \frac{\mathbf{e}^T \mathbf{e}'}{\|\mathbf{e}\|\|\mathbf{e}'\|}; \quad (5)$$

$$\text{Bilinear:} \quad \text{Sim}(\mathbf{e}, \mathbf{e}') = \tanh(\mathbf{e}\mathbf{A}\mathbf{e}' + b); \quad (6)$$

where $\mathbf{A}$ is a trainable matrix, and the output of the bilinear layer is re-scaled into $[-1, 1]$ with $\tanh$ function to align with the output of the cosine similarity. We discuss the design choices for the softened Fill module in section 4.1.

FIND. When seeing a question *"How is a promoter sequence recognized?"*, we expect "a promoter sequence" to be in the context, and the answer should be near it. We locate the word "promoter" in the context sentence *"The promoter is recognized and bound by ..."*, even though "promoter" and "a promoter sequence" are slightly different in their surface forms. Our FIND module tries to capture this by relocating a keyword in the question to its corresponding span in the context. This module is similar to the find module in (Jiang & Bansal, 2019) in its motivation, but we

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[1]We only need to encode the sentence with BERT once and cache it. Pooling after this step is fast and efficient.
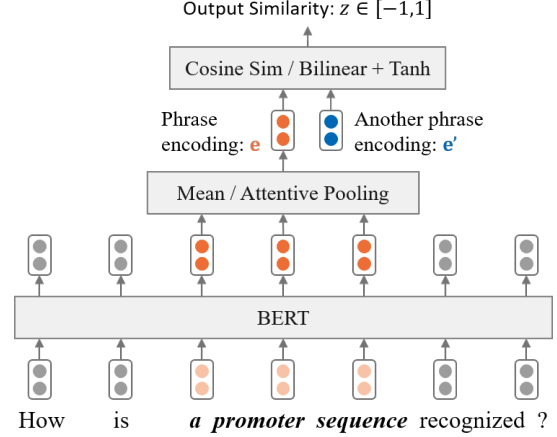

Figure 3. Model structure of the Fill and Find module for encoding the phrase *"a promoter sequence"*.

specifically design ours to be a ranking based model with discrete boundaries instead of continuous attention weights, so that the output fits in the search algorithm and answering procedure in Sec. 3.3.

The strict version of FIND module directly looks for exact matches of the key (*i.e.*, directly look for "a promoter sequence" in the context in the above example). However, in real cases, the phrases have different surface forms due to reasons such as synonym ("provide" vs. "offer"), spelling difference ("color" vs. "colour"), and co-reference ("Henry V" vs. "He"). Therefore we build a softened version of FIND to deal with these situations; that is, given as input a question q_{ref}, a context sentence s, and a span p_{ref} in q_{ref}, FIND will predict matched spans p in s and gives the confidence scores. The model structure for the softened Find module and procedures are similar to the FILL module. We discuss the design choices for the softened FIND module in section 4.1.

COMPARE. One type of explanations supported in our framework is "X is within d_0 words after Y." Here we consider the basic comparison of $d_1 \leq d_0$. The strict version of compare module outputs $P(d_1 \leq d_0) = 1$ when $d_1 \leq d_0$ and outputs 0 otherwise.

In the soften version of COMPARE, we empirically design the following function so that $P(d_1 \leq d_0)$ represents "to what extent $d_1 \leq d_0$ is correct". As an example, $P(d_1 \leq d_0) = 0.95$ means $d_1 > d_0$, but the difference is small. The intuition in Eq. (7) is that the comparative difference $\frac{d_1 - d_0}{|d_0|}$ is taken into consideration.

$$P(d_1 \leq d_0) = \begin{cases} 1 & d_1 \leq d_0; \\ \max(1 - \frac{1}{4}(\frac{d_1 - d_0}{|d_0|+1})^2, 0) & d_1 > d_0. \end{cases} \quad (7)$$

LOGIC. Logic operations such as "and" and "or" may be mentioned in the explanations. Also, one explanation may contain multiple sentences, so that we put an "@And" operation at the top level to aggregate them. In the strict version of LOGIC, only boolean output of True (1) and False (0) are allowed. In the softened version, we use soft logic to aggregate two probabilities.

$$\begin{aligned} \text{AND}(p_1, p_2) &= \max(p_1 + p_2 - 1, 0) \\ \text{OR}(p_1, p_2) &= \min(p_1 + p_2, 1) \end{aligned} \qquad (8)$$

3.2. Parsing Explanation to Executable Rules

We previously mentioned terms such as variables and rules without formally introducing them. In this subsection, we give formal definitions to these terms and describe how they are parsed and extracted from an NL explanation.

Natural Language (NL) Explanations. NL explanations are sentences describing high-level abstractions (*i.e.*, deduction process) of reading comprehension ability. Specifically, we believe this deduction process can be characterized by (1) defining variables; (2) describing the clues and relations between the variables, *i.e.*, rules. Such information is suitable to be transformed into structured and executable form in later steps; meanwhile, they are decisive in locating answer span $a = (s, t)$ from context c. Though the explanation collection interface allows free-form text input, we specifically encourage annotators to follow our guidelines and write from these two perspectives. Examples of explanations are previously shown in Table 1 and Fig. 1 (left).

Variables. Variables are the phrases that may be substituted or generalized in the question. In the example question "What is the <u>atomic number</u> for <u>Zinc</u>?", the underlined words are defined as variables. When the phrases are substituted in a new question, e.g. "What is the <u>telephone number</u> for <u>Sunshine Cafeteria</u>?", we may use the same deduction strategy as for the example question. Annotators are guided to mark the important spans in the explanation with sentences like "X is atomic number". The notion of variables is closely related to the design of FILL module as FILL aims to propose potential assignments to these variables. When we relate "atomic number" to "telephone number", the process can be characterized by assigning value "telephone number" to variable X.

Rules. Rules are statements that describe characteristics of variables and relationships between them. Given that all variables in a rule are assigned, execution of this rule will output either True or False (in strict version) or a probability between 0 and 1 (in softened version). Following previous work (Srivastava et al., 2017; Wang et al., 2020), we first use a Combinatory Categorial Grammar (CCG) based semantic parser $\mathbb{P}$ (Zettlemoyer & Collins, 2012) to transform explanations into structured parses. Two examples of such

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Explanation e: The answer is directly after X.
Parse p_j: @Is(Answer, @Direct(@Right(X)))
Execution f_j: COMPARE(DISTANCE(Ans,FIND(X)),0)

Explanation e: The answer is within 3 words before Z and within 4 words after Y.
Parse p_j: @Is(Answer,@And(@LessThan(@Left(Z), 3), @LessThan(@Right(Y, 4)))
Execution f_j: AND(COMPARE(DISTANCE(FIND(Z),Ans),3), COMPARE(DISTANCE(Ans,FIND(Y)),4))

Table 3. **Rules in three equivalent forms: explanation, parse and underlying execution.** Natural language explanations are first parsed (with semantic parsing) and later transformed to executable functions (with lambda calculus). The execution form is composed of atomic modules (Sec. 3.1).

transformation are shown in Table 3 (from e to p_j). We build a domain-specific lexicon for frequently-used expressions in the explanations and their semantics. We then implement the operation for each supported predicate (*e.g.*, "@Is", "@Direct", "@Left"), which may require calling atomic modules internally. These predicate implementations, together with the inherent λ-calculus hierarchy from CCG parsing, will yield the final executable function f_j as shown in Table 3.

An explanation e_i may contain multiple sentences, so we add a top-level "@And" operation as the last step. Note that for each sentence, the semantic parser $\mathbb{P}$ may further produce multiple successful parses $\{p_1, p_2, ..., p_m\}$ and each parse p_j corresponds to an executable function f_j. To determine the correct one, we validate each parse by applying the function f_j to the reference instance (q_i, c_i, a_i) and the variable assignment specified in e_i. We only keep the parse that outputs True.

3.3. Rule Execution for Answer Span Extraction

Rules introduced in Sec 3.2 can be executed to *verify* whether variable assignments and an answer span is correct (or "to what extent" it is correct in softened version). To actively *output* an answer, we formulate this step into a combinatorial search problem searching for the combination of variable assignments[2].

Specifically, when applying explanation e_i to a new question, candidates for each variable are first proposed by FILL module. We then look for the combination of variable assignments that achieves the highest confidence scores when it is evaluated on rules generated from e_i. As a minimal example, if FILL proposes $\{x_1, x_2\}$ as potential assignments to variable X, and $\{a_1, a_2\}$ to ANS, we evaluate the four possible combinations $\{(x_1, a_1), (x_2, a_1), (x_1, a_2), (x_2, a_2)\}$ by applying e_i and select the one combination achieving highest score. As the number of combinations expands sig-

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[2]Answer is considered as a special variable. The best combination will imply a best answer span.

Algorithm 1 Learning with Compositional Explanations

Input: Tiny Labeled Dataset $\mathcal{S}_o = \{(q, c, a)\}$
    Unlabeled Dataset $\mathcal{S} = \{(q, c)\}$
    Confidence Threshold t
Output: MRC Model $\mathbb{F} : (q, c) \rightarrow a$
 1: // Construct Neural Module Teachers
 2: $\mathbb{G} \leftarrow \varnothing$
 3: **for** $(q_i, c_i, a_i) \in \mathcal{S}_o$ **do**
 4:    Parse e_i and construct a neural module teacher $\mathbb{G}_i$
 5:    **if** $\mathbb{G}_i(q_i, c_i) = (a_i, 1.0)$ **then**
 6:       $\mathbb{G} = \mathbb{G} \cup \{\mathbb{G}_i\}$ // $\mathbb{G}_i$ is validated
 7:    **end if**
 8: **end for**
 9: // Annotate Data
10: $\mathcal{S}_a \leftarrow \varnothing, \mathcal{S}_p \leftarrow \varnothing$
11: **for** $(q, c) \in \mathcal{S}$ **do**
12:    $(a, z) = \mathbb{G}(q, c)$ // z is confidence score
13:    **if** $z = 1$ **then**
14:       $\mathcal{S}_a \leftarrow \mathcal{S}_a \cup \{(q, c, a)\}$ // Strict Match
15:    **else**
16:       $\mathcal{S}_u \leftarrow \mathcal{S}_u \cup \{(q, c)\}$ // Unlabeled
17:       **if** $z > t$ **then**
18:          $\mathcal{S}_p \leftarrow \mathcal{S}_p \cup \{(q, c, a, z)\}$ // Softened Match
19:       **end if**
20:    **end if**
21: **end for**
22: // Train Downstream RC Model $\mathbb{F}$
23: $\mathbb{F} \leftarrow \text{Train}(\mathcal{S}_a, \mathcal{S}_p)$
24: **return** $\mathbb{F}$

Dataset	SQuAD	NQ
# Exps (Raw)	2065	1220
# Exps (Accepted)	570	343
# Exps (Parsable)	163	109
# Exps (Validated)	130	89
Avg. # Sentence/exp	4.31	4.51
Avg. # Tokens/exp	38.87	41.28
Avg. # Variables/exp	1.96	1.47

Table 4. Statistics of the collected explanations used in our experiments on SQuAD and Nature Question datasets.

4.1. Pre-training of Fill and Find Module

The softened Fill module is pre-trained with pairs of questions with the same syntactical structures and their matched key phrases obtained from strictly-matching results $\mathcal{S}_a$. For each pair of matched questions, their answers are considered matched, and thus the pair of contexts and answers are also used to train the model. Other chunks in sentence s extracted by Stanford CoreNLP parser (Manning et al., 2014) are used as negative training instances. For the Fill module, we conduct an evaluation on the test split of the strictly-matched data $\mathcal{S}_a$. Statistics of training, development, and test data for the Fill module are shown in Table 7. We tested with various model designes mentioned in section 3. The performance is not significantly different. And we choose to use attentive pooling and bilinear layer for the softened Fill module.

Unlike the Fill module that looks at syntactic patterns, the softened Find module looks at semantic meanings of the phrases. For this task, it's hard to find appropriate training data. We tried various data as proxies, including coreference resolution data (coreference result on the SQuAD dataset produced by the Stanford CoreNLP (Manning et al., 2014)) and existing paraphrase data (PPDB (Pavlick et al., 2015)). The module is manually evaluated on the collected explanations: the reference phrases p_{ref} are the key phrases in questions identified by annotators, and we inspect on the model's predictions on the corresponding context. We tested with various training data and found that pre-training the module only makes the performance worse. We conjecture it may be caused by data bias (the training data not aligning with the purpose of the module) or overfitting issues (fine-tuning BERT with small number of data may lead to severe overfitting). Therefore we do not pre-train the softened Find module. We use mean pooling and cosine similarity for the module and rely on BERT's pretrained weights to capture the semantic meanings of the phrases. Manual evaluation results for the Fill and the Find module are shown in Table 8.

4.2. Downstream MRC Model Learning

We assume a freely-available, large set of unlabeled data $\mathcal{S} = \{(q, c)\}$ in our problem setting and aim to curate su-

nificantly with the number of variables and their candidates, we solve this problem with beam search by progressively fill each variable and keep the most promising combinations in each step. Details of the searching method are specified in the appendix with Algorithm 2 and Figure 7.

This formulation enables answer span a and confidence score z as function output. It then completes our construction of neural module teacher $\mathbb{G}_i$ from NL explanation e_i. We use $(a, z) = \mathbb{G}_i(q, c)$ to denote that given question q and context c, neural module teacher $\mathbb{G}_i$ identifies the answer span a (from c) with a confidence score z. Multiple neural module teachers $\mathbb{G}_i$ may be ensembled into $\mathbb{G}$ by listing all answer spans outputted by each $\mathbb{G}_i$ and selecting the one with the highest z.

4. Learning to Augment with NMTeacher

In the previous section, we introduced the necessary steps to construct a neural module teacher from NL explanations. In the overall framework, there are several learnable components, including the softened version of FILL and FIND module, and the downstream reading comprehension model $\mathbb{F}$. We discuss their design choices and training objectives in this section.

pervision from $\mathcal{S}$ in data programming paradigm. To train the downstream model, we attempt to answer each (q, c) instance using our ensemble neural module teacher $\mathbb{G}$ constructed in Sec 3. If an answer is found with confidence score $z = 1$, we consider this as a strict match and add this instance to $\mathcal{S}_a$. We denote an unlabeled set $\mathcal{S}_u = \mathcal{S} \backslash \mathcal{S}_a$ and will use it for comparison with semi-supervised baselines. If an answer with z above a pre-defined threshold t is found, we consider it to be a softened match and add it to $\mathcal{S}_p$. This procedure is also described in Algorithm 1 (Line 11-21).

Compared to the tiny labeled set $\mathcal{S}_o$ in the beginning, we now have stronger supervision signals with strictly-matched set $\mathcal{S}_a$ and softly-matched set $\mathcal{S}_p$. The most straightforward way would be training the downstream MRC model $\mathbb{F}$ with $\mathcal{S}_a$ and traditional supervised learning. Meanwhile, $\mathcal{S}_p$ is significantly larger in size and may contain useful information for training $\mathbb{F}$. We blend in supervision from $\mathcal{S}_p$ by adding a weighted loss term to the original supervised loss. That is, we sample a batch $\mathcal{B}_a$ sampled from $\mathcal{S}_a$ and a batch $\mathcal{B}_p$ sampled from $\mathcal{S}_p$ simultaneously. The loss term for $\mathcal{B}_a$ is calculated in a traditional supervised way, while the loss term for $\mathcal{B}_p$ is weighted and normalized by the confidence score z from NMTeacher $\mathbb{G}$,

$$w_i = \frac{\exp(\theta_t z_i)}{\sum_{j=1}^{|\mathcal{B}_p|} \exp(\theta_t z_j)}, \tag{9}$$

$$\mathcal{L}(\mathcal{B}_p) = \sum_{i=1}^{|\mathcal{B}_p|} w_i \cdot \texttt{MRC\_Loss}_i. \tag{10}$$

θ_t in Eq. 9 is a temperature that controls the normalization intensity. We then aggregate the loss terms from $\mathcal{S}_p$ and $\mathcal{S}_a$ with a co-efficient β selected on development set, i.e.,

$$\mathcal{L} = \mathcal{L}(\mathcal{B}_a) + \beta \mathcal{L}(\mathcal{B}_p). \tag{11}$$

This formulation enables the downstream MRC model $\mathbb{F}$ to learn from both strictly-matched and softly-matched data.

5. Experiment Setup

5.1. Datasets

SQuAD (Rajpurkar et al., 2016) contains more than 10k instances collected from crowd-sourcing. Annotators are shown a paragraph first and required to ask questions. Here we limit our scope to SQuAD v1.1, which contains answerable questions only and fits our setting of extractive MRC.

Natural Questions (Kwiatkowski et al., 2019) is a dataset of questions collected from anonymized Google search entries and paired with related Wikipedia articles. To keep consistent, we adopt the setting where "the long answer is given, and a short answer is known to exist" (Kwiatkowski et al., 2019). We also discard the instances where the long answer is not free-form text (*e.g.*, table, list).

5.2. Explanation Collection

Our interface for collecting natural language explanations with Amazon Mechanical Turk is shown in Figure 8 in the appendix. Annotators are required to first read a short paragraph of high-level instructions and then read five examples carefully. After that, they are required to write an explanation for a provided answered (q, c, a) triple in one single text input box, using suggested expressions in a provided table. Finally, annotators are required to double-check their explanation before they submit. The reward for each accepted explanation is $0.5. We automatically rejected responses not following instructions (e.g., not mentioning any variables, quoted words do not appear in context) with a script. Statistics of the collected explanations on SQuAD and NQ datasets are shown in Table 4.

We constructed and modified our parser simultaneously with the explanation collection process. The accuracy of semantic parsing is 91.93% by manual inspection on 35 parsed explanations (161 sentences).

5.3. Downstream Reading Comprehension Models

As stated in Sec. 2, our approach augments training from the data perspective and thus is model-agnostic, as long as the downstream model $\mathbb{F}$ is trainable. We use the following three models as our downstream reading comprehension model $\mathbb{F}$. (1) **BiDAF** (Seo et al., 2016), a classical reading comprehension model that adopts hierarchical architecture and attention mechanism to model the interaction between the question and the context; (2) **BERT** (Devlin et al., 2019), a pre-trained language representation model[3]; (3) **ALBERT** (Lan et al., 2019), a more recent pre-trained model and one of the state-of-the-art models on SQuAD leaderboard. We also refer to these models as "base models" in our analysis.

5.4. Semi-supervised Methods

We show that NMTeacher, as a data augmentation approach, is complementary to semi-supervised methods. To demonstrate this, we use BERT-large as a base model, and applies the following semi-supervised variants: (1) **Self Training (ST)** (Rosenberg et al., 2005) which iterative annotate unlabeled instances with maximal confidence in each epoch until all instances are used up; (2) **Pseudo Labeling (PL)** (Lee, 2013) which trains a weak model on labeled data first to annotate unlabeled data. (3) **Mean Teacher (MT)** (Tarvainen & Valpola, 2017), which leverages unlabeled data by keeping consistency loss between a student model and a teacher model (constructed with an exponential moving average of student models over previous steps).

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[3] We use BERT-l as a short hand for BERT-large and BERT-b for BERT-base in following analysis

#Explanations ($|\mathcal{S}_a|$, $|\mathcal{S}_p|$)	13 (131, 314)		26 (424, 1048)		52 (766, 2329)	
	EM	F1	EM	F1	EM	F1
BiDAF ($\mathcal{S}_a$)	3.66 ± 0.92	7.80 ± 0.84	5.49 ± 0.50	9.91 ± 0.34	8.21 ± 0.25	14.15 ± 0.40
+ NMTeacher ($\mathcal{S}_p$)	5.15 ± 0.45	8.51 ± 0.22	6.65 ± 0.34	11.46 ± 0.49	12.63 ± 0.86	19.99 ± 1.06
BERT-b ($\mathcal{S}_a$)	10.52 ± 1.57	17.88 ± 2.09	19.90 ± 1.53	30.42 ± 1.53	28.84 ± 1.69	39.26 ± 2.12
+ NMTeacher ($\mathcal{S}_p$)	13.80 ± 1.29	23.39 ± 1.43	22.30 ± 2.78	32.96 ± 5.00	30.74 ± 2.48	41.28 ± 3.14
BERT-l ($\mathcal{S}_a$)	13.27 ± 1.09	21.11 ± 2.26	25.90 ± 2.55	38.35 ± 2.38	34.66 ± 0.65	47.32 ± 0.60
+ NMTeacher ($\mathcal{S}_p$)	15.80 ± 1.64	27.45 ± 2.32	28.07 ± 2.27	41.95 ± 2.95	39.05 ± 1.36	51.65 ± 2.08
ALBERT-b ($\mathcal{S}_a$)	30.12 ± 1.00	42.95 ± 1.65	39.24 ± 1.80	53.40 ± 2.87	44.57 ± 1.90	58.09 ± 0.59
+ NMTeacher ($\mathcal{S}_p$)	$\mathbf{34.13 \pm 1.23}$	$\mathbf{46.59 \pm 1.16}$	$\mathbf{40.79 \pm 0.78}$	$\mathbf{55.22 \pm 0.29}$	$\mathbf{46.55 \pm 1.04}$	$\mathbf{59.80 \pm 0.64}$

Table 5. **Performance comparison on SQuAD dataset using different numbers of explanations.** Best results are **bold**. $\mathcal{S}_a$ is the set of strictly matched instances annotated by neural module teachers (NMTeacher) constructed from explanations. $|\mathcal{S}_a|$ denotes its size. $\mathcal{S}_p$ is the set of softly matched instances by using softened modules in rule execution. $\mathcal{S}_p$ constantly brings improvements over model trained solely on $\mathcal{S}_a$, demonstrating that the usage of softly-matched but noisy data are beneficial in low-resource scenarios. Such improvement is more significant in extreme cases with 13 explanations.

#Explanations ($|\mathcal{S}_a|$, $|\mathcal{S}_p|$)	18 (98, 539)		36 (107, 647)		54 (273, 1047)	
	EM	F1	EM	F1	EM	F1
BERT-l ($\mathcal{S}_a$)	15.13 ± 0.42	24.87 ± 1.06	17.67 ± 0.31	26.19 ± 0.45	17.85 ± 1.53	28.04 ± 1.69
+ NMTeacher ($\mathcal{S}_p$)	14.81 ± 0.29	27.10 ± 1.49	20.49 ± 1.62	31.48 ± 1.42	19.00 ± 1.08	30.16 ± 0.83
ALBERT-b ($\mathcal{S}_a$)	$\mathbf{21.30 \pm 1.89}$	29.22 ± 2.44	24.26 ± 2.35	32.93 ± 2.93	$\mathbf{23.63 \pm 1.50}$	33.70 ± 1.32
+ NMTeacher ($\mathcal{S}_p$)	20.49 ± 2.59	$\mathbf{30.71 \pm 3.32}$	$\mathbf{26.67 \pm 3.68}$	$\mathbf{37.26 \pm 4.24}$	23.41 ± 1.47	$\mathbf{33.88 \pm 0.61}$

Table 6. **Performance comparison on Natural Questions dataset using different numbers of explanations.** Best results are **bold**. Notations are the same as in Table 5.

5.5. Evaluation

For fast and convenient comparison in various settings, we choose not to use the official hidden test sets of SQuAD or Natural Question. We randomly split the provided dev set of SQuAD into two halves, consisting of 5537 and 5033 questions respectively. Similarly, we split the provided dev set of Natural Questions into a 1631-question dev set and a 1632-question test set. Hyper-parameters and the best checkpoint are selected on the dev set. Exact Match (EM) and F1 score as described in (Rajpurkar et al., 2016) is reported on the test set.

6. Experiment Result

6.1. Main Results

In Table 5 and Table 6 we show results of different base models on two datasets, with different number of explanations used. Most notably, the models achieve plausible performance on both datasets with ALBERT—a strong pre-trained language model. With the power of pre-training and rapid data augmentation using natural language explanations, models already start to demonstrate a certain level of machine reading comprehension ability. We also observe that softly-matched set $\mathcal{S}_p$ constantly brings improvements to models trained with strictly-matched set only.

This demonstrates that noisy labels are still of great value in low-resource settings.

6.2. Performance Analysis

Different Number of Explanations We show model performance using different numbers of explanations on the SQuAD dataset in Fig. 5. The figure demonstrates that softly-matched instances can improve on the base model in most of the cases, especially for data-hungry base models such as BiDAF. For a strong base model like ALBERT, this effect becomes marginal.

Ablation Study on Modules To evaluate the effect of the softened module execution, we consecutively turn on the softened version of Find, Fill and Compare in NMTeacher matching process, train the downstream model $\mathbb{F}$ and report the final performance. The evaluation results are presented in Fig. 4. Softening in each module contributes to performance improvement.

Performance of Fill and Find module The Fill module is evaluated on hard-matched question pairs and context pairs, respectively, and the Find module is evaluated through manual inspection on model's predictions on 100 question-context pairs. For each sentence in the testing data, we
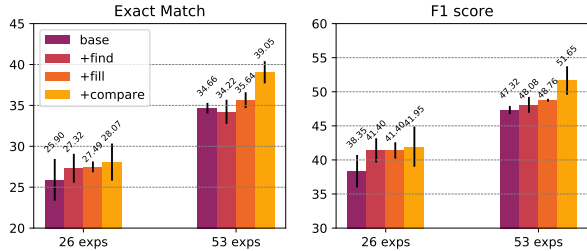
Figure 4. **Ablation study on atomic modules.** Fill, Find and compare modules are switched to softened mode consecutively. Rule softening in each module contributes to improve final MRC model performance.
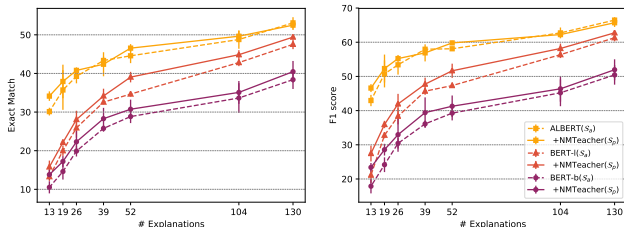

Figure 5. **Performance on SQuAD dataset with respect to number of explanations used.** This shows our proposed method "scales" as performance continues to grow with more explanations.

Module	Data Source	Train	Dev	Test
Fill	Question pairs	69,361	9,936	19,856
	Context pairs	38,600	5,542	11,060

Table 7. Data Statistics (number of question and context pairs used) for pre-training and evaluating the Fill module.

Recall (%)	Top-1	Top-3	Top-5	Top-10
Fill (Questions)	68.50	88.01	94.66	98.93
Fill (Contexts)	95.64	97.45	98.22	98.73
Find	41.00	-	-	-

Table 8. Performance of the Fill (evaluated on the testing data) and Find (manually evaluated on collected explanations) module.

#Explanations ($|\mathcal{S}_a|, |\mathcal{S}_p|$)	52 (766,2329)	
	EM	F1
BERT-l ($\mathcal{S}_a$)	34.66 ± 0.65	47.32 ± 0.60
+ NMTeacher ($\mathcal{S}_p$)	39.05 ± 1.36	51.65 ± 2.08
+ Self Training ($\mathcal{S}_u$)	38.14 ± 1.53	50.55 ± 1.57
+ Mean Teacher ($\mathcal{S}_u$)	39.19 ± 0.94	52.26 ± 1.28
+ Pseudo Labeling, PL ($\mathcal{S}_u$)	52.29 ± 4.03	64.38 ± 5.31
+ NMTeacher($\mathcal{S}_p$) + PL ($\mathcal{S}_u$)	$\mathbf{54.63 \pm 0.58}$	$\mathbf{66.66 \pm 0.73}$

Table 9. Performance of training BERT-l with semi-supervised methods and unlabeled dataset $\mathcal{S}_u$. Best results are **bold**. Softly-matched set $\mathcal{S}_p$ generated by NMTeacher is complementary to semi-supervised method pseudo labeling (PL).

6.3. Analysis on Matching Quality.

Though achieving plausible performance with limited supervision, our proposed method, in accordance with any data programming method, inevitably suffers from labeling noise and data bias issues. To examine the distribution of matched data, we list the question heads in $\mathcal{S}_a$ and found the top 8 to be: when did (22.08%); what year (8.51%); how many (8.1%); who was (7.27%); what did (6.43%); what percentage (5.39%); what does (5.26%); how long (4.35%). This observation demonstrates the explanations we collect cover a wide range of question types. Yet, the distribution of input data has far more aspects than question heads. Our current implementation and design may not explain complex questions that require multi-step reasoning abilities, and this may result in strong biases in $\mathcal{S}_a$ and $\mathcal{S}_p$.

To examine the labeling accuracy, we directly evaluate annotations obtained with the neural module teacher against human annotations. On SQuAD with 52 explanations, 72.19% EM and 83.35% F1 is achieved on the 766 strictly-matches instances in $\mathcal{S}_a$. Noises in annotations generated with neural module teachers $\mathbb{G}$ will also cause performance downgrade in the final model $\mathbb{F}$.

To further examine the matching quality, we designed a set of controlled experiments to evaluate the impact of these two factors. Specifically, we use 52 SQuAD explanations

enumerate all possible spans, let the model rank the spans, and take top-n ($n = 1, 3, 5, 10$ for Fill module and $n = 1$ for Find module) spans as output. Because our goal is to find the correct span, we use recall (at n) $r_n = \frac{p}{q}$ as metric for evaluation, where p is the number of correct spans found in top-n outputs and q is the number of all correct spans. Evaluation results for Fill and Find module are shown in Table 8. As n gets large, the top-n outputs from the Fill module are able to cover most of the correct spans.

Using Unlabeled Data with Semi-supervised Methods. We maintain an unlabeled set $\mathcal{S}_u$ as described in Sec. 4.2, which could be beneficial to model learning with semi-supervised methods. We train and evaluate several semi-supervised baselines and list the performance in Table 9. To further see if $\mathcal{S}_p$ generated by softening the constraint is useful, we consider a simple "hybrid" variant that alternatively samples a batch from $\mathcal{S}_p$ (with NMTeacher annotation) and $\mathcal{S}_u$ (with pseudo labels generated by $\mathbb{F}$ itself). We add loss term from this batch to the supervised loss in the way similar to Eq. 11. We show that applying semi-supervised methods with $\mathcal{S}_u$ is beneficial to the model trained with $\mathcal{S}_a$ only. Meanwhile, softly-labeled set $\mathcal{S}_p$ is bringing improvements on top of the semi-supervised method pseudo labeling.

No.	Training Supervision	EM	F1
(1)	$\mathcal{S}_a$	44.57 ± 1.90	58.09 ± 0.59
(2)	$\mathcal{S}_a + \mathcal{S}_p$	46.55 ± 1.90	59.80 ± 0.64
(3)	$\mathcal{S}_a^*$	52.14 ± 2.02	64.25 ± 1.89
(4)	$\mathcal{S}_a^* + \mathcal{S}_p^*$	59.67 ± 0.33	71.55 ± 0.34
(5)	$\mathcal{S}_r(|\mathcal{S}_r| = |\mathcal{S}_a|)$	59.15 ± 0.88	71.40 ± 0.61
(6)	$\mathcal{S}_r(|\mathcal{S}_r| = |\mathcal{S}_a| + |\mathcal{S}_p|)$	69.27 ± 0.30	80.09 ± 0.66

Table 10. **Analysis on Matching Quality.** $\mathcal{S}_a$ and $\mathcal{S}_p$ are obtained with 52 SQuAD explanations. $\mathcal{S}_a^*$ denotes a train set containing instances in $\mathcal{S}_a$ but with human annotations provided in original SQuAD train set. $\mathcal{S}_r$ is randomly sampled from SQuAD train set but with its size controlled to be equal to $|\mathcal{S}_a| = 766$ or $|\mathcal{S}_a| + |\mathcal{S}_p| = 3095$. ALBERT-b is used as base model.
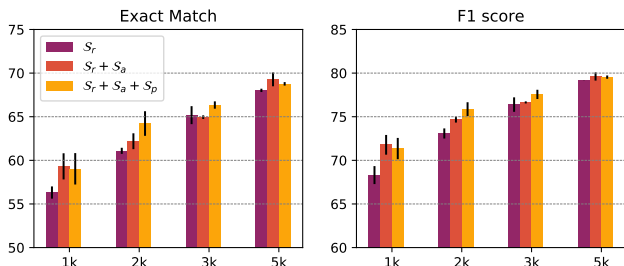

Figure 6. **Augmenting Labeled Instances with Explanations.** $\mathcal{S}_r$ of size $\{1k, 2k, 3k, 5k\}$ contains human-annotated instances randomly sampled from SQuAD. Instances generated by NMTeacher ($\mathcal{S}_a$ and $\mathcal{S}_p$) still brings improvements over models trained with $\mathcal{S}_r$ only, demonstrating that NMTeacher is applicable in medium-resource scenarios.

to get strictly-matched set $\mathcal{S}_a$ and softly-matched set $\mathcal{S}_p$. Then we train an ALBERT-b model with supervision from the following six settings: (1) $\mathcal{S}_a$; (2) $\mathcal{S}_a$ and $\mathcal{S}_p$, loss term formed as in Eq. 11; (3) $\mathcal{S}_a^*$, where $\mathcal{S}_a^*$ denotes instances in $\mathcal{S}_a$ with their human-annotated answer spans; (4) $\mathcal{S}_a^*$ and $\mathcal{S}_p^*$, loss term formed as in Eq. 11; (5) $\mathcal{S}_r$, a set randomly sampled from SQuAD train set and has the same size as $\mathcal{S}_a$; (6) $\mathcal{S}_r$ of size $|\mathcal{S}_a| + |\mathcal{S}_p|$. Results are listed in Table 10. By comparing (1) and (3), we observe a 6.16% F1 score gap caused by labeling noise. By comparing (3) and (5), we further see a 7.15% F1 score gap mainly caused by dataset biases. We believe addressing these two issues will improve model performance, and we will leave this as future work.

6.4. Augmenting Labeled Instances with Explanations

Previously we focus on low-resource scenarios, where a tiny labeled set S_o is assumed in the beginning. In this subsection, we show that employing NMTeacher could further augment the training process when a medium-sized labeled set is available. We randomly sample $k \in \{1000, 2000, 3000, 5000\}$ human-annotated instances from SQuAD as $\mathcal{S}_r$, and use $\mathcal{S}_r$ together with $\mathcal{S}_a$, $\mathcal{S}_p$ generated with 52 explanations to train the base model BERT-l. We compare with the baseline of training BERT-l with $\mathcal{S}_r$ only.

Results are shown in Figure 6. In cases where a medium-size labeled dataset is already available, augmenting training data with NMTeacher is still beneficial to overall performance. A practical situation will be, when certain defect is detected in the trained model (e.g., certain type of question can not be answered), an additional set of explanations can be collected rapidly, so that NMTeacher generates supervision to these specific types of question and tries to remedy the defect.

7. Related Work

Learning with Explanations. Srivastava et al. (2017) first introduced the notion of natural language (NL) explanation in concept learning. Each natural language statement is first parsed into logical form with a CCG parser and acts like a binary feature function. They trained the concept learning and semantic parsing models jointly. More recently, Hancock et al. (2018) proposed BABBLELABBLE for training classifiers with NL explanations, and succeeded in three relation extraction tasks. BABBLELABBLE used logical forms to provide labels as *supervision* instead of augmenting the feature input. This is similar to the data programming setting (Ratner et al., 2016; 2017) and enables semi-supervised learning on unlabeled corpora. Wang et al. (2020) proposed NEXT framework to increase the generalization ability of NL explanations in unlabeled corpora. NEXT modularized the parsed logical forms and proposed to change the original labeling process from exact matching to fuzzy matching, thus expanding the coverage of each explanation in unlabeled corpus. Both BABBLELABBLE and NEXT focus on improving annotation efficiency in low-resource settings.

However, all of these works are confined to sentence classification tasks. Reading comprehension is intrinsically more complicated in that (1) there is no given anchor word (*e.g.*, subject and object in relation extraction task); (2) there is no pre-defined, finite set of labels. We are the first to extend this stream of work to more challenging and unstructured reading comprehension tasks by customizing suitable modules and introducing variable search strategies.

Another line of meaningful work on NL explanations focuses on *generative* approaches. Li et al. (2018) formulated visual question answering as multi-task learning by requiring the model to generate an explanation based on the hidden representation constructed from image and question. Rajani et al. (2019) leveraged a pre-trained GPT model (Radford et al., 2018) to generate an explanation sentence with the question and candidate answers as the previous sentence. Camburu et al. (2018) annotated NL explanations for Stanford Natural Language Inference dataset and demonstrated these explanations as useful implicit supervision.

Learning to Augment. The work presented in this paper is a data augmentation approach, which is also related to

semi-supervised learning (Chapelle et al., 2009). A notable line of work in data augmentation focuses on using consistency training to regularize model predictions to be invariant to small noise applied to inputs (Xie et al., 2019; Yu et al., 2018). This kind of methods aims at augmenting data by applying transformations to a training example without changing its label. For NLP tasks, input sentences can be transformed by back-translation, word replacement, etc. Our work is close to another line of work that uses a boot-strapping method to boost model performance by iteratively predicting on unlabeled data, adding examples with high confidence to the training data (using model predictions as labels), and retraining the model (Carlson et al., 2009; Yang et al., 2018a). In this paper, we focus on learning a neural module teacher from limited labeled data with explanations provided by human annotators. The neural module teacher is able to make reliable predictions on unlabeled examples and augment training data for a downstream question-answering model.

Neural Module Networks. Neural module networks (NMNs) are dynamically composed of individual modules with different capabilities. Previously, it has been successfully applied to visual question answering tasks where operations over different modalities are needed (Andreas et al., 2016b;a; Hu et al., 2017). More recently, reading comprehension tasks requiring multi-hop reasoning (Welbl et al., 2018; Yang et al., 2018b), and discrete reasoning (Dua et al., 2019; Amini et al., 2019) are proposed and widely studied. Recent works (Jiang & Bansal, 2019; Gupta et al., 2020), in general, adopt a parser (or controller), which takes the question as input and a sequence of operations as output. Generic modules and task-specific modules are executed to fulfill the operations and derive the final answer. In the broader context, NERD framework with domain-specific language (Chen et al., 2020) is proposed to bridge "symbolic and distributed representations", which can also be interpreted as breaking down a complex task into individual modules.

Our work differs in that the network layout is constructed by parsing *natural language explanations* instead of the question itself. Moreover, the goal of our NMN is to annotate instances for downstream training as data augmentation, instead of training an NMN as a reading comprehension model in a supervised manner. We choose text-based, single-paragraph, extractive QA to exemplify the strength and efficiency of our work, though the proposed framework may be extended to a wide range of scenarios.

8. Conclusion

We propose a novel framework, neural module teacher, for extractive machine reading comprehension that efficiently learns from human-provided natural language explanations to annotate unlabeled instances and augment training data. The system works by first parsing natural language explanations into executable rules and then annotating instances using a neural module teacher with strict or softened constraints. Experiments on two datasets and several base models demonstrate the efficiency of our system under the low-resource setting. Obtaining plausible results on extraction-based one-hop question answering, we look forward to extending this framework for more challenging tasks like knowledge acquisition and multi-hop reasoning. We would also like to explore denoising neural module teacher annotations by jointly training neural modules in $\mathbb{G}$ with downstream MRC model $\mathbb{F}$.

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A. Beam Search for Neural Module Teacher

Algorithm 2 Beam Search for Neural Module Teacher

Input: Neural Module Teacher $\mathbb{G}_i$, Instance (q, c), Variable Candidates, Beam Width w, Threshold t
m = number of variables in $\mathbb{G}_i$
Initialize PREVSTATES.
for $j = 1$ **to** m **do**
    CURRENTSTATES $\leftarrow \varnothing$
    for STATE in PREVSTATES **do**
        $V \leftarrow$ next unfilled variable
        for CANDIDATE in CANDIDATES for V **do**
            Fill one unfilled variable in STATE
            Eval all rules in $\mathbb{G}_i$ on STATE, get confidence score z
            if $z > t$ **then**
                CURRENTSTATES.append(STATE)
            end if
        end for
    end for
    Sort (descending) CURRENTSTATES by confidence z
    PREVSTATES $\leftarrow$ top w states in CURRENTSTATES
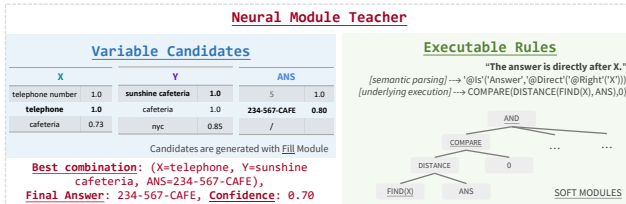**end for**
return CURRENTSTATES

Figure 7. **Example for Beam Search and Selecting an Answer.** Candidates are proposed by Fill module. The best combination is selected by ranking and conducting beam search on possible combinations. Ranking is done by softened execution of rules.

B. Case Study

Strict Match. Table 11 shows two examples of strictly-matched instances. In the first example, the explanation specified how to answer questions like "In what year did X (`sth.`) begin". Intuitively, the answer should be a year number right after "since", and the entity before "begin" should be a keyword. In the second example, questions following the pattern "when was X (`sth.`) Y (`done`)" are explained and the answer is typically a date after "on". Also, the verb "`done`" should be directly before "on" and the answer.

Softened Match. Table 12 shows two examples of softly-matched instances. In the first example, the distance be-

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Reference Instance
Q: In what year did *Film Fest New Haven* begin?
C: ... The *Film Fest New Haven* has been held annually since 1995. ...
A: 1995

NL Explanation
X is "Film Fest New Haven". The question starts with "In what year", so the answer should be a year. "begin" is in the question. X is directly after "did" and directly before "begin" in the question. "since" is directly before the answer.

Strictly-matched Instance
Q: In what year did *the Music of the Night* begin?
C: ... Since 1992 *the Music of the Night* has been performed in the Royal Citadel by the 29 Commando Regiment and local performers to raise money for local and military charities. ...
A: 1992

Reference Instance
Q: When was Queen Victoria's *funeral* **held**?
C: Her *funeral* was **held** on Saturday, 2 February, in St George's Chapel, Windsor Castle, and after two days of lying-in-state ...
A: Saturday, 2 February

NL Explanation
X is "funeral". Y is "held". In the question X is within 4 words after "when was" and Y is directly after X. "on" is directly before the answer. Y is within 2 words before the answer. X is within 3 words left of Y. The question starts with "when", so the answer should be a date.

Strictly-matched Instance
Q: When was *independence* **declared**?
C: ... *Independence* was unilaterally **declared** on 24 September 1973.
A: 24 September 1973

Table 11. Examples of strictly-matched instances.

tween Y and Z is three in the question, while the explanation specifies there should be less than two words between them. With COMPARE module, the correct answer is found with high confidence of 97.22%. In the second example, the explanation specifies Y to be an adjective phrase. With FILL module, a verb in the past tense, "purified", is also listed as a potential fit for variable Y, and this gives the correct answer "a secret lake" with a confidence score of 72.48%.

C. Crowd-sourcing Interface

Our interface for collecting natural language explanations is shown in Figure 8. The annotators are required to first read a short paragraph of high-level instructions and then read five examples carefully. After that, they are required to write an explanation for a provided answered (q, c, a) triple in one single text input box, using suggested expressions in a provided table. Finally, annotators are required to double-check their explanation before they submit.

Instructions:
Please read carefully to get accepted!
(1) You're **not** required to answer the question. The answer is already provided and marked in red. **Read examples below carefully to learn about what we want!**
(2) Identify **important short phrases** that appear **both** **in the question and in the context**.
   Important: The two appearances of the phrase should be **exactly the same** (trivial differences like plural form or past tense are still acceptable).
   Important: Write sentences like *Y is "Switzerland"*. Make sure there is **no typo** in what you quote.
(3) **Explain** how you locate the answer with the phrases you marked; **Only use the suggested expressions** in the table in the bottom.

Example 1:
Question: How long has Switzerland traditionally been neutral?
Context: Traditionally, Switzerland avoids alliances that might entail military, political, or direct economic action and has been neutral since the end of its expansion in 1515.
Answer: since the end of its expansion in 1515
Explanation: X is "been neutral". Y is "Switzerland". X and Y appear both in the question and in the context. The answer directly follows X. The answer starts with "since".

[4 Examples Omitted Here]

Your turn to write explanations:
Question: who is the author of brave new world
Context: Brave New World is a dystopian novel by English author Aldous Huxley . Published in 1932 , it propounds that economic chaos and unemployment will cause a radical reaction in the form of an international scientific empire that manufactures its citizens in the laboratory on a eugenic basis , without the need for human intercourse .
Answer: Aldous Huxley

You're **required** to **only** use the expressions in the table below.
☐   This question is complicated; I **cannot** explain it with the expressions in the table below. (in this case please also input "None" in the text box below)

Objective	Expression	Example
0. Mark the Phrase	is, means	X is "been neutral". Y is "Switzerland".
1. Relative Position	before, after, between, left, right, follow, precede, sandwich	"may be" is between X and Y. "near" is before X. X and Y sandwich "is".
2. Distance	within, less than, directly	The answer is within 2 words left of X. The answer directly precedes Z.
3. Contain	start with, end with, contain	The answer starts with "by". The question contains "who".
4. Phrase (NER) Type	person, time, location, organization	X should be a person. The answer should be a time.
5. Phrase (chunk) Type	noun, verb, adjective, adverb, prepositional phrase	The answer is a noun. The answer is a prepositional phrase.

Your explanation for the question answering example above: (i.e. How to locate the answer with XYZs?)

Before you submit, double check the following, or you may get rejected.
(1) XYZ are phrases that appear both in the question and the context. There is **no typo** when you quote these phrases.
(2) You explain how to locate the answer with XYZ by **only** using expressions in the table.
(3) What you describe sticks to the question answering example on this page.
Thank you!

Submit

Figure 8. **Crowd-sourcing Interface on Amazon Mechanical Turk.** The interface has four parts: (1) High-level instruction; (2) 5 examples; (3) QA instance requiring explanation and an input box; (4) Final check instructions.

Reference Instance

Q: Who did *Estonia* **rebel against** in <u>1343</u>?

C: ... In <u>1343</u>, the people of northern *Estonia* and Saaremaa **rebelled against** German rule in the St. George's Night Uprising , which was put down by 1345. ...

A: German rule

NL Explanation

X is "Estonia". Y is "rebel against". Z is "1343". In the question, Y is directly after X and Z is within 2 words after Y. Z is a year. The answer directly follows Y. X is within 3 words before Y.

Softly-matched Instance

Q: *The Slavs* **appeared on** whose borders around <u>the 6th century</u>?

C: ... Around <u>the 6th century</u>, *Slavs* **appeared on** Byzantine borders in great numbers. ...

A: Byzantine borders (Confidence = 97.22%)

Note

Z (the 6th century) is 3 words after Y (appeared on) in the question, which slightly breaks the constraint "Z is within 2 words after Y". This is captured by COMPARE module.

Reference Instance

Q: Where is *hydrogen* **highly soluble**?

C: ... *Hydrogen* is **highly soluble** in many rare earth and transition metals and is soluble in both nanocrystalline and amorphous metals. ...

A: many rare earth and transition metals

NL Explanation

X is "hydrogen". Y is "highly soluble". Y is directly after X and X is directly after "where is" in the question. X is within 5 words before Y. Y is within 2 words before the answer. "in" directly before the answer. "is" is between X and Y.

Softly-matched Instance

Q: Where is *the divinity herself* **purified**?

C: ... Afterwards the car, the vestments, and, if you like to believe it, *the divinity herself*, are **purified** in a secret lake. ...

A: a secret lake (Confidence = 72.48%)

Note

In the reference instance, Y (highly soluble) is supposed to be an adjective phrase. In the new instance, FILL module suggested "purified" to be a promising candidate for variable Y.

Table 12. Examples of softly-matched instances.