Ape210K: A Large-Scale and Template-Rich Dataset of Math Word Problems

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Abstract

Automatic math word problem solving has attracted growing attention in recent years. The evaluation datasets used by previous works have serious limitations in terms of scale and diversity. In this paper, we release a new large-scale and template-rich math word problem dataset named Ape210K. It consists of 210K Chinese elementary school-level math problems, which is 9 times the size of the largest public dataset Math23K (Wang et al., 2017). Each problem contains both the gold answer and the equations needed to derive the answer. Ape210K is also of greater diversity with 56K templates, which is 25 times more than Math23K. Our analysis shows that solving Ape210K requires not only natural language understanding but also commonsense knowledge. We expect Ape210K to be a benchmark for math word problem solving systems. Experiments indicate that state-of-the-art models on the Math23K dataset perform poorly on Ape210K. We propose a copy-augmented and feature-enriched sequence to sequence (seq2seq) model, which outperforms existing models by 3.2% on the Math23K dataset and serves as a strong baseline of the Ape210K dataset. The gap is still significant between human and our baseline model, calling for further research efforts. We make Ape210K dataset publicly available at https://github.com/yuantiku/ape210k.

1 Introduction

Math word problem (MWP) solving is a task that a system needs to derive the numeric answer given the natural language description of a math problem. One major difficulty lies in the generation of intermediate equations from the natural language descriptions. The text description generally contains some numbers and unknown variables. In the early years, people solve math word problems with rule-based (Bobrow, 1964) and statistical learning-based methods (Hosseini et al., 2014; Kushman et al., 2014). However, math word problem solving is a challenging task. As the diversity of the datasets increases, the performances of the aforementioned systems often drop dramatically. Recently, deep learning models like Deep Neural Solver (Wang et al., 2017) and GTS (Xie and Sun, 2019) show promising empirical results.

In Table 1, we provide an example of math word problems, including the problem description, the intermediate equation, the equation template, and the final numeric answer. A “template” is an equation with the numbers replaced with symbols $d_i$, where $i$ is the index of the corresponding number, numbers that do not appear in the problem description are kept as they are. In this example, the given numbers are “274” and “23”, and the unknown variable $x$ refers to “鸡有多少只( the number of chickens in the cage)”. Solving this problem needs basic arithmetics and commonsense knowledge that “a chicken has 2 legs, and a rabbit has 4 legs”.

There are two limitations to the datasets used...
by previous works. First, the scales of existing datasets are small. The most widely used dataset Math23K (Wang et al., 2017) only consists of 23K problems, other datasets like Alg514 (Kushman et al., 2014) and Dolphin1878 (Shi et al., 2015) have less than two thousand problems. It prevents the application of data-driven approaches such as neural networks. Another limitation is the lack of diversity in problems. Math23K contains only 3K equation templates, which raises a serious question on the generalization capability of the models trained on Math23K.

In this paper, we introduce Ape210K, a large-scale and diverse math word problem dataset, with 210K Chinese elementary school-level problems and 56K unique equation templates. Additionally, a large proportion of problems require generating numbers that do not appear in the problem descriptions. All problems come from our online production system and are created by humans. We hope Ape210K can help push the frontier for automatically solving math word problems.

We also propose a copy-augmented and feature-enriched seq2seq model, which outperforms the current state-of-the-art system by 3.2% on the Math23K dataset and serves as a strong baseline.

Our contributions are summarized as follows:

1. We present a new large-scale and template-rich math word problem dataset Ape210K, including 210K problems and 56K templates. Ape210K is much larger and diverse than existing datasets.
2. We conduct extensive analysis and reveal some interesting properties of our dataset.
3. We propose a strong seq2seq model with good empirical performance on both the Math23K and Ape210K datasets, which can be used as a baseline for future research.

2 Background

2.1 Problem Formulation

A math word problem \( p \) is a sequence of words \( W = \{W_i\}_{i=1}^{W} \), containing a set of variables \( V_p = \{v_1, \ldots, v_m\} \cup \{x_1, \ldots, x_k\} \), where \( v_1, \ldots, v_m \) are known numbers and \( x_1, \ldots, x_k \) are variables whose values are unknown. \( C = \{C_i\}_{i=1}^{C} \) is a set of frequently used constants, such as 1, 2, 3 and \( \pi \) etc. A problem \( p \) can be solved by a mathematical equation \( E_p \) formed by \( V_p \), \( C \) and mathematical operators, such as “+”, “-”, “x”, “f” etc. In this paper, Ape210K only focuses on the problems with only one unknown variable. We leave the problems with multiple unknown variables for future work.

2.2 Template Formulation

If we encode the numbers in \( W \) as a list of symbols \( d_1, \ldots, d_m \), then the equations can be converted to equation templates. For those numbers in the equations that do not appear in \( W \), they remain the same. Take the problem in Table 1 as an example. First, after encoding the numbers in \( W \), we get the following problem description and the mapping between numbers and symbols.

Chickens and rabbits are in the same cage, and there are \( d_1 \) feet in total. Suppose that there are \( d_2 \) more chickens than rabbits, then how many chickens are in the cage?

\[
\{d_1 = 274, d_2 = 23\}
\]

Then we replace the numbers in the equation with the symbols, and get the equation template “\((d_1 + d_2 \times 4)/(2 + 4)\)”. In this example, “the chicken has 2 legs” and “the rabbit has 4 legs” do not appear in the question text and the numbers 2 and 4 remain the same.

3 Dataset Construction

3.1 Equation Extraction

The original problems come from our online production system. All of them are created by humans. Initially, we have about 900K Chinese math word problems for elementary school students. We filter the following problems.

- The problems without answers based on regular expression matching.
- The problems whose answers are not numbers (e.g., “a+b”).
- The problems without numbers in the text description.
- The problems containing images or tables in the description.
- The problems with multiple questions.

About one-third of the original problems have multiple questions. In this paper, we only focus on the math word problems with one unknown variable and leave the other problem types for future work.

The original problems do not list the equations explicitly but instead provide human-readable rationales in natural language. We show one example rationale for the problem in Table 1:
### Problems

| Dataset                  | # Problems | # Templates | w/ EC(%) |
|-------------------------|------------|-------------|----------|
| Alg514 (Kushman et al., 2014) | 514        | 28          | -        |
| Dolphin1878 (Shi et al., 2015) | 1,878      | 1,183       | -        |
| AllArith (Roy and Roth, 2017) | 831        | -           | -        |
| MAWPS (Koncel-Kedziorski et al., 2016) | 2,373    | -           | -        |
| Dolphin18K (Huang et al., 2016) | 18,460     | 5,871       | -        |
| Math23K (Wang et al., 2017) | 23,160     | 2,187       | 0.80%    |
| Ape210K                 | 210,488    | 56,532      | 37.70%   |

Table 2: Comparison between Ape210K and existing math word problem datasets. “w/ EC(%)” refers to the percentage of equations with external constants other than 1 and \( \pi \).

设鸡有x只，则兔有\((x-23)\)只，则\(2x+(x-23)\times4=274\); 解得\(x=61\); 故答案为: 61.

Here we also list the preprocessing rules for the problem description.

- Convert commonly used units to the same form based on some pre-defined rules, for example, map “kilogram/kg/KG/Kg” to “kg”.
- Convert full-width characters to the corresponding half-width characters if possible.
- Convert texts like “eight”, “half” to arabic numbers “8”, “0.5”.

As a result, we get the Ape210K dataset, with 210K math word problems and 56K templates, each with a numeric answer and an intermediate equation.

### Dataset Analysis

In this section, we present a detailed analysis of our proposed Ape210K dataset and compare it with other existing datasets.

There are many publicly available math word problem datasets, as shown in Table 2, including Alg514 (Kushman et al., 2014), Dolphin1878 (Shi et al., 2015), Dolphin18K (Huang et al., 2016), and Math23K (Wang et al., 2017) etc. Alg514 consists of 514 problems from algebra.com \(^1\) with only 28 templates. Dolphin1878 contains 1,878 problems built from algebra.com and Yahoo! answers. Nonetheless, these datasets are too small in scale to train models that can generalize well to unseen problems. Our proposed Ape210K dataset has 210,488 problems and 56,532 templates, which is 9 times the size of the Math23K dataset and has 25 times more templates. 37.70% of the equations in Ape210K contain external constants \(^2\), in contrast to only 0.80% in the Math23K dataset. This indi-

\(^1\)https://www.algebra.com/

\(^2\)In this paper, unless explicitly specified, “external constants” do not include 1 and \( \pi \).
cates that Ape210K is a much more diverse and challenging dataset.

Ape210K covers a wide variety of elementary school math word problems with one unknown variable. The problem-solving rationales and answers are written by professional math teachers. We extract equations from the rationales and validate the equations with the answers. Each of the math word problems in the Ape210K dataset is published with a problem description, an intermediate equation, and a numeric answer. It can serve as a large-scale benchmark.

| Problem | 一个等腰三角形的周长是42厘米，底长12厘米，腰长多少厘米？ |
| Translation | The circumference of an isosceles triangle is 42 cm, the base is 12 cm long, how many cm is the side? |
| Problem | 一个圆柱的体积是36.15立方米，与它等底等高的圆锥的体积是多少。 |
| Translation | The volume of a cylinder is 36.15 $m^3$, what is the volume of a cone with equal height and equal bottom surface area? |

Table 3: Two examples that requires external knowledge.

External constants are numbers in equations that do not appear in the problem description. Usually, the external constants need to be inferred based on commonsense or domain-specific mathematical knowledge. We show two examples in Table 3. In the first problem, the knowledge that “a triangle has 3 edges, and the sides of an isosceles triangle have equal length” is needed. In the second problem, we need to know the relation between the volume of the circular cone and the cylinder. It is easy for humans to have commonsense knowledge but hard for machines.

We collect some detailed statistics of Math23K and Ape210K, shown in Table 4. We report the number of problems, the number of sentences, the number of templates, the percentage of external constants (abbreviated as “EC”), and the percentage of templates that contain external constants (templates w/ EC).

|                | Math23K | Ape210K |
|----------------|---------|---------|
| # questions    | 23,160  | 210,488 |
| # sentences    | 54,764  | 477,439 |
| # templates    | 2,187   | 56,532  |
| % EC           | 0.19%   | 7.72%   |
| % templates w/ EC | 0.80%  | 37.70%  |

Table 4: Detailed statistics of Math23K and Ape210K datasets. “EC” is short for “external constants”.

Math23K. There are only 0.19% external constants in Math23K, but 7.72% in Ape200K. This is mainly because Ape210K tries to keep as many problem types as possible, even the equation templates contain external constants.

4 Method

To evaluate the difficulty of our proposed dataset and provide a good starting point for future research, we build a customized baseline model. In this section, we briefly introduce our feature-enriched and copy-augmented seq2seq model.

If we treat the encoded problem description as the source sequence and the encoded equation template as the target sequence, then math word problem solving can fit into the framework of seq2seq learning. In fact, seq2seq models have become the state-of-the-art approaches for this task. In this paper, our base architecture follows the encoder-decoder approach with soft attention (Bahdanau et al., 2014), as shown in Figure 1.

**Embedding Layer** transforms the high-dimensional and sparse one-hot encoded vectors to dense vectors through the embedding matrix. We segment the problem description using an open-source Chinese word segmentation tool **jieba**.
Each word consists of at least one character. In this layer, we use five handcrafted features, listed below.

1. The character of the current position.
2. The part-of-speech tag of the word in the current position.
3. The word of the current position.
4. Whether the character of the current position is a number or not based on regular expression matching.
5. Sort all the numbers in the problem description in descending order, and then assign each number an index starting from 0.

The five features $f_i^j$, $j \in [1, 5]$ of each position are embedded into vectors, and then combined using linear weighted sum. The final embedding outputs are $v_1, \ldots, v_n$.

$$v_i = \sum_{j \in (1 \ldots 5)} \alpha_j W^T_j f_i^j$$

Pre-trained Embeddings have proven to be highly useful in neural network models for NLP tasks. In this paper, we use all problem description texts to pre-train the character embeddings and word embeddings using word2vec (Mikolov et al., 2013). The embeddings of the other handcrafted features are randomly initialized.

Encoder We use 4-layer Bi-LSTMs (Hochreiter and Schmidhuber, 1997) as our encoder. To compute the representations for the problem description texts, we send the feature embeddings to the first 2 Bi-LSTM layers, and then send the sum of the internal hidden states and the input embeddings to the last 2 Bi-LSTM layers to get the final semantic representations of the problem description texts $h_1, \ldots, h_n$.

$$\hat{h}_1, \ldots, \hat{h}_n = BiLSTM_{(1,2)}(v_1, \ldots, v_n)$$

$$\hat{v}_i = v_i + \hat{h}_i, \ i \in [1, n]$$

$$h_1, \ldots, h_n = BiLSTM_{(3,4)}(\hat{v}_1, \ldots, \hat{v}_n)$$

Decoder The decoder predicts the next word $w_t$ indexed by $t$, given the encoder's final hidden states. We use 2 layers Bi-LSTM as our decoder and the input-feeding approach (Luong et al., 2015), in which attentional vectors $\hat{h}_t$ are summed with inputs at the next time steps. In this way, the model is fully aware of the previous predictions.

$$\hat{h}_t = BiLSTM_{(1)}(v_1 + d_1, \ldots, v_{t-1} + d_{t-1})$$

$$\hat{d}_t = Attn(\hat{h}_t, h_1, h_2, \ldots, h_n)$$

$$h'_t = BiLSTM_{(2)}(\hat{d}_1, \ldots, \hat{d}_{t-1})$$

$$d_t = Attn(h'_t, h_1, \ldots, h_n)$$

Copying Mechanism Copying mechanism was proved effective on text summarization (See et al., 2017), semantic parsing (Jia and Liang, 2016), and grammatical error correction (Zhao et al., 2019) etc. In this paper, we apply the copying mechanism on the math word problem for the first time. The copying mechanism returns a distribution over the tokens that appear in the problem description text and the target vocabulary. The balancing between the copying and generation is controlled by a balancing factor $\alpha \in [0, 1]$ at each time step $t$.

$$p(w) = \alpha \times p_{copy}(w) + (1 - \alpha) \times p_{vocab}(w)$$

The copying mechanism can boost the scores of the tokens that appear in the problem description.

5 Experiments

5.1 Setup

Datasets To compare with the previous works, we evaluate our model both on Math23K and Ape210K datasets. Math23K is a relatively small dataset, and the test set given by the original author is too small, so most of the previous experiments use 5-fold cross-validation to evaluate their models' performance. In this paper, we also use 5-fold cross-validation on Math23K to have a fair comparison.

Ape210K is a large-scale dataset, and we split the whole dataset to train, valid, and test subsets. Both valid and test subsets have 5000 examples, and we leave the rest as the training examples, as listed in Table 5.

| Subset   | # Examples | # Templates |
|----------|------------|-------------|
| Train    | 200,488    | 54,425      |
| Valid    | 5000       | 2,835       |
| Test     | 5000       | 2,732       |

Table 5: Details of the train/valid/test subset in Ape210K.
Model and Training Settings  We use the same neural architecture for Math23K and Ape210K. For the embedding layer, the dimension of each feature embedding is 500. The LSTM hidden sizes of the encoder and decoder are both 500. The maximum source sequence length is 200, and the maximum target sequence length is 100. The encoder and decoder share the same vocabulary built from the training dataset.

We use different optimizers for Math23K and Ape210K based on empirical performance. When training Math23K, we use SGD as our optimizer, and the initial learning rate is 0.9. While training Ape210K, we use Adam as our optimizer, and the initial learning rate is $10^{-3}$. The two datasets share the same learning rate schedule. The number of training steps is 200K, and the learning rate starts decaying every 20K steps after 40K steps. The batch size is 128. All experiments are conducted on a single P40 GPU.

During decoding, we use a beam-size of 5 and normalize the sequence scores by length. We choose the top one result with a valid equation. An equation is valid if it can be evaluated, and the answer is a non-negative number since the answers to the math word problems of the elementary school are mostly non-negative. Our implementation is based on OpenNMT *4 (Klein et al., 2017).

Evaluation  For a given math word problem, there may be multiple ways to get the correct answer. Following previous works, we use accuracy as the evaluation metric. A predicted equation is considered correct if it produces the same numeric answer as the groundtruth.

5.2 Main Results

In this section, we compare our feature-enriched and copy-augmented approach with state-of-the-art systems on both Math23K and Ape210K datasets. Besides, we show the ablation study results of our approach on Ape210K dataset.

Results on Math23K Dataset  We compare our model with the well-known math word problem solvers ranging from 2017 till now on the Math23K dataset, and show the results in Table 6. Our approach achieves an accuracy of 77.5 on the Math23K dataset and outperforms the previous state-of-the-art system by 3.2%.

Results on Ape210K Dataset  We choose two state-of-the-art open-source models StackDecoder

| Model                  | Accuracy |
|------------------------|----------|
| DNS (Wang et al., 2017)| 64.7     |
| StackDecoder (Chiang and Chen, 2018) | 65.8     |
| Seq2SeqET (Wang et al., 2018) | 66.7*    |
| T-RNN (Wang et al., 2019) | 66.9*    |
| Group Attention (Li et al., 2019) | 66.9     |
| TreeDecoder (Liu et al., 2019) | 69.5     |
| GTS-model (Xie and Sun, 2019) | 74.3     |
| **Our Approach**       | **77.5** |

Table 6: The performance of models on Math23K. The results without asterisks are evaluated with 5-fold cross-validation. The results with asterisks are evaluated on the test set published by Wang et al.

(Chiang and Chen, 2018) and GTS (Xie and Sun, 2019) to compare with our model on the Ape210K dataset.

StackDecoder is a neural seq2seq model. The encoder is designed to get the semantic embeddings of the numbers in the problem description, and the decoder is designed to construct the equation. The decoder generates the equation in a suffix manner by applying stack actions on a stack.

GTS-model uses a two-layer Bi-GRU to encode the problem description texts to contextual representations. Given a goal vector $q$, the decoder predicts the token $\hat{y}$ which implies a decision about how to achieve the goal. If the predicted token $\hat{y}$ is a numeric value or a constant number, then the goal is marked as achieved. Otherwise, the predicted token $\hat{y}$ is an operator, and the goal $q$ will be realized by a left sub-goal $q_l$ and a right sub-goal $q_r$. When decoding the right subtree, the left subtree will be used and is embedded via a recursive neural network.

| Model                  | Accuracy |
|------------------------|----------|
| StackDecoder           | 52.28    |
| GTS-model              | 56.56    |
| **Our Approach**       | **70.20**|

Table 7: The performance of models on Ape210K test dataset.

The evaluation results are listed in Table 7. The StackDecoder’s performance is poor since it can not handle examples with external constants other than one and $\pi$. In Ape210K, our approach serves as a strong baseline, with an accuracy of 70.2 on the test dataset and outperforms the other systems.
### Analysis

#### 6.1 Ablation Study

Our model outperforms the current state-of-the-art systems by a large margin both on Math23K dataset and Ape210K dataset. In this section, we compare our approach with and without the optimizations we propose.

| Experiment            | Acc  | Diff |
|-----------------------|------|------|
| Baseline              | 70.20| -    |
| - input features except char | 67.30 | -2.90 |
| - copying mechanism   | 67.28| -2.92|
| - pre-trained embeddings | 68.98 | -1.22 |
| - equation normalization | 69.20 | -1.00 |
| - All Above            | 66.22| -3.98|

Table 9: The ablation study results of our approach on Ape210K.

We verify if the rich input features are useful by removing the other 4 features except for the character feature on the input. As illustrated in Table 9, there is a drop of 2.9% in terms of accuracy. With more detailed experiments, we find that the part-of-speech feature plays the most important role among the 4 features.

We compare our approach with and without copying mechanism. As illustrated in Table 9, without copying mechanism, the score drops from 70.02 to 67.28, proving that the copying mechanism is also effective for the Ape210K dataset. It boosts the scores of the tokens that appear in the problem description and improves the performance of the model. Besides, the pre-trained embeddings and the equation normalization also have positive impacts on the results. The result drops to 66.22 if we remove all the optimizations.

#### 6.2 Error Analysis

The math word problem is a complicated task since there are too many equation templates, and commonsense knowledge is often required to solve a problem. In this section, we analyze our system’s performance on different templates.

We list the 10 most frequent templates of Math23K and Ape210K datasets in Table 8.

| Index | Math23K | Ape210K |
|-------|---------|---------|
| x = d1 × d2 | 6.19 | 3.14 |
| x = d1 / d2 | 3.93 | 3.12 |
| x = d2 / d1 | 3.31 | 2.32 |
| x = d1 × d2 / d3 | 2.28 | 1.80 |
| x = d1 × (1 - d2) | 2.27 | 1.18 |
| x = d1 × d2 + d3 | 2.18 | 0.99 |
| x = d1 × d2 × d3 | 2.16 | 0.83 |
| x = d1 | 2.11 | 0.73 |
| x = d2 / (1 - d1) | 1.36 | 0.66 |
| x = (d1 - d3) / d2 | 1.31 | 0.66 |

Table 8: The 10 most frequent templates in Math23K and Ape210K datasets.

We also experiment to see on which subset of
the examples the model performs terribly. As illustrated in Table 10, we can see the accuracy of examples whose equation length is at least 15, and the examples whose equation template only occurs once, are well below 50%. The performance on examples whose equation contains external constants is 52.89%. The model performs poorly on the examples with long templates, examples whose templates contain external constant numbers and examples with less common templates. How to solve those long-tail cases will pose a great challenge.

7 Related Work

Math Word Problem Datasets There exists several public math word problem datasets, including Alg514 (Kushman et al., 2014), Dolphin1878 (Shi et al., 2015), Dolphin18K (Huang et al., 2016), AllArith (Roy and Roth, 2017), Math23K (Wang et al., 2017), ASDiv (Miao et al., 2020), and MAWPS (Koncel-Kedziorski et al., 2016) etc. Though the aforementioned datasets are of high quality, the largest dataset Math23K only contains 23k problems, which limits the use of powerful deep learning models. Math23K contains Chinese math word problems for elementary school students. It comes from multiple online education websites, but a large number of templates are discarded, with only 23,160 math problems and 2,187 templates left. Specifically, Math23K hardly retains examples with external constants, and our experiment results in Section 6.2 show that Math23K only covers an easy and small subset of the math word problems in elementary school. AQuA (Ling et al., 2017) is a multiple-choice algebraic problem dataset that provides rationales instead of equations. ASDiv (Miao et al., 2020) provides richer annotations and proposes to measure the lexicon usage diversity of MWP datasets. MathQA (Amini et al., 2019) is another challenging large-scale dataset and includes more types of problems such as geometry and physics problems.

Math Word Problem Models In the early stages, people solve math word problems with rule-based and statistical learning-based methods (Hosseini et al., 2014; Kushman et al., 2014). The performances of the rule-based and statistical learning-based methods drop dramatically as the number of templates increases.

Deep Neural Solver (DNS) (Wang et al., 2017) is a pioneering deep neural model designed for one unknown variable math word problems. It is an RNN seq2seq model, which translates the math word problem descriptions into equation templates. Experimental results show that their model outperforms the state-of-the-art statistical learning methods at that time. Seq2SeqET (Wang et al., 2018) uses the same method as DNS, but changes the output sequence to an expression tree. Equation normalization was the first time applied to unify the duplicate representations of the expressions. StackDecoder (Chiang and Chen, 2018) is also a seq2seq model, with an encoder to extract semantic meanings of the numbers in the question and a stack-equipped decoder to generate the operation sequences. Group Attention (Li et al., 2019) introduces a group attention method to enhance the model’s capacity to aggregate various types of math word problem-specific features.

Another line of research applies semantic parsing (Jia and Liang, 2016) based approach to solve math word problems (Zou and Lu, 2019; Dong and Lapata, 2016; Shi et al., 2015). A problem is first parsed into an expression tree and then solved by evaluating the expression tree. It has better interpretability than seq2seq models (Ling et al., 2017), but often requires additional supervision to train.

8 Conclusion

We propose a large-scale and template-rich math word problem dataset named Ape210K, which covers a wide variety of elementary school-level math word problems with one unknown variable. This dataset is significantly larger in scale and more diverse than the previous ones in terms of the number of templates. A large portion of our dataset requires both the ability of natural language understanding and commonsense reasoning. Experiments also confirm that Ape210K is more challenging than the Math23K dataset.

We propose a feature-enriched and copy-augmented seq2seq model to serves as a solid baseline for Ape210K. Our approach outperforms the current state-of-the-art models by 3.2% on Math23K, and achieves 70% accuracy on Ape210K. Due to the complexity of the Ape210K dataset, there is still a long way to approach human performance. We make both our dataset and baseline code public to facilitate further research on automatic math word problem solving.
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