Supplementary for "Learning Pipelines with Limited Data and Domain Knowledge: A Case Study in Diagram Parsing"

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1 Contents

In this supplementary, we describe the text parsing component, the diagram parsing component, the reconciliation component, and the final question answering step in our model. We describe them one by one along with empirical results using our Nuts&Bolts approach. Finally, we also provide 10 successfully answered questions and 10 unsuccessfully answered questions to give the reader an idea of what are the sources of errors in our technique.

2 Text Parsing

We propose a two-stage pipeline model for question text parsing. This process is pictorially shown in Figure 1. The first stage identifies concepts in the logical language (i.e. constants, variables, functions, or predicates). In the second stage, relations are predicted with these concepts as arguments, provided some type constraints for the arguments are satisfied. For instance, the *distance* relation must take a constant which has the type *length* such as 3.00m as the second argument. Similarly, the *direction* relation must take one of the constants among $\{left, right, up, down\}$ as the second argument.

2.1 Pipeline Details

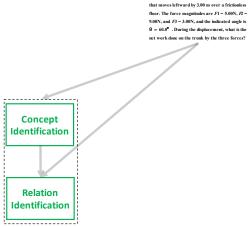


Figure 1: A pipeline for text parsing with various stages of (possibly multiple) pre-trained functions, existing software and rules.

Next, we describe the individual stages of the text parsing pipeline. Both stages: Concept identifica-

tion and Relation identification are performed by a number of rules mentioned in Table 1. R_1 represents the set of rules for concept identification using a manually curated lexicon map and a regular expression. The relation identification step again uses manually curated rules based R_2 on syntax information.

In the post-processing step, we build a simple rule-based math parser to handle mathematical formulas and equations. This parser takes in a math expression such as F = ma and parses it into our formal representation "equals(F, prod(m, a))". As another post procession step, we identify anaphoric and coreferential expressions in the text using Stanford CoreNLP and replace all coreferential expressions in the learnt logical formula with their corresponding antecedents.

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R_1	Lexicon Map Regex for constants and explicit variables	Indicator that the word or phrase maps to a predicate in a lexicon created by us. We derive correspondences between words/phrases and keywords and concepts in the logical language using manual annotations in the training data. For instance, our lexicon contains ("direction:left", <i>left, leftward</i>) including all possible realizations for the concept "direction:left". Indicator that the word or phrase satisfies a regular expression to detect numbers or explicit variables (e.g. "3.00m", "2gm", "g m/s ² "). These regular expressions were built as a part of our system.	
	Dependency	Shortest distance between the words of the concept nodes in the dependency tree.	
	tree distance	We use rules for distances of -3 to 3. Positive distance shows if the child word is at	
		the right of the parent's in the sentence, and negative otherwise.	
	Word dis-	Distance between the words of the concept nodes in the sentence. We have rules for	
	tance	distances 0 to 3.	
-3	Dependency	Indicator functions for outgoing edges of the parent and child for the shortest path	
R	edge	between them.	
	Part of	Indicator functions for the POS tags of the parent and the child	
	speech tag		
	Relation type	Indicator functions for unary / binary parent and child nodes.	
	Return type	e Indicator functions for the return types of the parent and the child nodes. Fo	
		example, return type of <i>Equals</i> is boolean, and that of <i>Distance</i> is length.	

Table 1: The rule set for our text parsing model. We use Turboparser[1] for POS and syntactic information.

2.2 Results

We compared the parses induced by our models with gold parses on the test set. Table 2 reports Precision, Recall and F1 scores of the parses induced. For comparison purposes, we built a rule-based parser baseline. A similar baseline was proposed in [3] for their geometry solver. The baseline uses a set of manually designed high-precision rules. Each rule compares the dependency tree of each sentence to pre-defined templates, and if a template pattern is matched, the rule outputs the relation corresponding to that template. Our text-based

	P	R	F1
Rule-based	0.82	0.27	0.41
Nuts&Bolts	0.63	0.75	0.68

Table 2: Precision, Recall and F1 scores of parses induced by our text parser compared to a rule based parser.

parser achieved a F1 score of 0.68, a significant improvement over the rule-based parser (0.41).

We further break down this evaluation into the two components of text parsing: concept and relation identification. Table 3 shows the precision, Recall and F1 scores for concept and relation identification. Our parser achieved a high F1 score (0.91) for concept identification and a good F1 score (0.78) for relation identification.

3 Reconciliation of Text and Diagram Parsing

In the third phase, we reconcile text and diagram parses. This is done in many ways. For example, we incorporate question text for object detection. Often, the corresponding question texts provide

important cues for detecting these visual elements. For example, the question in Figure 1 of the main document mentions the object 'trunk'. While it is unlikely that the object recognition component will correctly recognize the object 'trunk' as 'trunk' doesn't appear again in the training dataset as an object, the mention of the noun phrase 'trunk' in the question text and the context in which it appears is an important cue for identifying that this object is 'trunk'. Hence, we built a text-based object detector that uses logistic regression to classify each noun phrase in the question text as an object or not. We used a small set of manually engineered features for the prediction problem: (a) if the noun phrase is included in a list of objects manually built by us by looking at the train set, (b) if the noun phrase is an object category in ImageNet, and (c) if the noun phrase is the agent/patient (determined using the Turbo dependency parser [1]) of a small list of actions taking place in our train set (e.g. pull, run, hit ...). We included these rules in our model.

	1	N	I'I
Concept	0.95	0.87	0.91
Relation	0.83	0.74	0.78
Table 2: Drasisian Decall and			

 $\mathbf{D} \mid \mathbf{D} \mid \mathbf{F1}$

Table 3: Precision, Recall and F1 scores of the concept and relation identification components of our text parser.

```
def vector_addition(Vectors vectors):
     result = zero vector()
     for vector in vectors
          result = result + vector
      return result
def angle_bw_vectors(Vector vec1, Vector vec2):
      return cos_inv(dot(vec1, vec2)/(norm(vec1)*norm(vec2)))
def project_vector(Vector vec, Direction theta):
      return (vec*cos(theta), vec*sin(theta))
def implicit_g_force(Mass m, Forces forces):
     if not forces.contains(("-mg i + 0 j")):
           forces.append(("mg i + 0 j"))
def Newton_II_law(Mass m, Forces forces, Accelerations accs):
     net force = vector additon(forces)
     net acceleration = vector addition(accs)
     return Constraint(net_force = m * net_acceleration)
def conservation_of_momentum(Mass m1, Velocity v1_initial, Mass m2, Velocity
v2_initial, Velocity v1_final, Velocity v2_final):
      preconditions = [external_force_on_system() == None]
     if preconditions:
           return Constraint(m1*v1_initial+m2*v2_initial = m1*v1_final+m2*v2_final)
```

Figure 2: Example programs in Parsing to Programs.

Finally, we incorporate bi-modal interactions between the diagram and text parsing components by incorporating a simple rule. The rule upvotes a parse predicate if it is scored by the text as well as the diagram parser. The rule is $Pred_{diag}(p) \wedge Pred_{text}(p) \rightarrow Pred(p)$.

4 Diagram Parsing Components

Question parsing results: We evaluated the various question parsing components. For diagram parsing, we computed the Jaccard similarity between the diagram elements detected by our diagram parser and compared them to gold elements. We considered *Edge Boxes* [4] – since it uses edge maps to propose objects and relies less on colors and gradients observed in natural images, and our diagram parser. Table 4 reports the diagram parsing results on the test set. Our diagram parser achieved a score of 81.0 which is much better than Edge Boxes. Prior computer vision techniques are tuned for natural images and hence, do not port well to diagrams as shown in the rows colored in cyan. However, our carefully engineered pipeline with ensembles of element detectors and explicit domain knowledge in the form of rules can work well even in this challenging domain.

5 Question Answering

Subject knowledge of Newtonian physics is a crucial component in our solver. We presented the domain knowledge to the system in the form of structured programs. Some example programs are shown in Figure 2.

Some of these programs perform basic functions such as vector addition, computing angle between vectors, unit conversion, etc. Others perform more complex functions such as applying Newton's laws of motion or conservation of momentum, etc. A number of axioms denote laws of physics as a mathematical expression. For example, the Newton's second law is expressed simply as $\vec{F}_{net} = m \times \vec{a}$. Here \vec{F}_{net} stands for the vector quantity representing the net force on a body. m stands for the mass of the body and \vec{a} stands for the acceleration of the body. These programs also define a set of preconditions which must be satisfied for it to be executable. When the preconditions are satisfied, the programs define the mathematical expression as a constraint on the output. These constraints are

Elements	<i>E.B.</i>	0.S.	
Low-level	57.4	86.5	
66.9, 76.2, 63.1, 74.7, 74.4			
Corner	-	90.7	
High-level	42.3	82.2	
Text	53.6	85.3	
76.5, 78.0			
Object	29.1	63.6	
43.5, 41.7, 38.5, 46.2, 40.7,			
47.9, 34.6, 60.4, 61.2			
Overall	43.8	81.0	

Table 4: Jaccard similarity b/w detected diagram elements and gold elements for Edge Boxes (E.B.) and our system. We report overall results as well as results for identifying various diagram elements. For low-level, text and object element detection, we also show performance of various methods in the ensemble (cyan). then solved to obtain the answer. Parsing to Programs has a total of 237 manually curated programs. Let \mathcal{P} represent this set of programs. Parsing to Programs uses this set of programs to answer the physics problems via the following deductive solver.

5.1 The Deductive Solver (Parsing to Programs [2])

Given access to the domain theory, we solve the physics problem by using the Parsing to Programs framework [2]. Parsing to Programs searches for program applications that can lead to the problem solution using a forward chaining search procedure exploring various possible program applications. Algorithm 1 describes the procedure.

A	Algorithm 1: Our Forward Chaining deductive solver		
Ι	Data: Weighted set of literals <i>L</i> representing the question		
	and Domain knowledge ${\cal P}.$		
1 I	Do		
2	1. Match Programs: Match the pre-conditions of the		
	programs against the set of literals i.e. find all		
	programs $p \in \mathcal{P}$ s.t. the precondition p^{pr} can be		
	unified with some set of literals <i>L</i> .		
3	2. Select Program: Sample a program (randomly		
	uniformly) among the matching programs. Stop if no		
	program can be applied.		
4	3. Apply Program: Apply the chosen program by		
	adding the result to the set of literals/constraint set.		
5 while #iterations < N _{upperbound} ;			

The program applications are scored as a function of the scores of various literals in the program's precondition. The score of a literal is given by the confidence score from the question parser. In case it is a derived literal (derived by an earlier program execution), its score is given by the function value of the program application that derived it. Various scoring functions: minimum, arithmetic mean, geometric mean and harmonic mean were explored for all literal scores and the harmonic mean of the precondition literals performed the best, and hence is used. They further used an off-the shelf library¹ to solve the constraints introduced by the programs. Then, the following answering interface uses the search results to answer the question.

Handling Various Question and Answer Types: The physics examinations consist of a number of question and answer types. While a majority of questions directly ask about a particular physical quantity, there are a substantial number of questions which do not fit in this paradigm. For example, there are some *which of these are not true, select the odd one out, match the following* questions. To handle a variety of questions, Parsing to Programs has an answering interface. The interface calls the deductive solver described above and answers the question based on the type of the question or the kind of answer sought. The results on using Parsing to Programs with the Nuts&Bolts framework are already provided in the main paper.

6 Error Analysis

Finally, we also provide 10 successfully answered questions and 10 unsuccessfully answered questions to give the reader an idea of what are the sources of errors in our technique.

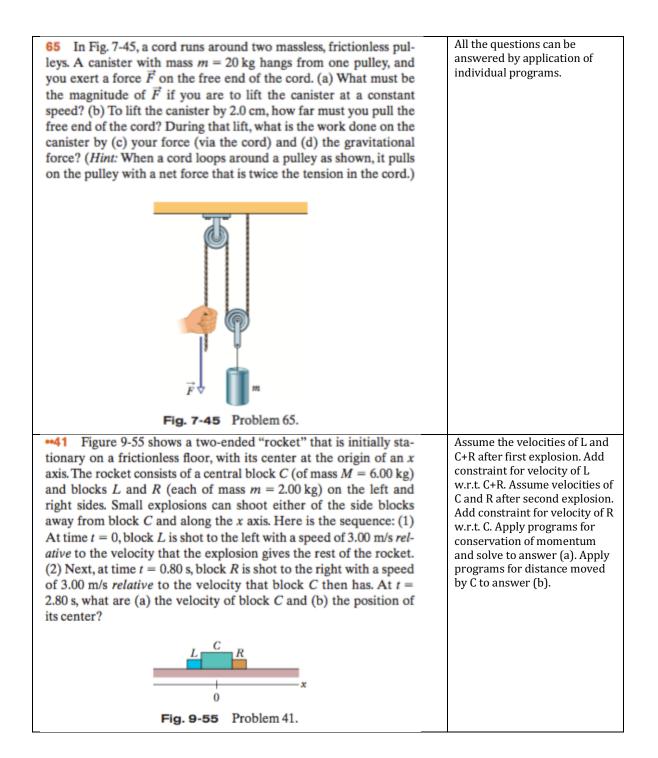
¹http://docs.sympy.org/dev/modules/solvers/solvers.html#sympy.solvers. solvers.nsolve

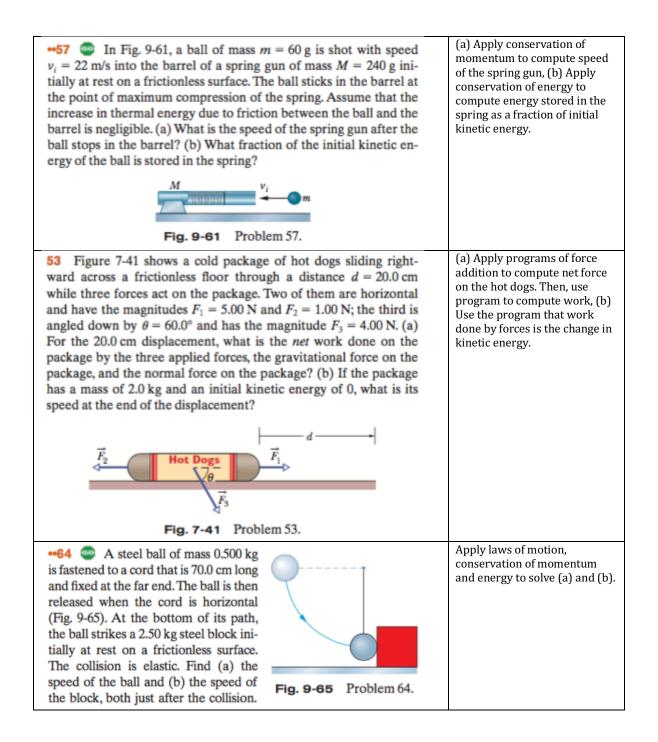
References

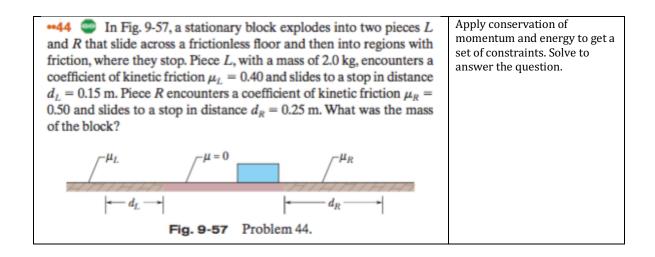
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- [2] Mrinmaya Sachan and Eric Xing. Parsing to programs: A framework for situated qa. In *Proceedings of the 24rd SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*, 2018.
- [3] Min Joon Seo, Hannaneh Hajishirzi, Ali Farhadi, Oren Etzioni, and Clint Malcolm. Solving geometry problems: combining text and diagram interpretation. In *Proceedings of EMNLP*, 2015.
- [4] C Lawrence Zitnick and Piotr Dollár. Edge boxes: Locating object proposals from edges. In *European Conference on Computer Vision*, pages 391–405. Springer, 2014.

10 Correctly Answered Questions:

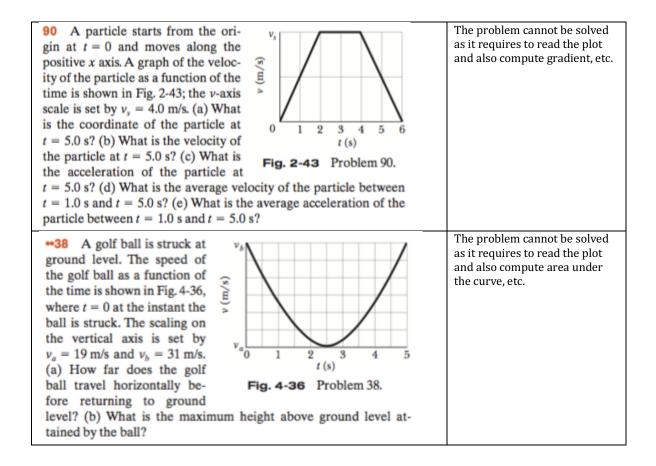
Questio	n	Comments
4 You are to launch a rocket, from j one of the following initial velocity vec $\vec{v}_0 = -20\hat{i} + 70\hat{j}$, (3) $\vec{v}_0 = 20\hat{i} - 70\hat{j}$, (coordinate system, x runs along level gro (a) Rank the vectors according to the la greatest first. (b) Rank the vectors accord projectile, greatest first.	 (a) The speed is computed by a program for computing magnitude of the velocity. The interface ranks the results. (b) Compute the flight time using the program encoding the formula for flight time. Interface ranks the results. 	
100 A parachutist bails out and freel chute opens, and thereafter she deceler the ground with a speed of 3.0 m/s. (a) in the air? (b) At what height does the f	rates at 2.0 m/s ² . She reaches How long is the parachutist	Apply programs for both stages: free fall and deceleration,. Then solve for (a) total time and (b) total height.
••32 ••32 ••32 ••32 ••32 ••32 ••32 ••32		Apply programs that encode formulas for projectile motion to answer (a), (b) and (c). The system wrongly answers (d) due to misinterpretation of the concept "highest point".
•••59 SSM ILW In Fig. 6-45, a 1.34 kg ball is connected by means of two massless strings, each of length $L = 1.70$ m, to a vertical, rotating rod. The strings are tied to the rod with separation $d = 1.70$ m and are taut. The tension in the upper string is 35 N. What are the (a) tension in the lower string, (b) magnitude of the net force \vec{F}_{net} on the ball, and (c) speed of the ball? (d) What is the direction of \vec{F}_{net} ?	Rotating rod Fig. 6-45 Problem 59.	Apply formula to enlist (pseudo) centripetal force. Now apply force balance and other formula theorems to solve the questions.

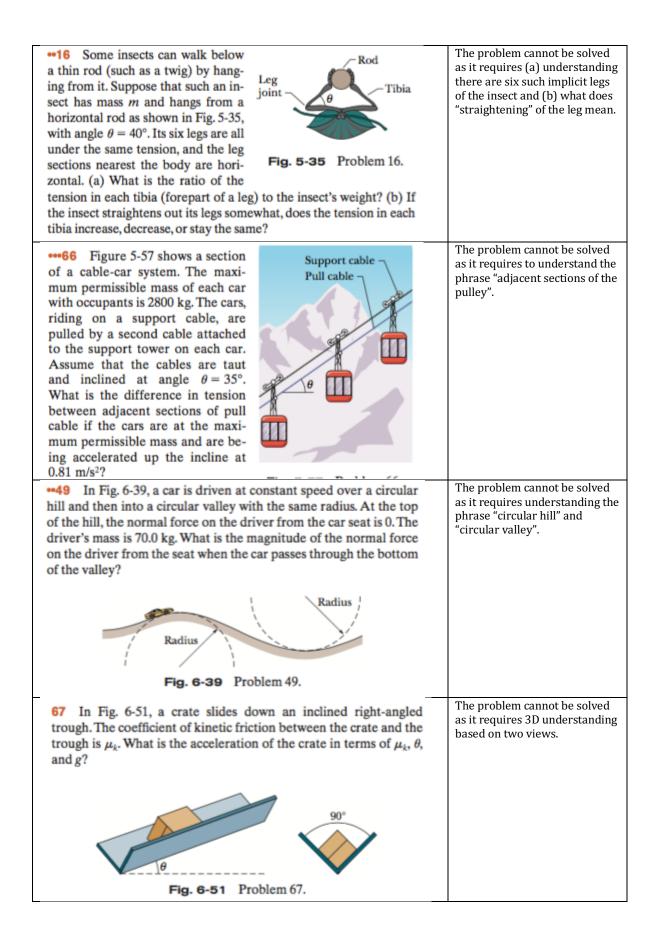






10 Incorrectly Answered Questions:





•••25 In Fig. 7-33, a 0.250 kg block of cheese lies on the floor of a 900 kg elevator cab that is being pulled upward by a cable through distance $d_1 = 2.40$ m and then through distance $d_2 = 10.5$ m. (a) Through d_1 , if the normal force on the block from the floor has constant magnitude $F_N = 3.00$ N, how much work is done on the cab by the force from the cable? (b) Through d_2 , if the work done on the cab by the (constant) force from the cable is 92.61 kJ, what is the magnitude of F_N ?

The problem cannot be solved

as the diagram parser fails to map the objects cab and cheese.

The problem cannot be solved

as it requires reading the scale

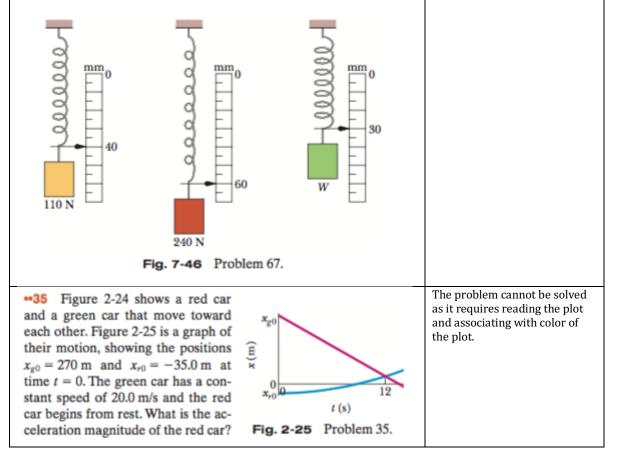
and recognizing that the scale

reading is a function of the

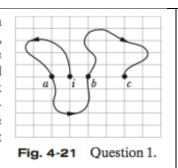
extension in the spring.

Fig. 7-33 Problem 25.

67 SSM A spring with a pointer attached is hanging next to a scale marked in millimeters. Three different packages are hung from the spring, in turn, as shown in Fig. 7-46. (a) Which mark on the scale will the pointer indicate when no package is hung from the spring? (b) What is the weight W of the third package?



1 Figure 4-21 shows the path taken by a skunk foraging for trash food, from initial point *i*. The skunk took the same time T to go from each labeled point to the next along its path. Rank points *a*, *b*, and *c* according to the magnitude of the average velocity of the skunk to reach them from initial point *i*, greatest first.



The problem cannot be solved as it requires reasoning based on the plot. It doesn't fall in the paradigm of programmatic solving chosen by us.