Standardized Tests as benchmarks for Artificial Intelligence?

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Machine Intelligence



Machine Intelligence



"It would someday be possible for a sufficiently advanced computer to think and to have some form of consciousness"

-- Computing Machinery and Intelligence, Mind 1950.

How do we measure progress? What tasks should drive the field?





Turing Test





Standardized Tests as drivers for Artificial Intelligence

[Brachman 2005, Levesqeue 2010, Clark 2014]

Standardized Tests



Why Standardized Tests

• Easily accessible

• Easily measurable

Do not cover all aspect.



Standardized Tests as Benchmarks for AI: Limitations

- Aspects of intelligence that are challenging for AI systems are very different from aspects of intelligence that are challenging to humans.
 - Standardized tests do not test knowledge that is obvious for people.

Nevertheless, passing standardized tests still requires better language/visual understanding and reasoning capabilities than those demonstrated by AI systems

Drivers for progress in AI

Outline

Machine Reading for Question Answering:

Reading Comprehension

- Feature Driven Models
 - MCTest
- Deep Learning Models
 - WikiQA
 - CNN & DailyMail
 - SQUAD
 - Etc.

Beyond Reading Comprehensions

- Elementary-level Science Exams
- Diagram QA
- Textbook QA

Mathematical Question Answering:

Advanced Math and Science Problems

- Algebra Word Problems
- Geometry Problems
- Newtonian Physics Problems

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Reading Comprehension for Humans

TOEFL Reading		Prev Explain Next
Section Scores Review Questions	Question 1 of 12	Time spent : 10
 With which of the following is the passage mainly concerned or summarizes the passage? A legal interpretation of the Dawes Act of 1887 The assimilation of Native Americans during the nineteenth century The settlement of the United States by Native Americans The policy of establishing Native American reservations 	From the first days of Americans have retreate nineteenth century, the i the eastern part of the U River in order to open up the corrupting influence 1850's whites were pour government adopted a p from the paths of white r In the late nineteenth on reservations had not impoverished, dependen increasingly concerned i Reflecting these sentim- two fundamental but err their tribal existence ann independent, productive recognized as a defining land was seen as a mee land in severalty policy r one, protect the Indians save the federal governn land in the same way as real estate to be bought Although the roots of i Dawes Allotment Act of tribal consciousness wit The idea was not only to accept the social and er considered this accepta Commissioner of Indian Darwinist philosophy ver of their natural resource	European settlement in North America, Native ed as white civilization advanced. In the early federal government began removing Indians living in Junited States to the region west of the Mississippi of Indian land for settlement, to protect the Natives from of white society, and to promote assimilation. By the ing into the trans-Mississippi West, and the federal olicy of concentrating tribesmen on reservations away migration. century, Americans found that concentrating Indians solved the "Indian problem", the problem of an it people living in a separate society, and they became with assimilating the Indians into white society. ents, government officials developed policies rooted in oneous assumptions: that the Indians should give up d become "civilized" and that they should become members of white society. Tribal organization was feature of Native identity, and private ownership of ans of civilizing the Indians. By allotting reservation makers hoped to replace tribal civilization with a white from unscrupulous whites, promote progress, and nent money. Native Americans, however, did not view a their white neighbors. They did not regard land as , sold, and developed. allotment extend back to the Colonial period, the 1867 was the first comprehensive proposal to replace th an understanding of the value of private property. D discourage native habits but to encourage Indians to conomic standards of white society. Americans nice essential if the Indians were to survive. Affairs, Francis Leupp, expressed this Social ry well. All primitive peoples, he wrote, were wasteful s. As the population of the "civilized" world increased,

Excerpt from https://learn.eazycoach.com/toefl-decoded/

Reading Comprehension

- Read a piece of text and answer questions
 - Often Multiple-choice
 - Timed!

<u>Note</u>: There are issues with both the aforementioned assumptions if we wish to use standardized tests to contrast machine and human intelligence!

RC for Machines A Historical NLP Perspective

- Charniak's PhD thesis (1972) *Background* model to answer questions about children's stories.
- Hirschmann et al. 1999 showed that bag of words pattern matching with some additional linguistic processing could achieve 40% accuracy for picking the sentence that best answers "who / what / when / where / why" questions on the Remedia dataset. Results on this dataset were later improved upon by Grois and Wilkins (2005); Harabagiu et al. (2003); Wellner et al. (2006).
- Riloff et. al 2000 developed a rule-based system, *Quarc*, which used similar lexical and semantic clues in the question and the story to answer questions about it. On RC tests given to children in grades 3-6, **Quarc** achieved an accuracy of around **40%**.
- Breck et. al 2001 collected 75 stories from Canadian Broadcasting Corporation's web site for children and generated 650 questions where each question was answered by a sentence in the text.
- Leidner et. al 2003 used the CBC4kids data and added layers of annotation (such as semantic and POS tags), thus measuring QA performance as a function of question difficulty.

Machine Comprehension

MCTest (Richardson et al. 2013)

- Freely available crowd-sourced set of 500 stories and associated questions:
 - 4 questions per story, 4 answer choices per question
- Open-domain yet restricted to concepts and words that a 7 year old is expected to understand
- As the stories are fictional, answers are typically in the passage itself.
 - This requires the system to deeply "understand" the stories rather than using IR methods or redundancy of the web.

MCTest

Once upon a time there a little girl named Ana. Ana was a smart girl. Everyone in Ana's school knew and liked her very much. She had a big dream of becoming spelling bee winner. Ana studied very hard to be the best she could be at spelling. Ana's best friend would help her study every day after school. By the time the spelling bee arrived Ana and her best friend were sure she would win. There were ten students in the spelling bee. This made Ana very nervous, but when she looked out and saw her dad cheering her on she knew she could do it. The spelling bee had five rounds and Ana made it through them all. She was now in the finals. During the final round James, the boy she was in the finals with, was given a really hard word and he spelled it wrong. All Ana had to do was spell this last word and she would be the winner. Ana stepped to the microphone, thought really hard and spelled the word. She waited and finally her teacher said "That is correct". Ana had won the spelling bee. Ana was so happy. She won a trophy. Ana also won a big yellow ribbon. The whole school was also happy, and everyone clapped for her. The whole school went outside. They had a picnic to celebrate Ana winning.

Q1: What made Ana very nervous?

- A) The other ten students
- B) Her best friend
- C) The bright lights
- D) The big stage

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MCTest

Small Dataset

 Simple Machine Learning Models with hand-engineered features

Core Idea

 Convert each Question/answer-choice pair to a hypothesis statement.



 Find which hypothesis statement is best "entailed" by the passage

Degree of Entailment

- The models mainly differ in how they measure entailment and feature engineering:
 - Sachan et al. 2015, 2016 Answer-entailing structures syntax, semantics and discourse - AMR
 - Wang et al. 2015 syntax, frames and semantic features.
 - Narasimhan et al. 2015 Discourse features.
- Challenging for Deep Models because of small data:
 - Trischler et al. 2016 use multiple shallow NNs to compare the question and answer candidates to the text using several distinct perspectives which mimic features: word-by-word, sequential and dependency view.

Similar

Answer-Entailing Structures

Alignment based approach (Sachan et al. 2015)

- Align an answer hypothesis to multiple sentences in the text (not necessarily contiguous)
 - Document Structure Entity and Event Co-reference, Rhetorical Structure Theory (Mann and Thompson'88)

elaboration

Text: ... The restaurant had a special on catfish ... Alyssa enjoyed the restaurant's special ...

Hypothesis:

hesis: Alyssa ate Catfish at the restaurant. (Question: What did Alyssa eat at the restaurant? Answer Candidate: Catfish)

Multi-task Learning

Language Representation

• AMR as a semantic representation

- Abstract Meaning Representation (Banarescu et al. 2013) captures many aspects of meaning in a single simple data structure:
 - PropBank style semantic roles
 - Within-sentence coreference
 - Named entities
 - Notion of types, modality, negation, quantification, etc.

Text: ... Katie also has a dog, but he does not like Bows. ... His name is Sammy. ...

Text: ... Katie also has a dog, but he does not like Bows. ... His name is Sammy. ...



Text: ... Katie also has a dog, but he does not like Bows. ... His name is Sammy. ...







Hypothesis: Sammy is the name of Katie's dog. Question: What is the name of Katie's dog. Answer: Sammy



Hypothesis: Sammy is the name of Katie's dog. Question: What is the name of Katie's dog. Answer: Sammy

Parallel Hierarchical Neural Network Model



State Of The Art on MCTest

Approach	Accuracy (%)
Sliding Window	54.28
RTE	55.01
Strong Lexical Matching Baseline (Smith et al. 2015)	65.43
Discourse features (Narasimhan et al. 2015)	63.75
Answer-entailing structures (Sachan et al. 2015)	67.83
Syntax, frames and semantic features (Wang et al. 2015)	69.94
Answer-entailing structures - AMR (Sachan et al. 2016)	70.33
Simple neural networks - not deep (Trischler et al. 2016)	71.00

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Larger datasets for neural nets

 WikiQA (2015), CNN/Daily Mail (2015), SQuAD (2016), TriviaQA (2017), LAnguage Modeling Broadened to Account for Disclourse Aspects (LAMBADA), QuizBowl questions, NewsQA dataset, MS MARCO ...

WikiQA (2015)

- Similar to TREC QA (est. 1999)
- 3k questions
- Answering for real user queries
 - "When was Barack Obama born?"
- Given a question, select the sentence (among 10) that best answers the question
- Is this really a "reading comprehension"?
 - Or is it "sentence retrieval"?

CNN & DailyMail QA (2015)

- News article & summary pair
- The task is to predict a masked entity in the summary (cloze test)
- Requires understanding of news article?

Context

The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the "Top Gear" host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon "to an unprovoked physical and verbal attack." ...

Query

Producer X will not press charges against Jeremy Clarkson, his lawyer says.

Answer

Oisin Tymon
A Thorough Examination of the CNN/Daily Mail RC Task

(Chen et al., ACL 2016)

- Simple, carefully designed systems can obtain SOTA performance. The dataset is easy!
- Distributed representations are effective at recognizing paraphrases.
- Best systems more have the nature of single-sentence relation extraction systems than larger-discourse-context text understanding.
- Most systems proposed are close to the ceiling of performance for single sentence and unambiguous cases.
- Prospects for getting the final 20% of questions correct are poor, since most of them involve issues in the data preparation.

SQuAD (Rajpurkar et al., 2016)

Gained a lot of popularity

- First massive and manually turked data; deep learning in full effect
- Factual questions: natural extension to real open-domain QA systems (Chen et al., 2017)
- Easy to use (small size context, Wikipediabased, etc.)

SQuAD

Second Epistle to the Corinthians The Second Epistle to the Corinthians, often referred to as Second Corinthians (and written as 2 Corinthians), is the eighth book of the New Testament of the Bible. Paul the Apostle and "Timothy our brother" wrote this epistle to "the church of God which is at Corinth, with all the saints which are in all Achaia".

Who wrote second Corinthians?

SQuAD

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100,000+

A lot of models!

SQuAD1.1 Leaderboard

Since the release of SQuAD1.0, the community has made rapid progress, with the best models now rivaling human performance on the task. Here are the ExactMatch (EM) and F1 scores evaluated on the test set of v1.1.

Daula	Madal	514	F4
Rank	Model	EM	F1
	Human Performance Stanford University (Rajpurkar et al. '16)	82.304	91.221
1 Oct 05, 2018	BERT (ensemble) Google A.I.	87.433	93.160
2 Oct 05, 2018	BERT (single model) Google A.I.	85.083	91.835
2 Sep 09. 2018	nlnet (ensemble) Microsoft Research Asia	85.356	91.202
2 Sep 26, 2018	nlnet (ensemble) Microsoft Research Asia	85.954	91.677
3 Jul 11, 2018	QANet (ensemble) Google Brain & CMU	84.454	90.490
4 Jul 08, 2018	r-net (ensemble) Microsoft Research Asia	84.003	90.147
5 Mar 19, 2018	QANet (ensemble) Google Brain & CMU	83.877	89.737
5 Sep 09. 2018	nlnet (single model) Microsoft Research Asia	83.468	90.133
5 [Jun 20, 2018]	MARS (ensemble) YUANFUDAO research NLP	83.982	89.796
6 Sep 01, 2018	MARS (single model) YUANFUDAO research NLP	83.185	89.547
7 Jan 22, 2018	Hybrid AoA Reader (ensemble) Joint Laboratory of HIT and iFLYTEK Research	82.482	89.281

Basic components of models

- Sequential Model F1 70%
 - RNNs (LSTM, GRU)
- +Cross-Attention F1 77% (+7%)
- +Self-Attention F1 82% (+5%)
- +Transfer Learning F1 86% (+4%)
 - Data Augmentation (back translation via MT)
 - Contextualized Vectors (CoVe, ELMo)
- +Other Tricks F1 90% (+4%)
 - Ensemble, Distillation
 - Sparse features (Chen et al., 2017)
 - Finetuning with RL (Xu et al., 2017)
- Just Attention F1 93% (+3%)
 - (Dublin et al., 2018)

Neural Sequential Model



SQuAD Baselines

Date	Model	F1	EM
May 2016	Feature-based	~50%	~40%
-	Neural Sequential	~70%	~60%

Issues with Sequential Model

 Question needs to be summarized into a fixed-size vector



"You can't cram the meaning of a whole %&!\$# sentence into a single \$&!#* vector!" -Ray Mooney

Attention Mechanism

- A mechanism to dynamically summarize a sequence of vectors
- Many variants exist:
 - Concat and linear (Bhadanau et al., 2015)
 - Memory intensive
 - Bilinear (Luong et al., 2015)
 - Transformer-style (Vaswani et al., 2017)
 - Memory efficient

Cross-Attention

- Common in early SQuAD models
- Choose what part of the question to look at for each context
 - match-LSTM (Wang et al., 2017)
- Often times the other direction is also considered
 - bi-attention (Seo et al., 2017)
 - co-attention (Xiong et al., 2017)

Cross-Attention Model



Cross-Attention Example



Seo et al. Bidirectional attention flow for 51 machine comprehension. ICLR 2017.

SQuAD Leaderboard

Date	Model	F1	EM
Aug 2016	+Cross-Attention	75~78%	66~68%

Cross-Attention Demo (BiDAF)

Bi-directional Attention Flow Demo

for Stanford Question Answering Dataset (SQuAD)

Direction : Select a paragraph and write your own question. The answer is always a subphrase of the paragraph - remember it when you ask a question!

\$

Select Paragraph

[05] Teacher

Paragraph

The role of teacher is often formal and ongoing, carried out at a school or other place of formal education. In many countries, a person who wishes to become a teacher must first obtain specified professional qualifications or credentials from a university or college. These professional qualifications may include the study of pedagogy, the science of teaching. Teachers, like other professionals, may have to continue their education after they qualify, a process known as continuing professional development. Teachers may use a lesson plan to facilitate student learning, providing a course of study which is called the curriculum.

Question

Where do most teachers get their credentials from?

new question!

Answer

a university or college

Reference : Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, Hannaneh Hajishirzi. "Bidirectional Attention Flow for Machine Comprehension" [link]

\$

Demo by : Sewon Min

http://allgood.cs.washington.edu:1995/

Issues with Cross-Attention

- Sequential models are not great for longterm dependency
 - even with gating mechanism
- Context (document) is long (200+ words)
 - Coreference?
 - Long sentence?

Self-Attention

- "Attend" on itself!
- Self-attention allows direct access to distant words
- Usually on top of cross-attention

Self-Attention



Self-Attention



Self-Attention Example



Clark and Gardner. Simple and effective multi-paragraph 60 reading comprehension. 2017.

SQuAD Leaderboard

Date	Model	F1	EM
Aug 2016	+Cross-Attention	75~78%	66~68%
Mar 2017	+Self-Attention	80~82%	71-73%

Is SQuAD big enough?

- Larger training data never hurts!
- Can we benefit from other larger corpus?

Transfer Learning

- Data Augmentation via back translation
 - QANet (Yu et al., ICLR 2018)
- Transfer learning from MT Model
 - CoVe (McCann et al., ICML 2018)
- Transfer learning from Language Model, trained on a large unlabeled corpus
 - ELMo (Peters et al., NAACL 2018)

Pretrained Language Model



Peters et al. Deep contextualized word representations. NAACL 2018.

Pretrained Language Model



representations. NAACL 2018.

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Other tricks

- Sparse feature
 - Putting 0/1 flag of whether each context word appears in the question
 - POS, NER
- Finetuning with RL
 - Optimize for F1 (soft) rather than EM (hard)

Super-human (Jan 2018)

f 💟 🚭 🔁 😵

Al systems are beating humans in reading comprehension

By Associated Press

TECH

January 24, 2018 | 2:25pm



iStockphoto

MORE ON: ARTIFICIAL INTELLIGENCE

Swiss bank digitally 'clones' chief economist PROVIDENCE, RI — Seven years ago, a computer beat two human quizmasters on a "Jeopardy" challenge. Ever since, the tech industry has been training its machines to make them even better at amassing knowledge and answering questions.

SQuAD Leaderboard

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Jan 2018	+Tricks	88~90%	82~85%

We thought it was the end...

Just Attention?

Transformer

- Multi-head self-attention
- No LSTM (unlike ELMo)

Scaled Dot-Product Attention





Just Attention?

Transformer

- Multi-head self-attention
- No LSTM (unlike ELMo)
- Concat context and question
- Trained masked language model on a large unlabeled corpus
 - cloze test instead of next word prediction
- Super-large model (64 TPUs)

Just Attention: BERT

- Basically, doing all three at once:
 - Cross-attention: via concat
 - Self-attention: using Transformer
 - Transfer learning: via masked LM



Devlin et al. BERT: Pre-training of deep bidirectional transformers for language understanding. 2018.

Pretrained Language Model



representations. NAACL 2018.

Pretrained LM with Transformer



SQuAD Leaderboard

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Sep 2018	Just Attention	93%	87%

SQuAD Leaderboard

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Jan 2018	+Tricks	88~90%	82~84%
Sep 2018	Just Attention	93%	87%
	Human	91%	82%

5% above human!
Al! Really? Adversarial Examples

(Jia and Liang, 2017)

- It is more about pattern matching!
- Can systems answer questions about paragraphs that contain adversarially inserted sentences automatically generated to distract without changing the correct answer or misleading humans?
- In this adversarial setting, the accuracy of sixteen published models drops from an average of 75% F1 score to 36%!
- When the adversary is allowed to add ungrammatical sequences of words, average accuracy on four models decreases further to 7%!

Al! Really? Adversarial Examples

Article: Nikola Tesla

Paragraph: "In January 1880, two of Tesla's uncles put together enough money to help him leave Gospić for Prague where he was to study. Unfortunately, he arrived too late to enroll at Charles-Ferdinand University; he never studied Greek, a required subject; and he was illiterate in Czech, another required subject. Tesla did, however, attend lectures at the university, although, as an auditor, he did not receive grades for the courses." Question: "What city did Tesla move to in 1880?" Answer: Prague Model Predicts: Prague





TriviaQA (Joshi et al., 2017)

- 95k Trivia questions
- Wikipedia articles are retrieved via IR.
- Distant supervision (string match)
- Simulates open-domain QA better
 - SQuAD is relatively artificial; the questions are created by looking at the documents

More recent datasets

• RACE (Lai et al. 2017)

Collected from real English exams for middle and high school Chinese students

NarrativeQA (Kočiský et al. 2017)

System must answer questions by reading the entire narrative (books or movie scripts).

MultiRC (Khashabi et al. 2018)

Questions can only be answered by taking into account information from multiple sentences

SQuAD 2.0 (Rajarpurkar et al. 2018)

 Unanswerable questions written adversarially by crowdworkers that are similar to answerable ones. Systems must determine when no answer is supported by the passage and abstain from answering

More new datasets at EMNLP

QuAC (Choi et al., 2018)

Multi-turn question answering in a conversation

CoQA (Reddy et al. 2018)

Similarly to QuAC, multi-turn QA in a conversation

HotpotQA (Yang et al. 2018)

Similarly to MultiRC, need to look at multiple sentences, but the answer is a span of the context

What's next? Semi-supervised Learning Joint Question Answering and Question Generation



What's next? Multi-task learning



McCann et al. The Natural language decathlon. Multitask learning as question answering. 2018.

What's next? Transfer learning

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	Average
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
BERTBASE	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
BERTLARGE	86.7/85.9	72.1	91.1	94.9	60.5	86.5	89.3	70.1	81.9
						_			

System	Dev F1	Test F1
ELMo+BiLSTM+CRF	95.7	92.2
CVT+Multi (Clark et al., 2018)	-	92.6
BERT _{BASE}	96.4	92.4
BERTLARGE	96.6	92.8

System	Dev	Test
ESIM+GloVe ESIM+ELMo	51.9 59.1	52.7 59.2
BERT _{BASE} BERT _{LARGE}	81.6 86.6	- 86.3
Human (expert) [†] Human (5 annotations) [†]	-	85.0 88.0

System	Dev		Test		
-	EM	F1	EM	F1	
Leaderboard (Oct	8th, 2	018)			
Human	-	-	82.3	91.2	
#1 Ensemble - nlnet	-	-	86.0	91.7	
#2 Ensemble - QANet	-	-	84.5	90.5	
#1 Single - nlnet	-	-	83.5	90.1	
#2 Single - QANet	-	-	82.5	89.3	
Publishe	d				
BiDAF+ELMo (Single)	-	85.8	-	-	
R.M. Reader (Single)	78.9	86.3	79.5	86.6	
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5	
Ours					
BERT _{BASE} (Single)	80.8	88.5	-	-	
BERT _{LARGE} (Single)	84.1	90.9	-	-	
BERT _{LARGE} (Ensemble)	85.8	91.8	-	-	
BERT _{LARGE} (Sgl.+TriviaQA)	84.2	91.1	85.1	91.8	
BERT _{LARGE} (Ens.+TriviaQA)	86.2	92.2	87.4	93.2	

Devlin et al. BERT: Pre-training of deep bidirectional transformers for language understanding. 2018.

What's next? Large-scale QA



Choi et al. 2017

What's next? Open-domain QA

Q: How many of Warsaw's inhabitants spoke Polish in 1933?



Chen et al. 2017

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RC vs QA?

- Reading comprehension is for evaluating machine's text understanding ability
- Question answering is a useful application for users

- They are correlated, but have different goals.
- Recent trends focus more on QA.

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Student Learning



- Elementary Science Exams
 - State exams
- Diagram/Visual QA
 - Given a diagram or image, answer questions about it
- Textbook QA
 - Read textbook, answer questions

Elementary-level Science Exam

State exams

Diagram/Visual QA

 Given a diagram or image, answer questions about it

Textbook QA

Read textbook, answer questions

Project Aristo@Al2



Q: Which of the following gases cause the greenhouse effect? A) O_2 and CO_2 B) O_2 , O_3 and CFC C) O_2 , CO, CO_2 and CFC D) CO_2 , CH_4 , O_3 and CFC

Project Aristo@Al2



Clark et al. AAAI 2016, Combining Retrieval, Statistics, and ⁹³ Inference to Answer Elementary Science Questions.

Project Aristo@Al2

NY Regents 4th grade science exams 75 71.3 70 65 60.7 60.6 60 55.4 54.3 55 50 47.5 43.8 45 40 35 30 IR SVM PMI RULE ILP Aristo Prior (ALL) System (Praline)

> Clark et al. AAAI 2016, Combining Retrieval, Statistics, and 94 Inference to Answer Elementary Science Questions.

Structured Knowledge

Country	Location	Hemisphere	Orbital Event	Month
France USA	north hemisphere north hemisphere	northern northern northern	summer solstice winter solstice autumn equinox	Jun Dec Sep
 Brazil Zambia 	south hemisphere south hemisphere	southern southern	summer solstice autumn equinox	Dec Mar

In USA, when is the summer solstice? (A) June

A path through joined rows in the knowledge tables match the question + answer

Domain-Targeted, High Precision Knowledge Extraction (Dalvi et al., TACL'17) IKE - An Interactive Tool for Knowledge Extraction (Dalvi et al., AKBC'16) 95 Automatic Construction of Inference-Supporting Knowledge Bases (Clark et al., AKBC'14)

Allen Al Science Challenge

8th Grade Science questions



Unfortunately, all the top models are fancy IR methods!

- **IR features** applied by searching over corpora compiled from **various sources** (study-guides, quizbuilding websites, open source textbooks, Wikipedia).
- **Features based on properties of questions -** length of question and answer, form of answer like numeric answer, answers containing none of the above, and relationships among answer options.
- Various weightings and stemming strategies. All the top models used gradient boosted trees!

Aristo Demo

Aristo Quiz: <u>https://aristo-quiz.allenai.org/</u>

Aristo Demo: http://aristo-demo.allenai.org/

- Elementary-level Science Exam
 - State exams
- Diagram/Visual QA
 - Given a diagram or image, answer questions about it
- Textbook QA
 - Read textbook, answer questions

Visual Question Answering

ses? Where is the child sitting? man fridge arms



arms

Who is wearing glasses?



Is the umbrella upside down?





How many children are in the bed?





VisualQA Challenge http://visualqa.org/

Diagram Question Answering



Khembhavi et al. ECCV 2016, A Diagram Is Worth A Dozen Images 100

Diagrams to Graph Representations



¹⁰¹ A Diagram Is Worth A Dozen Images. Khembhavi et al. 2016

Semantic Parsing to Probabilistic Programs



Krishnamurthy et al. EMNLP 2016

Semantic Parsing to Probabilistic Programs



- Elementary-level Science Exam
 - State exams
- Diagram/Visual QA
 - Given a diagram or image, answer questions about it
- Textbook QA
 - Read textbook, answer questions

Textbook QA



Kembhavi et al. CVPR 2017, Are You Smarter Than A Sixth Grader? Textbook Question Answering for Multimodal Machine Comprehension.

Textbook QA

Text Question Leaderboard - Final

Rank	Entrant	Accuracy
1	mlh	0.4208
2	beethoven	0.4200
3	tuanluu	0.4100
4	Daesik	0.4021
5	akshay107	0.3822
6	freerailway	0.3436

Diagram Question Leaderboard - Final

Rank	Entrant	Accuracy
1	beethoven	0.3175
2	mlh	0.3139
3	tuanluu	0.3050
4	Daesik	0.2588
5	akshay107	0.2581

CVPR 2017 Workshop on Visual Understanding Across Modalities Challenging Task!

Story so far



What's to come

Liz had 9 black kittens. She gave some of her kittens to John. John now has 11 kittens. Liz has 5 kittens left and 3 have spots. How many kittens did John get?



As shown in the Figure, \angle MAO = 30^o and the radius of the circle with center O is 4cm. Find the value of x.



Figure above shows three forces applied to a trunk that moves leftward by 3.00 m over a frictionless floor. The force magnitudes are $F_1 =$ 5.00N, $F_2 = 9.00$ N, and $F_3 = 3.00$ N, and the indicated angle is $\theta = 60.0^{\circ}$. During the displacement, what is the net work done on the trunk by the three forces?

Coffee Break!

Machine Reading: Beading Comprehension

Reading Comprehension

- Feature Driven Models
 - MCTest
- Deep Models
 - WikiQA
 - CNN & DailyMail
 - SQUAD
 - Etc.

Multi-View/Multi-modal QA

- Elementary-level Science Exams
- Diagram QA
- Textbook QA

Mathematical Question Answering:

- Algebra Word Problems
- Geometry Problems
- Newtonian Physics Problems

- Machine Reading for Question Answering:
 - Reading Comprehension
 - Feature Driven Models
 - MCTest
 - Deep Learning Models
 - WikiQA
 - CNN & DailyMail
 - SQUAD
 - Etc.

Beyond Reading Comprehensions

- Elementary-level Science Exams
- Diagram QA
- Textbook QA

Mathematical Question Answering:

- Algebra Word Problems
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 - Etc.

Beyond Reading Comprehensions

- Elementary-level Science Exams
- Diagram QA
- Textbook QA

Mathematical Question Answering:

- Algebra Word Problems
- Geometry Problems
- Newtonian Physics Problems
Arithmetic Word Problems

Liz had 9 black kittens. She gave some of her kittens to John. John now has 11 kittens. Liz has 5 kittens left and 3 have spots. How many kittens did John get?

- Solving math and science problems is a long-standing AI challenge, since 1963!
- Interesting problem for NLP

Quantitative Reasoning

Emanuel spent **\$13.6 million** from July until **the Feb. 24 election** and spent **an additional \$6.3 million** in **the following five weeks**.

How can you answer how much money Emanuel spent?

For each number one needs to extract

- Unit of the number (which numbers indicate currency)
- Associated verb ("spent" implies expenditure)
- Associated arguments (Knowing that "Emanuel" is the subject for both numbers)

114 Reasoning About Quantities in Natural Language (Roy et al., TACL 2015).

Quantity Entailment

T: A bomb in a Hebrew University cafeteria killed **five Americans** and **four Israelis**.

H: A bombing at Hebrew University in Jerusalem killed **nine people**, including **five Americans**.

Given a statement **T** and a quantity **q** in **H**, do the **quantities in T** entail **q** ? (Assuming upward monotonicity to be true)

Does the quantities in T entail "nine people"?

Reasoning About Quantities in Natural Language (Roy et al., TACL 2015).

Variety of problems across different domains



- No prior constraint on syntax or vocabulary
 - Requires world knowledge

Variety of problems across different domains



- No prior constraint on syntax or vocabulary
 - Requires world knowledge

There were 7,000,000 people living in a country. Last year, 90,000 children were born, and 16,000 people immigrated to it. How many new people began living in the country last year?



Irrelevant Information

Liz had 9 black kittens. She gave some of her kittens to John. John now has 11 kittens. Liz has 5 kittens left and 3 have spots. How many kittens did John get?

Missing information

There were 6 roses in the vase. Mary cut some more roses from her flower garden. There are now 16 roses in the vase. How many roses did she cut?

• Ambiguity (requires context):

Sara's high school won 5 basketball games this year. They lost 3 games. How many games did they play in all? 5+3 = x

John has 8 orange balloons, but lost 2 of them. How many orange balloons does John have now? 8-2=x

Is now an active area of research in AI:

[Lei et al, 2018, Roy et al 2018, Wang et al. 2017, Shyam et al, 2016, Hosseini et al 2014, Kushman et al 2014, Roy and Roth 2015, Zhou et al., 2015, etc]

A Historical Perspective

STUDENT program (Bobrow, 1964)

- Restricted set of English language
- A set of rules form a set of equations representing the problem

WORDPRO (Fletcher, 1985)

Introduced the concept of "schemas", Rule based

Domain specific solvers

- CHIPS (Briars, 1984), ARITHPRO (Dellarosa, 1986) and ROBUST (Bakman, 2007) – word problems
- CARPS i.e. Calculus Rate Problem Solver (Charniak, 1968)
- HAPPINESS (Gelb, 1971) simple probability questions

Datasets

- <u>AddSub</u> Data from Learning to Solve Arithmetic Word Problems with Verb Categorization (Hosseini et al., 2014).
- <u>SingleOp</u> Data from Reasoning About Quantities in Natural Language (Roy et al., 2015).
- <u>MultiArith</u> Data from Solving General Arithmetic Word Problems (Roy and Roth, 2015)
- <u>SingleEQ</u> Data from Parsing Algebraic Word Problems into Equations (Koncel-Kedziorski et al., 2015)
- <u>Algebra.com</u> Data from Learning to Automatically Solve Algebra Word Problems (Kushman et al., 2014).

3221 Questions are paired with equations

Koncel-Kedziorski et al. NAACL 2016, MAWPS: A Math Word Problem ₁₂₂ Repository http://lang.ee.washington.edu/MAWPS/

More Datasets

Math23K

23K math word problems from a couple of online education web sites for elementary school students

Linear algebra questions with only one variable

More Datasets

AQUA-RAT (Algebra Question Answering with Rationales)

100,000 crowdsourced algebraic word problems with natural language rationales (Ling et al. 2017)

```
Problem 1:
Question: Two trains running in opposite directions cross a
man standing on the platform in 27 seconds and 17 seconds
respectively and they cross each other in 23 seconds. The ratio
of their speeds is:
Options: A) 3/7 B) 3/2 C) 3/88 D) 3/8 E) 2/2
Rationale: Let the speeds of the two trains be x m/sec and y
m/sec respectively. Then, length of the first train = 27x meters,
and length of the second train = 17 y meters. (27x + 17y) / (x + 17y)
y = 23 \rightarrow 27x + 17y = 23x + 23y \rightarrow 4x = 6y \rightarrow x/y = 3/2.
Correct Option: B
Problem 2:
Question: From a pack of 52 cards, two cards are drawn to-
gether at random. What is the probability of both the cards
being kings?
Options: A) 2/1223 B) 1/122 C) 1/221 D) 3/1253 E) 2/153
Rationale: Let s be the sample space.
Then n(s) = 52C2 = 1326
E = event of getting 2 kings out of 4
n(E) = 4C2 = 6
P(E) = 6/1326 = 1/221
Answer is C
Correct Option: C
```

Techniques

- Template-based
 - Kushman et al., 2014
- Verb-Categorization
 - Hosseini et al., 2014
- Parsing word problems to equation trees
 - Koncel-Kedziorski et al., 2015
 - Roy et al., 2015
- Deep Learning

Learning to Automatically Solve Algebra Word Problems

Derivation 1			
Word problem	An amusement park sells 2 kinds of tickets. Tickets for children cost \$ 1.50. Adult tickets cost \$ 4. On a certain day, 278 people entered the park. On that same day the admission fees collected totaled \$ 792. How many children were admitted on that day? How many adults were admitted?		
Aligned template	$u_1^1 + u_2^1 - n_1 = 0$ $n_2 \times u_1^2 + n_3 \times u_2^2 - n_4 = 0$		
Instantiated equations	x + y - 278 = 0 1.5x + 4y - 792 = 0		
Answer	$\begin{array}{rcl} x &=& 128\\ y &=& 150 \end{array}$		
Derivation 2			
Word problem	A motorist drove 2 hours at one speed and then for 3 hours at another speed. He covered a distance of 252 kilometers. If he had traveled 4 hours at the first speed and 1 hour at the second speed, he would have covered 244 kilometers. Find two speeds?		
Aligned template	$n_1 \times u_1^1 + n_2 \times u_2^1 - n_3 = 0$ $n_4 \times u_1^2 + n_5 \times u_2^2 - n_6 = 0$		
Instantiated equations	$2x + 3y - 252 = 0 \qquad \qquad 4x + 1y - 244 = 0$		
Answer	$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$		

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Kushman et al., 2014

Learn to Solve Word Problems with Verb Categorization

- Representation:
 - State transitions



Liz gave some of her kittens to John.

Learn to Solve Word Problems with Verb Categorization

- Representation:
 - State transitions
- Learning:
 - Learn state transitions based on verb categories
- Inference:
 - Form equations based on state transitions



Representation: State Transitions

Transitions based on verb categories and containers



Give: transfer entities from one container₁ to container₂

 <u>Verb Categories</u>: Transfer or initialization of quantities in containers {Construction, destruction, positive, negative, positive transfer, negative transfer, initialization}

Algorithm: ARIS





Expression Trees



LCA(2,3) = subtraction

LCA(4,3) = subtraction

LCA(2,4) = addition

Expression Tree for **2 + 4 - 3**

Decompose word problems into simpler decision problems, where each decision problem is to predict **lowest common ancestor operation** for a pair of numbers in the problem.

Solving General Arithmetic Word Problems (Roy et al., EMNLP 2015).

Typed Equation Trees

On Monday, 375 students went on a trip to the zoo. All 7 buses were filled and 4 students had to travel in cars. How many students were in each bus?



- Semantically augmented equation trees:
 - Leaves: typed entities
 - Intermediate nodes: math operations

Units

- Units associated with quantities provide information essential to support quantitative reasoning.
- Unit Dependency Graph as a way to capture and reason about units mentioned in a problem.
- Reduces the error of math solvers by over 10%

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Unit Dependency Graph

Isabel picked 66 flowers for her friends wedding. She was making bouquets with 8 flowers in each one. If 10 of the flowers wilted before the wedding, how many bouquets could she still make?



Unit Dependency Graph

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Unit Dependency Graph



Mapping to Declarative Rules

4 Declarative Knowledge Classes



For each class, we have a few declarative rules

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Roy and Roth 2018

Deep Neural Solver

seq2seq model for transforming problem text to a math equation

Method	Math23K	Alg514
ZDC (Zhou et al., 2015 - Improved version of Kushman et al., 2014)	42.1%	79.7%
Seq2seq Model	58.1%	16.1%

Program Induction by Rationale Generation

Problem 1:

Question: Two trains running in opposite directions cross a man standing on the platform in 27 seconds and 17 seconds respectively and they cross each other in 23 seconds. The ratio of their speeds is: **Options:** A) 3/7 B) 3/2 C) 3/88 D) 3/8 E) 2/2 **Rationale**: Let the speeds of the two trains be x m/sec and y m/sec respectively. Then, length of the first train = 27x meters, and length of the second train = 17 y meters. (27x + 17y) / (x + 17y) $y = 23 \rightarrow 27x + 17y = 23x + 23y \rightarrow 4x = 6y \rightarrow x/y = 3/2.$ **Correct Option**: B **Problem 2**: Question: From a pack of 52 cards, two cards are drawn together at random. What is the probability of both the cards being kings? **Options:** A) 2/1223 B) 1/122 C) 1/221 D) 3/1253 E) 2/153 **Rationale**: Let s be the sample space. Then n(s) = 52C2 = 1326E = event of getting 2 kings out of 4n(E) = 4C2 = 6P(E) = 6/1326 = 1/221Answer is C **Correct Option**: C

Ling et al. 2017

Generation

Jim walked 0.2 of a mile from school to David's house and 0.7 of a mile from David's house to his own house. How many miles did Jim walk in all?

Star Wars

Uncle Owen walked 0.2 of a mile from hangar to Luke Skywalker's room and 0.7 of a mile from Luke Skywalker's room to his own room. How many miles did Uncle Owen walk in all?

Cartoon

Finn squished 0.2 of a mile from cupboard to Melissa's dock and 0.7 of a mile from Melissa's dock to his own dock. How many miles did Finn squish in all?

Western

Duane strolled 0.2 of a mile from barn to Madeline's camp and 0.7 of a mile from Madeline's camp to his own camp. How many miles did Duane stroll in all?

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Koncel-Kedziorski et al. 2016, A Theme-Rewriting Approach for Generating Algebra Word Problems

Generation



Koncel-Kedziorski et al. 2016, A Theme-Rewriting Approach for Generating Algebra Word Problems

Illinois, Al2 Demo

Al2 Demo: http://euclid.allenai.org/

Illinois Demo: https://cogcomp.org/page/demo_view/Math

Outline

- Machine Reading for Question Answering:
 - Reading Comprehension
 - Feature Driven Models
 - MCTest
 - Deep Learning Models
 - WikiQA
 - CNN & DailyMail
 - SQUAD
 - Etc.

Beyond Reading Comprehensions

- Elementary-level Science Exams
- Diagram QA
- Textbook QA

Mathematical Question Answering:

Advanced Math and Science Problems

- Algebra Word Problems
- Geometry Problems
- Newtonian Physics Problems

Situated Question Answering

 Situated QA requires the system to answer questions about a very large, yet, constrained environment.



As shown in the Figure, \angle MAO = 30^o and the radius of the circle with center O is 4cm. Find the value of x.



- Figure above shows three forces applied to a trunk that moves leftward by 3.00 m over a frictionless floor. The force magnitudes are $F_1 =$ 5.00N, $F_2 = 9.00$ N, and $F_3 = 3.00$ N, and the indicated angle is $\theta = 60.0^\circ$. During the displacement, what is the net work done on the trunk by the three forces?
- Situated QA poses two key challenges:
 - How to interpret the question
 - How to build background knowledge about the environment (i.e. subject knowledge) and then how to the use background knowledge to determine the answer.

Geometry QA: A Historical Perspective

Theorem Proving for geometry

- (Feigenbaum and Feldman 1963)
- Wus method (Wen-Tsun 1986)
- Grobner basis method (Kapur1986)
- Angle method (Chou et al. 1994)

Geometric analogies (Evans, 1964)

Tutoring systems:

- Geometry Expert (Gao and Lin, 2002)
- Geometry Explorer (Wilson and Fleuriot 2005)

Synthesizing geometry problems:

- Synthesize constructions given logical constraints (Gulwani et al. 2011, Itzhaky et al. 2013)
- Generate geometric proof problems (Alvin et al. 2014a)

Physics QA: A Historical Perspective

MECHO (Bundy et al. 1979)

 Mechanics problems (pulley problems, statics problems, motion on smooth complex paths and motion under constant acceleration) stated in English

ISAAC (Novak, 1976)

Read, understand, solve and draw pictures of physics problems stated in English

ALBERT (Oberem, 1987)

 A tutoring system that understands and solves physics (kinematics) problems but can teach a student how to solve them

Chang et al. (2014)

Simple vector addition, tension, and gravitation ranking problems

Klenk et al. (2005)

Physical reasoning problems by analyzing sketches



As shown in the Figure, \angle MAO = 30^o and the radius of the circle with center O is 4cm. Find the value of x.



Figure above shows three forces applied to a trunk that moves leftward by 3.00 m over a frictionless floor. The force magnitudes are $F_1 =$ 5.00N, $F_2 = 9.00$ N, and $F_3 = 3.00$ N, and the indicated angle is $\theta = 60.0^{\circ}$. During the displacement, what is the net work done on the trunk by the three forces?

Minjoon Seo, Hannaneh Hajishirzi, Ali Farhadi and Oren Etzioni. Diagram understanding in geometry questions. In AAAI 2014 Minjoon Seo, Hannaneh Hajishirzi, Ali Farhadi, Oren Etzioni and Clint Malcolm. Solving geometry problems: combining text and diagram interpretation. In EMNLP 2015

Mrinmaya Sachan, Avinava Dubey and Eric P. Xing. From Textbooks to Knowledge: A Case Study in Harvesting Axiomatic Knowledge from Textbooks to Solve Geometry Problems. *In EMNLP 2017*

Mrinmaya Sachan, Eduard Hovy and Eric P. Xing. Discourse in Multimedia: A Case Study in Information Extraction.

Mrinmaya Sachan, Eric P. Xing. Parsing to Programs: A Framework for Situated QA. In KDD 2018

Mrinmaya Sachan, Avinava Dubey, Tom Mitchell, Dan Roth and Eric P. Xing. Learning Pipelines with Limited Data and Domain Knowledge: A Study in Parsing Physics Problems. In NIPS 2018.

Mrinmaya Sachan, Minjoon Seo, Hannaneh Hajishirzi and Eric P. Xing. Parsing to Programs: A Framework for Situated Question Answering

Parsing to Programs


Formal Language



The Formal Language

A subset of typed first-order logic

Constants

- Known numbers or geometry/physics entities
 - e.g. 5 cm, 60^o, 3.00m, 5.00N

Variables

- Unknown numbers or geometry/physics entities
 - e.g. O, AB, F₁, θ

Predicates

- Geometric/Physical or arithmetic relations
 - e.g. isLine, isTriangle, isAtRest

Functions

- Properties of geometrical/physical entities
 - e.g. lengthOf, areaOf, mass, distance, force, momentum, work...150

The Formal Language

- Every element in the language has either boolean (e.g. true), numeric (e.g. 4), or entity (e.g., *line*, *circle*, *object*, *force*, *mass*, *velocity*) type.
- We refer to all symbols in the language as **concepts**.
- We use the term literal to refer to the application of a predicate to a sequence of arguments (e.g., IsTriangle(ABC)).
- Questions are represented as (Weighted) Logical formulas containing constants, variables, functions, existential quantifiers and conjunctions over literals (e.g., ∃x, IsTriangle(x) ∧ isIsosceles(x)).
 - Weight corresponds to our model's confidence in it.

Lexicon

- We built lexicon from training data and textbooks
- Lexicon maps geometry-related words (or phrases) to concepts
- Some concepts are obtained via simple regular expressions
- Single word can map to two or more concepts

Word or phrase	Concept
"Perpendicular"	Perpendicular
"Lies on"	PointLiesOnLine, PointLiesOnCircle
"CD"	line, arc
"ABC"	triangle, angle

Question Parsing



Diagram Parsing

As shown in the figure, \angle MAO = 30^o and the radius of the circle with center O is 4cm. Find the value of x.



G-Aligner - Seo et. al. 2014 Use both diagram and text

Text Parsing

GEOS - Seo et. al. 2015

- Concept Identification
 - Identify numbers and explicit variables (e.g. "5", "AB", "O") using regular expressions
- Relation Identification
 - Predict if a particular relation holds between concepts

Diagram-aided text parsing



Step 1. Literal over-generation

In triangle ABC, line DE is parallel with line AC, DB equals 4, AD is 8, and DE is 5. Find AC. (a) 9 (b) 10 (c) 12.5 (d) 15 (e) 17



Over-generated literals

IsTriangle(ABC) Parallel(AC, DE) Parallel(AC, DB) Equals(LengthOf(DB), 4) Equals(LengthOf(AD), 8) Equals(LengthOf(DE), 5) Equals(4, LengthOf(AD))

Step 1. Generating literals



Step 1. Generating literals



Concepts



Relations



Relations



IsLine(EF)

Relations



Perpendicular (AB, CD)

Step 2. Text scores of literals



Relation score



Relation classification

- Supervision: annotated logical forms
- Training data: all possible relations from training questions
 - Relations found in annotations: positive
 - All others: negative

IsLine->AB IsLine->CD IsLine->EF Perpendicular->AB, CD Perpendicular->CD, EF Perpendicular->AB, EF

- Logistic regression with L2 regularization
- Features:
 - Stanford dependency parse
 - Part of speech tags
 - Type of concept (line, circle, triangle, predicate, etc.)

Text scores of literals



 $\mathcal{A}_{text}(l) = \sum \log P_{\theta}(y_i = 1 | r_i, t)$

- *l* Literal
- y_i Label for edge
- r_i Edge (relation)
- t Question text

θ Logistic
 regression
 parameters to be
 learned

Step 3. Diagram scores of literals



Step 3. Diagram scores of literals



Step 3. Diagram scores of literals



Step 4. Subset selection



Step 4. Subset selection



...

 $L^* = \operatorname*{argmax}_{L' \subset L} \mathcal{F}(L')$

Optimization algorithm

$$L^* = \operatorname*{argmax}_{L' \subset L} \mathcal{F}(L')$$

Bad news: combinatorial optimization is NP-hard **Good news**: objective function is *submodular*

Greedy algorithm efficiently finds a solution with bounded distance to the optimum.

Starting from empty set, greedily add the next best literal to the set.

$$l_{j} = \underset{l_{j} \in L \setminus L'}{\operatorname{argmax}} \mathcal{F}(L' \cup \{l_{j}\}) - \mathcal{F}(L')$$

Solver



Programmatic Solving: Numerical solver

Translate literals to numeric equations

Literal	Equation
Equals(LengthOf(AB),d)	$(A_x-B_x)^2+(A_y-B_y)^2-d^2=0$
Parallel(AB, CD)	$(A_x-B_x)(C_y-D_y)-(A_y-B_y)(C_x-D_x) = 0$
PointLiesOnLine(B, AC)	$(A_x-B_x)(B_y-C_y)-(A_y-B_y)(B_x-C_x) = 0$
Perpendicular(AB,CD)	$(A_x-B_x)(C_x-D_x)+(A_y-B_y)(C_y-D_y) = 0$

- Find the solution to the equation system
- Use off-the-shelf numerical minimizers (Wales and Doye, 1997; Kraft, 1988)
- Numerical solver can choose <u>not</u> to answer question

Dataset

- Training questions (67 questions, 121 sentences)
 - Seo et al., 2014
 - High school geometry questions
- Test questions (119 questions, 215 sentences)
 - We collected them
 - SAT (US college entrance exam) geometry questions
- Manually annotated the text parse of all questions
- Dataset is publicly available at: geometry.allenai.org

Results



*** 0.25 penalty for incorrect answer

Results



*** 0.25 penalty for incorrect answer

Demo (geometry.allenai.org/demo)



In the figure to the left, triangle ABC is inscribed in the circle with center O and diameter AC. If AB=AO, what is the degree measure of angle ABO?



But some are really hard



Requires complex reasoning: Cannot understand that the polygon is "hidden"

In the figure at the left, a shaded polygon which has equal angles is partially covered with a sheet of blank paper. If x+y=80, how many sides does the polygon have?

(a) 10 (b) 9 (c) 8 (d) 7 (e) 6

Domain Knowledge



Domain Knowledge

Axiom	Premise	Conclusion
Midpoint Definition	midpoint(M, AB)	length(AM) = length(MB)
Angle Addition	interior(D, ABC)	angle(ABC) = angle(ABD) + angle(DBC)
Supplementary Angles	perpendicular(AB,CD) \land liesOn(C,AB)	$angle(ACD) + angle(DCB) = 180^{\circ}$
Vertically Opp. Angles	intersectAt(AB, CD, M)	angle(AMC) = angle(BMD)
	$length(AB) = length(DE) \land$	
SSS Congruence	$length(BC) = length(EF) \land$	congruent(ABC, DEF)
	length(CA) = length(FD)	

May be curated by a domain expert or extracted from textbooks

Axiomatic Solver

Datastructure

sort point = {A, B, C, D, O, M}
sort line = {AB, BC, CA, BD, DA, OA, OM}
sort angle = {ABC, BCA, CAB, ABD, BDA, DAB, AMO, MOA, OAM, BMO}
sort triangle = {ABC, ABD, AMO}
sort circle = {O}

183 *ProbLog: A probabilistic Prolog,* De Raedt et al. IJCAI'07

Where do Axioms come from?

From textbooks to Knowledge

Sachan et. al. 2017

Key Ideas

- Leverage the redundancy and shared ordering across multiple textbooks to harvest axioms.
- Use rich contextual and typographical features extracted from textbooks

Theorem 8.4 Pythagorean Theorem



isTriangle(ABC) ^ measure(ACB, 90) => BC² + AC² = AB²
3 stage procedure

- Joint Axiom Identification and Alignment
- Axiom Parsing into horn clause rules
- Horn clause resolver

3 stage procedure

- Joint Axiom Identification and Alignment
- Axiom Parsing into horn clause rules
- Horn clause resolver

Joint Axiom Identification and Alignment



Joint model for Axiom Identification and Alignment





- EM where we use a Constrained Metropolis Hastings sampler in the E step.
 - Sample Y and Z alternatively
 - For better mixing, we sample Y in blocks

3 stage procedure

- Joint Axiom Identification and Alignment
- Axiom Parsing into horn clause rules
- Horn clause resolver

Base Axiomatic Parser



 $L_p => L_c$

3 stage procedure

- Joint Axiom Identification and Alignment
- Axiom Parsing into horn clause rules
- Horn clause resolver

Horn Clause Resolver



Beam of horn clause parses sorted by parse score for each axiom

Majority Voting Average Score Learn Source Confidence Predicate Scoring ¹⁹³

Dataset for Harvesting Axioms

- Collection of grade 6-10 high school math textbooks by four publishers (20 textbooks) to train our axiom extraction model.
- We manually annotated geometry axioms, alignments and parses
 - We use grade 6, 7 and 8 textbook annotations for development, training, and testing, respectively.

Results

	Textbook	Practice	Official
Avg. Student	44	58	53
Numerical Solver	32	61	49
Axiomatic Solver	51	64	55

Demo

http://www.cs.cmu.edu/~mrinmays/demo/

eometry.allenal.org/demo/	v C Search	•	Â	ø	≡
GeoS Demo – An End to End Geometry Problem Solver		A	12		

In the figure to the left, triangle ABC is inscribed in the circle with center O and diameter AC. If AB=AO, what is the degree measure of angle ABO?



Newtonian Physics Problems



Figure above shows three forces applied to a trunk that moves leftward by 3.00 m over a frictionless floor. The force magnitudes are $F_1 =$ 5.00N, $F_2 = 9.00$ N, and $F_3 = 3.00$ N, and the indicated angle is $\theta = 60.0^{\circ}$. During the displacement, what is the net work done on the trunk by the three forces?



Domain Knowledge as Rules

eometry	Polygon: A geometric shape consisting of a number of points and an equal number of line segments, namely a cyclically ordered set of points where no three successive points are collinear and line segments join consecutive pairs of the points. Circle, Centre: A set of points that are equidistant from a given point. The point is called the centre. Tangent, Secant: Tangent is a line that touches the circle at ex-	$ \land $	
G	actly one point. Secant is a line that intersects the circle in two distinct points.	\wedge	
	Arrow: The central (stem) line is the longest of the three lines, the two arrowhead lines are roughly of the same length, and the two angles subtended by the arrowhead lines with the arrow	Ð	
	Dotted line : The various lines should be in a straight line, roughly the same sized lines and equi-spaced		
ysics	allel lines which subtend roughly the same angle with it, their end-point lies on the solid line and the smaller lines are on the same side with respect to the solid line		
Phi	Coordinate System : Three arrows where the arrow tails are in- cident on the same point. Two lines are mutually perpendicular (i.e. angle= 90°) and the third roughly bisects the complemen- tary (270°) angle		
	Block: Four lines which form a rectangle Wedge: Three lines which form a triangle		
	Pulley: A circle with two lines tangent to it. An end-point of the two lines lies on the circle		199

Domain Knowledge as Rules

Arrow: The central (stem) line is the longest of the three lines, the two arrowhead lines are roughly of the same length, and the two angles subtended by the arrowhead lines with the arrow stem line must be roughly equal

$$\begin{split} C_1 &= isLine(line1) \wedge isLine(line2) \wedge isLine(line3) \\ C_2 &= length(line1) > length(line2) \wedge length(line1) > length(line3) \quad \text{ i.e. line1 is stem} \\ C_3 &= roughly_equal(angle(line1, line2), angle(line1, line3)) \\ C_1 \wedge C_2 \wedge C_3 \rightarrow H_{line} \end{split}$$

Sachan et al. 2018

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Domain Theory as Programs

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] return Constraint(m1*v1_initial+m2*v2_initial = m1*v1_final+m2*v2_final)

Datasets

- Newtonian Physics questions taken from popular pre-university physics textbooks and few AP Physics C: Mechanics courses.
 - Training set: Questions taken from three popular pre-university physics textbooks: *Resnick Halliday Walker, D. B. Singh* and *NCERT*.
 - Millions of students in India study physics from these books every year and these books are available online.
- > 4941 questions (1019 w/ associated diagrams)
 - 1000 training, 500 development and 3441 test questions.
- We annotated ground truth logical forms for the training and dev question texts and diagrams.
- Evaluated datasets: Section 1 of three AP Physics C Mechanics tests:
 - > AP Physics C Mechanics practice test 10 questions
 - > AP Physics C Mechanics official tests (1998) 75 questions
 - > AP Physics C Mechanics official tests (2012) 35 questions

Results

	Textbook	Practice	1998	2012
Avg. Student	63	52	44	48
P2P	68	50	42	54

Conclusion and Takeaways

- Standardized tests can serve as drivers for AI.
 - They can provide us with interesting challenges that can help us make progress towards the general goals of linguistic and visual understanding and reasoning.
 - Issues with this: adversarial examples, interpretability, ...
- (Domain/Background) Knowledge, Common Sense and Reasoning are important
 - Non-Symbolic Methods (e.g. Deep Learning) + Symbolic Methods

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