	Math Understanding	Math Retrieval	Future Work	The End

The MCAT Math Retrieval System for NTCIR-10 Math Track

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Introd	luction
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Introduction

Introduction

Introduction

Unneccessary

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Math Ur	nderstanding			
Objective				
Extract des	criptions of math exp	ressions from the	text	

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Math	Understanding			

Extract descriptions of math expressions from the text

Assumption

Descriptions are noun phrases in the same sentence as the math expression

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Method

Identify noun phrases using Stanford parser Train a linear-kernel SVM classifier for (math, description) pairs

SVM Features

Apposition?	set IN
Colon?	set: IN
Comma?	set, IN
Intervening expression?	set A IN
Parenthetical?	N (set)
Word distance	set (4 words) IN
After description?	set $\mathbb N$
2-word description context	in/IN the/DT set/NN ℕ/MATH of/IN
3-word expression context	in/IN the/DT set/NN IN/MATH of/IN natural/JJ numbers/NNS
First word of description	set/NN
Last word of description	set/NN
Unigrams	in/IN, the/DT, set/NN, $\mathbbm{N}/\text{MATH},$ of/IN, natural/JJ, numbers/NNS
Bigrams	in/IN the/DT, the/DT set/NN, set/NN \mathbbm{N}/\mbox{MATH} , \mathbbm{N}/\mbox{MATH} of/IN
Trigrams	in/IN the/DT set/NN, set/NN IN/MATH of/IN
First intervening verb	set \ldots shows \ldots $\mathbb N$

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Experiment	t			
Deceline				
Baseline				
Noun phrase in	n apposition to the	mathematical exp	ression	

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Experiment

Baseline

Noun phrase in apposition to the mathematical expression

Runs

Full descriptions, all features Full descriptions, without apposition feature Short descriptions, all features Short descriptions, without apposition feature

Results

Run	Р	R	F-1
Strict Matching	Evaluatio	n	
full, baseline	43.10	23.85	30.96
MCAT: full, all features	61.94	37.03	46.35
MCAT: full, no apposition	61.92	37.33	46.58
short, baseline	55.35	29.94	38.86
MCAT: short, all features	68.24	40.42	50.77
MCAT: short, no apposition	67.67	40.22	50.45
Soft Matching E	valuation		
full, baseline	64.21	34.73	45.08
MCAT: full, all features	85.48	47.41	61.24
MCAT: full, no apposition	87.25	48.30	62.18
short, baseline	64.21	34.73	45.08
MCAT: short, all features	81.68	42.81	56.18
MCAT: short, no apposition	81.24	42.61	55.90

Math Understanding Conclusions

Conclusions

Apposition feature slightly harms full description extraction (because of discontinuous descriptions), but helps short description extraction (since they mostly are appositions) Unsurprisingly, soft matching works better on full descriptions than on short descriptions (larger text region: more chances of overlap) In strict matching runs, 64% of full and 75% of short descriptions appear as noun phrases.

In soft matching runs, 89% of full and 87% of short descriptions appear as noun phrases.

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Math	Retrieval			

Provide a search system for mathematical expressions

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Requirements

Flexibility: focus on recall (sacrifice precision) Encode structure as well as tokens Allow full-text search on descriptions

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Provide a search system for mathematical expressions

Requirements

Flexibility: focus on recall (sacrifice precision) Encode structure as well as tokens Allow full-text search on descriptions

Engine

Starting with full-text search requirement, we selected Apache Solr (Lucene) for our database.

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Indexing				
Papers				
Papers are pla fields for <mark>titles</mark>	ced in a separate and <mark>abstracts</mark> , ar	index, with full-to nd general fields f	ext, language-dep or <mark>authors</mark> .	endent

Indexing

Papers

Papers are placed in a separate index, with full-text, language-dependent fields for titles and abstracts, and general fields for authors.

Expressions

Expression descriptions are indexed as full-text, language-dependent fields. Expression MathML structure is encoded into three whitespace-separated, multivalued fields: ordered paths, unordered paths and sisters.

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A Note on Descriptions

Due to time constraints, we did not use the extracted descriptions, but used a fixed 10-word context instead.

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Key Fields

(Additionally, there are various primary and foreign keys.)

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Expression	Indexing			

Ordered Paths

Encode all vertical paths to the leaves, including the left-to-right position of each node (Equivalently, encode all vertical paths from root to leaves, repeat recursively for each non-trivial subtree)

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Unordered Paths

Same, but without the position information

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Same, but without the position information

Sisters

Collection of sister nodes in the same subtree

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Example	e Encoding			

Expression

the polynomial $\sum_{i=1}^{n} a_i x^i$

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Example	Encoding			

Expression

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MathML Tree mrow mo msubsup msub Σ mi mo mi mi Σ mi mo mi mi mi i i i i i i i i i i i i i i i

Example opaths

1#2#2#mo#=

Example Encoding

Encoding

```
opaths: 1#msubsup 1#1#mo#Σ 1#2#1#mi#i 1#2#2#mo#= 1#2#3#mn#1
    1#3#mi#n 2#msub 2#1#mi#a 2#2#mi#i
opaths: msubsup 1#mo#∑ 2#1#mi#i 2#2#mo#= 2#3#mn#1 3#mi#n
opaths: 1#mi#i 2#mo#= 3#mn#1
opaths: msub 1#mi#a 2#mi#i
upaths: #msubsup ##mo#∑ ###mi#i ###mo#= ###mn#1 ##mi#n #msub
    ##mi#a ##mi#i
upaths: msubsup #mo#Σ ##mi#i ##mo#= ##mn#1 #mi#n
upaths: #mi#i #mo#= #mn#1
upaths: msub #mi#a #mi#i
sisters: mi#i mo#= mn#1
sisters: mo\#\Sigma mi#n
sisters: mi#a mi#i
sisters: msubsup msub
sisters: msubsup msub
description_en: the polynomial (indexed as: polynomi)
```

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Querying				

Querying

Encode the query MathML and description (whichever is provided) in the

same way

Perform a disjunctive query on Lucene

Lucene scores matching terms, modified by tf/idf and length normalization

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Document Queries

Document queries (with author, title or abstract terms) are done using a Lucene join query.

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Jokers

Jokers implemented by simply leaving off the term from the query. Alternately, due to the flexibility of the encoding, a single wrong leaf will only slightly penalize the score, not reject the result.

Results

	P-10	P-5	MAP	Pre-
	avg	avg	avg	cision
	Formu	la Search		
Relevant	0.229	0.219	0.162	0.065
Partially	0 500	0.476	0 370	0.220
Relevant	0.500	0.470	0.579	0.220
	Fullte	kt Search		
Relevant	0.293	0.320	0.297	0.103
Partially	0 660	0.680	0 534	0 300
Relevant	0.000	0.000	0.554	0.309

Introduction

Math Retrieval

Math Retrieval Conclusions

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The current approach achieves satisfactory recall (for the first effort). Precision is low, as there is no clear cutoff where the results stop being relevant.

Term-based search somewhat mitigates inconsistencies in representation.

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Overall Conclusion

The approach, although simple, seems fruitful, and we intend to continue refining it.

Future Work

Future Work

- Normalization of commonly interchangeable MathML elements.
- Usage of Content MathML instead of Presentation MathML.
- Giving more weight to operators and structure.
- Implementation of common subexpression unification rules, which would additionally penalize the results where the instances of the same subexpression are replaced by different subexpressions.
- Restriction of the number of disjunct terms, since their number adversely impacts search times.
- Usage of actual *pq*-grams.
- Usage of extracted descriptions.
- Post-search reordering of top results using a more precise similarity measure.
- Extraction of more advanced features for the math understanding subtask, such as information from dependency trees.

Introduction



Thank you for your attention