Joint word embeddings & soft cosine measure at ARQMath

Math StackExchange *singing and dancing* ♫

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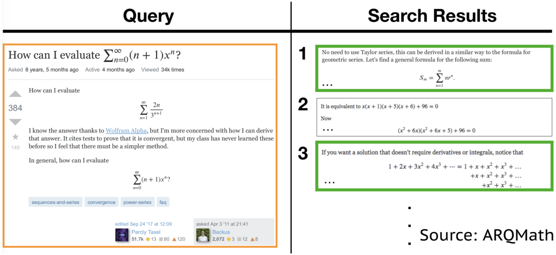
Introduction

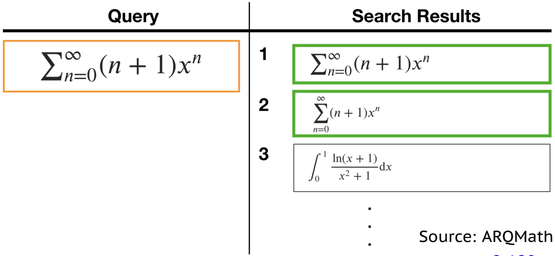
Answer Retrieval for Questions on Math (ARQMath) is a competition aimed at building a math-aware search engine for **Math StackExchange**. ARQMath consists of two tasks:

Task 1: Find Answers Given a posted question as a query, search all answer posts and return relevant answers.



Source: ARQMath

Task 2: Formula Search Given a formula from a question as a query, search all question and answer posts for relevant formulae.



Source: ARQMath

Challenges

Compared to standard question answering and similarity search tasks, task 2 requires a representation of mathematical formulae, and task 1 requires a representation of mathematical documents that contain both text and mathematical formulae.

Source: formula1.com

Our search engines

The **Math Information Retrieval (MIR-MU)** research group has prepared several mathematical search engines that will compete in ARQMath:

CompuBERT (task 1) Search engine with a BERT-based [1] representation of both text and LaTeX mathematical formulae (preprocessed with the WordPiece tokenizer [2]). English BERT model is fine-tuned by learning to rank Math StackExchange answers by number of votes.

Joint Word Embeddings & Soft Cosine Measure (SCM) (tasks 1 and 2) Search engine with a tf-idf soft vector space model (VSM) [3, 4] representation of both text and mathematical formulae. Various representations of mathematics are used.

Formula2Vec (tasks 1 and 2) Same as above, but with Doc2Vec [5] representation.

Math Indexer and Searcher (MIaS) (tasks 1 and 2) Search engine with a tf-idf VSM representation of both text and MathML mathematical formulae. Deployed in the **European Digital Mathematical Library (EuDML)** since 2013. Entered three competitions during 2013–2016, earning medal-winning results. [6]

Representations of mathematics

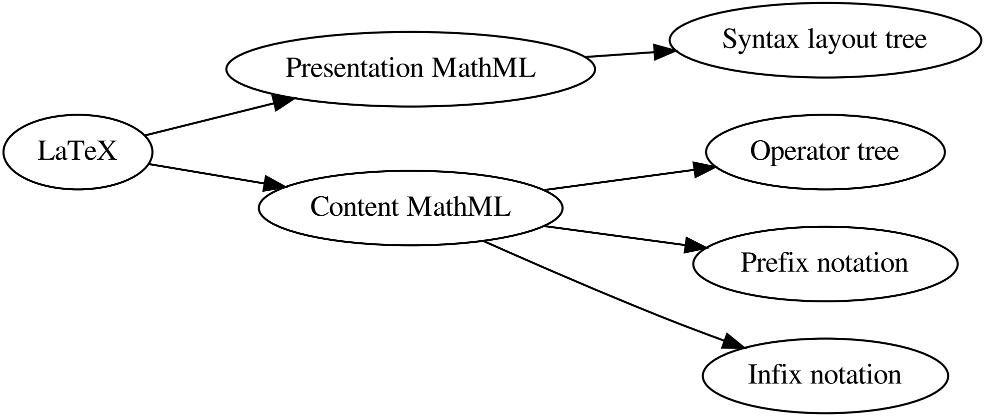


Figure: Preprocessing of input LaTeX mathematical formulae into output representations

LaTeX

Math StackExchange questions, answers, and comments are provided in the same format in which the users type them, in LaTeX:

LaTeX representation of formula $x!! - y^2 = 0$

```
$x!!-y^2=0$
```

LaTeX representation is easy to type, but it is purely syntactic. Since LaTeX is Turing-complete, static tokenization is difficult with complex LaTeX commands.

MathML

Presentation MathML (PMML)

Using LaTeXML [7] and MathML Canonicalizer [8], mathematical formulae in LaTeX are converted to the MathML 3.0 [9] XML language:

PMML representation of formula $x!! - y^2 = 0$

```
<mrow>
  <mi>x</mi><mo>!!</mo>
  <msup>
    <mi>y</mi><mn>2</mn>
  </msup>
  <mo>=</mo><mn>0</mn>
</mrow>
```

Presentation MathML is still purely syntactic, but it solves tokenization of LaTeX.

MathML

Content MathML (CMML)

CMML representation of formula $x!! - y^2 = 0$

```
<apply><eq/><apply><minus/>
  <apply><csymbol cd="latexml">double-factorial</csymbol>
    <ci>x</ci></apply>
  <apply><csymbol cd="ambiguous">superscript</csymbol>
    <ci>y</ci><cn type="integer">2</cn></apply>
</apply><cn type="integer">0</cn></apply>
```

Content MathML is no longer purely syntactic. It is independent on the presentation aspects of the formula and encodes semantically equivalent formulae the same.

Syntax layout tree (SLT)

From PMML, we extract a syntax layout tree (SLT) typed representation [10]:

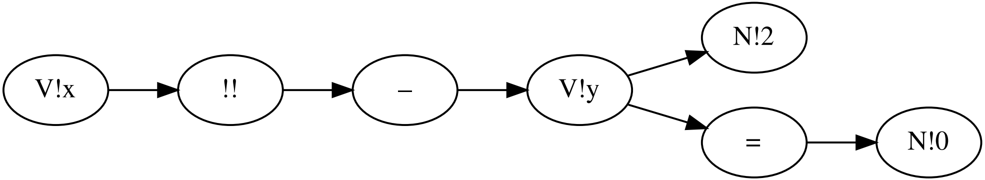


Figure: SLT representation of formula $x!! - y^2 = 0$

In our system, we tokenize the SLT into paths in depth-first-search order:

Tokenized SLT representation of formula $x!! - y^2 = 0$

```
V!x !! n -, V!x - nn -, !! - n n, !! V!y nn n, - V!y n nn,
- N!2 na nn, - = nn nn, V!y N!2 a nnn, N!2 0! n nnna,
V!y = n nnn, V!y N!0 nn nnn, = N!0 n nnnn, N!0 0! n nnnnn
```

Operator tree (OPT)

From CMML, we extract an operator tree (OPT) typed representation [10]:

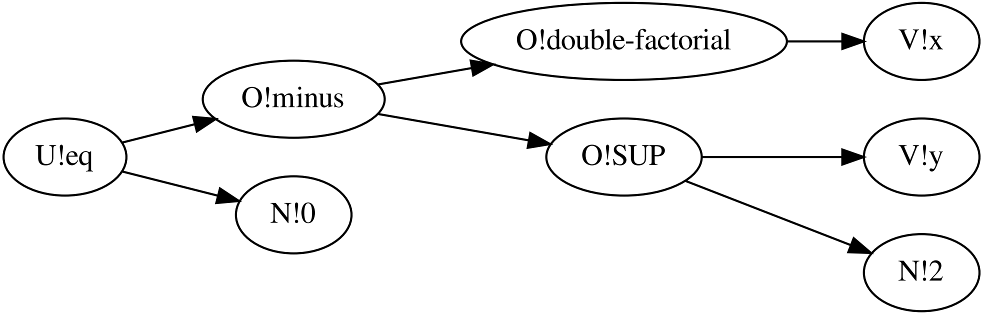


Figure: OPT representation of formula $x!! - y^2 = 0$

Operator tree (OPT)

Tokenization into paths

In our system, we tokenize the OPT into paths in depth-first-search order:

Tokenized OPT representation of formula $x!! - y^2 = 0$

```
U!eq O!minus 0 -, U!eq O!SUP 01 -,
U!eq O!double-factorial 00 -, O!minus O!double-factorial 0 0,
O!minus V!x 00 0, !double-factorial V!x 0 00, V!x 0! 0 000,
O!minus O!SUP 1 0, O!minus N!2 11 0, O!minus V!y 10 0,
O!SUP V!y 0 01, V!y 0! 0 010, O!SUP N!2 1 01, N!2 0! 0 011,
U!eq N!0 0 -, N!0 0! 0 0
```

Operator tree (OPT)

Tokenization into prefix (Polish) and infix notation

In our system, we also tokenize the OPT into visited nodes in depth-first-search order (also known as topological sort, prefix notation, or Polish notation):

Tokenized OPT representation of formula $x!! - y^2 = 0$

```
U!eq O!minus O!double-factorial V!x O!SUP V!y N!2 N!0
```

By parenthesizing and recognizing infix operators, we also tokenize into infix notation:

Tokenized OPT representation of formula $x!! - y^2 = 0$

```
((O!double-factorial(V!x) O!minus O!SUP(V!y, N!2)) U!eq N!0)
```

The infix notation is the closest to the LaTeX representation. When used in a search engine with a tf-idf vector space model (VSM) representation of mathematical formulae, prefix and infix notations are equivalent.

Tf-idf vector space model (VSM)

In our system, we use a tf-idf soft vector space model (VSM) for the representation of both text and mathematical formulae. We use the following representations of mathematical formulae:

- SLT tokenized into paths in depth-first-search order,
- OPT tokenized into paths in depth-first-search order, and
- OPT tokenized into nodes in prefix notation.

Tokens from several representations of mathematical formulae can be combined, and previous work shows the usefulness of this approach [10]. The best combination of representations will be selected by parameter optimization.

Soft cosine measure (SCM)

Whereas the VSM and the cosine similarity measure only take matching tokens into account when retrieving documents, we use the soft VSM with the soft cosine measure (SCM) [11, 3, 4, 12, 13, 14, 15], which also take the similarity of tokens into account, solving the issue of synonymy. We use the following sources of similarity between textual and mathematical tokens:

- a FastText model [16] trained jointly on text and mathematical formulae, and
- a linear combination of token similarities produced by two FastText models, one trained on text and the other trained on mathematical formulae.

The best source of token similarity and FastText parameters will be selected by parameter optimization.

Conclusion

The **MIR-MU** research group will compete in the **ARQMath** competition using four math-aware search engines. In this talk, we discussed system design and the representations of mathematical formulae used by the search engines. Hopefully, we will make **Math StackExchange** sing and dance. Fingers crossed!

Source: formula1.com

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