MATHWRITING: A DATASET FOR HANDWRITTEN MATHEMATICAL EXPRESSION RECOGNITION

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March 2024

We introduce MathWriting, the largest online handwritten mathematical expression dataset to date. It consists of **230k** human-written samples and an additional **400k** synthetic ones. MathWriting can also be used for offline HME recognition and is larger than all existing offline HME datasets like IM2LATEX-100K [6]. We introduce a benchmark based on MathWriting data in order to advance research on both online and offline HME recognition.

$$\left[\sqrt{\frac{2}{\pi}} \cos\left(ut\right)\right] = \left[A = \begin{pmatrix} 2 & 1 \\ -1 & 0 \end{pmatrix}\right] = \left[\frac{\partial y}{\partial t} + A \frac{\partial y}{\partial x} = 0\right]$$

Three examples of HME from MathWriting. More examples can be found in appendix D.

Partial dataset (1.5 MB):

https://storage.googleapis.com/mathwriting_data/mathwriting-2024-excerpt.tgz
Full dataset (2.9 GB):

https://storage.googleapis.com/mathwriting_data/mathwriting-2024.tgz
Associated code:

https://github.com/google-research/google-research/tree/master/mathwriting

1 Introduction

Online *text* recognition models have improved a lot in the past few years, because of improvements in model structure and also because of bigger datasets. Mathematical expression (**ME**) recognition is a more complex task that has not received as much attention. However, the problem is different from text recognition in a number of interesting ways which can prevent improvements on one transfering to the other. Though MEs share with text most of their symbols, they follow a more rigid structure which is also two-dimensional. Where text can be treated to some extent as a one-dimensional problem amenable to sequence modeling, MEs cannot, because the relative position of symbols in space is meaningful. It is not just a segmentation problem either because the output of a recognizer has to contain the relationship between symbols, serialized in some form (LATEX, a graph, InkML, etc.). Similarly to the case of text, *handwritten* MEs (**HME**) are more difficult to recognize than *printed* ones because they are more ambiguous, and for several other reasons that we elaborate on below.

In terms of data, handwritten samples are costly to obtain because they have to be written by human beings, which is compounded in the case of online representation (**ink**) by the necessity to use dedicated hardware (touchscreen, digital pen, etc.). By publishing the MathWriting dataset, we hope to alleviate some of the need for data for research purposes.

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Samples include a large number of human-written inks, as well as synthetic ones. MathWriting can readily be used with other online datasets like CROHME [16] or Detexify [2] - we publish the data in InkML format to facilitate this. It can also be used for offline ME recognition simply by rasterizing the inks, using code provided on the Github page³.

MathWriting is to the best of the authors' knowledge the largest set of online HME published so far - both humanwritten and synthetic. It significantly expands the set of symbols covered by CROHME [16], enabling more sophisticated recognition capabilities. Since inks can be rasterized, MathWriting can also been seen as larger than existing offline HME datasets [6, 17, 1]. For these reasons we introduce a new benchmark, applicable to both online and offline ME recognition.

This work's main contributions are:

- a large dataset of HME
- ground truth expressions in normalized form to simplify training and to make evaluation more robust
- a new benchmark based on the dataset, with several baselines.

The present paper focuses on the high-level description of the dataset: creation process, postprocessing, train/test split, ground truth normalization, statistics, and a general discussion of the dataset content to help practitioners understand what can and cannot be achieved with it. All the low-level technical information like file formats can be found in the readme.md file present at the root of the dataset archive linked above. We also provide code examples on Github³, to show how to read the various files, process and rasterize the inks, and tokenize the LaTeX ground truth.

2 Benchmark

2.1 Dataset Overview

MathWriting contains online HMEs, that is sequences of touch points (coordinates) obtained from a touch screen or digital pen:

- 253k human-written expressions, with three splits: train, valid, test (respectively 230k, 15k, and 7k samples.). See section 3.3
- 6k human-written isolated symbols, extracted from samples from the train split above
- 396k synthetic expressions, obtained by stitching together isolated symbols in bounding boxes obtained using the LATEX compiler. See Section 3.4.

MathWriting covers 244 mathematical symbols plus 10 syntactic tokens that are described in Appendix C, and a large variety of structures, including matrices. All samples have a label in normalized LATEX notation to be used as ground truth (Section 4). The raw (un-normalized) LATEX labels are also provided (see figure 1 for an example). No symbol-level segmentation information is provided. LATEX labels come predominantly from Wikipedia with the exception of a small fraction that were generated with code (Section 3.5).

MathWriting has been placed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International⁴.

2.2 Benchmark Definition

We propose the benchmark based on the MathWriting dataset that evaluates the quality of handwriting math expression recognition. This benchmark includes two major parts:

- evaluation samples: the test split of MathWriting.
- metric: character error rate (CER) [11], where a "character" is a LATEX token as defined by the code in Appendix B.

We provide a reference implementation of the evaluation metric at the Github page ³. We propose the use of CER as a metric to make results comparable to other recognition tasks like text recognition [4]. The use of L^{ATEX} tokens instead of unicode characters means that errors on a single non-latin letter (e.g. \alpha instead of a) will be counted as a single error instead of multiple.

³https://github.com/google-research/google-research/tree/master/mathwriting

⁴https://creativecommons.org/licenses/by-nc-sa/4.0/



Figure 1: An example from the train split, with its labels: Raw: f(x)=\frac1e\cdot \sum_{n=0}^{\infty}{n^{x}\over n!} Normalized: f(x)=\frac{1}{e}\cdot\sum_{n=0}^{\infty}\frac{n^{x}}{n!}

2.3 Baseline Recognition Models

In Table 1 we provide results for different models on the MathWriting benchmark. All models are trained exclusively on the MathWriting dataset apart from the OCR API that was trained on the mixture of tasks. The following models were picked based on most popular approaches in handwriting recognition.

CTC Transformer This model is encoder-only with a Connectionist Temporal Classification loss (**CTC**) [9]. We trained from scratch and exclusively on MathWriting a model similar to [4], replacing LSTM layers by Transformer layers. It contains 11 layers with an embedding size of 512. More details about this baseline are provided in Appendix D of [7].

OCR This is Google's publicly available Document AI OCR API [8], which processes bitmap images. It has been trained partly on samples from MathWriting. We sent inks rendered with black ink on a white background and searched for optimal image size and stroke width to get the best evaluation result from the model.

VLM We fine-tuned a large Vision-Language Model PaLI [5] on MathWriting dataset. It receives as input both the ink as a sequence (like CTC Transformer) and its rasterized version (like OCR). Results come from [7].

Table 1: Recognition results for different models. The evaluation metric is reported on both the valid and test splits.

Model	Input	Parameters	CER on valid	CER on test
OCR [8]	Image	-	6.50	7.17
CTC Transformer [7]	Ink	35M	4.41	5.56
PaLI [7]	Image+Ink	700M	4.47	5.95

Table 1 shows the evaluation comparison between the four models. The OCR model has no information about the order of writing and speed (offline recognition), which explains its lower performance than methods that take time information into account (online recognition). The two other methods – PaLI and CTC Transformer perform significantly better than OCR. These results show that our dataset can be used to train classical recognition models like CTC transformer as well as more recent architectures like VLM.

Figure 2 shows examples of mistakes that models make. Two of the main causes of mistakes are mixing up similar looking characters like "z" and "2", and incorrectly nesting a subexpression like not placing it in a subscript or superscript.

3 Dataset Creation Process

3.1 Ink Collection

Inks were obtained from human contributors through an in-house Android app. The task consisted in copying a rendered mathematical expression (prompt) shown on the device's screen using either a digital pen or a finger on a touch screen. Mathematical expressions used as prompt were first obtained in LATEX format, then rendered into a bitmap through the LATEX compiler (see Appendix A for the template used). 95% of MathWriting expressions were



Figure 2: Examples of recognition mistakes from CTC Transformer model. We observe similar mistakes from other models.

obtained from Wikipedia. The remaining ones were generated to cover underrepresented cases in Wikipedia, like isolated letters with nested sub/superscripts or complicated fractions (see Section 3.5).

Contributors were hired internally at Google. 6 collection campaigns were run between 2016 and 2019, each lasting between 2 to 3 weeks.

3.2 Postprocessing

We applied no postprocessing to the collected inks other than dropping entirely those that were completely unreadable or had stray marks. Inks are provided in their original form, as they were recorded with the collection app. What we *did not do* was to discard samples that were very hard to read or ambiguous, because we believe this type of sample to be essential in training a high-quality model.

Some cleanup was performed on the labels (ground truths). The goal was to make the dataset better suited to training an ML model, and eliminate unavoidable issues that occurred during the collection. After training some initial models, we manually reviewed samples for which they performed poorly. This helped identify a lot of unusable inks (nearblank, lots of stray strokes, scribbles, etc.), and a lot of ink/label discrepancies. A fairly common occurrence was a contributor forgetting to copy part of the prompted expression. We adjusted the label to what was actually written unless the ink contained a partially-drawn symbol, in which case we discarded the sample entirely. In this process we eliminated or fixed around 20k samples.

The most important postprocessing step was to normalize the labels: there are many different ways to write a mathematical expression in LATEX format that will render to images that are equivalent in handwritten form. We applied a series of transformations to eliminate as many variations as possible while retaining the same semantic. This greatly improved the performance of models and made their evaluation more precise. We publish both the normalized and raw (unnormalized) labels, to enable people to experiment with other normalization procedures.

This normalization is similar to what [6] did, but pushed further because of the specifics of handwritten MEs. See Section 4 for more detail.

3.3 Dataset Split

MathWriting is composed of five different sets of samples, which we call 'splits': train, valid, test, symbols, and synthetic.

The valid and test splits are the result of multiple operations performed between 2016 and 2019. The first split operation, performed on the data available in 2016, was based on the contributor id: any given contributor's samples would not appear in more than one split (either train, valid, test). This is common practice for handwriting recognition systems, to test how the recognizer performs on unseen handwriting styles.

Experiments then showed that a more important factor than the handwriting style was whether the *label* had already been seen during training. Subsequent data collection campaigns focused on increasing label variety, and new samples were added to valid and test, this time split by label: a given normalized mathematical expression would not appear in more than one split. In the published version, valid has a 55% (8.5k samples) intersection with train based on unique normalized labels, and test has an 8% intersection (647 samples). We chose to have a low intersection between train and test in order to correctly measure generalization of trained models to unseen labels.

3.4 Synthetic Samples and Isolated Symbols

In order to further increase the label diversity used in training we created synthetic samples. This also enabled compensating for another limitation of the human collection which was the limited length of expressions - because of the screen size. We used LATEX expressions from Wikipedia that were not present in the data collection, with a 90 percentile of expression length in characters of 68 characters, compared to 51 in train. This is especially important as deep neural nets often fail to generalize to inputs longer than their training data [3, 14]. Using synthetic long inks together with the original human-written inks successfully eliminated that problem [13].

The synthesis technique is as follows: starting from a raw LATEX mathematical expression, we computed a DVI file using the LATEX compiler, from which we extracted bounding boxes. We then used those bounding boxes to place handwritten individual symbols, resulting in a complete expression. See Figure 3 for an example of extracted bounding boxes and the resulting synthetic example.



Figure 3: example of a synthetic ink created from bounding boxes with label ((p+q)+(p-q))/2=q

Inks for those individual symbols are all from the symbols split. They have been manually extracted from inks in train. For each symbol we wanted to support we manually selected strokes corresponding to this symbol for 20-30 distinct occurrences in train, and used that information to generate a set of individual symbols.

A significant difference between synthetic and human-written inks is the stroke order. For synthetic inks, stroke order follows the order of the bounding boxes in the DVI file, which can be different from the usual order of writing for mathematical expressions. However, the writing order within a given symbol is consistent with human writing.

Similar synthesis techniques have been used by [16] with inks, [6] and [1] with raster images.

3.5 Acquisition of LATEX Expressions

The labels we publish mostly come from Wikipedia (95% of all samples have labels from Wikipedia). A small part were generated, to cover deeply nested fractions, number-heavy expressions, and isolated letters with nested superscripts and subscripts, which are rare in Wikipedia.

The extraction process from Wikipedia followed these steps:

- download an XML Wikipedia dump which provides Wikipedia's raw textual content. enwiki-20231101-pages-articles.xml was used for synthetic samples, older dumps for humanwritten ones
- extract all $\[Mathebaarefore]{MTEX}$ expressions from that file. This gives the list of all mathematical expressions in $\[MTEX]$ notation from Wikipedia
- keep those which could be compiled using the packages listed in Appendix A. Wikipedia contains a significant number of expressions that are not accepted by the LATEX compiler, because of syntax errors or other reasons
- \bullet keep only those which can be processed by our normalizer which only supports a subset of all $\mbox{LM}_{E\!X}$ commands and structures

For expressions used for synthesis, the following extra steps were performed:

• keep only the expressions whose normalized form contains more than a single LATEX token. Example: \alpha is rejected but \alpha^{2} is kept. This step is useful to eliminate trivial expressions that wouldn't add any useful information

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Sub/superscript are put in braces, \over is replaced by \frac
Raw
              \operatorname{hu^2}+{1 \operatorname{ver 2}}{k_{ap}g_zh^2}
              \operatorname{line}_{hu^{2}}+\int_{z_{k_{ap}g_{z}h^{2}}}
Normalized:
Subscripts are put before superscripts, extra space is dropped
Raw:
              int^a_{-a}f(x) dx=0
Normalized:
              \int \left( \frac{-a}{a} \right)^{a} f(x) dx = 0
Single quotes are replaced by a superscript
Raw
              f'(\overline x)
              f^{\prime}(\overline{x})
Normalized:
Text formatting commands like \rm are dropped
              ~A_{0}=\frac{ND}{\sigma_{\rm as}+\sigma_{\rm es}}~
Raw:
Normalized:
              A_{0}=\frac{ND}{\sigma_{as}+\sigma_{es}}
Matrix environments with delimiters like bmatrix are replaced by matrix surrounded by delimiters
Commands like \cos are replaced by the series of letters
              \begin{bmatrix} -\sin t \\ \cos t \end{bmatrix}
Raw
              [\begin{matrix}-sint\\ cost\end{matrix}]
Normalized:
Delimiter size modifiers like \big are dropped
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Raw: \big(\tfrac{a}{N}\big)
Normalized: (\frac{a}{N})
```

Figure 4: Examples of expression normalization. See Section 4 for details.

- de-duplicate expressions based on their normalized form. e.g. \frac12 and \frac{1}{2} normalize to the same thing, we kept only one of them in raw form
- restrict the list of expressions to the same set of tokens used in the train split: if the normalized form of an expression contained at least one token that was not also present somewhere in train, it was discarded.

4 Label Normalization

All samples in the dataset come with two labels: the LATEX expression that was used during the data collection (annotation label in the InkML files), and a normalized version of it meant for model training, which is free from a few sources of confusions for an ML model (annotation normalizedLabel). See figure 4 for some examples, and the following sections for more detail.

Label normalization covers three categories:

- variations used in print that can't be reproduced in handwriting e.g. bold, italic, or that haven't been reproduced consistently by contributors.
- non-uniqueness of the LATEX syntax. e.g. \frac{1}{2} and 1\over 2 are equivalent.
- visual variations that can reproduced in handwriting but can't reliably be inferred by a model. This includes size modifiers like \left, \right.

We provide the raw labels to make it possible to experiment with alternative normalization schemes, which could lead to better outcomes for different applications.

4.1 Syntactic Variations

There are several ways to change a LATEX string without changing the rendered output significantly. The normalization we implemented does the following:

- all unnecessary space is dropped
- all command arguments are consistently put in curly braces
- superscripts and subscripts are put in curly braces and their order is normalized. e.g. a^2_1 becomes a_{1}^{2} .
- redundant braces are dropped
- infix commands are replaced by their prefix versions. e.g. \over is replaced by \frac
- a lot of synonyms are collapsed. e.g. \le and \leq, \longrightarrow and \rightarrow, etc. Some of the synonyms are only synonyms in handwriting. For example \star (*) and * are different in print (5-prong and 6-prong stars), but the difference was not expressed in handwriting by our contributors.
- functions commands like \sin are replaced by the sequence of letters of the function name (e.g. \sin is replaced by sin). This reduces the output vocabulary, and eliminates a source of confusion because we found that LATEX expressions from Wikipedia come with a mix of function commands and sequences of letters.
- expansion of abbreviations. e.g. \cdots, \ldots, etc. have been replaced by the corresponding sequence of characters.
- matrix environments are normalized to use only the 'matrix' environment surrounded by the proper delimiters like brackets or parentheses.
- \binom is turned into a 2-element column matrix. Expressions from Wikipedia did not use those consistently, so we made the choice to normalize \binom away.

4.2 Differences Between Print And Handwriting

The following characteristics can not be represented in handwriting and have been normalized away:

- color
- accurate spacing: e.g. ~, \quad.
- font style and size: e.g. \mathrm, \mathit, \mathbf, \scriptstyle.

There are others that can be represented in handwriting, but that are not consistent enough in MathWriting to be preserved:

- font families: Fraktur, Calligraphic. In practice, only Blackboard (\mathbb) has been written consistently enough by contributors that we were able to keep it: \mathcal and \mathfrak are dropped.
- some character variations. e.g. \varrho, \varepsilon
- size modifiers like \left, \right, \big. Similarly, variable-width diacritics like \widehat.

4.3 Limitations

The normalization process is purely syntactic, and can not cover cases where the meaning of the expression has to be taken into account. For example, a lot of expressions from Wikipedia use cos instead of \cos . It is often clear to a human reader whether the sequence of characters c,o,s represents the \cos command or simply three letters. However, this can not be reliably inferred by a syntactic parser, for example in tacos vs ta \cos . An alternative would be to update the raw labels, which we didn't do because we wanted to keep the information that was used during the collection as untouched as possible.

Similarly, cases like 10^{-1} usually mean $\{10\}^{-1}$, though they render exactly the same. We made the choice to normalize to the former because it's the only option with a purely syntactic normalizer. It's also better than not removing these extra braces because it gives more consistent label structures, which simplifies the model training problem.

5 Detailed Description

In this section we describe the main properties of MathWriting dataset and compare it to the existing CROHME23 dataset [16].

Table 2: Statistics on different subsets of MathWriting dataset.

	train	synthetic	validation	test
# distinct inks	230k	396k	16k	8k
# distinct labels	53k	396k	8k	4k

5.1 Label Statistics

MathWriting contains 457k unique labels after normalization (Section 4). From Table 2 we see that most unique expressions are covered by the synthetic portion of the dataset. However, the absolute number of unique expressions in human-written part is still high. This underlines the importance of synthetic data as it allows models to see a much bigger variety of expressions. It is important to note that the synthetic split has essentially no repeated expressions. On the other hand, in real data multiple different writings of the same expression are quite common, see Figure 5. This fact allows us to separately evaluate model's quality on expressions that were observed during training and that model hasn't seen before. As seen in Table 3 the biggest intersection in expressions is between validation and train. Therefore, the performance gap between validation and test on MathWriting dataset shows how well models generalize to expressions that were not seen in train.



Figure 5: Counts of inks corresponding to the same normalized expression, ordered by increasing count. Each position on the horizontal corresponds to a unique normalized expression. Almost 5k unique expressions have been written 10 times or more by contributors.

Table 3: Counts of unique labels shared between splits	Table 3:	Counts	of uniq	ue labels	shared	between s	plits
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	train	synthetic	valid	test
train	-	0	3.6k	355
synthetic	0	-	0	0
valid	3.6k	0	-	239
test	355	0	239	-

The median length of expressions in characters is 26 which is comparable to one of the most popular English recognition datasets IAMonDB [10], which has median of 29 characters. However, it is important to note that LATEX expressions have symbols that span multiple characters like frac. The median length of expressions in tokens (provided in Appendix C) is 17, thus making training a model on tokens rather then characters easier due to shorter target lengths [15, 12]. We want to emphasize that MathWriting can be used with a different tokenization scheme and token vocabulary from what we propose in Appendix C. In Figure 6 we show the number of occurrences for the most frequent tokens. Tokens { and } are by far the most frequent as they are integral to the LATEX syntax.



Figure 6: Histogram of the most frequent tokens in MathWriting.

	10th percentile	median	90th percentile
# strokes	5	14	39
# points	131	350	1069
writing time (sec)	1.88	6.03	16.42
aspect ratio	1.32	3.53	9.85

Table 4: Ink statistics of MathWriting dataset.

5.2 Ink Statistics

Each ink in MathWriting dataset is a sequence of strokes $I = [s_0, ..., s_n]$, each stroke s_i consisting of points. A point is represented as a triplet (x, y, t) where x and y are coordinates on the screen and t is a timestamp. In Table 4 we provide statistics on number of strokes, points and duration of writing.

It's important to note that, as inks were collected on different devices, the absolute coordinates values can vary a lot. In human-written data the time information t always starts from 0 but it is not always the case in the synthetic split. Different samples often have different sampling rates due to the use of different devices. Sampling rate is the number of points that a device has written in one second. This value varies across different inks as seen in Figure 7. One consequence is the fact that the same ink written on two different devices can result in inks with a different number of points. For human-written inks, the sampling rate is consistent between strokes, but it is not the case for synthetic ones. In order to accommodate a model and make sequences shorter, inks can be resampled in time as shown in Figure 8. The work [7] resampled inks to a rate of 20ms.



Figure 7: Histogram of sampling rates in human-written data of MathWriting dataset.



Figure 8: Examples of time resampling with different time periods. Larger periods result in shorter sequences of points.

Device type	Ink
Google PixelBook	51k
Google Nexus 5X	28k
Coolpad Mega 2.5D	14k
OnePlus One	13k
Google Nexus 5	11k
Google Nexus 6	11k
Google Nexus 6P	11k
Coolpad Mega 3	8k
LG Optimus L9	8k
Galaxy Grand Duos	7k
Google Pixel XL	6k
Samsung Galaxy S7	5k

Table 5: Top-12 devices used, with the number of samples obtained from each device. The bias towards Google devices simply reflects the conditions in which inks were collected.

5.3 Devices Used

Around 150 distinct device types have been used by contributors. In most cases inks were written on smartphones using a finger on a touchscreen. However, there are cases where tablets with styluses were used. The main device used in this case is Google Pixelbook, which accounted for 51k inks total (see Table 5). Out of all device types, 37 contributed more than 1000 inks. Note that writing on a touchscreen with a finger or a stylus results in different low-level artifacts.

All devices were running the same Android application for ink collection, regardless of whether their operating system was Android or ChromeOS.

5.4 Comparison With CROHME23

In this section we compare main dataset statistics of CROHME23 [16] and MathWriting. We normalize LATEX expressions in both datasets (details in Section 4) in order to estimate label intersection between MathWriting and CROHME23.

In terms of overall size, MathWriting has nearly 3.9 times as many samples and 4.5 times as many distinct labels after normalization, see Table 6. A significant number of the labels can be found in both datasets (47k), but the majority is dataset-specific. It is also important to note that both datasets include synthetic data. The MathWriting dataset has more human-written inks than CROHME23 as seen in Table 7.

MathWriting contains a much larger variety of tokens than CROHME23. It has 254 distinct tokens including all Latin capital letters and almost the entire Greek alphabet. It also contains matrices, which are not included in CROHME23. Therefore, more scientific fields like quantum mechanics, differential calculus, and linear algebra can be represented using MathWriting.

	MathWriting	CROHME23	Common
Inks	650k	164k	0
Labels	457k	102k	47k
Vocabulary tokens	254	105	104

Table 6: Counts of inks, distinct labels and distinct tokens used in MathWriting and CROHME23. The single token present in CROHME23 but not in Mathwriting is the literal dollar sign \\$.

	MathWriting	CROHME23
Human-written inks	253k	17k
Synthetic inks	396k	147k

Table 7: Count of human-written and synthetic inks for MathWriting and CROHME23. Human-written inks represent 38% of the total for MathWriting, and 10% for CROHME23.

6 Discussion

We discuss in this section other aspects of MathWriting not mentioned above, to give a better idea of what can be achieved with the data.

6.1 Differences in Writing Style

The number of contributors was large enough that a variety of writing styles are represented in the dataset. Two examples can be seen in Figures 9 and 10. Similar though less obvious differences exist for other letters. Style differences also show through writing order. Figure 11 shows different ways of writing a simple fraction – writing fractions top-down or bottom-up is likely influenced by the language one speaks.

6.2 Sources of Noise

The result of any task performed by humans will contain mistakes, and MathWriting is no exception. We've done our best to remove most of the mistakes, but we know that some remain.

Stray strokes These do not carry any meaning and should be ignored by any recognizer. Since they also appear in real applications, there could be some benefit in having some in the dataset to teach the model about them. That said, it being usually easier to add noise rather than to remove it, we made the choice of discarding as many inks containing stray strokes as possible. Not all inks with stray strokes have been found and removed though (e.g. train/9e64be65cb874902.inkml that was discovered post-publication). The fraction of inks containing stray strokes is significantly lower than 1%, and should not be an issue for training a model.

Incorrect ground truth Contributors did not always copy the prompt perfectly, leading to a variety of differences. In most of the cases we spotted, we were able to fix the label to match what had actually been written. A short manual review once the dataset was in its final state showed the rate of incorrect ground truth to be between 1% and 2%. Most of the mistakes are very minor, usually a single token added, missing or incorrect. Errors here also come from ambiguities or misuse of the LATEX notation: expressions coming from Wikipedia contain some misuse like using \Sigma where \sum was more appropriate, \triangle instead of \Delta, \triangledown instead of \nabla,



Figure 9: Three ways of writing a lowercase 'r'. From anecdotal evidence, we associate the style on the left with parts of Europe and the style on the right with India.



Figure 10: Two ways of writing lowercase s.



Figure 11: Examples of various writing orders found in the training set. Red arrows show the movement of the pen between strokes. Top left: most common writing order (top-down, fraction bar drawn left-to-right), top right: fraction bar written first, bottom left: fraction bar drawn right-to-left, bottom right: fraction written bottom-up. Anecdotally, we associate this latter style with the Chinese language where fractions are read bottom-up.

\begin{matrix}\end{matrix} instead of \binom, and also some handwriting-specific ambiguities like \dagger vs \top vs T. There are also some instances where reference numbers or extra punctuation are included.

Aggressive normalization While the above sources of noise are unavoidable, normalization is a postprocessing operation that can in theory be tweaked to perfection. In practice, it's a compromise between reducing accidental ambiguities (i.e. removing synonyms), and removing information. Examples: we made the choice of treating \binom as a synonym for a 2-element matrix. While it does improve recognition accuracy by making the problem easier, it also moves the burden of distinguishing between the two cases to downstream steps in the recognition pipeline. Similar things can be said about removing all commands that indicate that their content is text instead of math (e.g. \mbox), dropping size modifiers, rewriting function commands (e.g. \sin, \cos), etc. Using a different normalization could prove beneficial depending on the context the recognizer is used in practice. However, for the purpose of a benchmark any reasonable compromise is adequate.

6.3 Recognition Challenges

MathWriting presents some inherent recognition challenges, which are typical of handwritten representations. For example, it's not really possible to distinguish these pairs from the ink alone: \frac{\underline{a}}{b} vs \frac{a}{\overline{b}}, and \overline\omega vs \varpi. We'd like to point out that these ambiguities are not an issue for humans in practice, because they rely on contextual information to disambiguate: a particular writing idiosyncrasy, consistency with nearby expressions, knowledge of the scientific domain, etc. See Figures 12 and 13 for more examples.



Figure 12: Left: character ambiguity. Is it $1 \le x_n < x_{n+1}$ or $1 \le n_\eta < n_{\eta+1}$? Right: what is the fraction nesting order?



Figure 13: Left: \binom or 2-element matrix? Right: $p^n a_{p^n} = a$ or $p^n a_p n = a$?

6.4 Dataset Applications and Future Work

Mathwriting can be used to train recognizers for a large variety of scientific fields, and is also large enough to enable synthesis of mathematical expressions. Combining it with other large datasets like CROHME23 would increase the variety of samples even further, both in terms of writing style and number of expressions, likely improving the performance of a model.

Bounding box information for synthetic samples is provided to enable researchers to experiment with synthetic ink generation. Synthetic samples published have been obtained through the straightforward process of pasting inks of individual symbols exactly where bounding boxes were located. This give samples that reflect the very regular structure generated by $\[mathscale{ETE}X$. It is possible to improve this process by modifying the location, size or orientation of bounding boxes prior to generating the synthetic inks. This would soften $\[mathscale{ETE}X$'s rigid structure and make synthetic data closer to human handwriting.

Another application of these bounding boxes would be to bootstrap a recognizer that would also return character segmentation information. This kind of output is critical for some UI features - for example, editing an handwritten expression.

MathWriting can also be improved by varying the label normalization. Changing it can have different benefits depending on the application, as mentioned above. We provide the source LATEX string for that reason.

Pushing the recognition performance past some of the inherent ambiguities present in the data will require some contextual information, like the scientific field, some information about the writer, etc. Some of this information could be added post-hoc. A language model trained on a large set of mathematical expressions would be a step in that direction.

Finally, exploring a different train/validation/test split could bring some improvements to the benchmark. The valid and test splits that we publish are the result of several decisions made over a long period of time and may not be the optimal way to assess a model's performance for practical applications. In particular, correctly assessing whether a HME recognizer properly generalizes is complex and requires more research.

7 Conclusion

We introduced MathWriting, the largest dataset of online handwritten mathematical expressions to date, and a new benchmark. We hope this will help research in online and offline mathematical expression recognition. We also encourage data practitioners to build on the dataset. We intentionally chose a file format for MathWriting close to the one used by CROHME to facilitate their combined use. We also provided original or intermediate representations

(raw LaTeX strings, bounding boxes) to enable experimentation with the data itself, and suggested a few directions (Section 6.4).

Acknowledgements

We warmly thank all the contributors without whom this dataset would not exist. We thank Henry Rowley and Thomas Deselaers for their contribution to organizing the data collection and supporting this effort for many years. We thank Ashish Myles and MH Johnson for related contributions that resulted in important data and model improvements. We thank Vojta Letal and Pedro Gonnet for their contributions to the CTC Transformer model as well as to synthetic data. We thank Peter Garst and Jonathan Baccash for their contribution to the label normalizer. We thank Blagoj Mitrevski and Henry Rowley for their useful suggestions regarding the text of the paper. We thank our product counsels Janel Thamkul and Rachel Stigler for their legal advice.

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A LATEX template for label rendering

All the packages and definitions that are required to compile all the normalized and raw labels:

```
\usepackage{amsmath}
\usepackage{amsfonts}
\usepackage{amssymb}
\newcommand{\R}{\mathbb{R}}
\newcommand{\C}{\mathbb{C}}
\newcommand{\Q}{\mathbb{Q}}
\newcommand{\Z}{\mathbb{Z}}
\newcommand{\N}{\mathbb{N}}
```

B Tokenization Code

Python code used in this work to tokenize LATEX mathematical expressions.

import re

```
_COMMAND_RE = re.compile(
    r'\\(mathbb{[a-zA-Z]}|begin{[a-z]+}|end{[a-z]+}|operatorname\*|[a-zA-Z]+|.)')
```

```
def tokenize_expression(s: str) -> list[str]:
  tokens = []
  while s:
    if s[0] == '\\':
      tokens.append(_COMMAND_RE.match(s).group(0))
  else:
      tokens.append(s[0])
    s = s[len(tokens[-1]):]
```

return tokens

C Tokens

Using the above code to compute tokens, the set of all samples in the dataset (human-written, synthetic, from all splits) contain the following after normalization:

- Syntactic tokens: _ ^{ } & \\ space
- Latin letters and numbers: a-z A-Z 0-9
- Blackboard capital letters \mathbb{A}-\mathbb{Z} \mathbb
- Latin punctuation and symbols: , ; : ! ? . () [] \{ \} * / + _ \& \# \% | \backslash
- Greek letters: \alpha \beta \delta \Delta \epsilon \eta \chi \gamma \Gamma \iota \kappa \lambda \Lambda \nu \mu \omega \Omega \phi \Phi \pi \Psi \Psi \rho \sigma \Sigma \tau \theta \Theta \upsilon \Upsilon \varphi \varpi \varsigma \vartheta \xi \Xi \zeta
- Mathematical constructs: \frac \sqrt \prod \sum \iint \int \oint
- Diacritics and modifiers Note the absence of the single-quote character, which is normalized to ^{\prime}: \hat \tilde \vec \overline \underline \prime \dot \not
- Matrix environment: \begin{matrix} \end{matrix}
- Delimiters: \langle \rangle \lceil \rceil \lfloor \rfloor \|
- Comparisons: \ge \gg \le \ll <>
- Equality, approximations: = \approx \cong \equiv \ne \propto \sim \simeq
- Set theory: \in \ni \notin \sqsubseteq \subset \subseteq \subseteq \subseteq \subseteq

- Operators: \times \bigcap \bigcirc \bigcup \bigoplus \bigvee \bigwedge \cap \cup \div \mp \odot \ominus \oplus \otimes \pm \vee \wedge
- Arrows: \hookrightarrow \leftarrow \leftrightarrow \Leftrightarrow \longrightarrow \mapsto \rightarrow \Rightarrow \rightleftharpoons \iff
- Dots: \bullet \cdot \circ
- Other symbols: \aleph \angle \dagger \exists \forall \hbar \infty \models \nabla \neg \partial \perp \top \triangle \triangleleft \triangleq \vdash \Vdash \vdots

D Examples of inks

This section shows a few examples of rendered inks, so that the reader can get a feel for the kind of data that is in MathWriting. All samples are from the training set. They have been manually picked to show a variety of sizes, characters and structures.

D.1 Human-Written Samples





D.2 Synthetic Samples: Expressions from Wikipedia





D.2.1 Synthetic Samples: Generated Fractions



