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ABSTRACT

Eye tracking is an emerging technology with a wide spectrum of applications, including non-invasive neurocognitive diagnosis. An advantage of the use of eye trackers is in the improved assessment of indirect latent information about several aspects of the subjects' neurophysiology. The path to uncover and take advantage of the meaning and implications of this information, however, is still in its very early stages. In this work, we apply ordinal patterns transition networks as a means to identify subjects with dyslexia in simple text reading experiments. We registered the tracking signal of the eye movements of several subjects (either normal or with diagnosed dyslexia). The evolution of the left-to-right movement over time was analyzed using ordinal patterns, and the transitions between patterns were analyzed and characterized. The relative frequencies of these transitions were used as feature descriptors, with which a classifier was trained. The classifier is able to distinguish typically developed vs dyslexic subjects with almost 100% accuracy only analyzing the relative frequency of the eye movement transition from one particular permutation pattern (plain left to right) to four other patterns including itself. This characterization helps understand differences in the underlying cognitive behavior of these two groups of subjects and also paves the way to several other potentially fruitful analyses applied to other neurocognitive conditions and tests.

We use Ordinal Patterns Transition Networks (OPTNs) to identify subjects with dyslexia on simple text reading experiments. The transitions between ordinal patterns in left-to-right eye movements during text reading were analyzed and characterized. The relative frequency transitions between patterns were used as feature descriptors to train a classifier able to distinguish normal from dyslexic subjects.

I. INTRODUCTION

Reading is one of the most relevant technological developments in human society. Most of the accumulated knowledge originated from our contemporary cultures, and also important portions of the information created and shared by the members of the society, are kept, transmitted, and learned in written form. The way in which this information is shared with each member of the society is largely through the implementation of children's schooling, where part of the information necessary to function operatively and efficiently in the society as a whole is transferred. At school, children learn to read, that is, to decode information that has been stored in written form. Since the beginning of the last century, school has become a structure that houses the children of societies massively. After this massification, differences present in children's development, and particularly neurodevelopment, began to become evident. The process of incorporating reading abilities involves a series of structural modifications in the brain. These anatomical and physiological changes occur as a consequence of the internal representations in the brain that are made between the graphemes that represent the written language and the phonemes of the oral language. The gradual incorporation of reading implies automation of that process. This occurs in the early years of schooling and depends largely on the transparency of the language being learned and the teaching techniques employed, among many other factors.

The massification of schooling has shown that there are children for whom this grapheme–phoneme transformation cannot be immediately automated or in any case occurs but with many difficulties. These children are called *dyslexics*. Dyslexic children, apart from their particular condition, can thrive as any other child in almost all intellectual and cognitive tasks. However, their diminished reading abilities usually determine a slower or even impaired learning trajectory and, therefore, they never achieve their full potential. Adequate screening, then, is essential to distinguish dyslexia from other neurocognitive conditions and then to provide adequate accompanying during the initial schooling stages. In this work, we will introduce and discuss non-invasive tools that allow us to detect distinct reading features of dyslexic children by registering the eye movements during reading, using ordinal pattern tools and machine learning techniques.

The study of eye movements during reading has a very long history. In the last 20 years, research in this area have focused on the development of models that account for the different mechanisms involved in the task.[1] Two fundamental principles govern the dynamics of reading: *where* to look and *when* to move the eyes to the next target. In an attempt to explain them, the developed models include a large number of elements that allow the reading process to be described in great detail.[1,2] Eye activities are analyzed in terms of *saccades*, which are rapid strides from one gaze position to another, and *fixations*, in which the eye still moves but only in very small and apparently chaotic movements around a tiny region with no net displacement. The most common elements usually included are fixation duration, saccade length, processing time (where first fixation duration, single fixation duration, or gaze duration are intertwined), skipped words, and regressions.[1] The more elements are included in the model, the more interactions must be taken into account. Thus, not only does the complexity of the analysis algorithms increase, but the descriptions become dependent on many specific details, which results in the loss of the ability to simply describe the phenomenon in general, beyond the particular details involved in each part of the process.

There is a large number of publications in which the saccadic movements and the fixations produced throughout the reading process are analyzed.[1–8] Based on these studies, the reading process can be regarded as a continuous time random walk. In itself, and as it was mentioned, reading is a succession of jumps and stops that occur in the given text to read. These sequences have several deterministic and also stochastic ingredients. Once the reader's "command" to jump from one place in the text to another has been given to the eye muscles, the jumping process is deterministic. However, the size of the jump and the moment in which it will occur can be modeled with a probability distribution that gives the process a stochastic characteristic. On the other hand, the waiting times in each fixation are also stochastic. Reading then is made up of a tangled succession of jumps (both forward and backward) and stops, whose order and frequency of occurrence can be understood as based on probability distributions. Recording the eye movements of reading subjects allows access to that information even though the way in which the information is framed may not be readily apparent from traditional statistical studies.

The analysis of eye movements and trajectories in terms of complexity theory is relatively new. Some attempts to describe them[9,10] have used representation of eye trajectories as Levy flights or fractional Brownian motion processes. Multifractal characterizations have also been attempted.[11] To the best of our knowledge, ordinal patterns and causality–complexity analyses were applied only recently.[12,13] In this work, we further these analyses incorporating the recently proposed Ordinal Pattern Transition Networks (OPTNs)[14] in the analysis of eye-tracking reading patterns in neurotypical and dyslexic children. The preliminary results show that the transition probability distributions of the OPTNs of these two groups differ significantly, and thus off-the-shelf machine learning techniques can be applied to detect from where a reading pattern belongs to any of these two classes with very high accuracy.

II. MATERIALS AND METHODS

A. Participants and experiments

Two children groups of both sexes aged 9–10 years participated in the study. The first group included 14 children diagnosed with dyslexia (DD), and the second were 29 children with typical development (TD) and normal reading abilities. All participants are native Spanish speakers. Informed consent was obtained from the legal guardian of each participant. The children also gave their consent to participate. All participants were treated in accordance with the Declaration of Helsinki. The children were asked to read aloud a short nine-line text in Spanish displayed over a computer screen, while their eye movements were recorded using an eye tracker Tobii Pro (Tobii AB, Sweden) at a sample rate of 90 Hz. The eye movements of the TD readers were recorded by professionals in the school they attend, an elementary school of medium socioeconomic level in the Metropolitan Area of Buenos Aires (Argentina). The institution also provided consent for the collection of data within the facilities. The records of DD children were taken in psycho-pedagogical clinics in the same urban area. The dyslexia diagnosis was performed by psychopedagogues specialized on reading disorders.

The data collected are a 2D time series $\{(t, x, y)\}$ indicating the eye position (x, y) on the screen at each sampled time t in milliseconds (ms). Positions on the screen were normalized to satisfy the ratio 16:9. Thus, in what follows, x ranges from 0 to 16 and y ranges from 0 to 9. Fixations and saccades were detected and labeled using

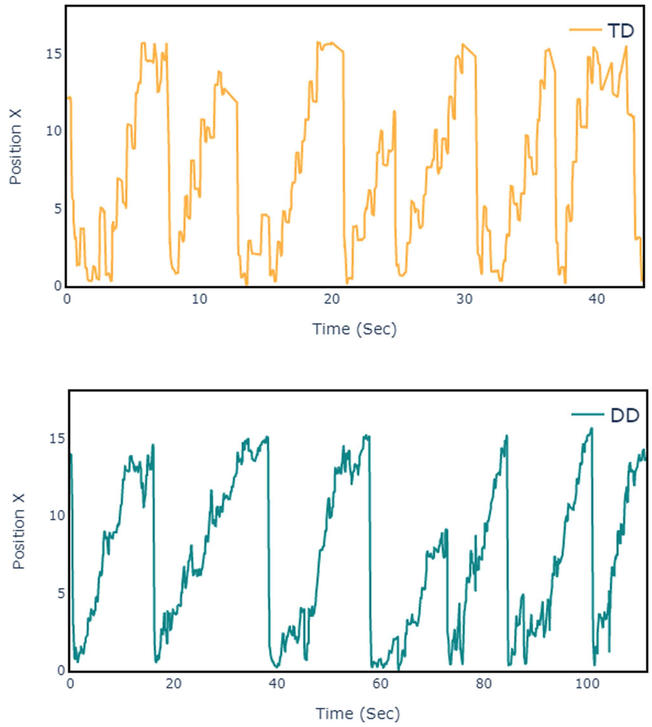

FIG. 1. Position vs time x_t signals from a typically developed subject (top) and a subject diagnosed with dyslexia (bottom).

an algorithm based on the ideas presented in Ref. 15. Saccades associated with blinking and return-sweeps (saccades that take the gaze from the end of one line to the beginning of the next) were eliminated from the analysis. Given that reading progresses mostly from left to right, we consider only the x part of the time series for our analysis. See Fig. 1 for examples of these acquisitions.

B. Ordinal pattern transition networks

Ordinal patterns, originally proposed by Bandt and Pompe,[16] takes sliding windows of fixed length n over the time series $\{x_f(t)\}$, where x_f represents the position of the fixations during reading (see Fig. 2). Each window is represented with a pattern according to the ordinal position of its x values. In this work, we used a window size of four consecutive x values, which leads to $4! = 24$ possible permutation patterns, which is well above the recommendable minimum, given the actual length of the acquisitions (about 200 fixations per experiment). Using the sequence of ordinal patterns of length four arising during reading experiments, OPTNs for the two groups were constructed. The networks have 24 nodes (one for each pattern) and weights for each of the edges were computed as the relative frequency of each pattern transitioning to the next, taking into account that not every transition is possible. The transition frequencies of each subject were normalized and then the transitions of each group were averaged. The resulting OPTNs for each group can be seen in Fig. 3.

FIG. 2. Reading patterns of a typically developed subject (top) and a subject diagnosed with dyslexia (bottom) under the same reading experiment. The size of the circles represent the fixation duration.

It is interesting to note that basically half of the patterns represent forward movements (reading ahead) and the other half backward movements. For instance, the pattern 0123 represents a plain forward movement, which can be followed by only four possible patterns, namely, 1230, 0231, 0132, and itself (this pattern and 3210 are the only ones that can transition to themselves). The full reading process can thus be reinterpreted as a succession of patterns instead

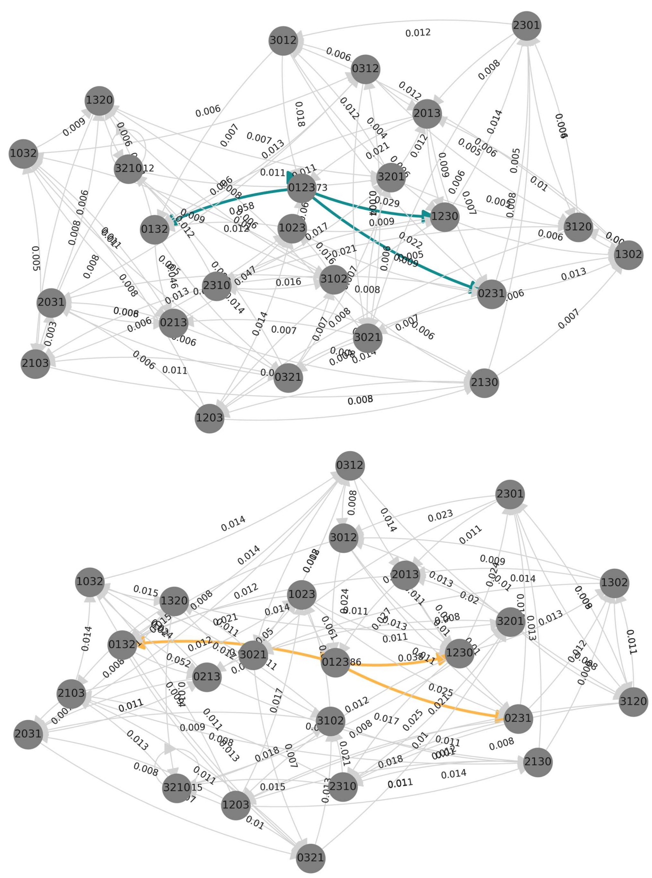

FIG. 3. OPTNs for dyslexic children (top) and normally developed (bottom). The tags in the links represent the relative frequency of the corresponding pattern transition.

TABLE I. Next pattern after pattern 0123 for NT and DD children.

Next pattern	Diag	0123	0132	0231	1230
Mean	DD	0,273	0,058	0,022	0,024
	TD	0,186	0,044	0,024	0,038
Std	DD	0,086	0,015	0,010	0,013
	TD	0,105	0,017	0,010	0,016
Min	DD	0,102	0,032	0,005	0,000
	TD	0,010	0,000	0,000	0,010
25%	DD	0,213	0,052	0,016	0,017
	TD	0,114	0,037	0,018	0,032
50%	DD	0,290	0,054	0,023	0,027
	TD	0,159	0,045	0,025	0,038
75%	DD	0,332	0,060	0,028	0,031
	TD	0,271	0,056	0,030	0,041
Max	DD	0,426	0,088	0,040	0,045
	TD	0,452	0,083	0,042	0,089

successions of fixations and saccades. In this way, the dynamics of the reading process can be interpreted as the likelihood of transitioning among patterns. In this way, a probabilistic characterization of these transitions among patterns can lead to the identification of behavioral qualities of the TD and DD subjects.

Significant differences between the two groups could be observed in the relative frequencies of the next pattern arising after the "plain forward" pattern 0123 (see Table I). In other words, since pattern 0123 arises when reading progresses left to right, the likelihood of what is the next movement pattern appears to differ between both groups. This means that the dynamic of reading differs between TD and DD in the way these patterns alternate. Figures 4 and 5 show, respectively, the average relative frequencies and their distribution of the next ordinal patterns arising after pattern 0123 for the two groups. As we will show in Sec. III, these relative frequencies allow to differentiate them.

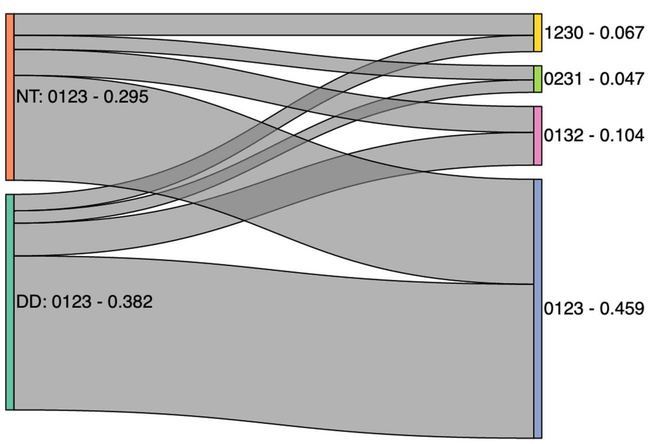

FIG. 4. Average relative frequencies of the next ordinal pattern arising after pattern 0123 in both populations.

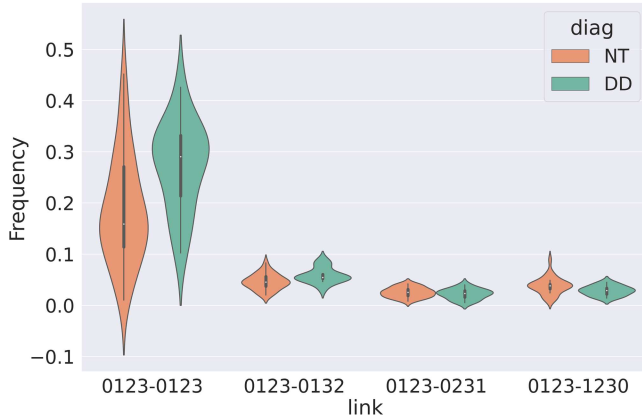

FIG. 5. Frequency distribution of the next ordinal pattern after pattern "0123" for normally developed (blue) and dyslexic children (orange).

III. PATTERN CLASSIFICATION

Six classic supervised machine learning methods were trained for classification (Decision Trees, Random Forest, Gaussian Naïve Bayes, K Nearest Neighbors, Support Vector Machines, and Logistic Regression). The relative frequencies of the ordinal patterns arising after pattern 0123 were used as feature descriptors of these classifiers, and the subject condition NT or DD was used as the target variable. To evaluate the overall performance of each classifier and in order to compare them, we calculated four typical metrics: accuracy, precision, recall, and F1-score. The number of sample was 43, of which 29 were typically developed and 14 dyslexics. We used varying train/test splits, starting with an 80/20 split, followed by a 90/10 split, and finally a 100/100 split. The results were found to be the same across all three splits, which was justifiable given the small dataset.

For tree-based methods, such as Decision Trees and Random Forest classifiers, the accuracy was 100%. In Fig. 6, the optimal Decision Tree is shown. In the case of Gaussian Naïve Bayes, the accuracy was 84%, while for K-Nearest Neighbors it was 81%. For the linear classification methods, such as Support Vector Machine and Logistic Regression, the accuracy was 67% in both cases.

These results can be seen in Table II. The Decision Tree model achieves optimal performance with the additional advantage of being a white box model (i.e, their functioning is transparent). To gain some insight into the trade-off between simpler albeit less accurate models, we also explored the training of regularized decision trees limiting their maximum depth. As compared to the 100% accurate Decision Tree (with depth 4) shown in Fig. 6, the accuracy is reduced to 0.91 and 0.86 for maximum respective depths of 3 and 2. In Fig. 7, the decision tree with depth 2 is shown.

It is remarkable to note that in both Decision Trees the most important transition probability (i.e., the root) is different. In the optimal tree, a probability of the transition from pattern 0123 to pattern 0132 larger than 0.05 splits most of the DD cases (11 out of 14). In the simpler tree, the same figures are achieved but considering the probability of the transition 0123–1230 larger than 0.033.

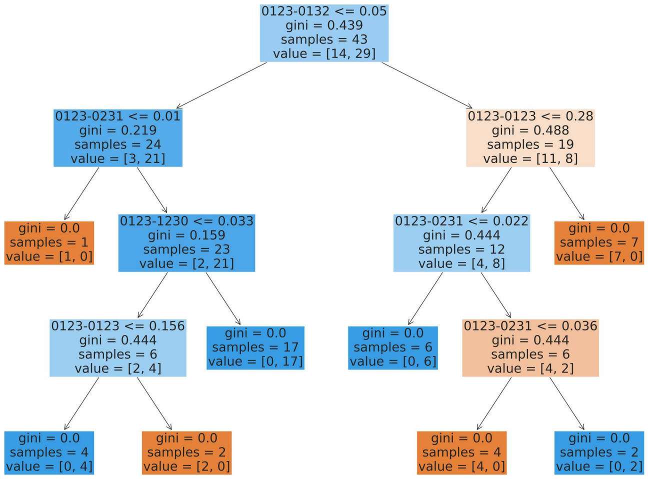

FIG. 6. Optimal Decision Tree for classifying TD from DD.

TABLE II. Comparison of classification methods.

Classifier	Acc	Class	Precision	Recall	F1-score
Decision Tree	1,00	DD	1,00	1,00	1,00
		TD	1,00	1,00	1,00
Random Forest	1,00	DD	1,00	1,00	1,00
		TD	1,00	1,00	1,00
Gaussian Naïve Bayes	0,84	DD	0,89	0,57	0,70
		TD	0,82	0,97	0,89
K-Neighbors	0,81	DD	0,80	0,57	0,67
		TD	0,82	0,93	0,87
Support Vector Machine	0,67	DD	0,00	0,00	0,00
		TD	0,67	1,00	0,81
Logistic Regression	0,67	DD	0,00	0,00	0,00
		TD	0,67	1,00	0,81

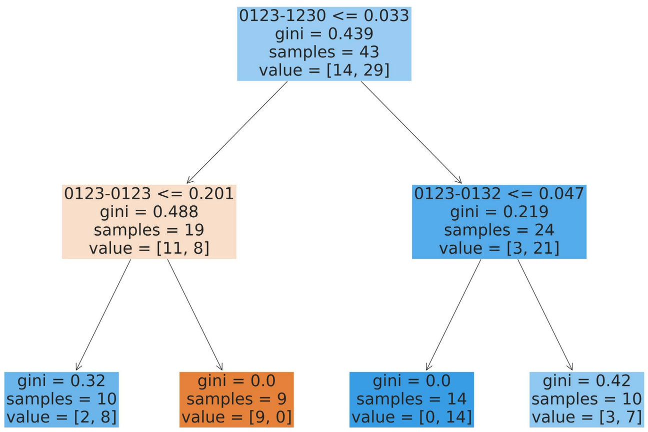

FIG. 7. Regularized Decision Tree (depth two) for classifying TD from DD.

In both cases, the transition between patterns is related to the way the plain left-to-right reading is interrupted by a backward movement. Both decision trees express what is visually appreciated when seeing all the signals. Dyslexic children tend to progress regularly from syllable to syllable or skip at most one syllable in between. If the subject detects that a syllable was not correctly decoded by the brain, they will make a new fixation on the previous syllable. This corresponds to the transition 0123–0132. Unlike children diagnosed with dyslexia, typically developed children tend to read fixating on the center of words, even skipping short words of up to three letters. When these children have doubts about the decoding of the words, they usually return to the first word of a sentence to reread it again or to résumé it from some previous words. This produces a saccadic movement to a fixation with the value of the X coordinate well below the value of X where the decoding doubt arose. This behavior corresponds to the transition 0123–1230. The decision trees are using these moves to discriminate the two typical behaviors seen in the two groups.

IV. DISCUSSION AND CONCLUSION

One of the most important functions of the school worldwide is to make all children acquire reading and writing skills. The acquisition of reading skills is not something that is natural for the human brain and because of that, it requires a significant effort for all school children. For the group of children generally called dyslexics, the incorporation of reading skills is more difficult and demands an even greater effort than in the case of those who had a typical development. In many situations, this difficulty becomes very significant even when the rest of the child's abilities are intact. For all these children, detecting reading difficulty appropriately and early can be of great help so that the adequacy of the activities to be done at school can be adapted to allow the child to reach full development. In this work, we combine different techniques to be able to identify the differences in the reading characteristics of children with dyslexia and typically developed. A text designed by professionals specialized in psychopedagogy combined with the register of eye movements was used. The collected data were organized in such a way that certain types of patterns could be defined and then machine learning tools were used to systematize the characteristics of said patterns.

The use of eye tracking techniques during reading in combination with OPTN shows great potential. It allows us to follow the dynamics of reading in a very interesting way. Reading can be understood as a dynamic process in which transitions occur in which the elements are not saccadic movements or fixations, but the way in which a certain succession of them alternate throughout the entire process. The transition probability between nodes provides information about how the process is carried out. This way of thinking about the reading process takes into consideration elements that include in a more elaborate way the behavior of the subjects, information related, for example, to how the subjects recheck what they are reading. This methodology shows great promise when modeling the reading process.

Among the various comparison of classification methods implemented in this contribution, we identify the decision tree as the most efficient and more convenient. Most of the methods tried show reasonably good results in differentiating children with and without dyslexic. Even when random forest seems to be equally efficient, a decision tree allow us to identify the line of decision needed to differentiate children with and without dyslexia. The tools implemented in this contribution are promising. The necessary resources are of relatively low cost, and this would make it possible to implement them as an evaluation method in the office of psychologists, psychopedagogues, and speech therapists professional offices, as well as, in schools.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Ethics Approval

Ethics approval for experiments reported in the submitted manuscript on animal or human subjects was granted. Informed consent was obtained from the legal guardian of each participant. The children also gave their consent to participate. All participants were treated in accordance with the Declaration of Helsinki. The institution also provided consent for the collection of data within the facilities.

Author Contributions

F. R. Iaconis: Conceptualization (equal); Data curation (equal); Formal analysis (equal); Investigation (equal); Methodology (equal); Software (equal); Validation (equal); Visualization (equal); Writing – original draft (equal). **M. A. Trujillo Jiménez:** Data curation (equal); Formal analysis (equal); Investigation (equal); Methodology (equal); Software (equal); Validation (equal); Visualization (equal); Writing – original draft (equal). **G. Gasaneo:** Conceptualization (equal); Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Methodology (equal); Resources (equal); Supervision (equal); Validation (equal); Writing – original draft (equal); Writing – review & editing (equal). **O. A. Rosso:** Conceptualization (equal); Formal analysis (equal); Supervision (equal); Writing – review & editing (equal). **C. A. Delrieux:** Conceptualization (equal); Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Methodology (equal); Supervision (equal); Writing – original draft (equal); Writing – review & editing (equal).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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