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The "Rubber-Mask" Technique—II. Pattern Storage and Recognition

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Abstract—This paper briefly summarizes much of the work in pattern recognition to date, and relates the rubber mask technique to previous work. A scheme for incorporating flexible-mask methods into a proposed pattern recognition and memory system is presented. A discussion based on some facts and on some conjecture of the human eye/brain system and how it recognizes patterns, possibly by flexible matching, is also presented.

Flexible templates Rubber masks Pattern recognition and memory system
Hypothesis testing and pattern watching Stereo random dot patterns

INTRODUCTION

THE PREVIOUS paper(1) presented a set of examples in which the principle of rubber masks was used in pattern measurement and analysis. The purpose of the present paper is to show how this principle might be used in pattern-recognition and information-storage systems. A further purpose is to speculate on how the functioning of a rubber-mask pattern-recognition system could compare with the functioning of the natural eye/brain system.

Many of the papers and books on pattern recognition that have appeared in the literature during the past decade have begun with a description of the general pattern-recognition system shown in Fig. 1. This representation has proven to be sufficiently general to cover almost any recognition scheme that has been devised.(2)

The preprocessor in Fig. 1 derives its input signal (usually a vector) from an array of photocells, or equivalently from a scanning image dissector for image processing; or from a microphone for speech recognition; or from some other sensory source. The preprocessor outputs go to the classifier, which may be a trainable adaptive system or which may be some form of signal separator whose design is based on *a priori* knowledge. The classifier outputs are coded representations of the pattern classifications.

A representative (but non-exhaustive) list of schemes for preprocessing is presented in Fig. 1. Among the preprocessing schemes, the *straight-through* scheme involves no preprocessing at all. The *random-scramble* scheme performs a type of preprocessing which is generally designed for specific expected pattern features but does perform some measure of non-specific preprocessing. The *feature-detection* schemes are designed to look for and enumerate or quantify certain salient pattern "landmarks"; while *property-measurement* schemes measure pattern parameters (by statistical means or otherwise) which are generally insensitive to size, rotation, and translation. *Heuristic feature detection* and *picture parsing* are primarily concerned with pattern segmentation and context (spatial or temporal) or with the way in which the picture parts are interrelated or interspersed.

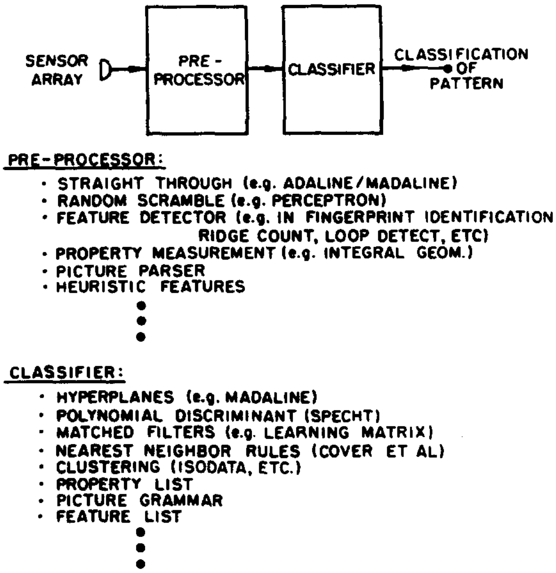


FIG. 1. Typical forms . . . classical system.

Also shown in Fig. 1 is a representative list of classifier schemes that have appeared in the literature. *Hyperplane* and *matched-filter* classifiers are in the same family, since they segment the pattern vector space with piecewise hyperplanar boundaries which can articulate as required to approximate higher-degree surfaces. All of these schemes lend themselves to adaptive or learning procedures for adjusting their parameters, with the learning process based on sets of identified reference or "training" patterns. *Nearest-neighbor rules* are easily implemented as learning schemes; as more training vectors are obtained, more identified points will be available in pattern-vector space with which to compare unknown vectors to be classified. Nearest-neighbor rules classify with boundaries that are also piecewise hyperplanar once the training data are assimilated. *Clustering techniques* involve a form of learning with unidentified input vectors. Pattern vectors that are in some sense close to one another and at the same time distant from all other vectors are clustered or associated. There are many ways to accomplish this automatically. The result is a set of vectors that are identified with respect to one another. The *property-list classifier* also forms separating boundaries in a vector space; the vector components are taken or encoded from measured pattern properties. Typical properties might be length, width, mass, color, or possibly the types of measures obtained by *integral geometry*. The *feature-list classifier* is a check list with which pattern features can be compared (as to their presence or absence) for classification purposes. Rules are established for the classifier tolerance to missing features and to "false-alarm" features. The *picture-grammar classifier* uses the feature-list principle in essence. In addition it uses contextual information derived from the picture parser.

The preprocessor and classifier systems described above, whether adaptive or non-adaptive, map pattern vectors into classification-space vectors, after which they implement boundaries for final pattern separation. The preprocessor/classifier scheme represents what we might call the classical approach to pattern recognition.

The next section considers the basic nature of the overall pattern-recognition problem. and attempts to present a new proposal for its eventual solution.

2. A RUBBER-MASK APPROACH TO PATTERN RECOGNITION

The fundamental problem in pattern recognition may be illustrated by the following example:

A person is now standing before you and you're trying to decide whether you've seen that person's face before. The face might have been seen previously with a slightly different shadow, with a different perspective, at a different distance, or with the head rotated at a somewhat different angle. With regard to all these aspects, the face has never been seen before quite as it is at present. Mentally, what one seems to do is to take previously encountered images and by distorting them in some reasonable way, determine whether a projection could be found that would give a good match between the remembered image and the actual image currently seen.

It is evident from the above example that the problem consists in recognizing the *essential pattern* that underlies and is common to the various views of a particular face that one is able to remember. This problem, the human eye/brain system seems to solve quite well. It is this problem that the rubber-mask approach addresses directly. R. L. GREGORY in his book *Eye and Brain*[3] points out that:

> ... perception is not determined simply by the stimulus patterns; rather it is a dynamic searching for the best interpretation of the available data...

In the field of automatic pattern recognition, classical methods have been tried with some success on specific problems. But no comprehensive approach has developed that has the possibility of solving general problems such as facial recognition, handwriting recognition, speech recognition, and others, in a manner analogous to that of the human eye/brain system in level of performance and means of function.

It is proposed that automatic machinery be built (or programmed) to perform pattern recognition tasks in a natural way using the principle of rubber masks. The system diagrammed in Fig. 2 could represent a significant step in this direction. The sensor

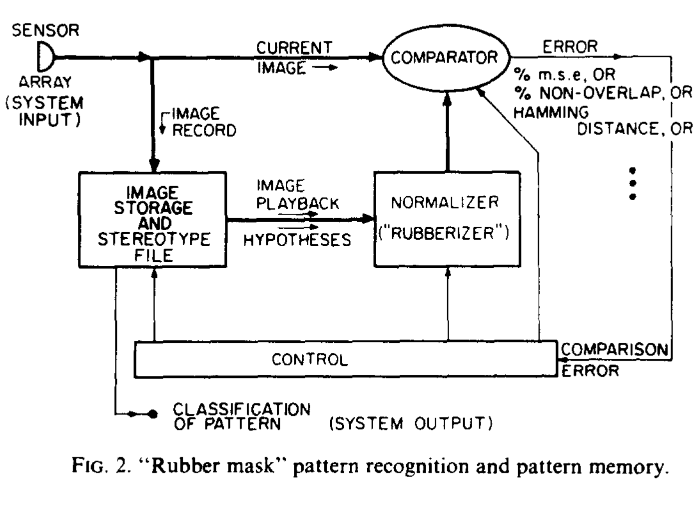


FIG. 2. "Rubber mask" pattern recognition and pattern memory.

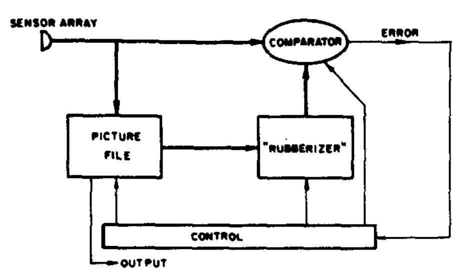
array feeds current image signal vectors into a comparator. Everything from the sensor array also goes into the image storage and stereotype file. From this store. patterns are fed through a normalizer ("rubberizer") and then compared against the current image. What is involved is a hypothesis-testing process. "Hypotheses" from the stereotype file are stretched and compared against unidentified input data. Each stereotype can be regarded as a hypothesis to be adjusted by the rubberizer for best fit to the current input image. The hypothesis that gives the best fit and/or requires the least stretching to achieve best fit is accepted. First and second runners-up would usually be recalled to resolve conflicts.

The functions of the various boxes of Fig. 2 are represented in Fig. 3 as follows: The comparator compares, fixates, windows, and tests hypotheses. By "to fixate" we mean to focus the center of the window (the field of view) on a particular portion of the image. The rubberizer rotates, translates, scales, distorts, shades, projects in perspective, outlines, edge-detects, etc.

The stereotype file contains short-term and long-term memory. records image-vector inputs. and plays back recorded images. The short-term memory stores distorted images during the hypothesis testing phase; the long-term memory stores input images. Image features are used for associative addressing for record and playback. The control box stimulates the whole system to make it go.

Since new templates may be formed and recorded from current input data as the system is exposed to its environment, a form of learning associated with the pattern-recognition process is possible. That is to say, the *intrinsic* pattern of the function being studied may gradually become apparent as template formation progresses. An example is found in the EEG and EKG studies in Ref. (1).

The proposed rubber-mask pattern-recognition system is intended to represent a practical approach to pattern recognition and pattern memory based on template storage,



COMPARATOR	: COMPARES, FIXATES, WINDOWS, TESTS HYPOTHESES.
NORMALIZER ("RUBBERIZER")	: ROTATES, TRANSLATES, SCALES, DISTORTS, SHADES, PROJECTS IN PERSPECTIVE, OUTLINES, EDGE-DETECTS,···
PICTURE FILE	: CONTAINS SHORT-TERM/LONG-TERM MEMORY, RECORDS PICTURE INPUTS, PLAYS BACK RECORDED IMAGES; COULD USE IMAGE FEATURES FOR ASSOCIATIVE ADDRESSING FOR RECORD AND PLAYBACK.
CONTROL	: STIMULATES PICTURE FILE TO PRODUCE IMAGE HYPOTHESES; ACTUATES RUBBERIZER TO OPTIMIZE IMAGE FIT; ACTUATES COMPARATOR TO TRY VARIOUS FIXATIONS AND WINDOWS; IMPLEMENTS CLASSIFICATION RULE MINIMIZING ERROR.

FIG. 3. "Rubber mask" system functions.

template stretching, and template matching. The system is organized to perform sequences of hypothesis tests, and to recognize and measure pattern images. Each stored template is a hypothesis available for comparison with the current data. Alternate hypotheses could be ranked in terms of closeness of fit and extent of stretch required to achieve best fit.

3. SOLVING RECOGNITION PROBLEMS WITH THE RUBBER-MASK SYSTEM

In this section, we illustrate the functioning of the system of Fig. 3 by describing how it might address a practical problem, that of facial recognition. Two approaches are possible. One is based on the use of *natural* templates, i.e. templates derived from observation of nature. The other is based on the use of *man-made* (artificial) standard templates.

(a) *Natural templates*

In the system of Fig. 2, many facial templates could be stored in the file. These might consist of actual photographs, digitized photographs, scanned photographs as in closed-circuit TV, or coded photographs. Whatever the form in which each image is stored, it would be *derived from nature* in some manner.

For a start on the problem of recognizing an unidentified image of an entire face, the eyes, sub-images, could be sought out and identified by template matching, using the rubberizer to obtain best fit to the remembered or recorded eyes by aligning, synthesizing, and stretching, as was done in the case of matching EKG waveforms in the previous paper.[1] For general usage in the system of Fig. 2, many eye templates from different people, taken under different lighting conditions, different perspectives, different amounts of rotation and translation, could be stored in the file. These would be direct images from nature, *before* any stretching or other distortion had been performed by the rubberizer to fit the remembered (or otherwise available) sample image. Separation between the eyes might be included in the matching process, i.e. an eye template could consist of a *pair* of eyes in various spatial relationships.

Such a procedure could be very powerful. For example, in the initial step a *defocused* image could be compared with a *defocused* template for a first crude elimination of totally unsuitable templates (pop eyes vs squinted eyes; almond-shaped eyes vs round eyes; and so on.) Allowing the comparison to sharpen after the first-stage elimination, the remaining candidate eye templates could be stretched and aligned to best-fit the data images—as a result of which, several likely individuals might well be selected from among hundreds of "possibles."

Next, the study might proceed to another important facial area— the mouth. Following the same procedure, several persons out of hundreds could possibly be selected as corresponding to an unidentified image on the basis of the mouth and its characteristic expression.

After tying down some good candidate examples of the eye and the mouth, the investigation might proceed to consideration of the nose, the ears, the hairline, the chin, and so on. True, the most likely sub-images as selected in each category are noted in terms of one or more candidate individuals who possess these sub-images; but the selected sub-images are ultimately viewed *in combination*. The entire unknown image is compared and matched to entire stored facial images made up of the selected sub-images arranged in various dimensional relationships to determine which candidate gives the best match. For example, when a candidate pair of eyes has been selected, this pair must be tried in an assembly of sub-images to simulate the remembered face.

A simple segmentation algorithm for the system of Fig. 2 having fairly general applicability in image analysis and recognition would look for regions within the image which contain significant fractions of the total area—regions which are rich in optical texture and which are isolated and self-contained. Such an algorithm would automatically choose the eyes, the mouth, the nose, and so on for isolation and study in facial analysis; and would eventually assemble these in various relationships for final recognition.

(b) *Artificial templates*

Another approach to facial recognition by means of rubber masks would utilize stored *artificial* templates. For eye recognition, a small number of man-made stereotypes could be stored, corresponding to a reasonable range of directly-viewed eye shapes (as would be used in a police identification kit).[4] The eyes of an unknown facial image could be given a numerical classification in terms of the identification number of the eye template that best fits when best-stretched or projected. Separations between the eyes of a pair could be included in the analysis. Many people out of hundreds would have the same eye classification number; but the inclusion of eye *separation* might reduce the number of candidates.

If a small number of artificial stereotypes were stored for each sub-image, then the sub-images of any unknown facial image of interest could be assigned numerical identifications from flexibly fitting the stored artificial templates. From the point of view of data reduction, each face of interest could be approximately but efficiently stored, not with an actual picture, but with a set of numbers listed by sub-image. It should be noted that relative positions of the salient portions of the facial image—not only spacing between the eyes, but also distances from the eyes to nose and mouth, etc.—are also significant facial features that could be measured by rubber-mask techniques.

From the point of view of pattern recognition, an unknown face would be recognized by comparing the list of sub-images and their assembly dimensions for the unknown face against the corresponding attributes of previously encountered known facial images.

4. IMPLEMENTATION OF RUBBER-MASK PATTERN-STORAGE AND RECOGNITION SYSTEM

Development of the complete system of Fig. 3, involving derivation of algorithms and their mathematical properties, is a long term goal of this research. Work is under way on the rubberizer and on the comparator. This work is being done in the context of the problems described in the previous paper, namely chromosome analysis, chromatogram measurement, and EEG and EKG analyses.

The image and stereotype file is a very complicated operation and little has been accomplished toward its realization so far. In the examples of the previous paper, the stereotype storage function has been very simple. In chromosome analysis, one merely stores the Denver Standards. In chromatogram analysis, one stores (or generates) a gaussian function. In EKG analysis, one would ultimately store a relatively small set of normal waveforms, and also small sets of waveforms to typify each disease state of interest. None of these storage functions compares, however, to that which develops in facial recognition using perhaps thousands of natural faces (or their components) as templates.

All of the functions of the system of Fig. 3 are mechanistic and should eventually be realizable. It is clear, however, that some of these operations require large amounts of computer time in their implementation if present general-purpose equipment is used. In the future, it may in fact be necessary to develop completely new kinds of computing machinery to perform such algorithms.

5. HYPOTHESIS TESTING AND PATTERN MATCHING IN THE EYE/BRAIN SYSTEM

We have implied that emulating (even in the most remote degree) the pattern-recognition performance of the human eye/brain system is an ultimate goal of the rubber-mask system. The latter involves primarily hypothesis fitting (stretching, adjusting parameters), hypothesis testing (checking the fit), and trying alternative hypotheses. Such a process of sequential hypothesis testing seems to be a very natural one; it appears to be central to the functioning of the human mind. The ability to match one intricate pattern to another in spite of limited but significant rotation, translation, scale change, projection distortion, etc., is a remarkable attribute of the human eye/brain system.

That when the eye sees an image, the mind forms alternative hypotheses as to the nature of the perceived object is readily demonstrated when viewing one of the many classic optical-illusion images that have appeared in the literature. One famous example is the Necker cube.[3] One can stare at the picture of this seeming cube of wire and see it clearly in a certain spacial context—when all of a sudden the mind "flips" and the cube now appears to be inside out. Both hypotheses of what is seen are equally acceptable to the mind, which seems to like to test alternative hypotheses. Usually, one possibility fits the data better than all the rest. Sometimes, as is the case with illusions, more than one alternative best fits; or it may be that the hypothesis that seems to fit best is completely incorrect.

Interesting statements on seeing, perception, and hypothesis testing are given by GREGORY.[3]

> ... Perception involves going beyond the immediately given evidence of the senses: this evidence is assessed on many grounds and generally we make the best bet, and see things more or less correctly. But the senses do not give us a picture of the world directly; rather they provide evidence for checking hypotheses about what lies before us. Indeed, we may say that a perceived object *is* a hypothesis, suggested and tested by sensory data ... When a perceptual hypothesis—a perception—is wrong we are misled as we are misled in science when we see the world distorted by a false theory.

The idea that intricate pattern-to-pattern comparisons can be made by the eye/brain system is suggested by the work of B. JULESZ[5] of the Bell Telephone Laboratories. In his experiments, two related patterns, constituting a "random dot stereogram," are shown simultaneously to the left and the right eye, respectively; and three-dimensional images are perceived by the eye/brain system in establishing the mutual connection between the images. The patterns consist of random dots. Individually, they appear in every respect to be feature-free.

As a simple example,* consider a planar area covered uniformly with white snow. Apply many black dots in a random array on top of the snow. Now look down on the scene with both eyes. Each eye sees the same random black dots on the white background.

* The reader should not blame Dr. Julesz for this illustration or for the implications drawn from it. The author assumes full responsibility!

The dot array appears to be identical to both eyes. It is true that the respective images are actually shifted with respect to each other because the eyes are physically displaced—but nevertheless, the brain perceives a *single* image of dots on a plane.

Next, imagine another planar area covered with fresh snow—undotted this time. In the midst of this area place a white polar bear. The bear is invisible, since he is white on white. Now put black dots on the snow and (oops!) on the polar bear. The observer's eye will see an image of black dots on a white background. The right eye will not simply see the same dot image as that of the left eye, since the dots on the polar bear will be displaced relative to the dots on the background because the polar bear "sticks up" from the snowy plane. The eye/brain then perceives the scene as a dotted polar bear *sticking up* from a dotted white background.

In this imaginary experiment, each eye sees only random dot patterns. Because of the relationship between the left-eye pattern and the right-eye pattern, however, the eye/brain perceives a three-dimensional image—a three-dimensional object made of dots—placed against a dotted background.

Julesz has generated random dot patterns by computer to represent three-dimensional objects such as cylinders, pyramids, and other geometrical shapes. Such patterns can be generated for sticking-up objects by starting with a random dot pattern for the left eye, and generating from it a pattern for the right eye by translating the dots that were within the original object silhouette by a small distance to the left relative to the background dots. (The silhouette of the object can never be seen in the individual dot patterns.) Vacated areas on the background are filled in by arbitrarily placing dots there. Overlapping background areas have their dot placements pre-empted by the object dot placements.

Remarkable three-dimensional effects are observed by viewing Julesz's random dot patterns.[5] The left-eye image and the right-eye image are addressed exclusively to the left eye and to the right eye, respectively, by using color-filter glasses—green for left eye, red for right eye—to view two superposed images printed in the two colors. Julesz has obtained even more spectacular results with random dot patterns by using polaroid glasses with projected polarized-light images.

Since the individual random-dot patterns are apparently feature-free, one might possibly conclude from such experiments either that the eye/brain does not use features, or that if it does use them, they are not completely necessary for object recognition. Such a conclusion may in fact be correct; but the experiments do not necessarily lead to it. The *differences* between the left-eye and right-eye patterns contain the object shape and could thus contain its features. One point is clear: the eye/brain is capable of making very intricate pattern-to-pattern comparisons, apparently using direct pattern data in full detail. Imagine the detail contained in the random dot patterns!

In a seminar presented at Stanford University several years ago, Dr. Julesz described experiments that were performed with an eidetic subject (i.e. one having a "photographic memory"). If the right eye is covered, and the left-eye image is presented to the left eye, a random-dot array is perceived by the subject. A day later, the left eye is covered, and the right-eye image is presented to the right eye. When this is done with an ordinary subject, only a random-dot pattern is perceived. When the same experiment is performed with an eidetic subject, the image appears to him to be raised from the plane of the background.

After hearing of this stunning experiment, the following question was posed: Was the subject's head clamped in place on the two occasions, with the dot images precisely supported and lighted, to insure identical conditions for the two image sightings? The answer was no. On both occasions the dot pictures were hand held, and lighting was not critically maintained. Even if the pattern at the second sighting was rotated by as much as $\pm 10°$ of the original orientation, and the distance of the pattern was changed as much as ± 10 per cent of the original distance, and if aspect angle was allowed a tolerance similar to that of the rotation angle, the three-dimensional image was easily perceived by the eidetic subject. An implication of this experiment is that the eye/brain is capable of matching very intricately-related patterns in spite of limited amounts of relative rotation, translation, scale change, aspect change, and so on.

Experiments along these lines with other kinds of distortions (twisting, differential stretching, etc.) would be very useful. The left-eye pattern could be a random dot array. The right-eye pattern could contain the dotted object (properly disposed relative to the left-eye pattern) including the desired distortion. Ordinary test subjects could be used, with both patterns presented to the eyes simultaneously. The interesting question is, how much distortion is permissible in the right-eye image relative to the left-eye image before the subject loses three-dimensional perception of the image?

The three-dimensional visual effect may well provide a medium for the experimental study of how the eye/brain matches one pattern against another and how it tests alternative hypotheses. The results of such experiments would give ideas on the types of functions that might be built into an automatic pattern-recognition system.

6. CONCLUSION

A complete memory and pattern-recognition system is suggested based on the rubber-mask concept. Three important functions are needed: Hypothesis testing (pattern matching); pattern stretching; and pattern memory. There is some evidence that these functions can be implemented in automatic equipment, and it is speculated that the same functions are performed in a natrual way in the eye/brain system.

One of the earliest thinkers to look at perception from the point of view of hypothesis formation and testing was Plato. He believed that man is endowed with a sense of beauty and perfection, and that man perceives natural objects as imperfect versions of perfect geometric forms such as straight lines, circles, and so on. Plato's models, which he called ιδεας (*archetypes* or perfect forms) were all in the mind and were by definition perfect—whether they represented perfect circularity, perfect equality, perfect justice, or any other idealized standard never achieved in the natural universe.

The basic character of geometric proofs was evidently known to Plato. For instance, he was undoubtedly familiar with Pythagoras' proof that the square on the hypothenuse of a right triangle is equal to the sum of the squares on the other two sides—a proof that had to be (and has to be today) based on purely mental concepts of the perfect circle, the perfect right angle, and so on. No such perfect forms could in the olden days be traced in the dust with a stick—nor can they today be drawn on vellum with compass and ruler nor reproduced by a computerized system of graphics!

It is interesting to read from PLATO's *Republic*[6] his ideas on hypotheses and idealizations. As reported by Plato, Socrates (into whose mouth Plato put many of his own theories) is engaged in a dialogue with his pupil Glaucon.

> ... You are aware that students of geometry, arithmetic, and the kindred sciences assume the odd and the even and the figures and three kinds of

angles and the like in their hypotheses, which they and everybody are supposed to know, and therefore they do not deign to give any account of them either to themselves or others; but they begin with them, and go on until they arrive at last, and in a consistent manner, at their conclusion?

Yes, he said, I know.

And do you not know also that although they make use of the visible forms and reason about them, they are thinking not of these, but of the ideals which they resemble; not of the figures which they draw, but of the absolute square and the absolute diameter, and so on—the forms which they draw or make, and which have shadows and reflections in water of their own, are converted by them into images, but they are really seeking to behold the things themselves, which can only be seen with the eye of the mind?

That is true.

Republic, Book VI (Jowett trans.)

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