Visual Recognition: Instances and Categories

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Instance-level recognition
Instance recognition

- Motivation – visual search
- Visual words: quantization, inverted index, bags of words
- Spatial verification: RANSAC, Hough
- Other text retrieval tools: tf-idf
- Example applications
Recognizing or retrieving specific objects

- Example: Visual search in feature films

Visually defined query

“Find this clock”

“Find this place”

“Groundhog Day” [Rammis, 1993]

[Source: J. Sivic]
Recognizing or retrieving specific objects

- Example: Search photos on the web for particular places

Find these landmarks ...in these images and 1M more

[Source: J. Sivic]
Google Goggles
Use pictures to search the web.

Get Google Goggles
Android (1.6+ required)
Download from Android Market.

Send Goggles to Android phone

Get Google Goggles
New! iPhone (iOS 4.0 required)
Download from the App Store.

Send Goggles to IPhone

New!

Text
Landmarks
Books
Contact Info
Artwork
Wine
Logos

Example: A menu from a restaurant is scanned and translated into English.
Why is it difficult?

- Want to find the object despite possibly large changes in scale, viewpoint, lighting and partial occlusion.
- We can’t expect to match such varied instances with a single global template...

[Source: J. Sivic]
Each patch / region has a descriptor, which is a point in some high-dimensional feature space (e.g., SIFT)

[Source: K. Grauman]
Indexing local features

- It can have millions of features to search.

[Source: K. Grauman]
Indexing local features: inverted file index

- For text documents, an efficient way to find all pages on which a word occurs is to use an index.
- We want to find all images in which a feature occurs.
- To use this idea, we need to map our features to visual words.
- Why?

[Source: K. Grauman]
Indexing local features: inverted file index

- Map high-dimensional descriptors to tokens/words by quantizing the feature space.
- Quantize via clustering, let cluster centers be the prototype words.
- Determine which word to assign to each new image region by finding the closest cluster.

[Source: K. Grauman]
Visual words

- Each group of patches belongs to the same visual word.
Visual vocabulary formation issues

- Vocabulary size, number of words.
- Sampling strategy: where to extract features?
Visual vocabulary formation issues

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- Clustering / quantization algorithm.
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- What corpus provides features (universal vocabulary?)
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Inverted File Index

- Database images are loaded into the index mapping words to image numbers.
Inverted File Index

- New query image is mapped to indices of database images that share a word.

<table>
<thead>
<tr>
<th>Word #</th>
<th>Image #</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1, 2</td>
</tr>
<tr>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>91</td>
<td>2</td>
</tr>
</tbody>
</table>
What else do we need to do?

- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
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Of all the sensory impressions proceeding to the brain, the visual experiences are the dominant ones. Our perception of the world around us is based essentially on the messages that reach us through our eyes. For a long time, the visual image was thought to be processed in visual centers in the brain. As it turns out, as a movie script is transformed into an image, the brain discards much of what we would know that an initial visual perception is more complex, occurring in a series of processes, each of which is associated with a specific part of the brain. The retina, the brain's visual cortex, Hubel and Wiesel have demonstrated that the message about the visual world is encoded in the retina and undergoes columnar analysis in a system of nerve cells, each having its specific function and is responsible for a specific detail in the pattern of the retinal image.

China is forecasting a trade surplus of $90bn (£51bn) to $100bn this year, a threefold increase on 2004's $32bn. The Commerce Ministry said the surplus would be created by a predicted 30% increase in exports to $750bn, compared with last year's $590bn. The US is expected to annoy the US government by proposing that China's trading practices be delisted from a US government list of unfair traders. China's government also needs to keep the Asian currency, the yuan, against the dollar. The yuan is weak against the dollar and permitted it to trade within a narrower range but the US wants the yuan to be allowed to trade freely. However, Beijing has made it clear that it will take its time and tread carefully before allowing the yuan to rise further in value.
Bags of visual words

- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.
Comparing visual Words

- Rank frames by normalized scalar product between their (possibly weighted) occurrence counts—nearest neighbor search for similar images

\[
\text{sim}(d_j, q) = \frac{<d_j, q>}{\|d_j\| \cdot \|q\|}
\]

[Image of histograms and visual words]
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Hierarchical clustering for large vocabularies, [Nister et al., 06].

- $k$ defines the branch factor (number of children of each node) of the tree.
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The same process is then recursively applied to each group.
Vocabulary Trees

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- First, an initial $k$-means process is run on the training data, defining $k$ cluster centers.
- The same process is then recursively applied to each group.
- The tree is determined level by level, up to some maximum number of levels $L$. 
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Constructing the tree

- Offline phase: hierarchical clustering.
Offline phase: hierarchical clustering.
Constructing the tree

- Offline phase: hierarchical clustering.

![Vocabulary Tree](image-url)
Constructing the tree

- Offline phase: hierarchical clustering.
Online phase: each descriptor vector is propagated down the tree by at each level comparing the descriptor vector to the $k$ candidate cluster centers (represented by $k$ children in the tree) and choosing the closest one.

The tree directly defines the visual vocabulary and an efficient search procedure in an integrated manner.

Every node in the vocabulary tree is associated with an inverted file.

The inverted files of inner nodes are the concatenation of the inverted files of the leaf nodes (virtual).
Vocabulary size

- Complexity: branching factor and number of levels
- Most important for the retrieval quality is to have a large vocabulary
Visual words/bags of words

Good
- flexible to geometry / deformations / viewpoint
- compact summary of image content
- provides vector representation for sets
- very good results in practice

Bad
- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear
- basic model ignores geometry must verify afterwards, or encode via features
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- How to score the retrieval results?
Spatial Verification

- Both image pairs have many visual words in common
- Only some of the matches are mutually consistent

[Source: O. Chum]
Two basic strategies

- RANSAC
- Generalized Hough Transform
Illustration: Least Squares Fit

[Source: K. Grauman]
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[Source: K. Grauman]
RANSAC

- RANdom Sample Consensus.
- Approach: we want to avoid the impact of outliers, so let's look for inliers, and use those only.
- Intuition: if an outlier is chosen to compute the current fit, then the resulting line won't have much support from rest of the points.
Loop

- Randomly select a seed group of points on which to base transformation estimate
- Compute model from seed group
- Find inliers to this transformation
- If the number of inliers is sufficiently large, re-compute estimate of model on all of the inliers

Keep the model with the largest number of inliers
RANSAC for line fitting

Repeat:

- Draw $s$ points uniformly at random
- Fit line to these $s$ points
- Find inliers to this line among the remaining points (i.e., points whose distance from the line is less than $t$)
- If there are $d$ or more inliers, accept the line and refit using all inliers

[S. Lazebnik]
Example of line fitting
Example of line fitting
RANSAC for line fitting example

1. Randomly select minimal subset of points
2. Hypothesize a model

[Source: R. Raguram]
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[Source: R. Raguram]
What about fitting a transformation?

- Select one match, count inliers
What about fitting a transformation?

- Select one match, count inliers

Find “average” translation vector
RANSAC

- Typically sort by BoW similarity as initial filter
- Verify by checking support (inliers) for possible transformations
- Success if find a transformation with $> N$ inlier correspondences
Fitting an affine transformation

- Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras

- **Affine** is \( p' = A\bar{p} \), with \( A \) an arbitrary \( 2 \times 3 \) matrix, i.e.,

\[
p' = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \end{bmatrix} \bar{p}
\]

- Parallel lines remain parallel under affine transformations.
Fitting an affine transformation

- For all points

\[
\begin{bmatrix}
... \\
x_i & y_i & 0 & 0 & 1 & 0 \\
0 & 0 & x_i & y_i & 0 & 1 \\
... \\
\end{bmatrix}
\begin{bmatrix}
  a_{00} \\
a_{01} \\
a_{02} \\
a_{10} \\
a_{11} \\
a_{12} \\
\end{bmatrix}
= \begin{bmatrix}
  ... \\
x'_i \\
y'_i \\
... \\
\end{bmatrix}
\]

- Least-squares fitting

\[
\min_{a_{00}, \ldots, a_{12}} \| Pa - P' \|^2_2
\]
Ransac Verification

[Source: K. Grauman]
Generalized Hough Transform

- It's not feasible to check all combinations of features by fitting a model to each possible subset.
- First, cycle through features, cast votes for model parameters: location, scale, orientation of the model object.
Generalized Hough Transform

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- Look for model parameters that receive a lot of votes, and verify them.
Spatial Verification

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- Noise & clutter features will cast votes too, but their votes should be inconsistent with the majority of good features.
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If we use scale, rotation, and translation invariant local features, then each feature match gives an alignment hypothesis (for scale, translation, and orientation of model in image).

[Source: S. Lazebnik]
Generalized Hough Transform

- A hypothesis generated by a single match is in general unreliable,
- Let each match vote for a hypothesis in Hough space.

[Source: K. Grauman]
Training phase: For each model feature, record 2D location, scale, and orientation of model (relative to normalized feature frame)

Test phase: Let each match between a test SIFT feature and a model feature vote in a 4D Hough space

- Use broad bin sizes of 30 degrees for orientation, a factor of 2 for scale, and 0.25 times image size for location
- Vote for two closest bins in each dimension

Find all bins with at least three votes and perform geometric verification. Estimate least squares affine transformation and search for additional features that agree with the alignment.
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Recognition Example

Background subtract for model boundaries

Objects recognized,

Recognition in spite of occlusion
Problems of Voting

- Noise/clutter can lead to as many votes as true target
- Bin size for the accumulator array must be chosen carefully
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Comparison Verification

Generalized Hough Transform

- Each single correspondence votes for all consistent parameters
- Represents uncertainty on the parameter space
- Complexity: Beyond 4D space is impractical
- Can handle high outlier/inlier ratio

Ransac

- Minimal subset of correspondences to estimate the model, then count inliers
- Represent uncertainty in image space
- Must look at all points to check for inliers at each iteration
- Scales better with high dimensionality of parameter space.
Scoring retrieval quality

Query

Database size: 10 images
Relevant (total): 5 images

precision = #relevant / #returned
recall = #relevant / #total relevant

Results (ordered):

[Source: O. Chum]
tf-idf weighting

- Term frequency – inverse document frequency
- Describe frame by frequency of each word within it, downweight words that appear often in the database

\[
t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}
\]

- \(n_{id}\) : number of occurrences of word \(i\) in document \(d\)
- \(n_d\) : number of words in document \(d\)
- \(N\) : total number of documents in the dataset
- \(n_i\) : number of documents word \(i\) occurs in (in the whole dataset)
Video Google System

- Collect all words within query region
- Inverted file index to find relevant frames
- Compare word counts
- Spatial verification
Object retrieval with large vocabularies and fast spatial matching

Results from 5k Flickr images (demo available for 100k set)
Google Goggles
Use pictures to search the web. ▶ Watch a video

Get Google Goggles
Android (1.6+ required)
Download from Android Market.

Send Goggles to Android phone

New: iPhone (iOS 4.0 required)
Download from the App Store.

Send Goggles to iPhone

New!

Menu

Text

Landmarks

Books

Contact Info

Artwork

Wine

Logos

The Amsterdam in Spring
Menu

English

Lammkoteletts vom Biobauern mit Schalotten, Tomatencoulis und Basilikum-Gnocchi

German (auto) → English

Lamb chops from the farmers with the shallots, tomato sauce and basil gnocchi
Pros:

- Effective when we are able to find reliable features within clutter
- Great results for matching specific instances

Cons:

- Scaling with number of models
- Spatial verification as post-processing – expensive for large-scale problems
- Not suited for category recognition
Matching local invariant features

Useful not only to provide matches for multi-view geometry, but also to find objects and scenes.

Bag of words representation: quantize feature space to make discrete set of visual words

- Summarize image by distribution of words
- Index individual words
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- Recognition of instances via alignment: matching local features followed by spatial verification
  - Robust fitting: RANSAC, Generalized Hough Transform
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Recognition of instances via alignment: matching local features followed by spatial verification

- Robust fitting: RANSAC, Generalized Hough Transform
Category-level recognition
General recognition problem
Challenges

- Realistic scenes are crowded, cluttered, have overlapping objects
Recognition framework

- **Build/train object model**
  - Choose a representation
  - Learn or fit parameters of model / classifier
- Generate candidates in new image: only one for global scene classifiers
- Score the candidates
Models can be divided on

- Window-based models: reason about the full object
- Part-based models: reason about parts and compose the information
Window-based model

1. Holistic: vector of pixel intensities – template matching
2. Holistic: grayscale/color histogram

- Pixel-based representations sensitive to small shifts
- Color or grayscale-based appearance description can be sensitive to illumination and intra-class appearance variation
- Possible solution: Consider edges, contours, and (oriented) intensity gradients
Window-based model

1. Summarize local distribution of gradients with histogram

- Locally orderless: offers invariance to small shifts and rotations
- Contrast-normalization: try to correct for variable illumination
Which Classifier to use?

So many choices

- Nearest Neighbors (NN)
- Support Vector Machines (SVMs)
- Gaussian processes (GPs)
- Boosting
- Neural networks
- Conditional Random Fields (CRFs)
- etc
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Generating and scoring candidates

- Try every possible location: not very efficient.
- Work at different scales
**Training:**
1. Obtain training data
2. Define features
3. Define classifier

**Given new image:**
1. Slide window
2. Score by classifier

[Source: K. Grauman]
Choices and Issues

What classifier?
- Generative or discriminative model?
- Data resources – how much training data?
- How is the labeled data prepared?
- Training time allowance
- Test time requirements – real-time?
- Fit with the representation
Choices and Issues

- What classifier?
- What features or representations?
- How to make it affordable?
- What categories are amenable?
  - Similar to specific object matching, we expect spatial layout to be fairly rigidly preserved.
  - Unlike specific object matching, by training classifiers we attempt to capture intra-class variation or determine discriminative features.
What categories work well with sliding window?

- tall building*
- highway*
- mountain*
- inside city*
- coast*
- forest*
Which detectors?

Window-based

NN + scene Gist classification
e.g., Hays & Efros

SVM + person detection
e.g., Dalal & Triggs

Boosting + face detection
Viola & Jones

Part-based

BOW, pyramids
e.g., [Grauman et al.]

ISM: voting
e.g., [Leibe & Shiele]

deformable parts
e.g., [Felzenszwalb et al.]

poselets
[Bourdev et al.]
IM2GPS: estimating geographic information from a single image

James Hays and Alexei A. Efros
Carnegie Mellon University

Abstract

Estimating geographic information from an image is an excellent, difficult high-level computer vision problem whose time has come. The emergence of vast amounts of geographically-calibrated image data is a great reason for computer vision to start looking globally – on the scale of the entire planet! In this paper, we propose a simple algorithm for estimating a distribution over geographic locations from a single image using a purely data-driven scene matching approach. For this task, we will leverage a dataset of over 6 million GPS-tagged images from the Internet. We represent the estimated image location as a probability distribution over the Earth’s surface. We quantitatively evaluate our approach in several geolocation tasks and demonstrate encouraging performance (up to 30 times better than chance). We show that geolocation estimates can provide the basis for numerous other image understanding tasks such as population density estimation, land cover estimation or urban/rural classification.

1. Introduction

Consider the photographs in Figure 1. What can you say about where they were taken? The first one is easy – it’s an iconic image of the Notre Dame cathedral in Paris. The middle photo looks vaguely Mediterranean. Perhaps a small

Figure 1. What can you say about where these photos were taken?
Where was this taken in the world?
Distribution of images

- Large collection of images from Flickr
- 6+ million geotagged photos by 109,788 photographers
**Representation**

- **Color Histograms** – L*A*B* 4x14x14 histograms, total of 784 dimensions.

- **Texton Histograms** – 512 entry, bank of filters with 8 orientations, 2 scales, and 2 elongations. For each image we then build a 512 dimensional histogram by assigning each pixel’s set of filter responses to the nearest texton dictionary entry.

- **Line Features** – Histograms of straight line stats (line angles and line lengths) to distinguishing between natural and man-made.

- **Geometric context** – compute the geometric class probabilities for image regions.

- **Gist scene descriptor** – 5 by 5 spatial resolution where each bin contains that image regions average response to steerable filters at 6 orientations and 4 scales.
A scene is a single surface that can be represented by global (statistical) descriptors

[Source: A. Oliva]
Spatial Envelope Theory of Scene Representation

V = \{\text{energy at each orientation and scale}\} = 6 \times 4 \text{ dimensions}

V_t \rightarrow \text{PCA} \rightarrow G

Gist descriptor

[Source: A. Oliva]
Classifier

- Assign label of nearest training data point to each test data point
- Voronoi partitioning of feature space for 2-category 2D data

Black = negative
Red = positive

Novel test example

Closest to a positive example from the training set, so classify it as positive.

from Duda et al.
Classifier improvement

- For a new point, find the k closest points from training data
- Labels of the k points vote to classify

Black = negative
Red = positive
Qualitative Results
Qualitative Results
Qualitative Results

[Images of various landscapes from different countries including Argentina, China, Costa Rica, and Iguazu Falls in Brazil.]
Qualitative Results
Results: size matters

![Graph showing the percentage of geolocations within 200km versus database size]

- **First Nearest Neighbor Scene Match**
- **Chance—Random Scenes**

**Y-axis:** Percentage of geolocations within 200km

**X-axis:** Database size (thousands of images, log scale)
Multi-features: We scale each features distances so that their standard deviations are roughly the same and thus they influence the ordering of scene matches equally.
Pros:

- Simple to implement
- Flexible to feature / distance choices
- Naturally handles multi-class cases
- Can do well in practice with enough representative data

Cons:

- Large search problem to find nearest neighbors, e.g., KD-trees, hashing, etc.
- Storage of data: non-parametric, we keep everything.
- Must know we have a meaningful distance function: metric learning
Histotograms of Oriented Gradients for Human Detection

Navneet Dalal and Bill Triggs
INRIA Rhône-Alps, 655 Avenue de l’Europe, Montbonnot 38334, France

Abstract
We study the question of feature sets for robust visual object recognition, adopting linear SVM based human detection as a test case. After reviewing existing edge and gradient based descriptors, we show experimentally that grids of Histograms of Oriented Gradient (HOG) descriptors significantly outperform existing feature sets for human detection. We study the influence of each stage of the computation on performance, concluding that fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all important for good results. The new approach gives near-perfect separation on the original MIT pedestrian database, so we introduce a more challenging dataset containing over 1800 annotated human images with a large range of pose variations and backgrounds.

1 Introduction

We briefly discuss previous work on human detection in §2, give an overview of our method §3, describe our data sets in §4 and give a detailed description and experimental evaluation of each stage of the process in §5–6. The main conclusions are summarized in §7.

2 Previous Work

There is an extensive literature on object detection, but here we mention just a few relevant papers on human detection [18, 17, 22, 16, 20]. See [6] for a survey. Papageorgiou et al [18] describe a pedestrian detector based on a polynomial SVM using rectified Haar wavelets as input descriptors, with a parts (subwindow) based variant in [17]. Depoortere et al give an optimized version of this [2]. Gavrila & Philomen [8] take a more direct approach, extracting edge images and matching them to a set of learned exemplars using chamfer distance. This has been used in a practical real-time pedestrian detection system [7]. Viola et al [22] build an efficient
Task to solve

- Pedestrian detection
Representation

- Histogram of gradients: [Schiele & Crowley, Freeman & Roth]
- Code available: http://pascal.inrialpes.fr/soft/olt/
Linear Classifier

- Find linear function to separate positive and negative examples
  \[ f(x) = w^T x + b \]
- \( f(x) > 0 \) if \( x \) is a positive example.
- \( f(x) < 0 \) if \( x \) is a positive example.
Input $x \in \mathbb{R}^D$, and outputs $y_i \in \{-1, 1\}$

General setup: training set sampled i.i.d. from $p(x, y)$, we want to find parametric predictor $f \in \mathcal{F}$ that minimizes

$$R(f) = E_{x_0, y_0} [L(f(x_0; \Theta), y_0)]$$

with $L$ the loss

Regularized ERM:

$$\hat{\theta} = \arg\min_{\theta} \sum_{i=1}^{N} L(f(x_i; \theta), y_i) + R(\theta)$$

Loss $L$: square loss (ridge regression, GP), hinge (SVM), log loss (logistic regression)
Linear Classifier

- Discriminative classifier based on optimal separating hyperplane
- Maximize the margin between the positive and negative training examples
Support Vector machines

- Maximize the margin between the positive and negative training examples

- Positive $y_i = 1$: $w^T x_i + b \geq 1$
- Negative $y_i = -1$: $w^T x_i + b \leq 1$
- Support vector: $x_i \cdot w + b = 1$
- Point line distance: $\frac{y(w^T x + b)}{|w|}$
- For support vectors: $\frac{1}{|w|}$
- Margin $M = \frac{2}{|w|}$
Find the max margin hyperplane

- Maximize the margin and classify all the points
- Quadratic optimization problem

\[
\begin{align*}
\min_w & \quad \frac{1}{2} \|w\|^2 \\
\text{subject to} & \quad y_i(b + w^T x_i) - 1 \geq 0, \quad i = 1, \ldots, N.
\end{align*}
\]

- We will associate with each constraint the loss

\[
\max_{\alpha \geq 0} \alpha \left[ 1 - y_i(b + w^T x_i) \right] = \begin{cases} 
0, & \text{if } y_i(w_0 + w^T x_i) - 1 \geq 0, \\
\infty & \text{otherwise (constraint violated).}
\end{cases}
\]

- We can reformulate our problem now:

\[
\min_w \left\{ \frac{1}{2} \|w\|^2 + \sum_{i=1}^{N} \max_{\alpha_i \geq 0} \alpha_i \left[ 1 - y_i(b + w^T x_i) \right] \right\}
\]
Find the max margin hyperplane

- Maximize the margin and classify all the points
- Quadratic optimization problem

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\min_w \quad \frac{1}{2} \|w\|^2 \\
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