Optimized corner detection and object detection

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Damian Eads, David Helmbold, Reid Porter, Tom Drummond

Optimizing the right thing

Two examples:

1. Corner detection
2. Object detection

What are they and how do you optimize them?

What is corner detection?

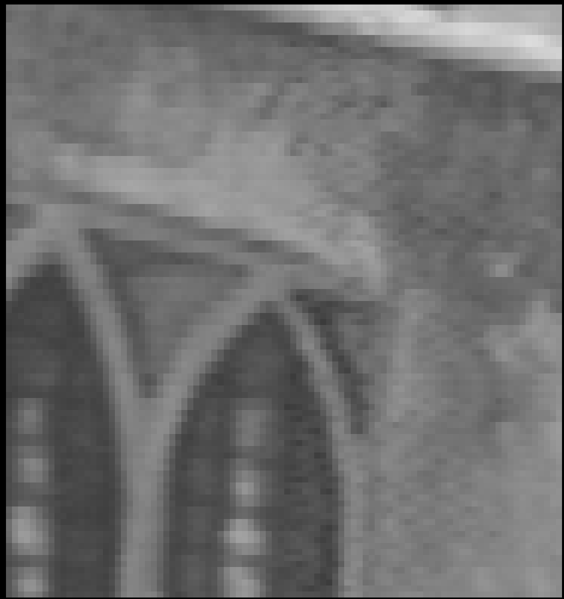
Useful for:

- 2D tracking, 3D tracking, SLAM, object recognition, etc.

- Visually ‘salient’ features.
- Localized in 2D.
- Sparse.
- High ‘information’ content.
- Repeatable between images.

Edward Rosten, Reid Porter, Tom Drummond

The segment-test detector



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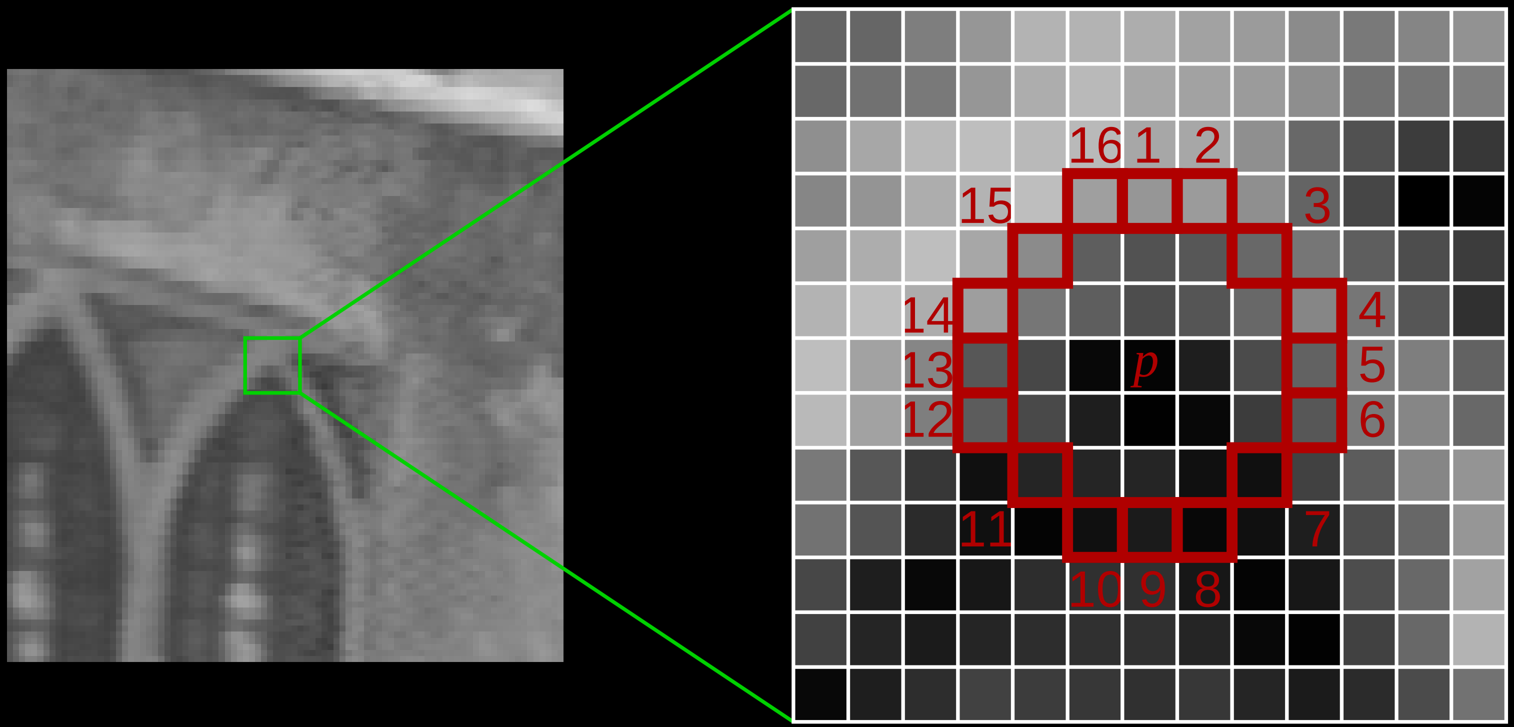

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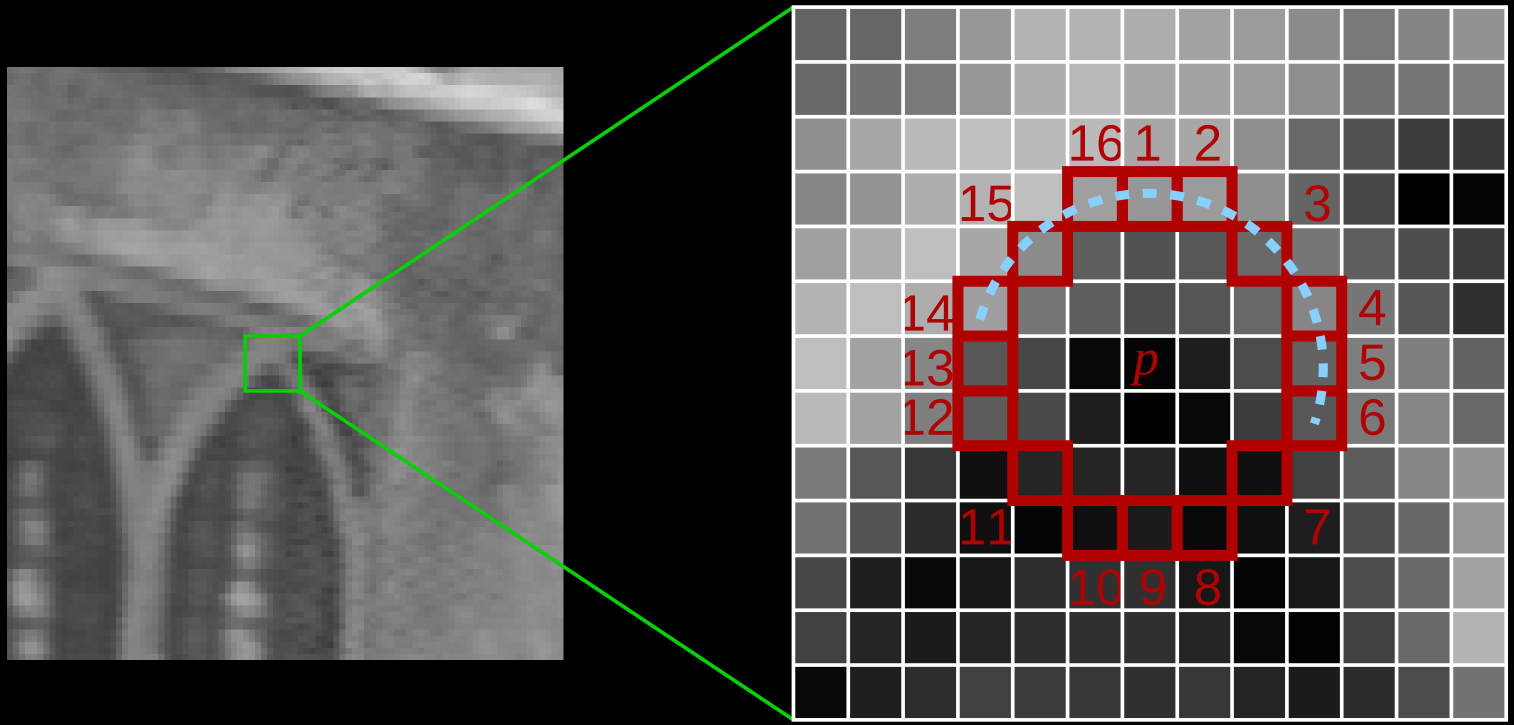


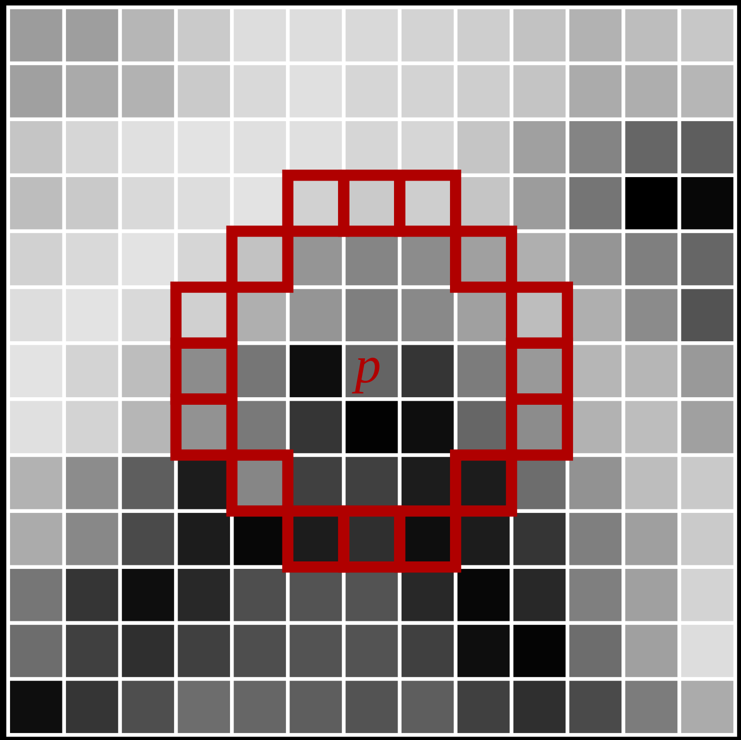
Contiguous arc of N or more pixels:

- All much brighter than p (brighter than $p + t$).

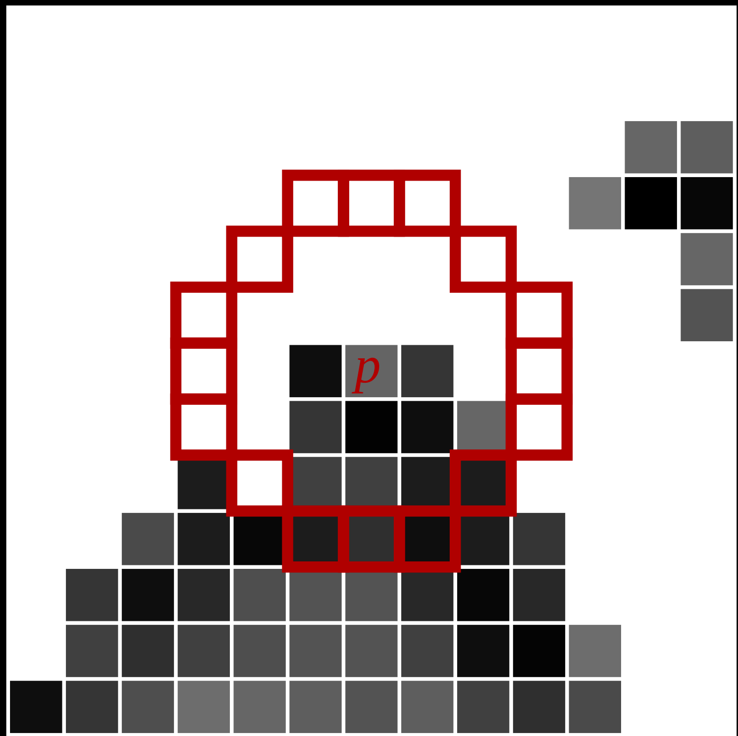
or

- All much darker than p (darker than $p - t$).

FAST feature detection

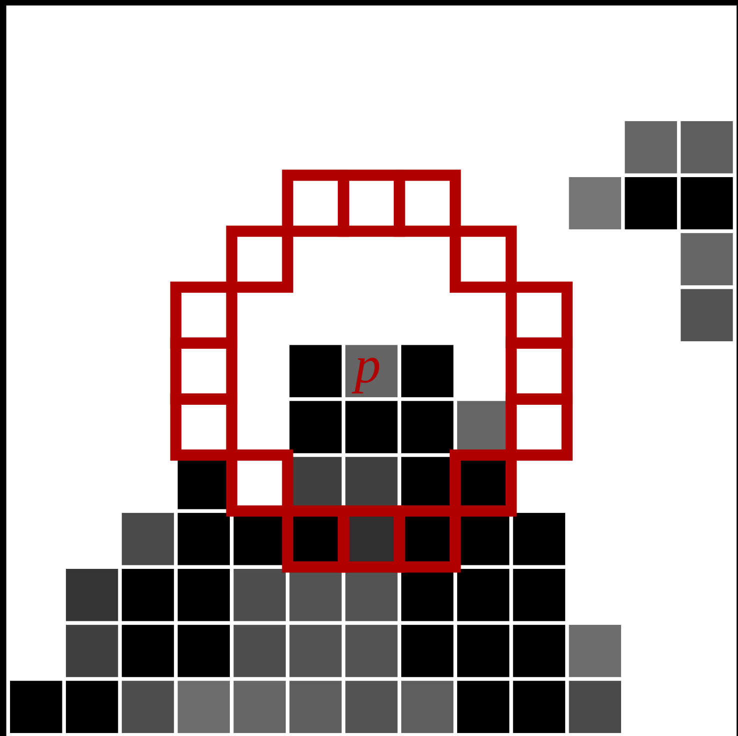


FAST feature detection



- Pixels are either:
  - Much brighter.

FAST feature detection



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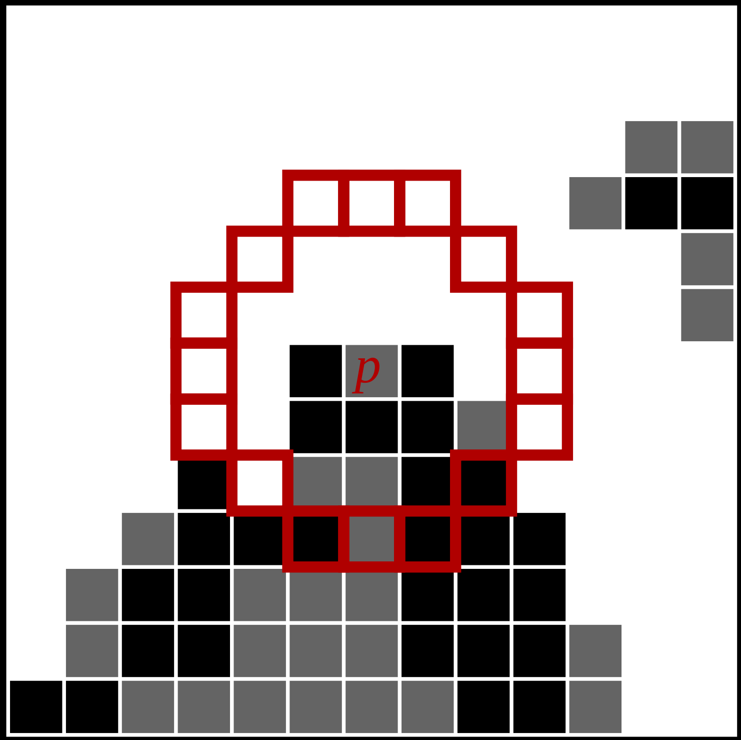
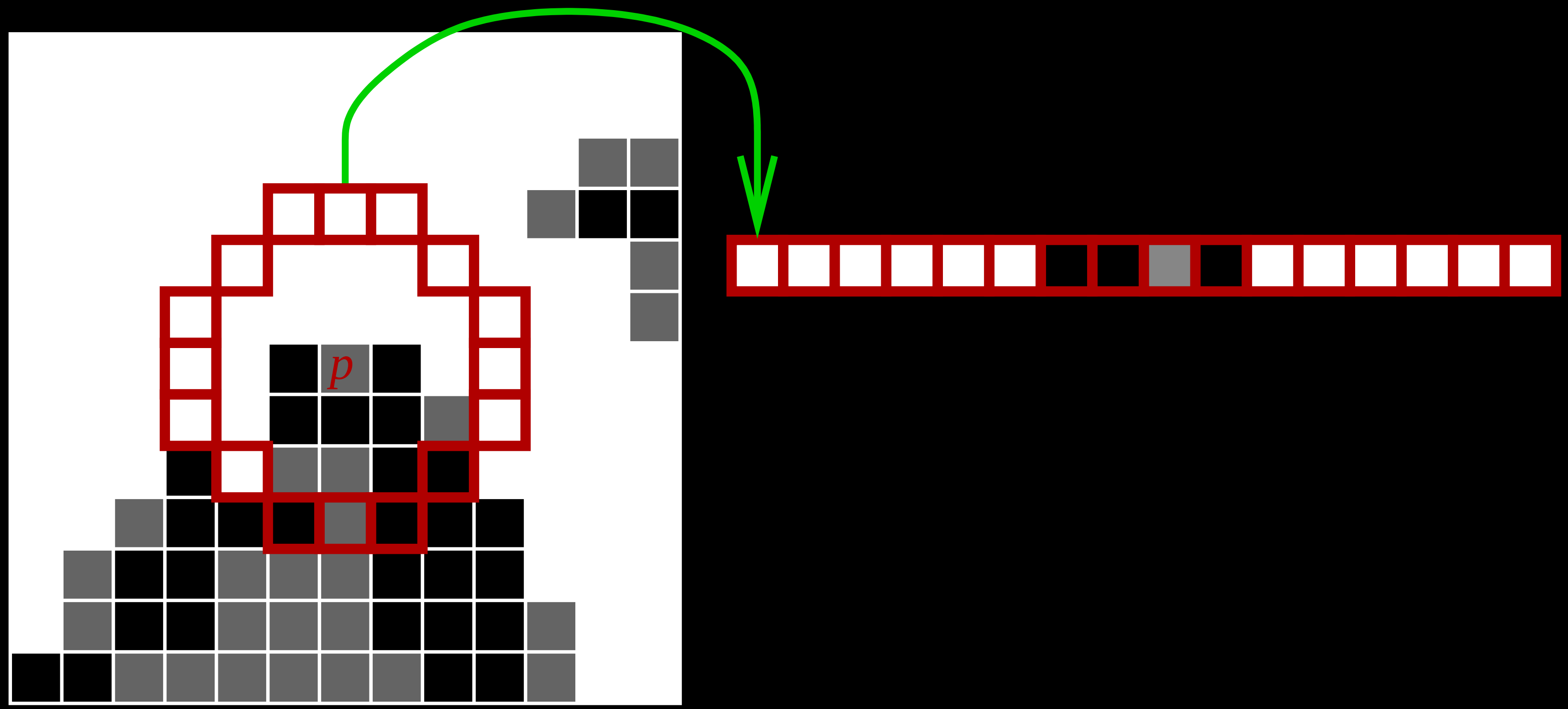


- Pixels are either:
  - Much brighter.
  - Much darker.
  - Similar.

FAST feature detection



- Pixels are either:
  - Much brighter.
  - Much darker.
  - Similar.
- Represent ring as a ternary vector.
- Classify vectors using segment test.

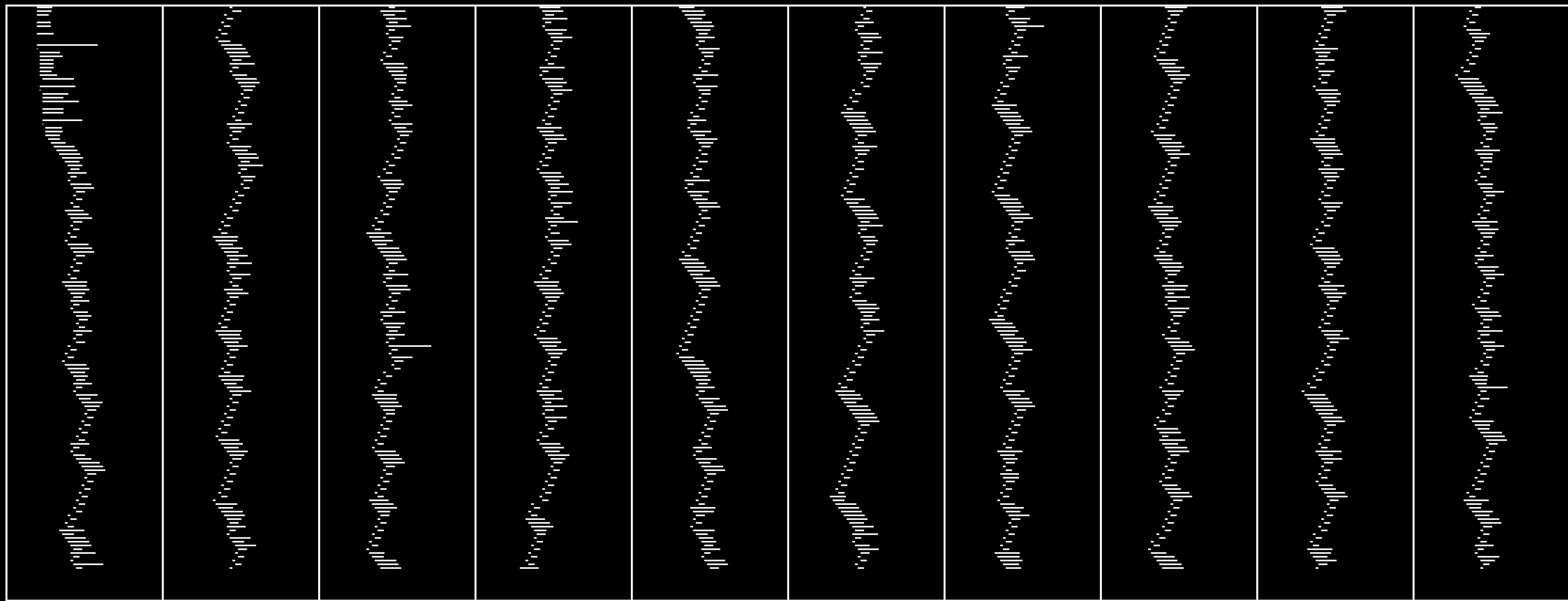
Train a classifier

- Decision tree classifiers are very efficient.
- Ask: “What is the state of pixel x?”
- Question splits list in to 3 sublists.
- Query each sublist.
- Recurse until list contains all features or all non features.
- Choose questions to minimize entropy (ID3).

- Use questions on new feature.
- Works for *any* N.

Output C++ code

A long string of nested if-else statements:



. . . which continues for 2 more pages.

```
for(y = 3 ; y < i.size().y - 3; y++)
        for(x=0; x < i.size().x;x++)
        {
                centre = image[y][x];
                if(image[y-3][x] > centre + threshold)
                        if(image[y+3][x+1] > centre + threshold)
                                if(...
                        else
                                ...
```

How FAST? (very)

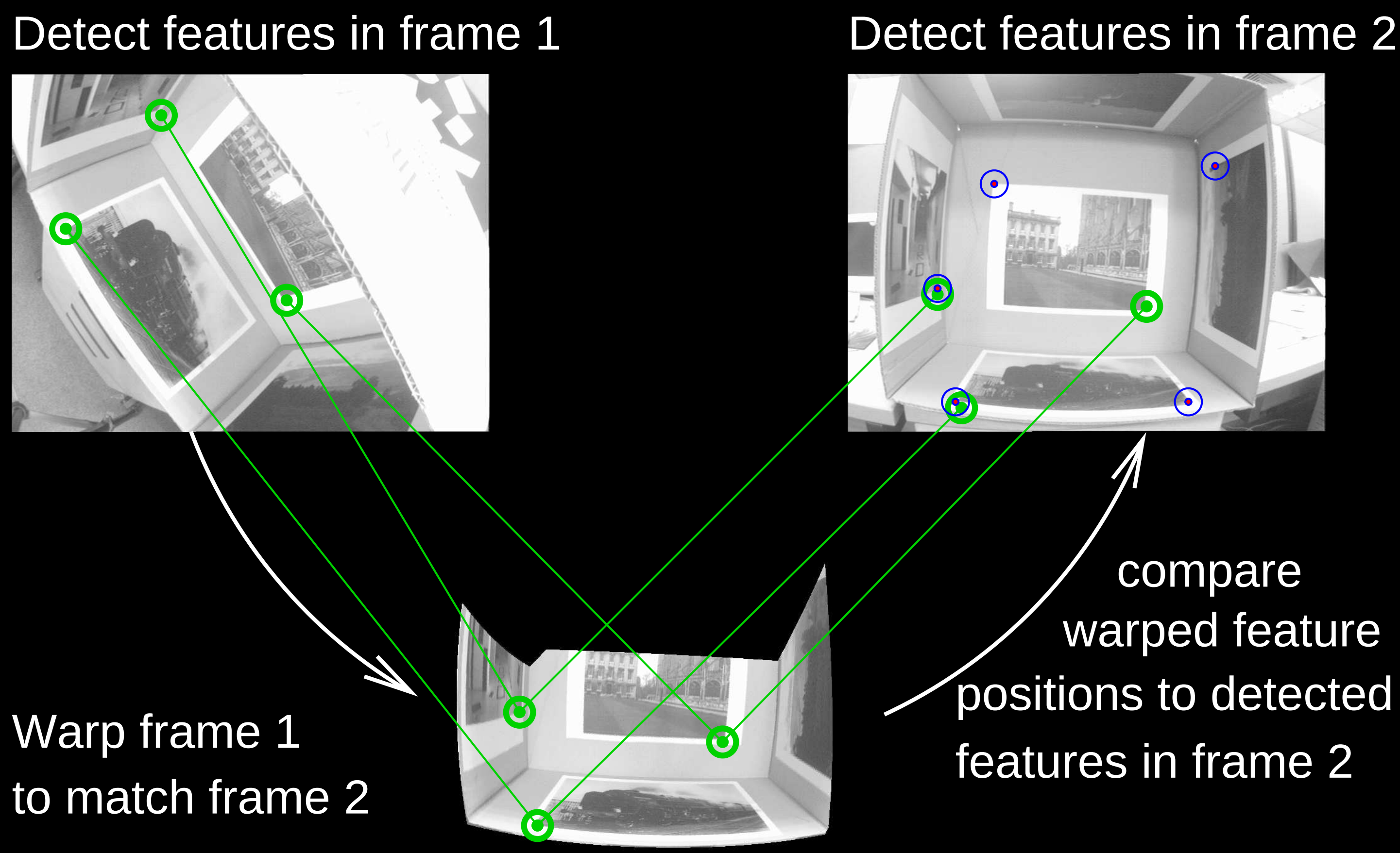
Detector	Set 1		Set 2	
	Pixel rate (MPix/s)	%	MPix/s	%
FAST $n = 9$	188	4.90	179	5.15
FAST $n = 12$	158	5.88	154	5.98
Original FAST ($n = 12$)	79.0	11.7	82.2	11.2
SUSAN	12.3	74.7	13.6	67.9
Harris	8.05	115	7.90	117
Shi-Tomasi	6.50	142	6.50	142
DoG	4.72	195	5.10	179

- 3.0GHz Pentium 4
- Set 1: 992×668 pixels.
- set 2: 352×288 (quarter-PAL) video.
- Percentage budget for PAL, NTSC, DV, 30Hz VGA.

Is it any good?

Repeatability

Is the same real-world 3D point detected from multiple views?



Repeat for all pairs in a sequence

FAST-ER: Enhanced Repeatability

- Define feature detector as:

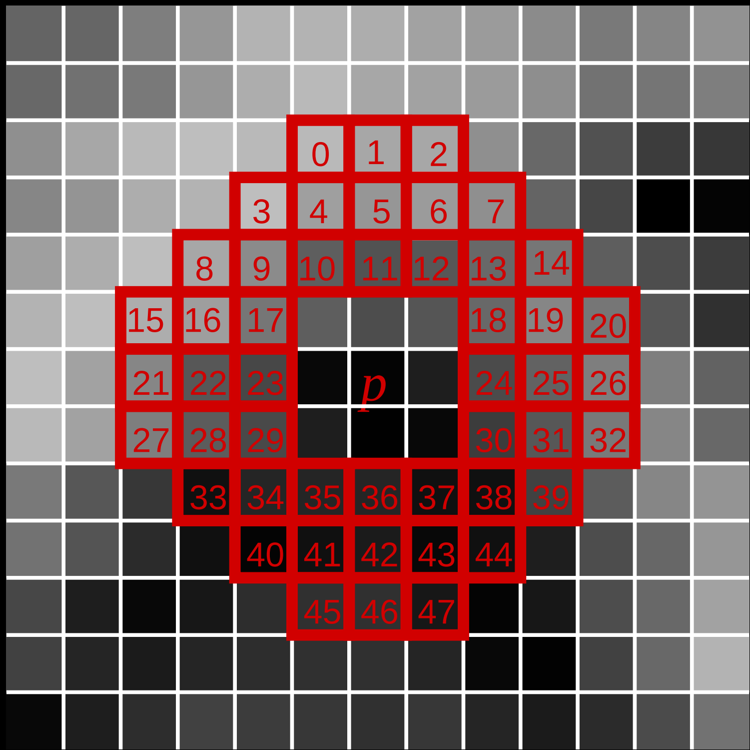
  A decision tree which detects points with a high repeatability.

- To evaluate repeatability:
  1. Detect features in all frames.
  2. Compute repeatability.

- That is hard to optimize!

  Optimize tree using simulated-annealing.
- Use more pixels than FAST.

FAST-ER: Enhanced Repeatability



- Use more pixels than FAST.

Cost function

1. Higher repeatability is better.
2. Every pixel is a feature $\Rightarrow$ repeatability is 100%.
3. A single detected feature can have 100% repeatability.

Multi-objective optimization needed:

$$cost = (1 + w_r R^{-2})(1 + w_n N^2)(1 + w_s S^2)$$

R = Repeatability.
N = Number of detected features.
S = Size of tree.

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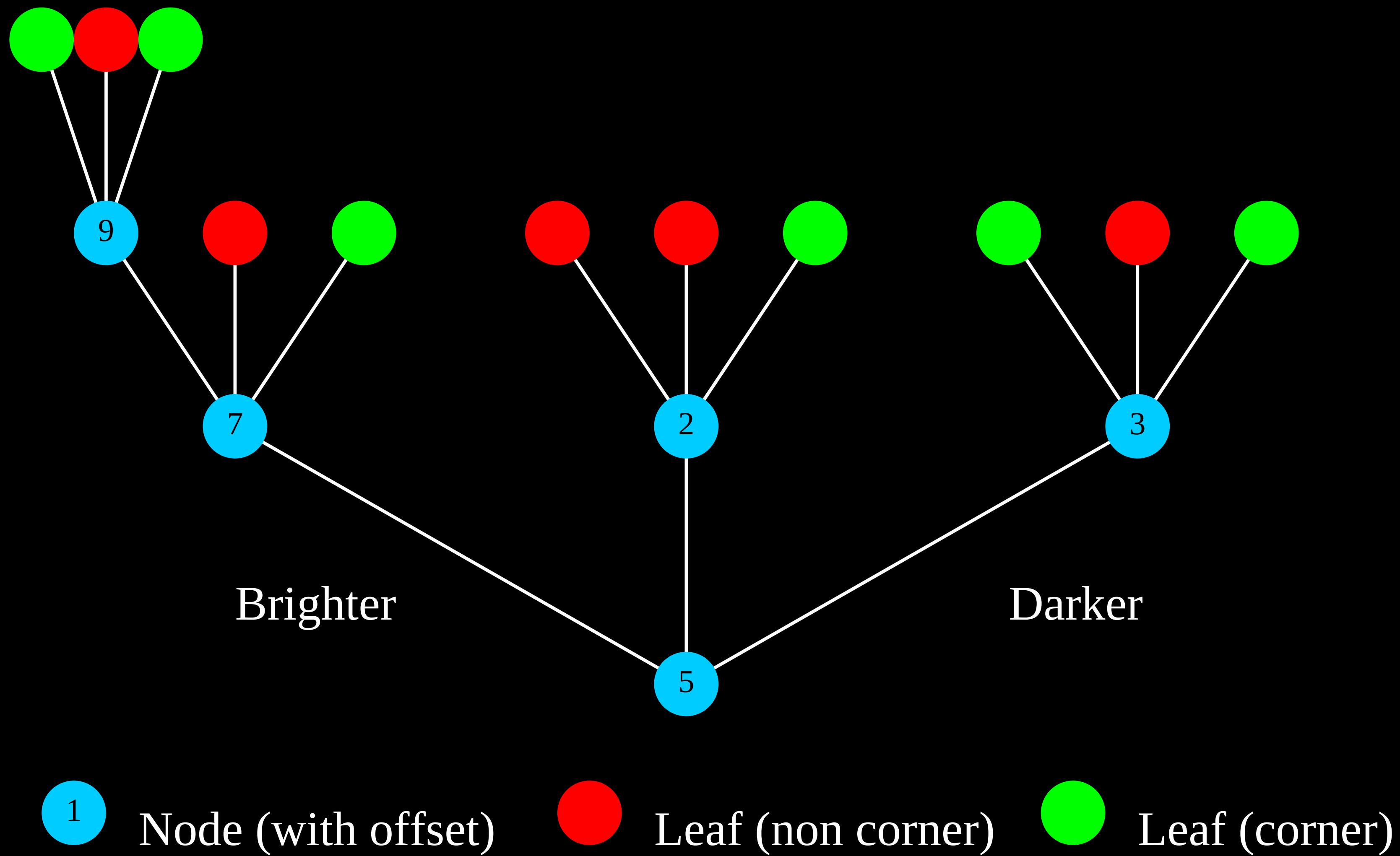
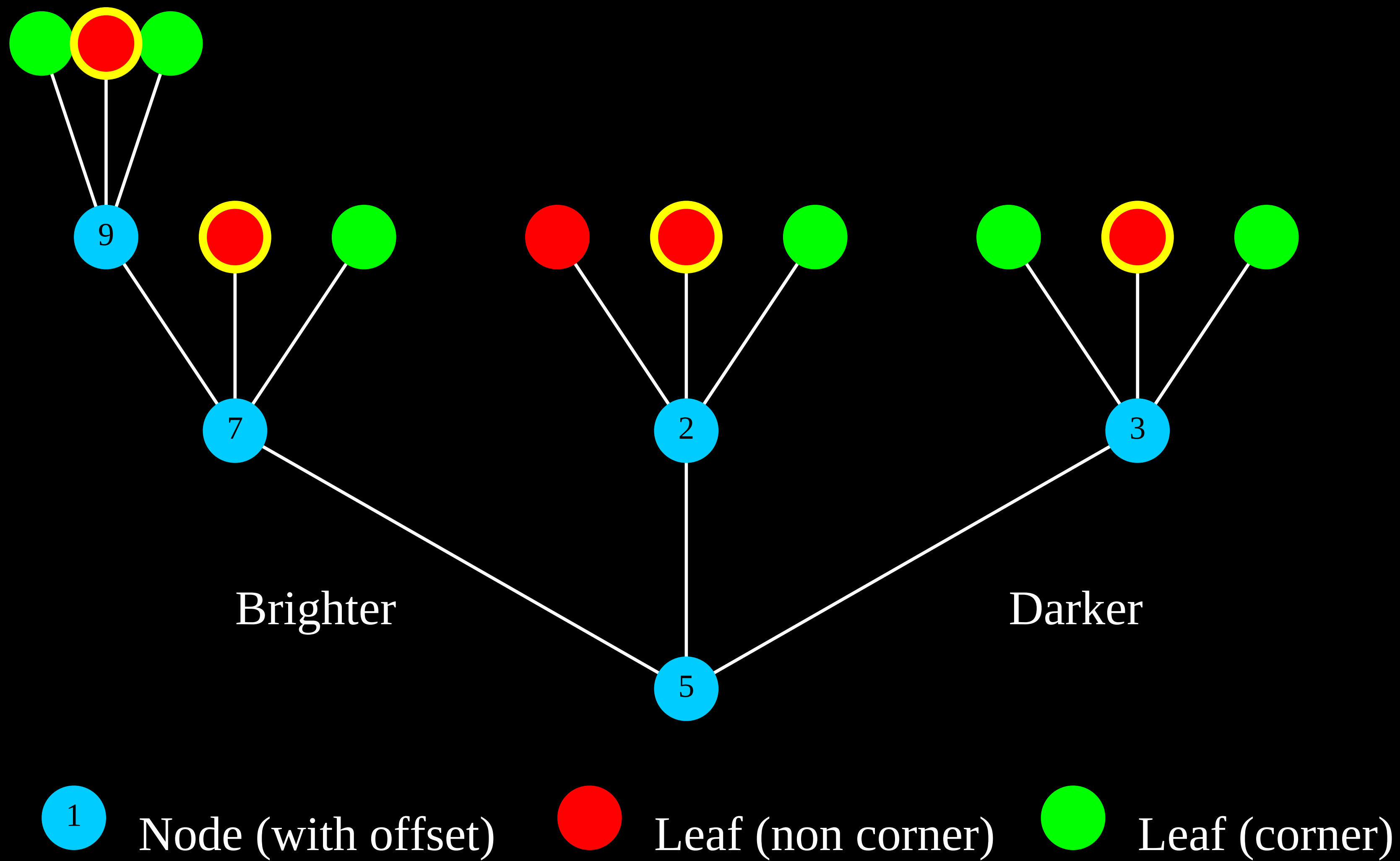
Operations



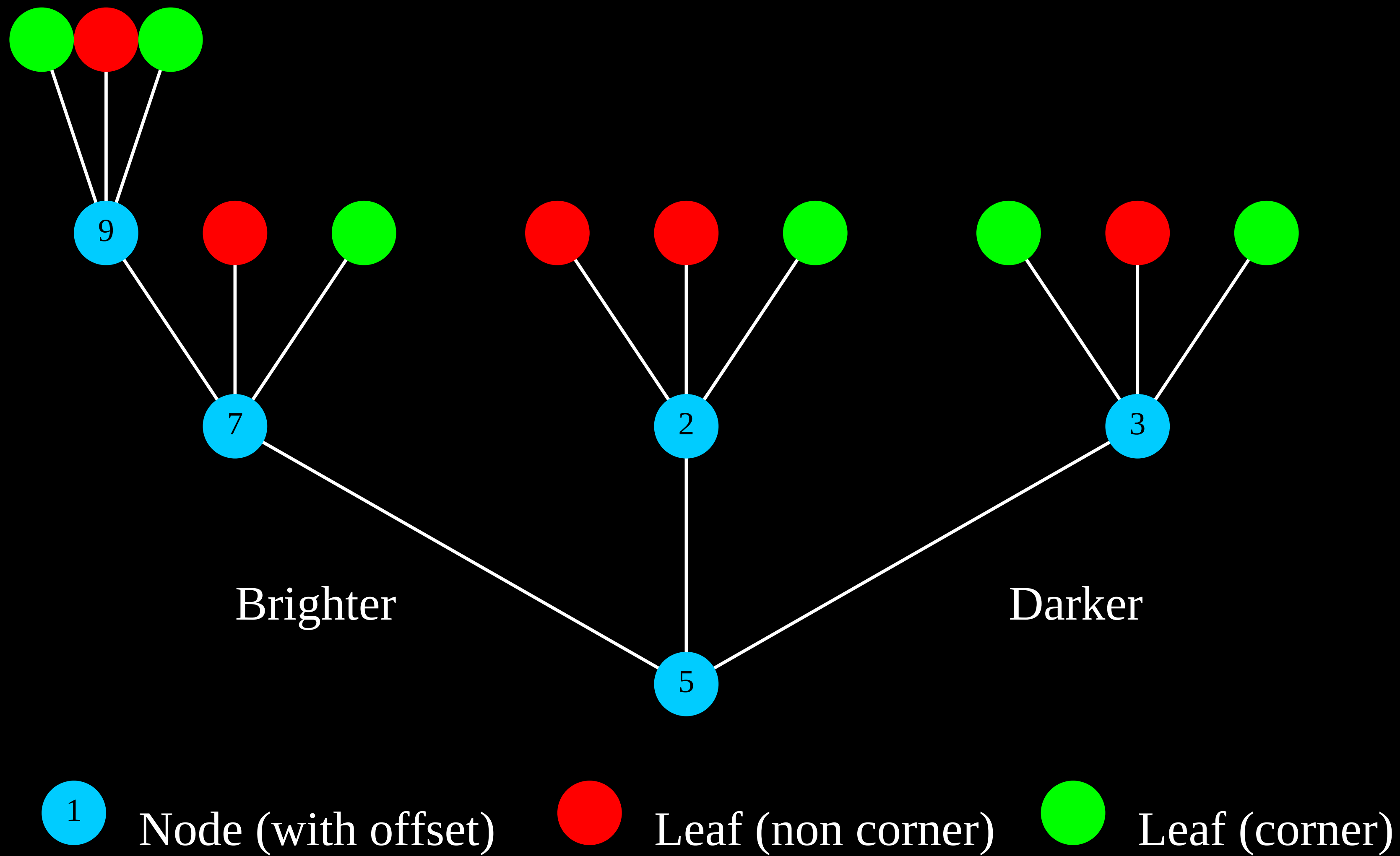
9
7
2
3
5
Brighter
Darker
1
Node (with offset)
Leaf (non corner)
Leaf (corner)

Operations

‘Similar’ leaf nodes are constrained.



Operations


9
7
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Node (with offset)
Leaf (non corner)
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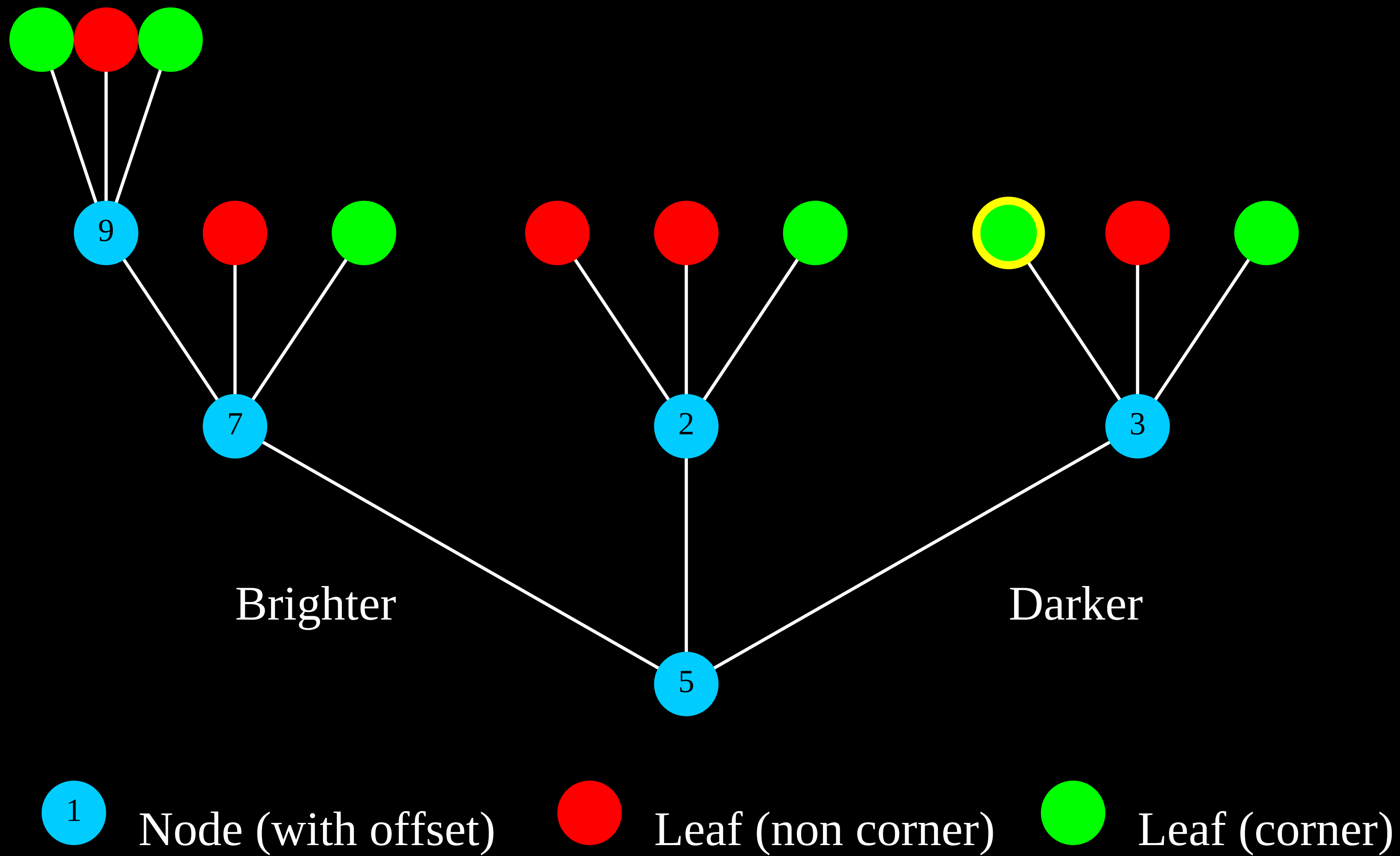
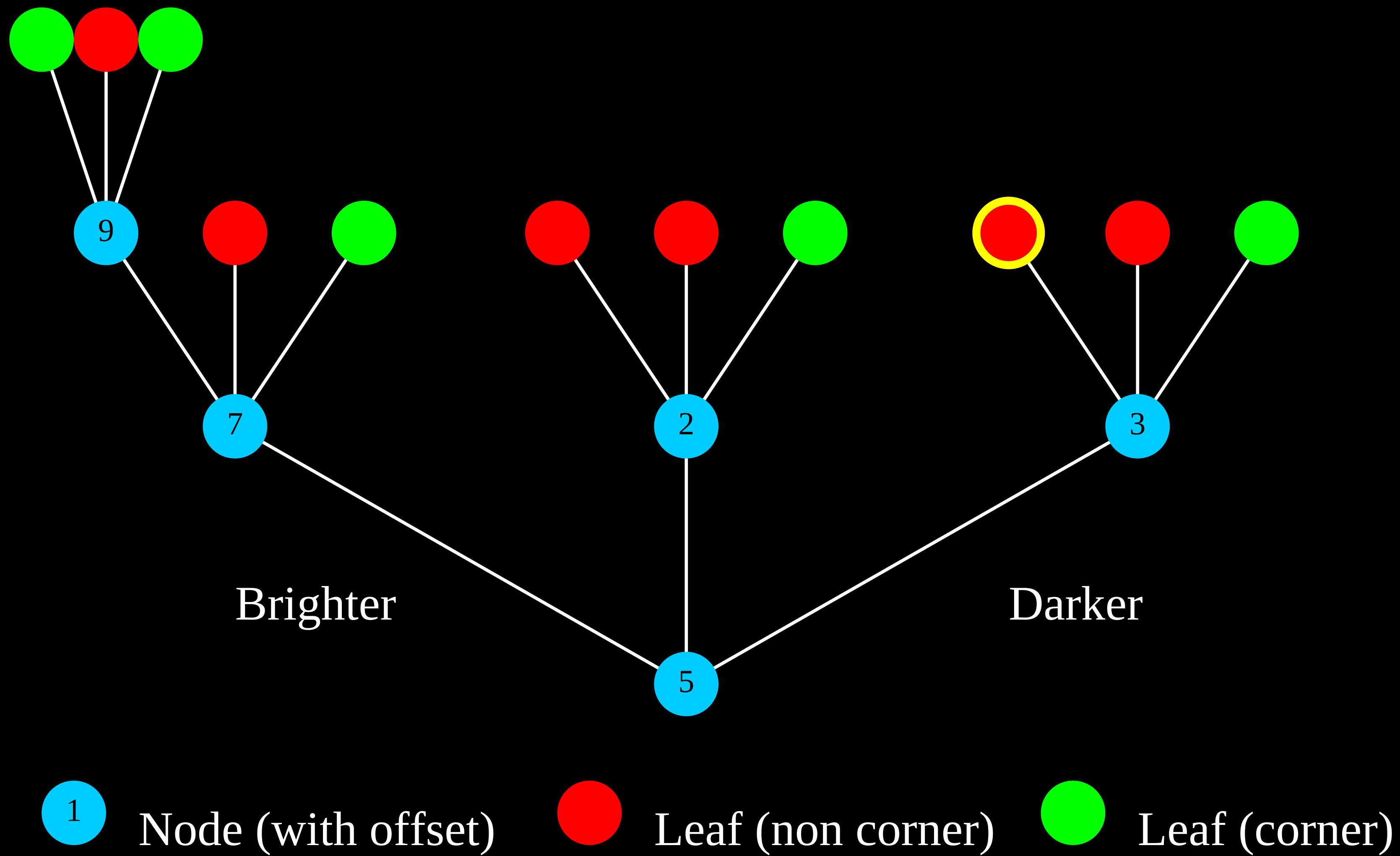
Operations

Select a random node. If node is a leaf:



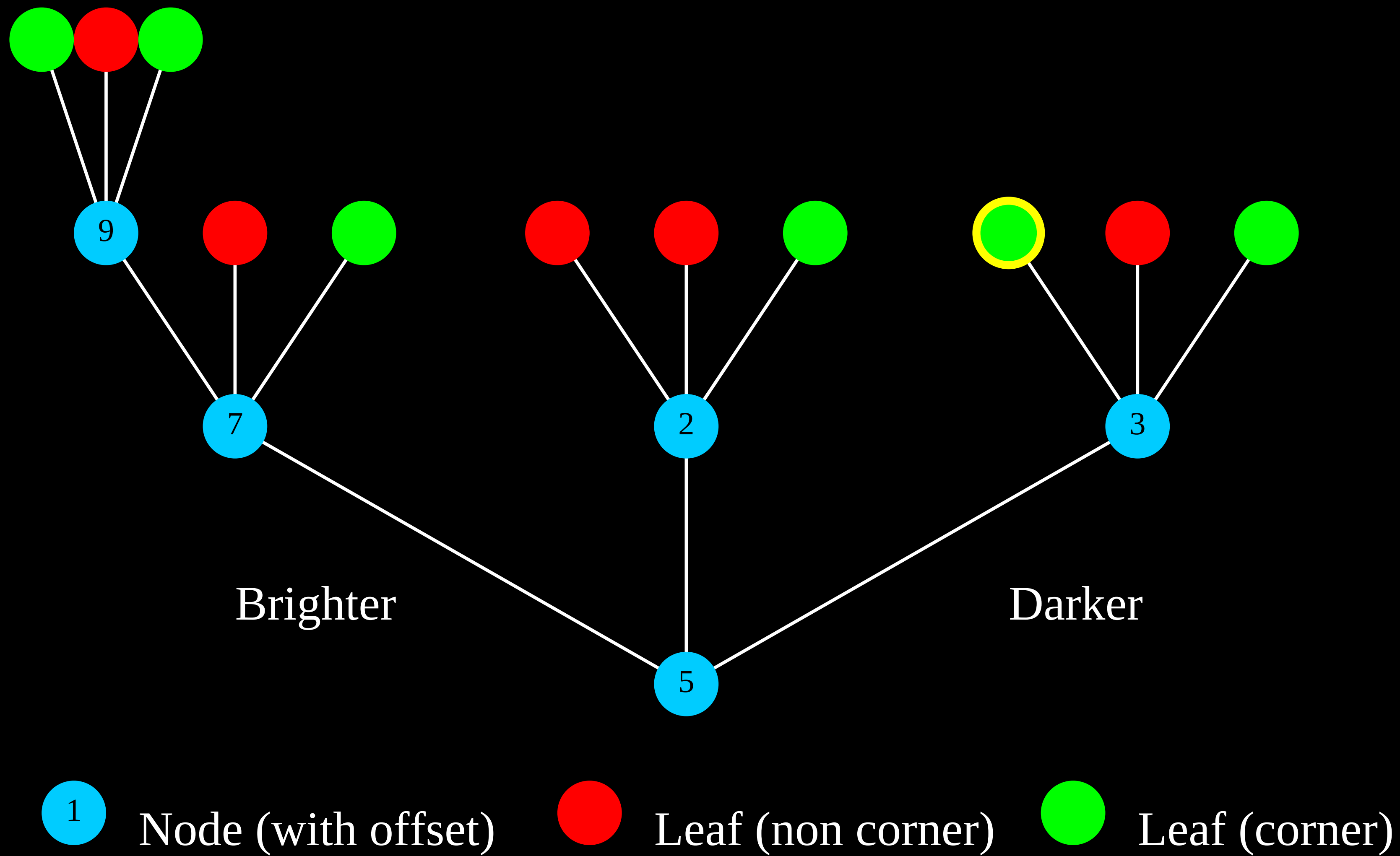
Operations

flip the class (if possible), . . .



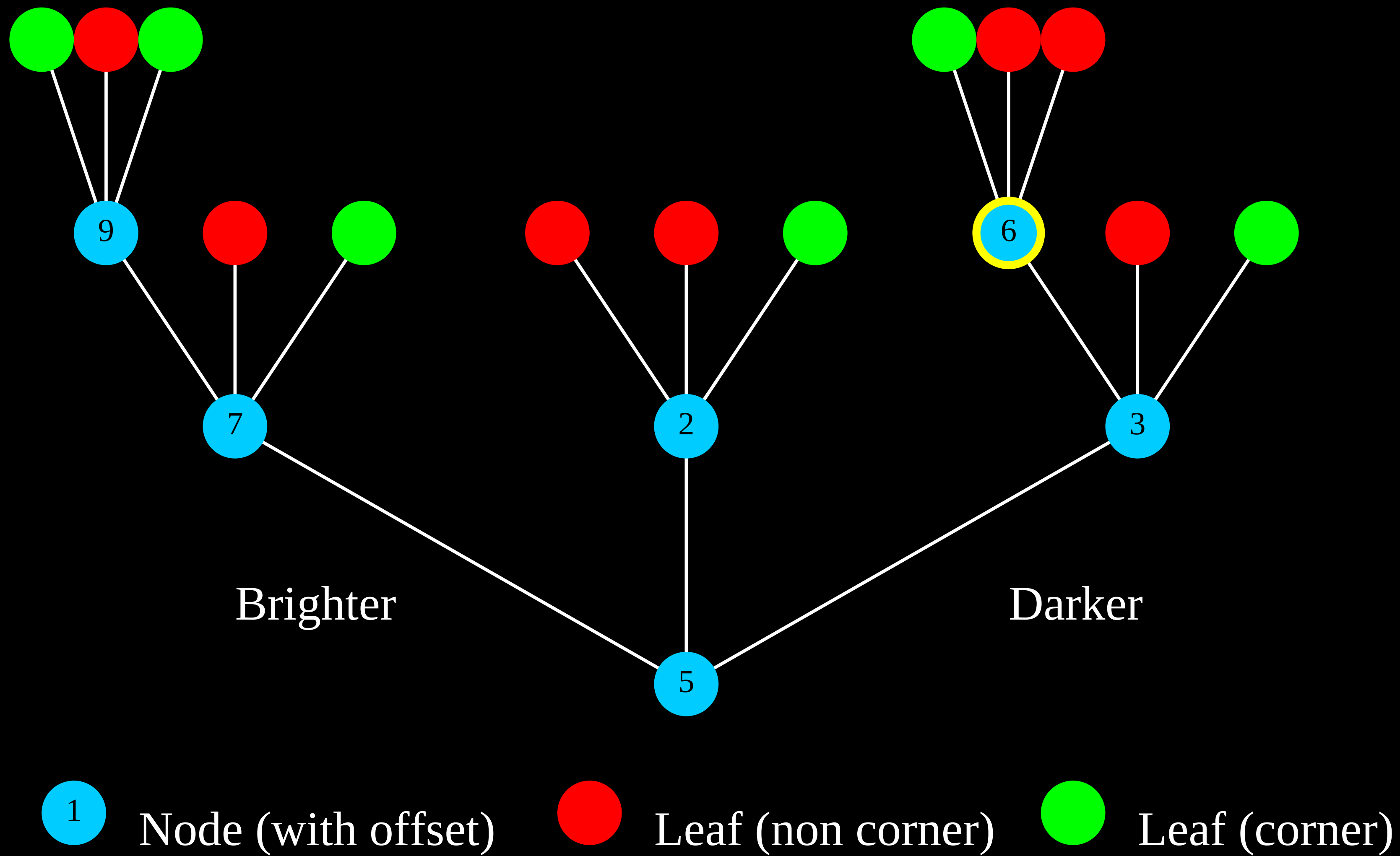
Operations

. . . or . . .



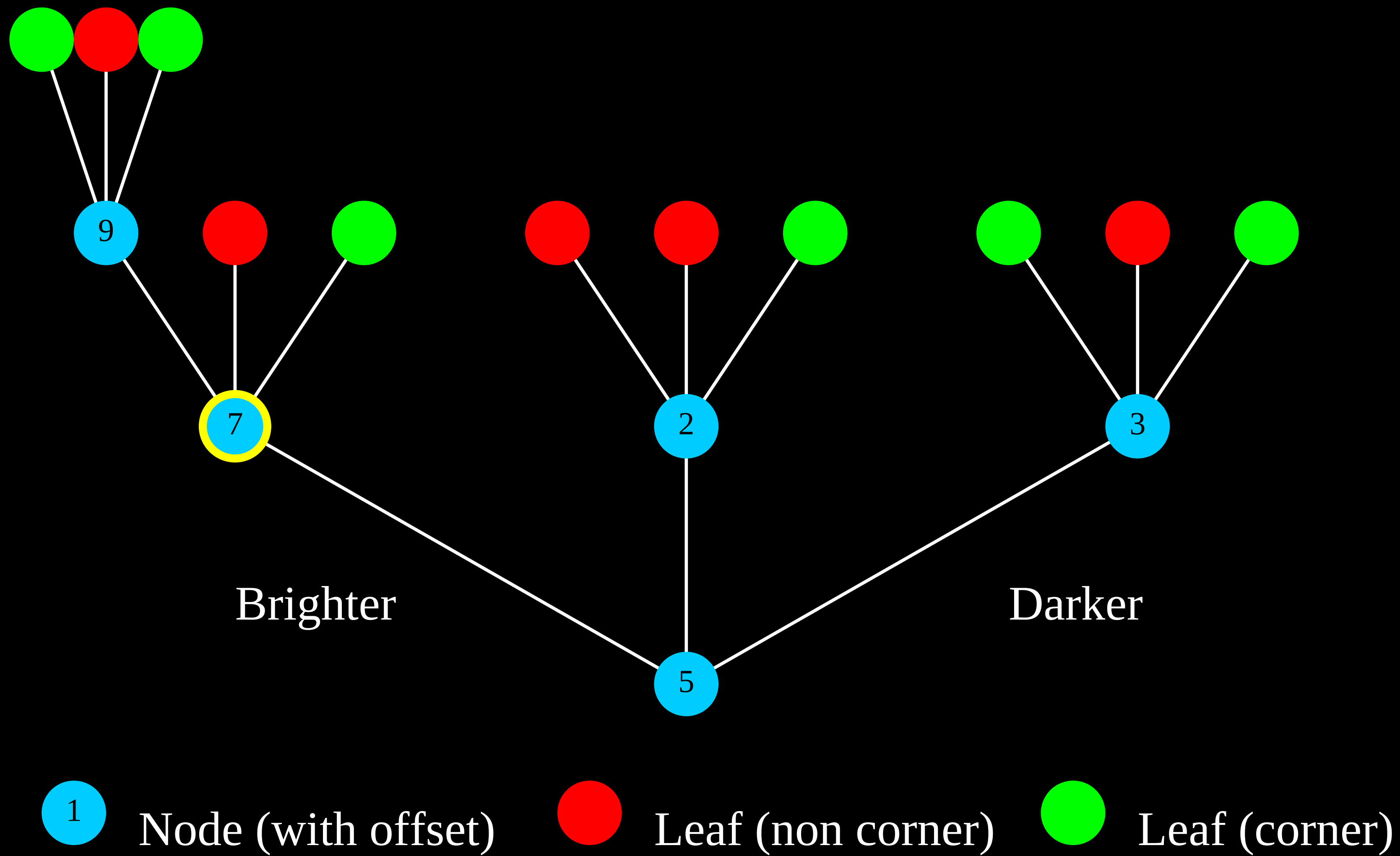
Operations

grow a random subtree.



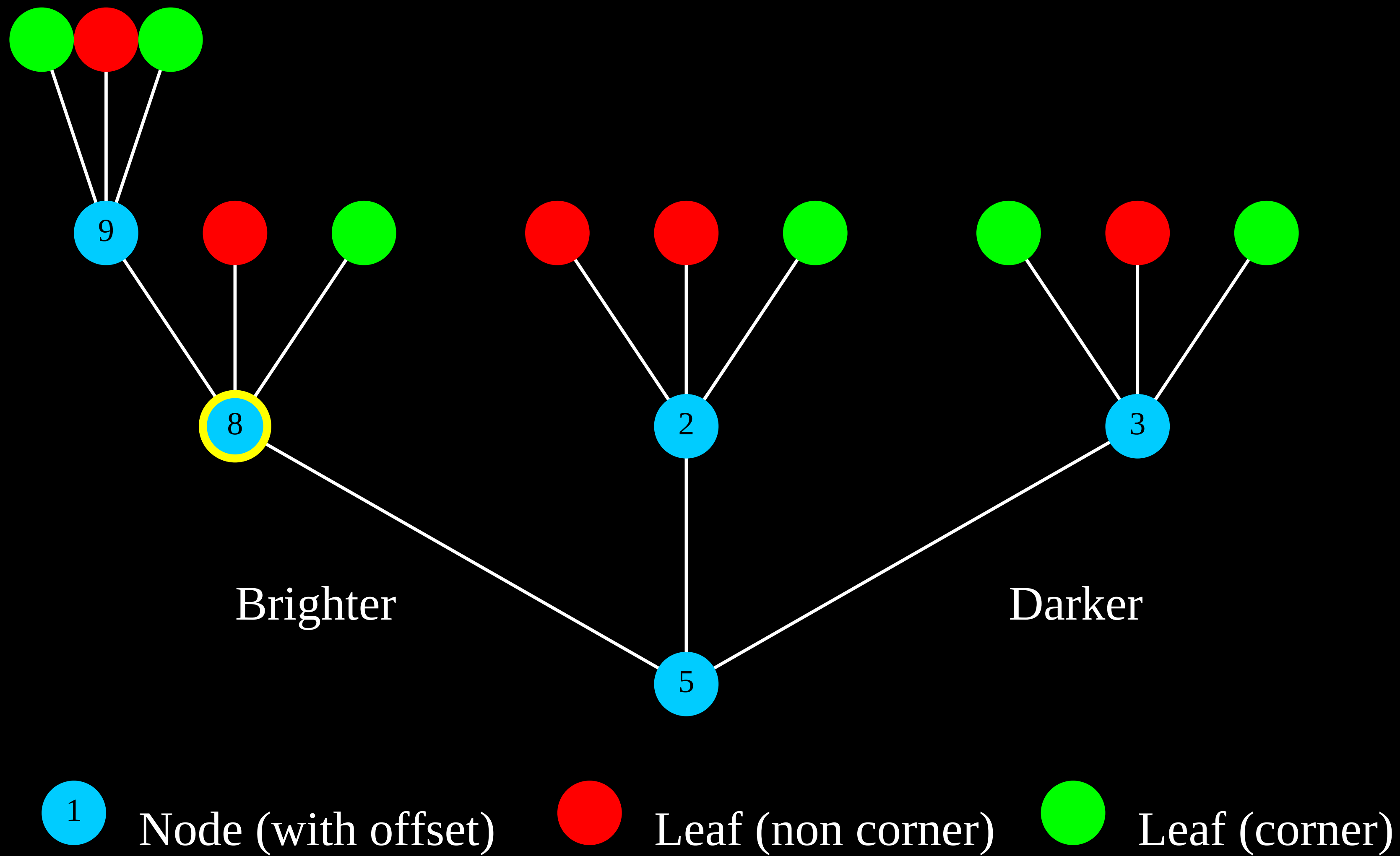
Operations

If node is a non-leaf:



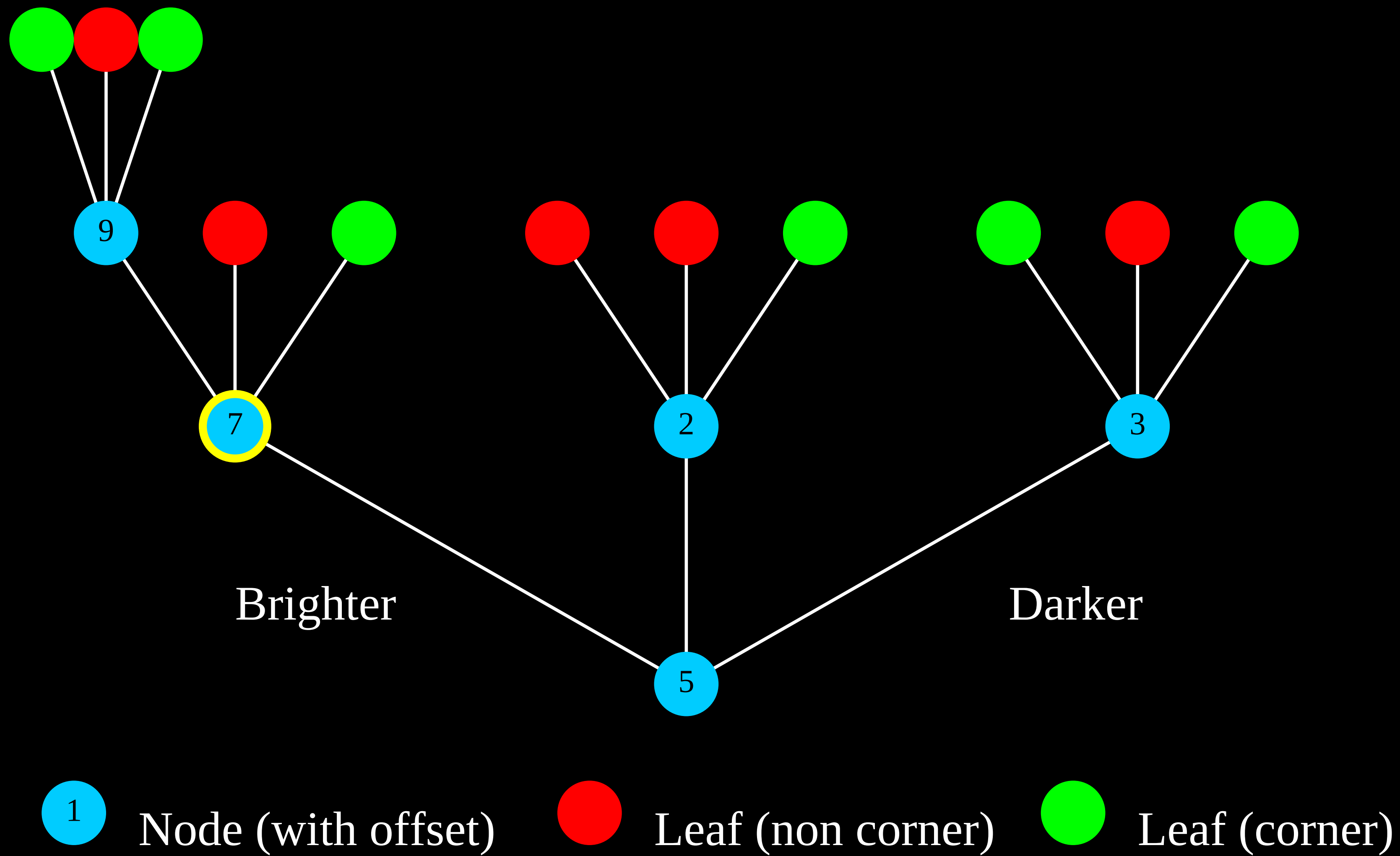
Operations

randomize the offset, . . .



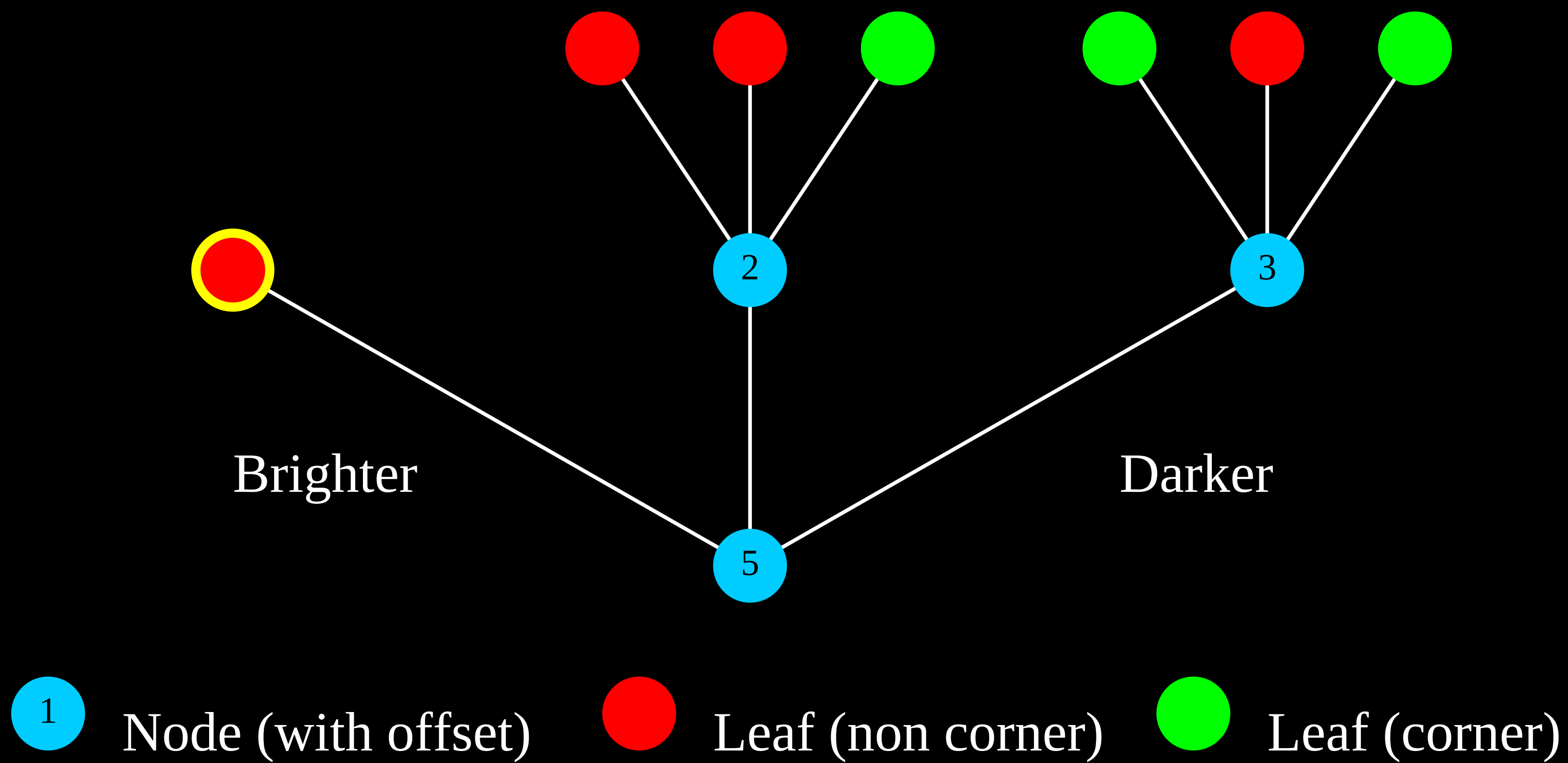
Operations

. . . or . . .



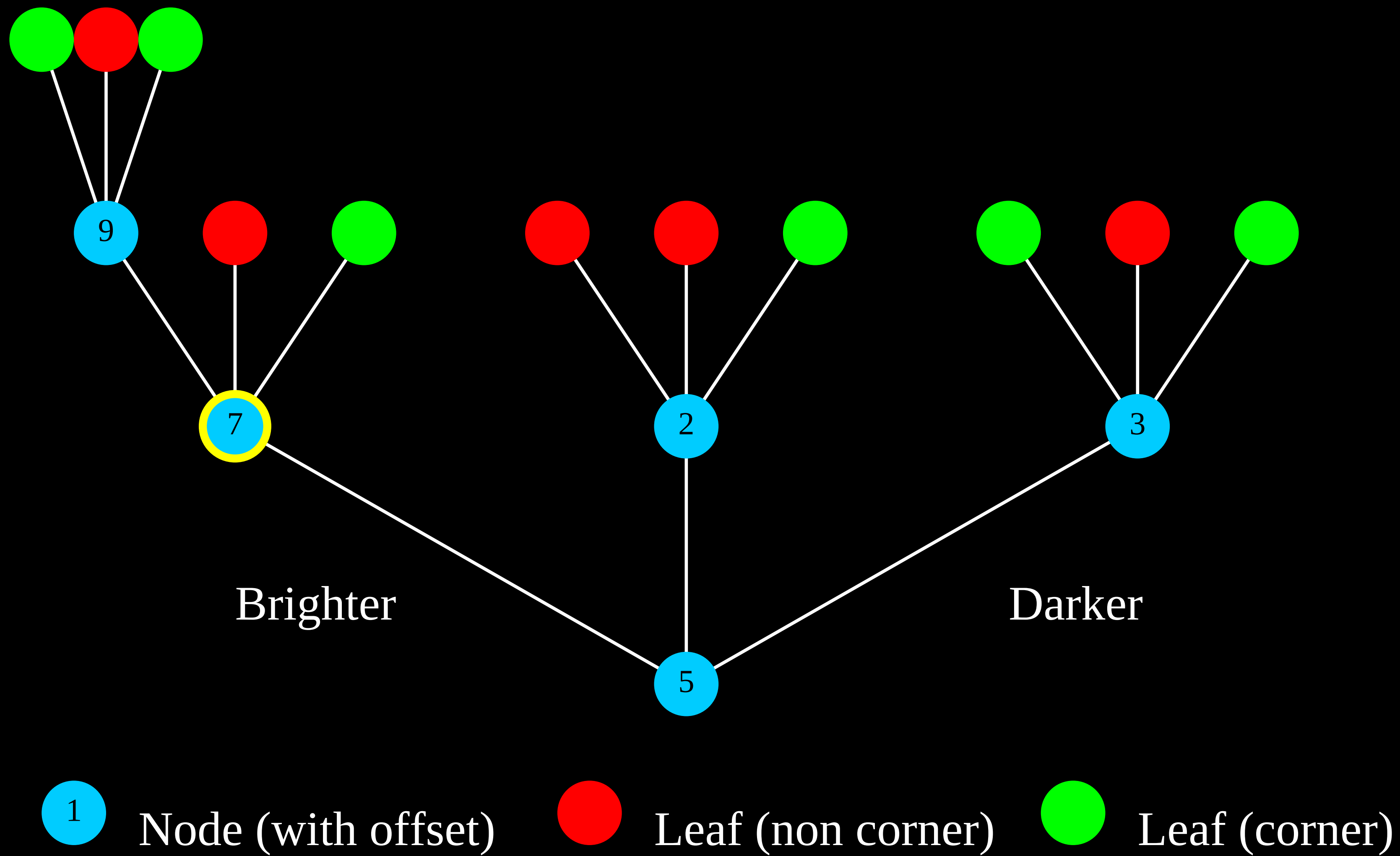
Operations

replace node with a leaf, . . .



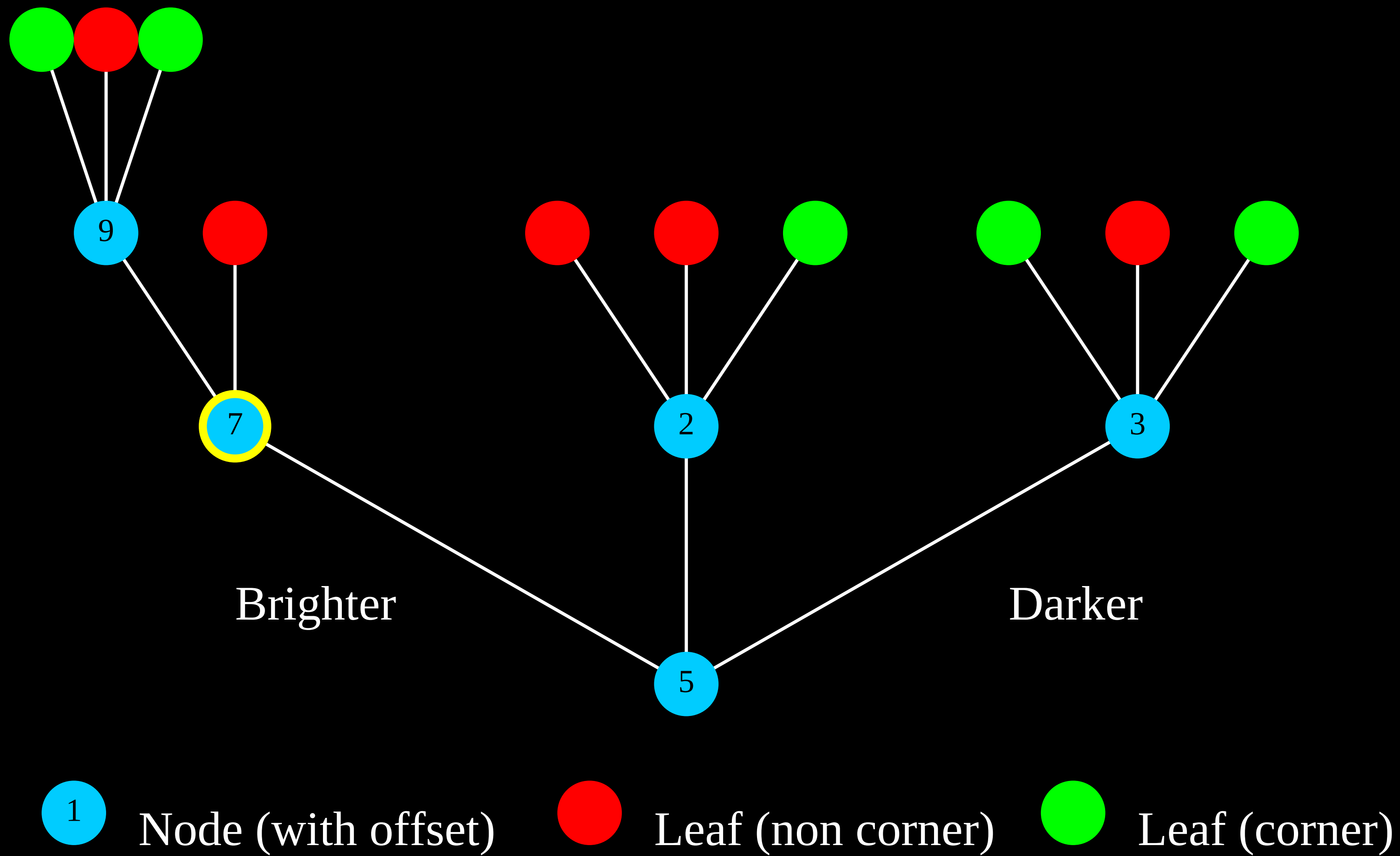
Operations

. . . or . . .



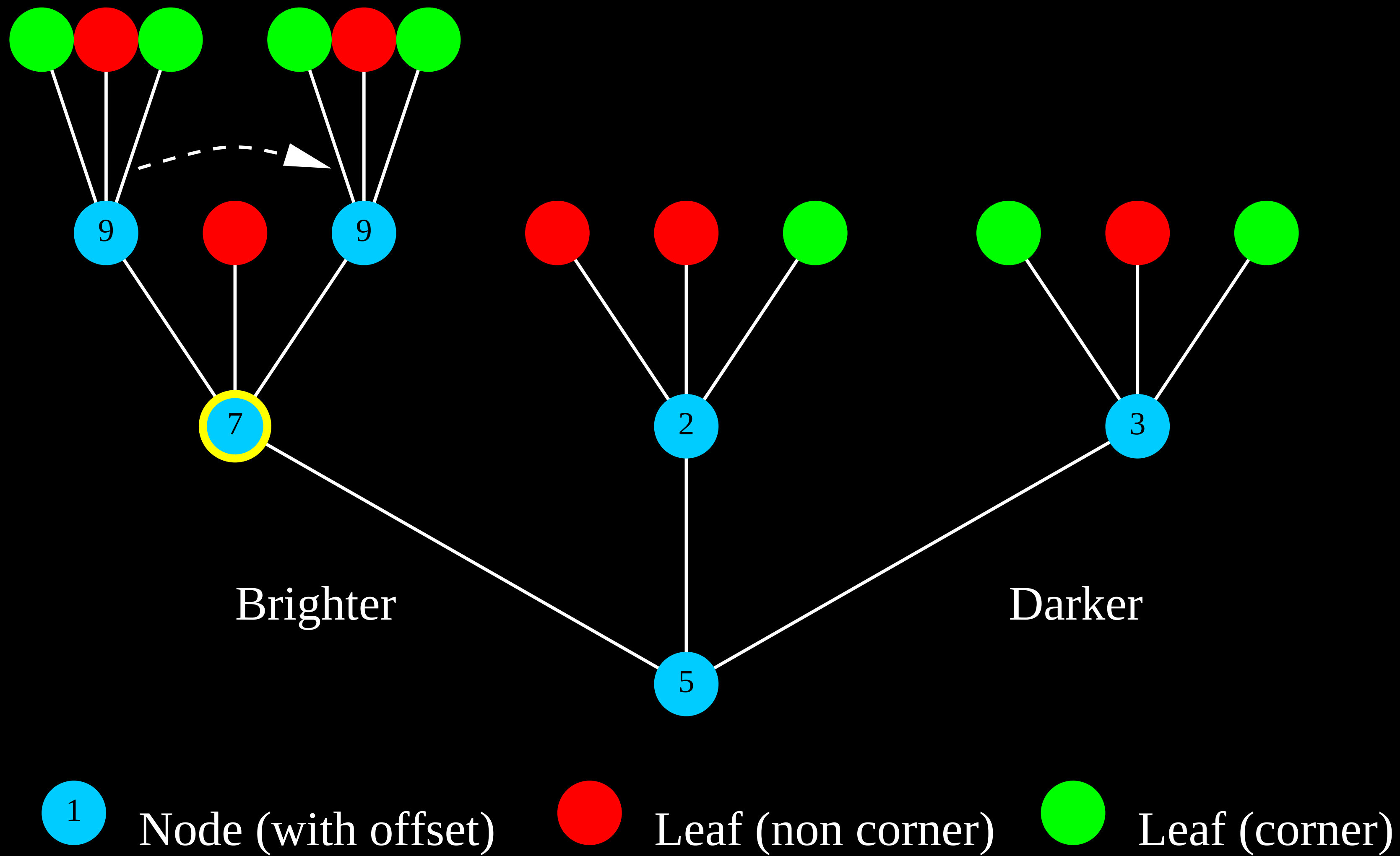
Operations

delete one subtree



Operations

and replace it with a copy of another subtree.



Reducing the burden on the optimizer

Corners should be invariant to:

- Rotation.
- Reflection.
- Intensity inversion.

There are 16 combinations:

- 4 simple rotations (multiples of $90°$).
- 2 reflections.
- 2 intensity inversions.

Run the detector in all combinations.

Iteration scheme

For 100,000 iterations:

1. Randomly modify tree.
2. Compile directly to machine code.
3. Detect features.
4. Compute repeatability.
5. Evaluate cost.
6. Keep the modification if:

$$e^{\frac{\mathrm{oldcost}-\mathrm{cost}}{\mathrm{temp}}} > \mathrm{rand}(0,1)$$

7. Reduce the temperature.

Now repeat that 200 times.

Training data for repeatability

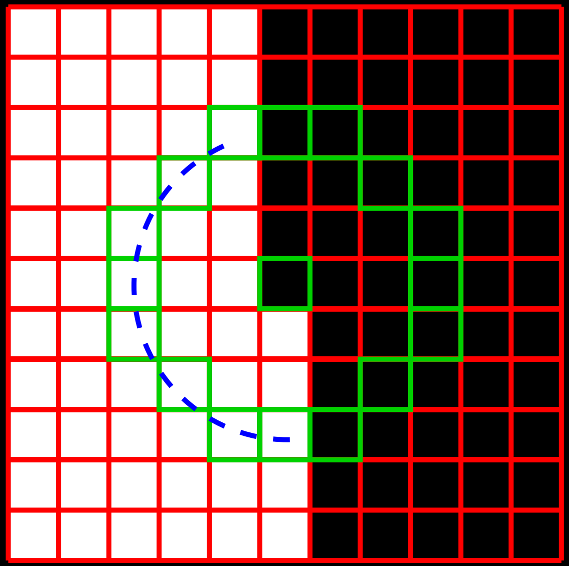
- Change in scale.
- Mostly affine warping.
- Varied texture.

Results

Comparisons

- FAST detectors
  - Which N is best?
  - Which of the 200 FAST-ER detectors is best?
- Other detectors
  - Harris
  - Shi-Tomasi
  - DoG (Difference of Gaussians)
  - Harris-Laplace
  - SUSAN
- What parameters should these detectors use?

Comparisons



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Results: repeatability curves

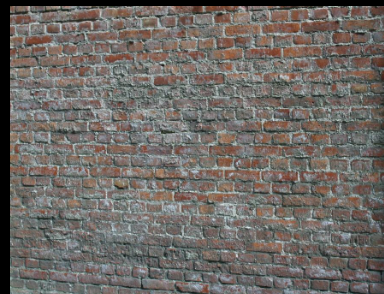






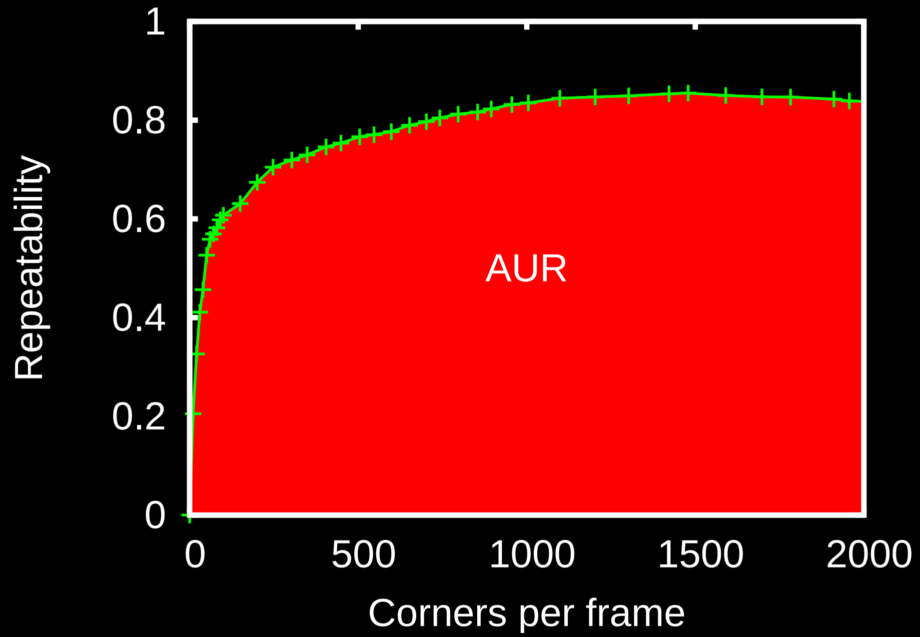






Aggregate results

Detector	AUR
FAST-ER	1313.6
FAST-9	1304.57
DoG	1275.59
Shi & Tomasi	1219.08
Harris	1195.2
Harris-Laplace	1153.13
FAST-12	1121.53
SUSAN	1116.79
Random	271.73



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- Set 1: 992×668 pixels.
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Conclusions on FAST

- FAST is very fast
  - And very repeatable.
- FAST-ER is even more repeatable.
- Source code is available:

`http://mi.eng.cam.ac.uk/~er258/work/fast.html`

Object Detection

Object detection

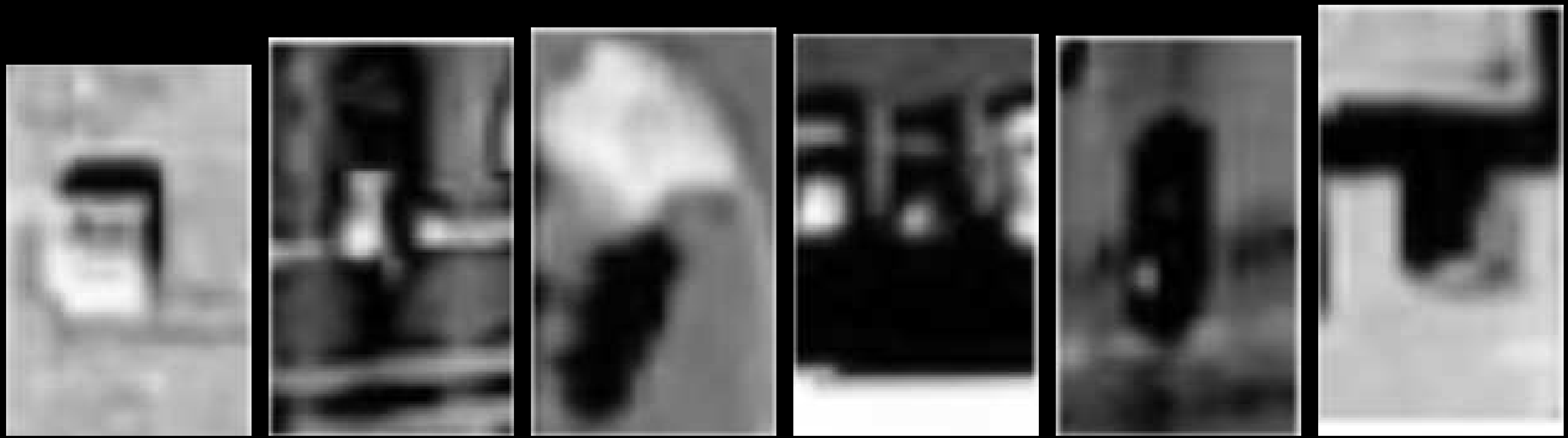
Target detection

Traffic analysis

Damian Eads, Edward Rosten, David Helmbold

Object detection: difficulties

Which ones are cars?

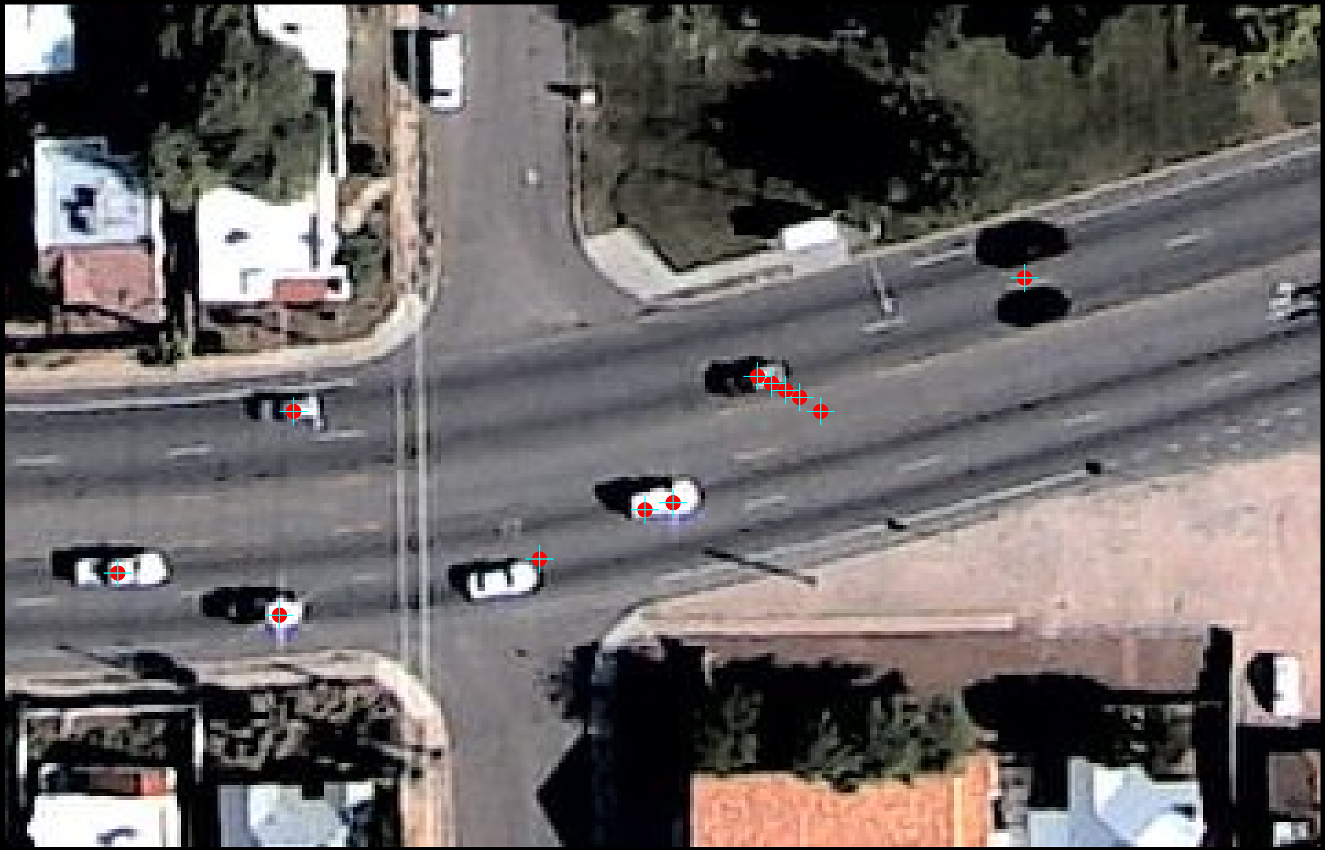


- Problem is unstructured

  Image $\longrightarrow \{(x_1, y_1), (x_2, y_2), \cdots\}$
- Number of objects unknown *a priori*
- Not a fixed set of labels

What is a detection anyway?

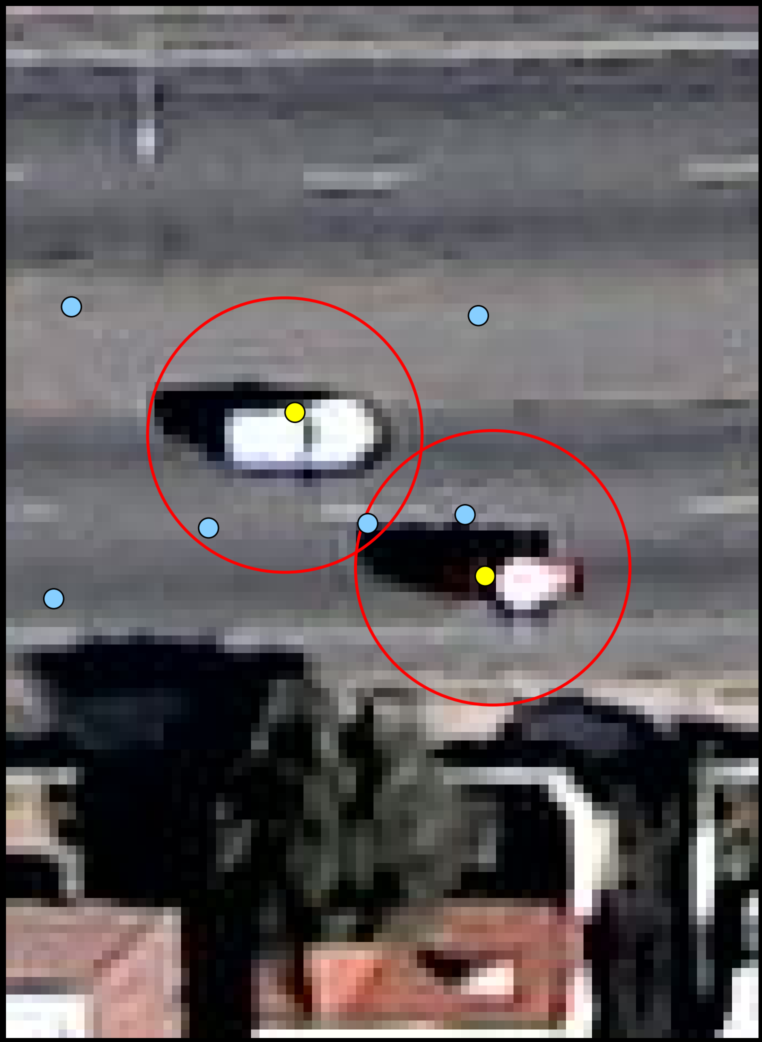
1. Not pixels! 50% of pixels on all of the objects is not the same as all of the pixels on 50% of the objects.
2. It depends...



Measures of performance

- Identification:
  - Within boundary
- Tracking
  - Nearby, but with unique assignment
- Counting
  - Unique assignment
  - Within radius of sliding window

Measures of performance



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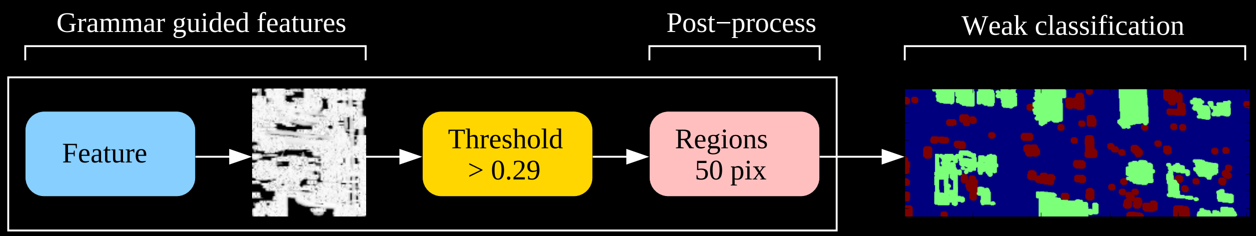
System layout



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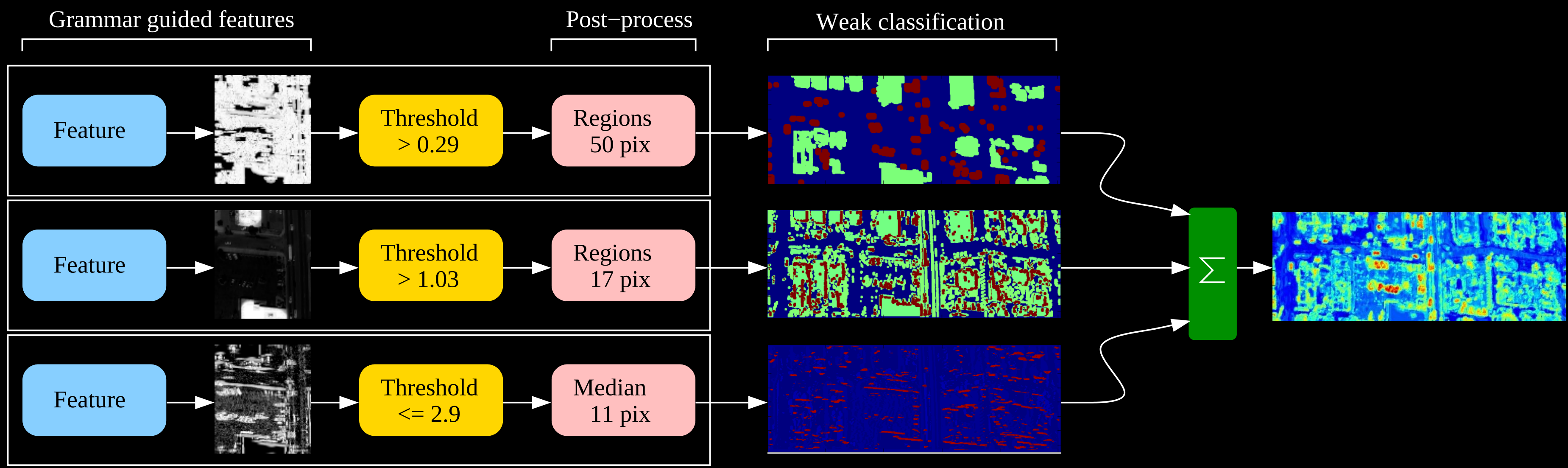

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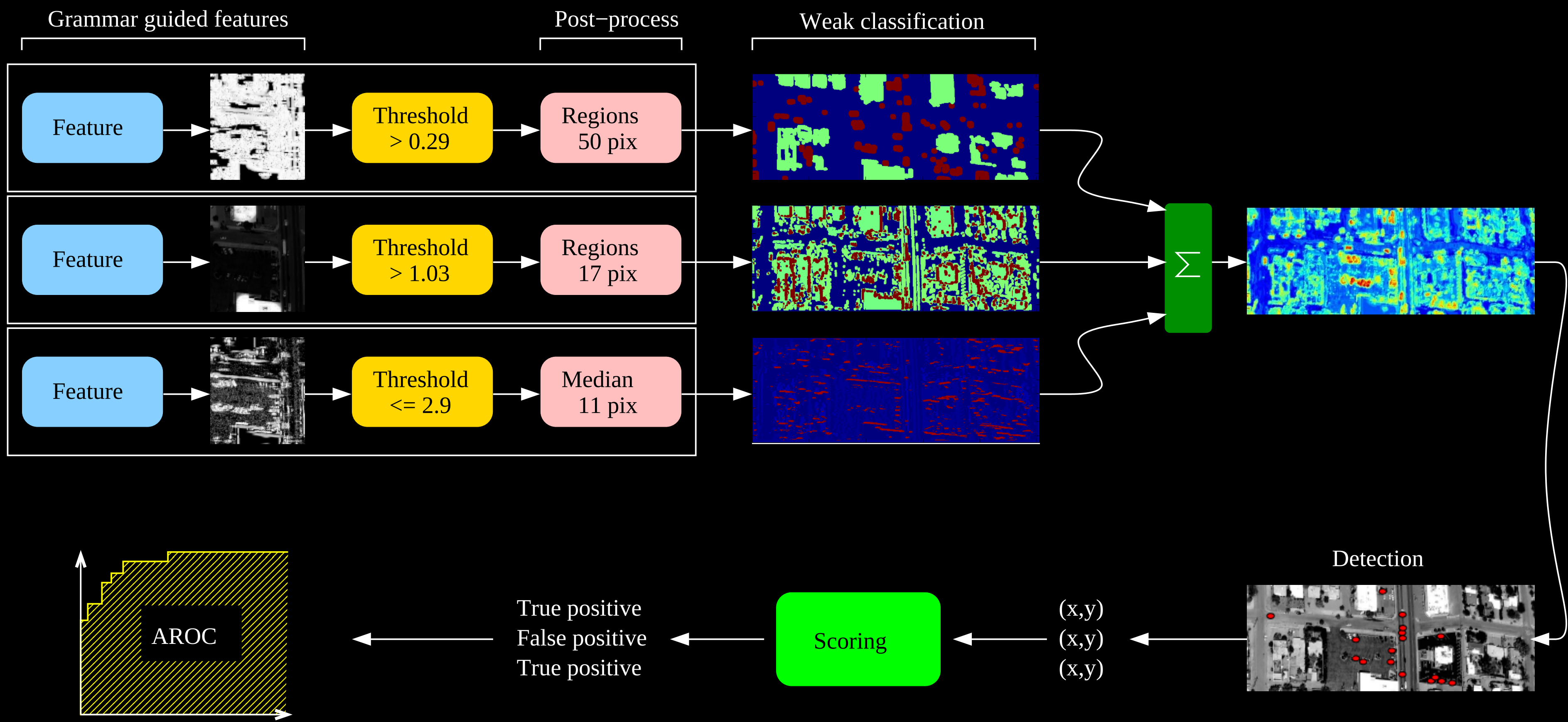
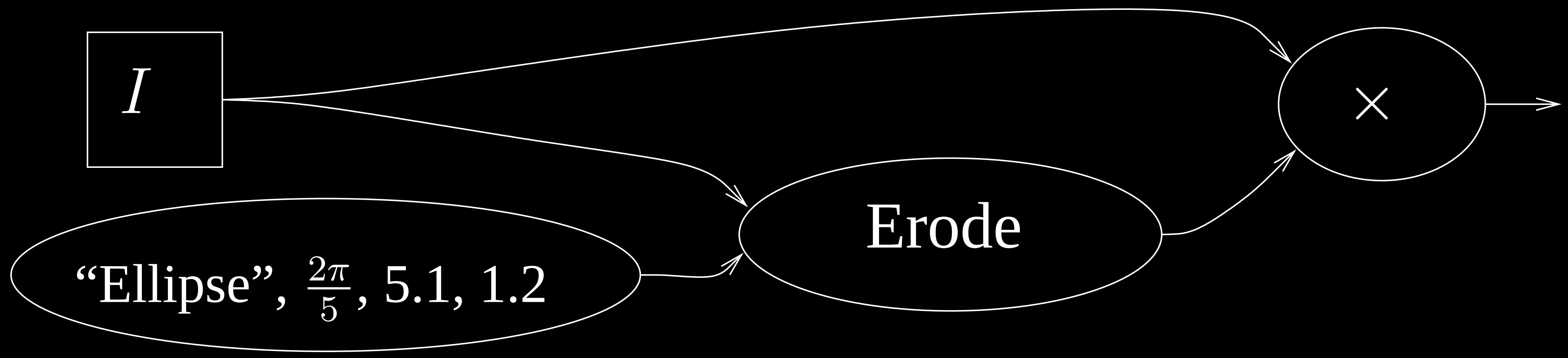


Feature extraction

- Features are small image processing programs.
- Stochastic generative grammar for making programs
- Composed of basic operators: morphology, percentiles, Gabor filters, Haar-like features, edges, …
- Combined using: addition, subtraction, multiplication, sigmoiding, …



Feature grammars

- A grammar consists of *productions*
  $$P \rightarrow A|B$$
- Productions are expanded stochastically:
- P can be turned into A or B
- P is *non-terminal*
- A and B are *terminal*
- Non-terminals expanded until only terminals remain
- Expansion rules have domain expertise built in
- Intelligent sampling of feature space

Example

$$
\begin{aligned}
\text{Feature}(x) &\rightarrow \text{Binary}(\text{Unary}(x), \text{Unary}(x)) \mid \text{Unary}(x) \\
\text{Unary}(x) &\rightarrow x \mid \text{Erode}(x, \text{RandomSE}()) \\
\text{Binary}(x, y) &\rightarrow \text{Add}(x, y) \mid \text{Multiply}(x, y) \\
\textbf{RandomSE()} &\rightarrow \text{Ellipse}\textbf{(}\mathcal{U}(0, \pi),\ \mathcal{U}(1, 10),\ \mathcal{U}(1, 10)\textbf{)}
\end{aligned}
$$

$f(x) = \text{Feature}(x)$

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$$f(x) = \text{Binary}(\text{Unary}(x), \text{Erode}(x, \text{Ellipse}(\tfrac{2\pi}{5}, 5.1, 1.2)))$$

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$$
f(x) = \mathrm{Binary}(x, \mathrm{Erode}(x, \mathrm{Ellipse}(\tfrac{2\pi}{5}, 5.1, 1.2)))
$$

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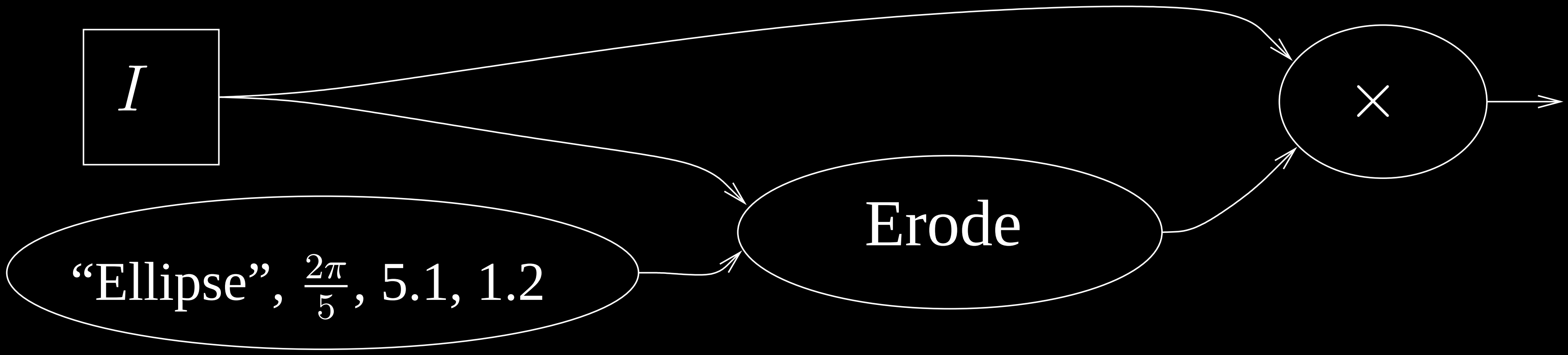
\end{aligned}
$$

$$f(x) = \text{Multiply}(x, \text{Erode}(x, \text{Ellipse}(\tfrac{2\pi}{5}, 5.1, 1.2)))$$

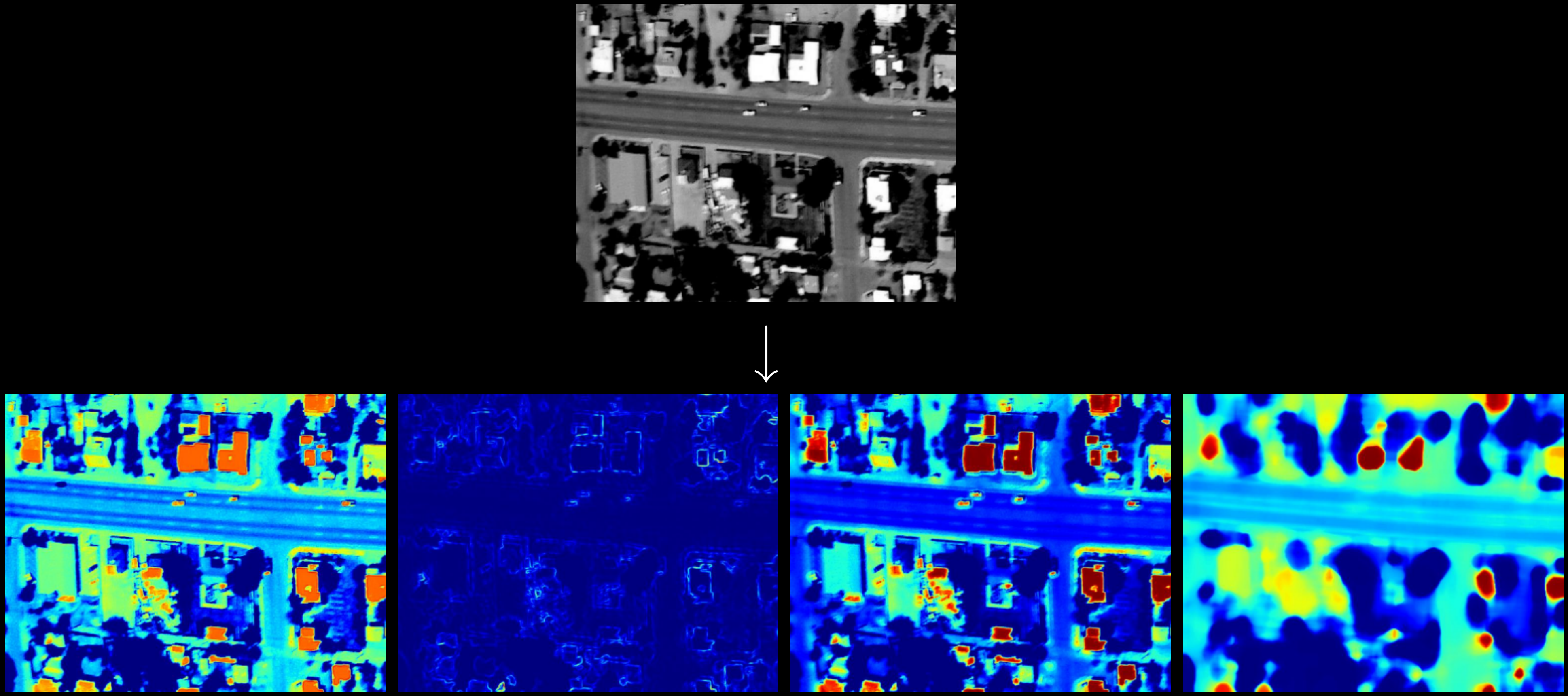
Example

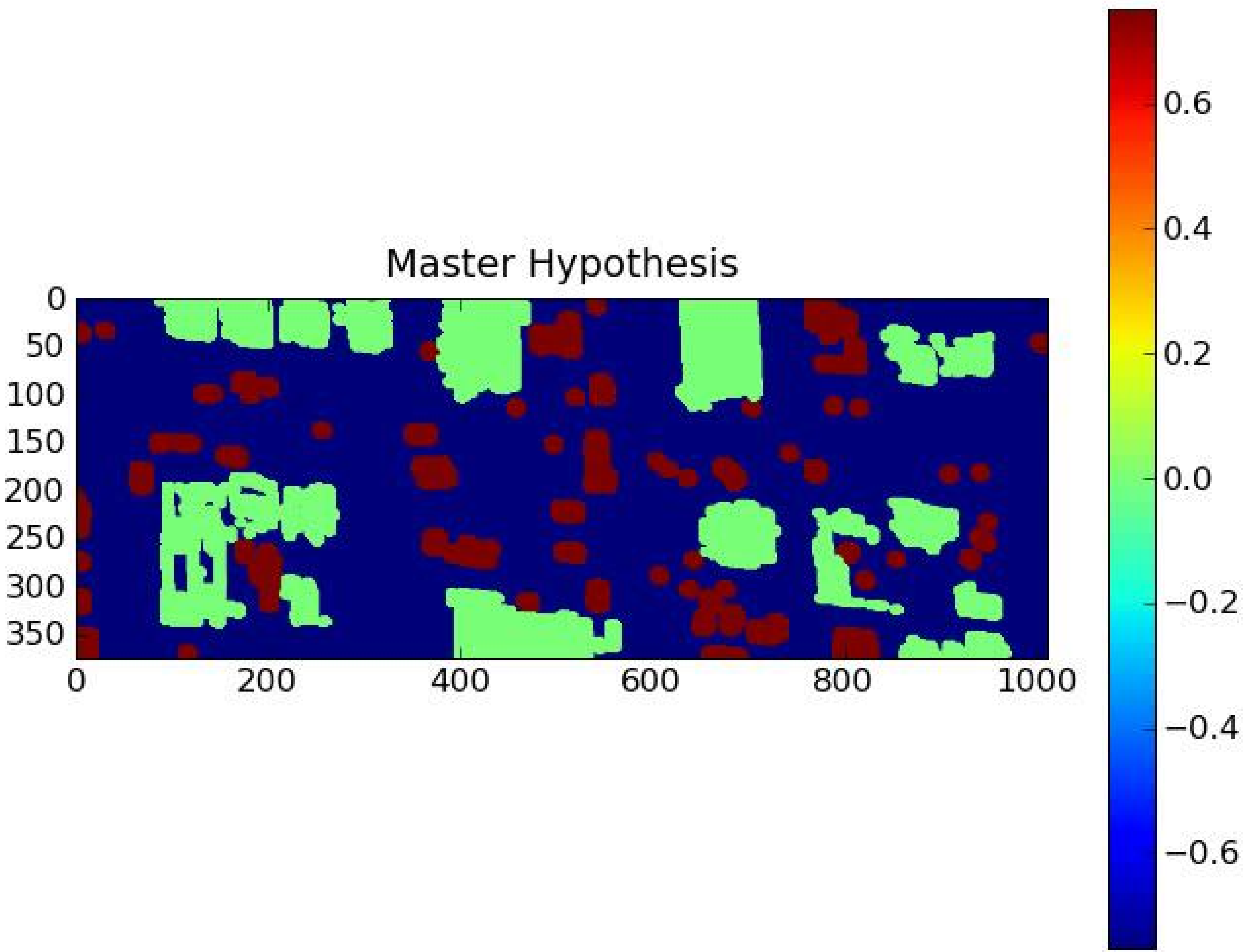
$$
\begin{aligned}
\text{Feature}(x) &\rightarrow \text{Binary}(\text{Unary}(x), \text{Unary}(x)) \mid \text{Unary}(x) \\
\text{Unary}(x) &\rightarrow x \mid \text{Erode}(x, \text{RandomSE}()) \\
\text{Binary}(x, y) &\rightarrow \text{Add}(x, y) \mid \text{Multiply}(x, y) \\
\text{RandomSE}() &\rightarrow \text{Ellipse}(\mathcal{U}(0, \pi), \mathcal{U}(1, 10), \mathcal{U}(1, 10))
\end{aligned}
$$

$$f(x) = \text{Multiply}(x, \text{Erode}(x, \text{Ellipse}(\tfrac{2\pi}{5}, 5.1, 1.2)))$$



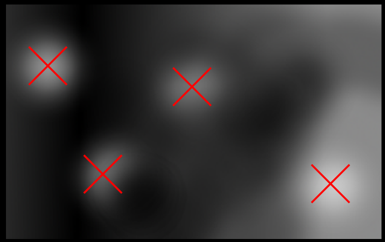
Some random features



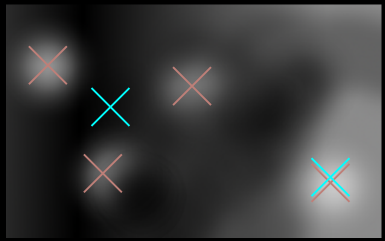


Master Hypothesis
0
50
100
150
200
250
300
350
0
200
400
600
800
1000
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

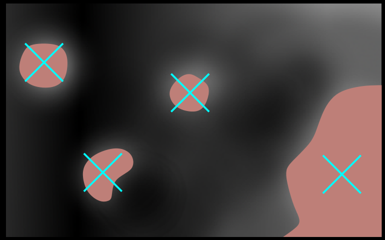
Turning pixels into objects



- Large local maxima
  Choice of pre-smoothing radius



- KDE on large local maxima
  Also kernel size

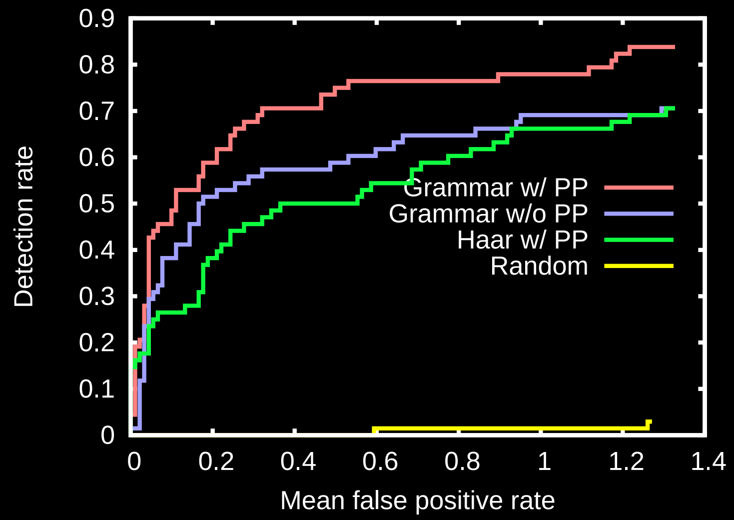


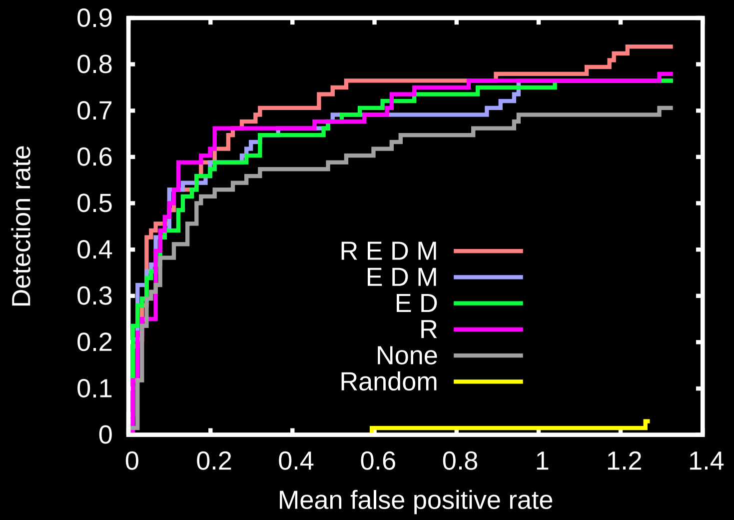
- Connected components
  Choice of threshold

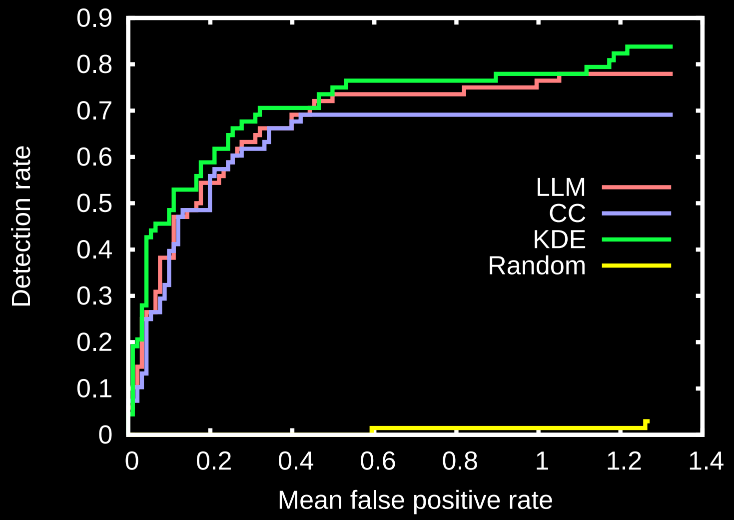
Optimize over data not used for boosting.

Results

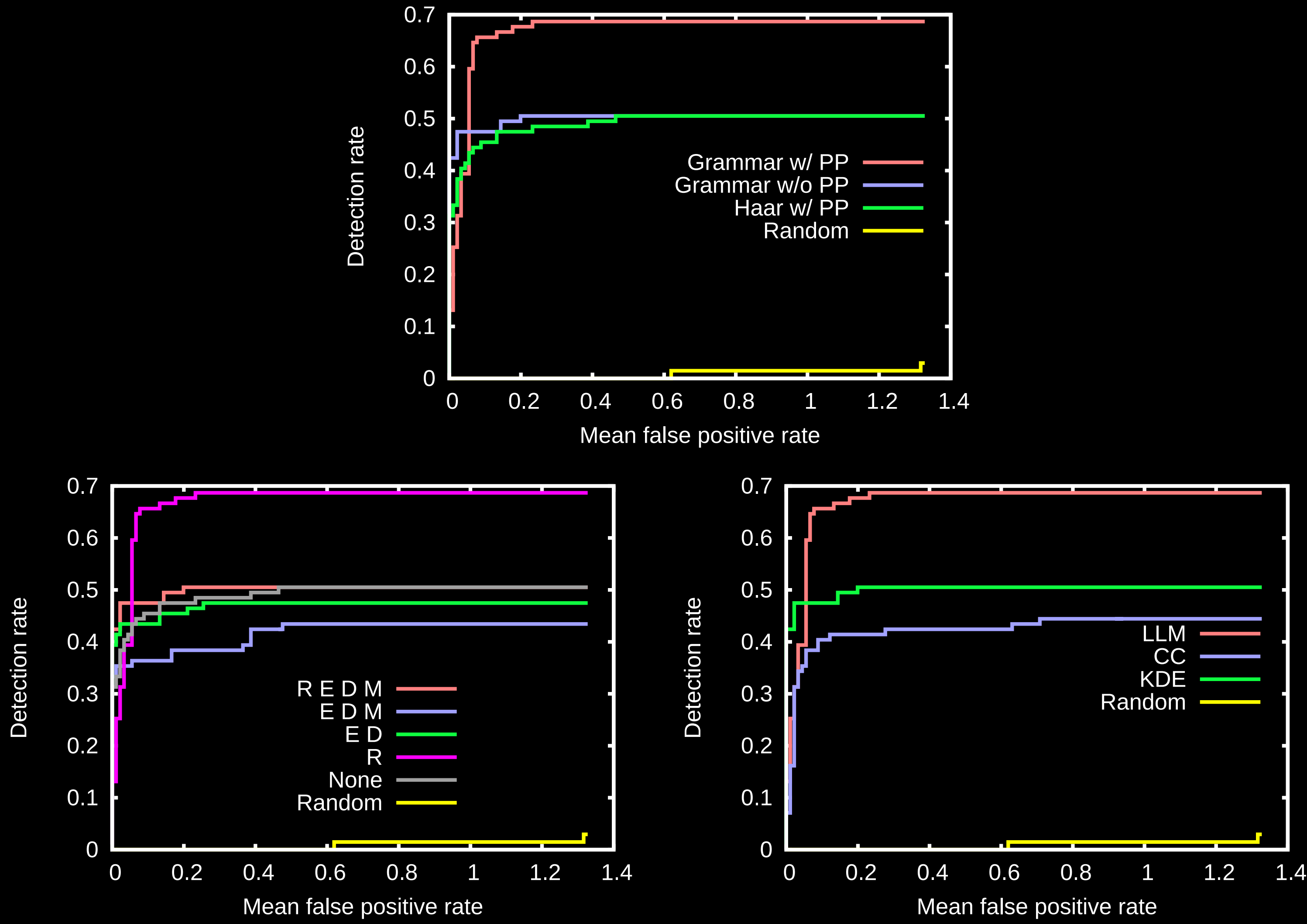
Results: Target detection







Results: Tracking



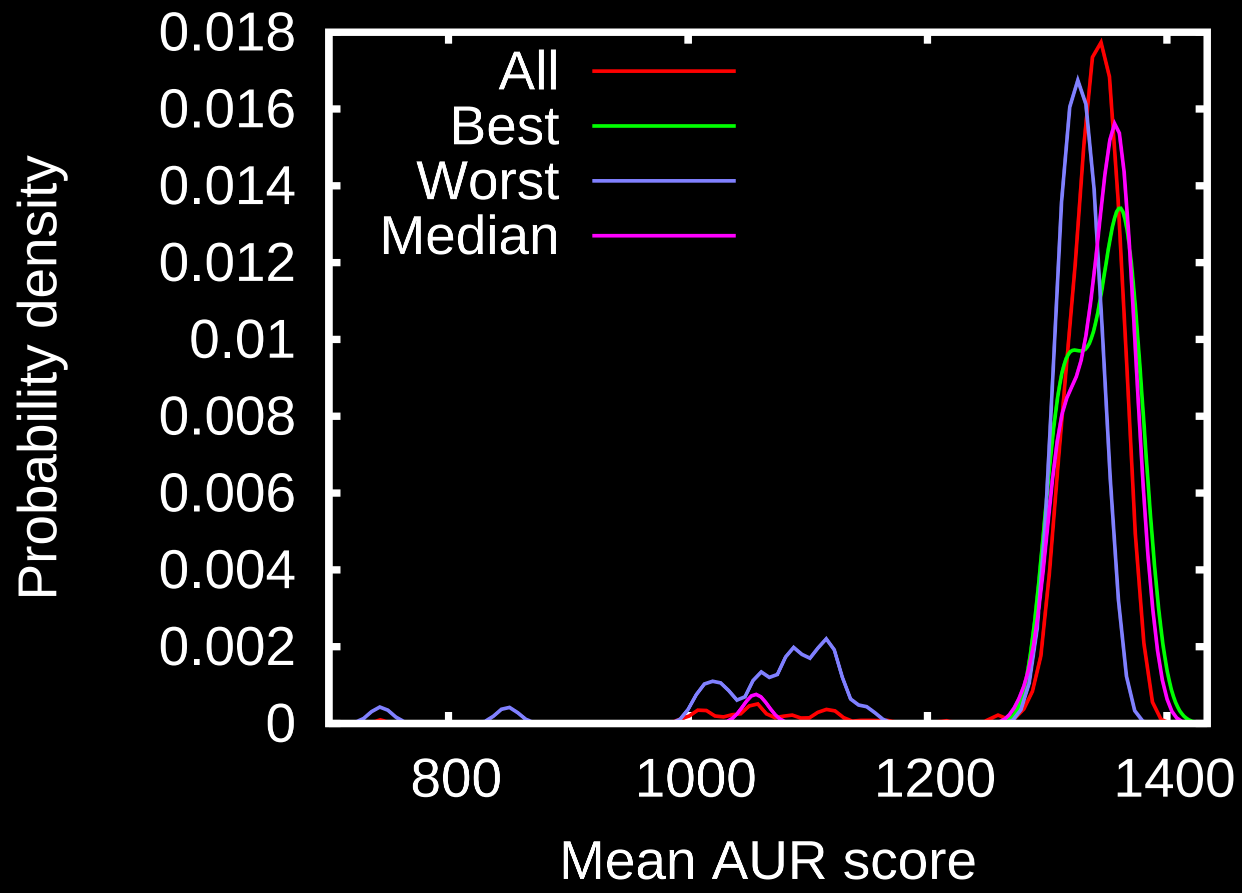
Conclusions

- New features: Grammar-guided features
- Training against scoring measures

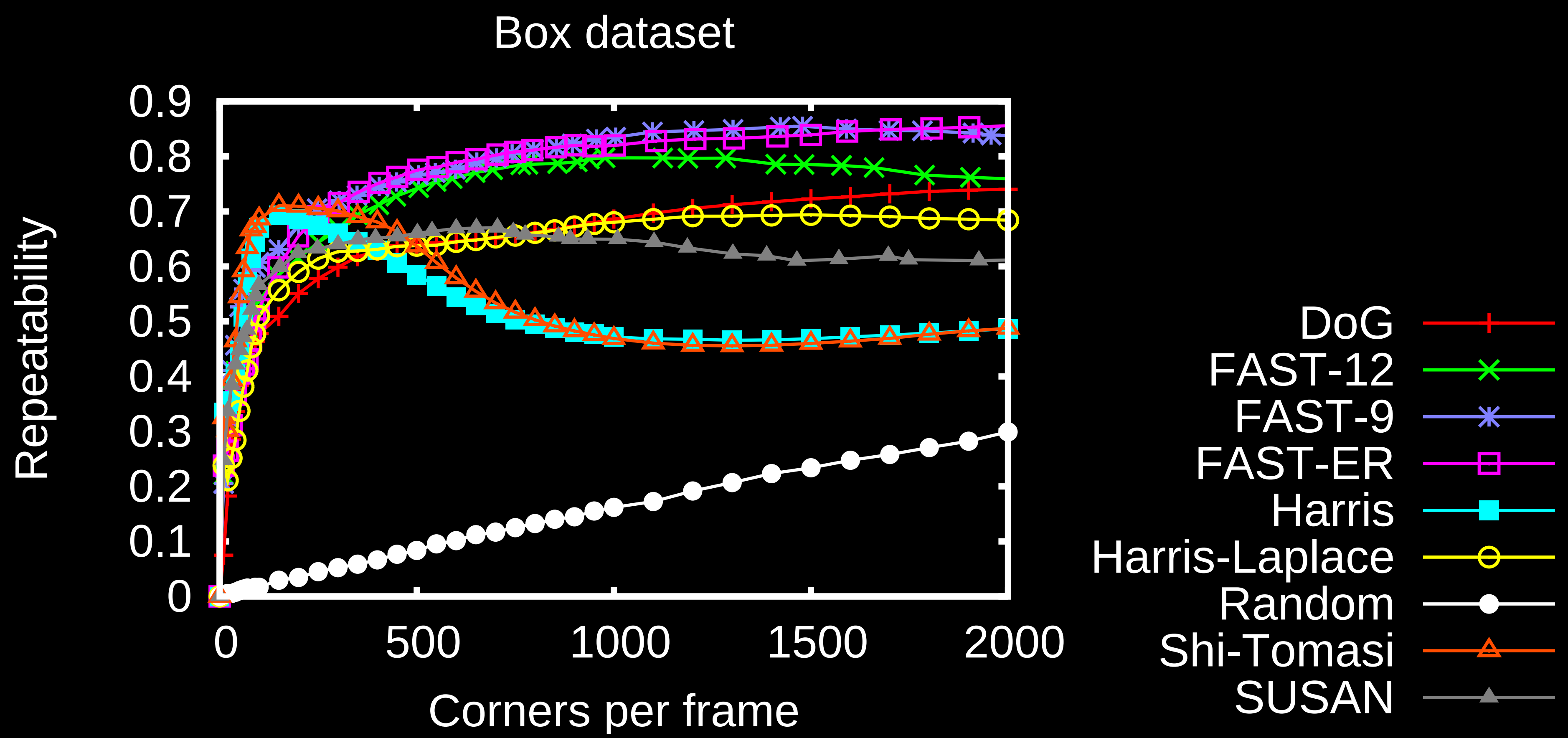
`http://users.soe.ucsc.edu/~eads/software.shtml`

More results

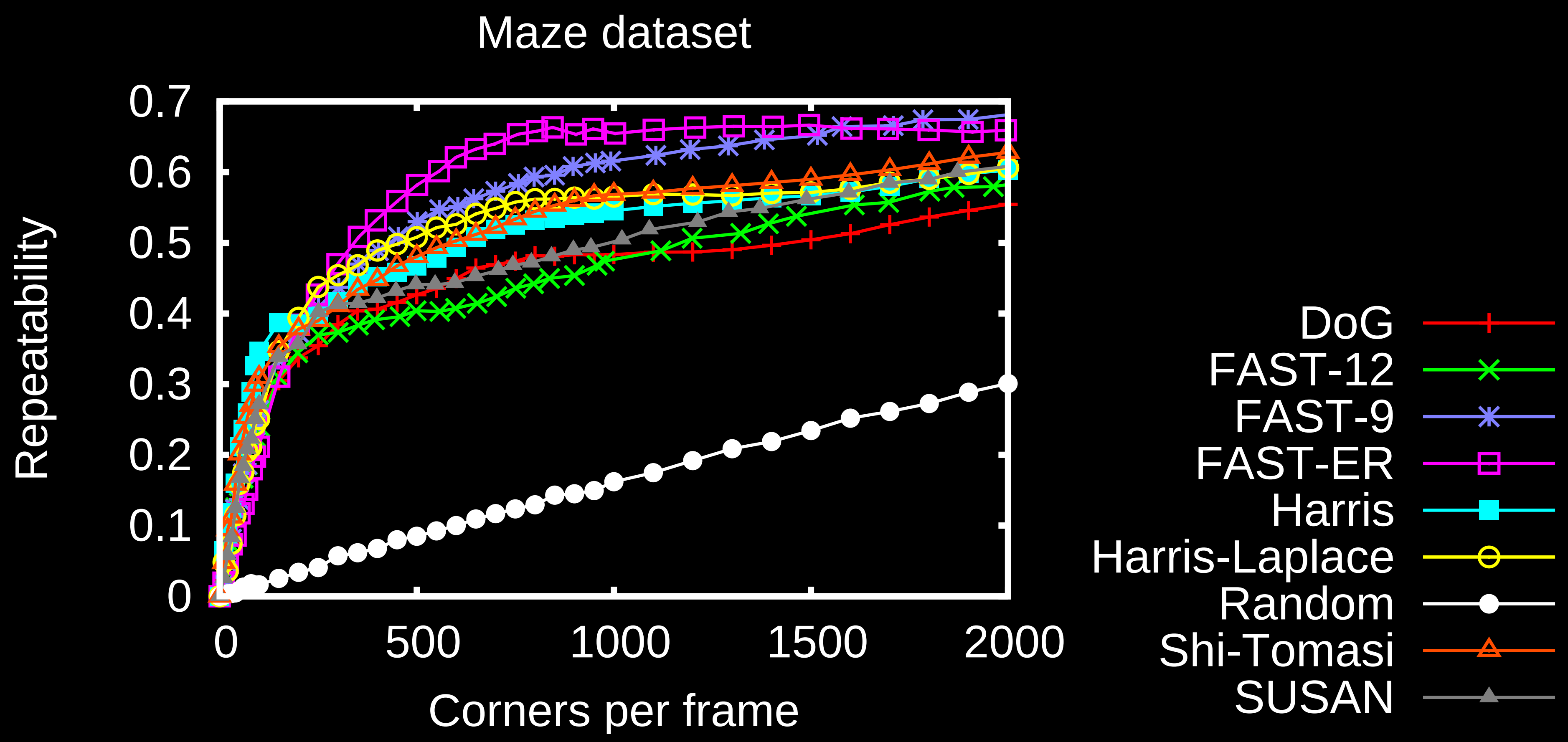
Sensitivity to w_i



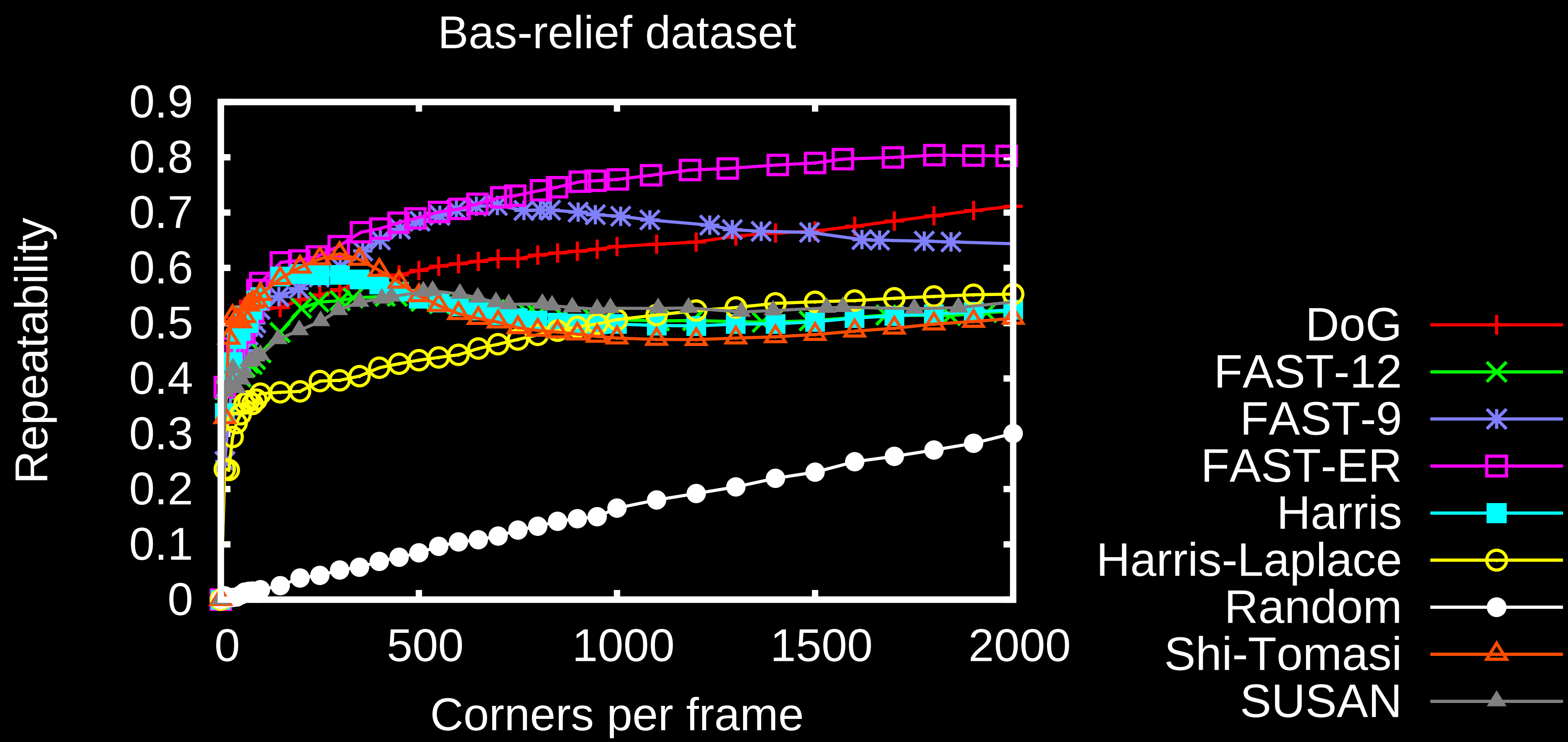
Results: Perspective (box) dataset



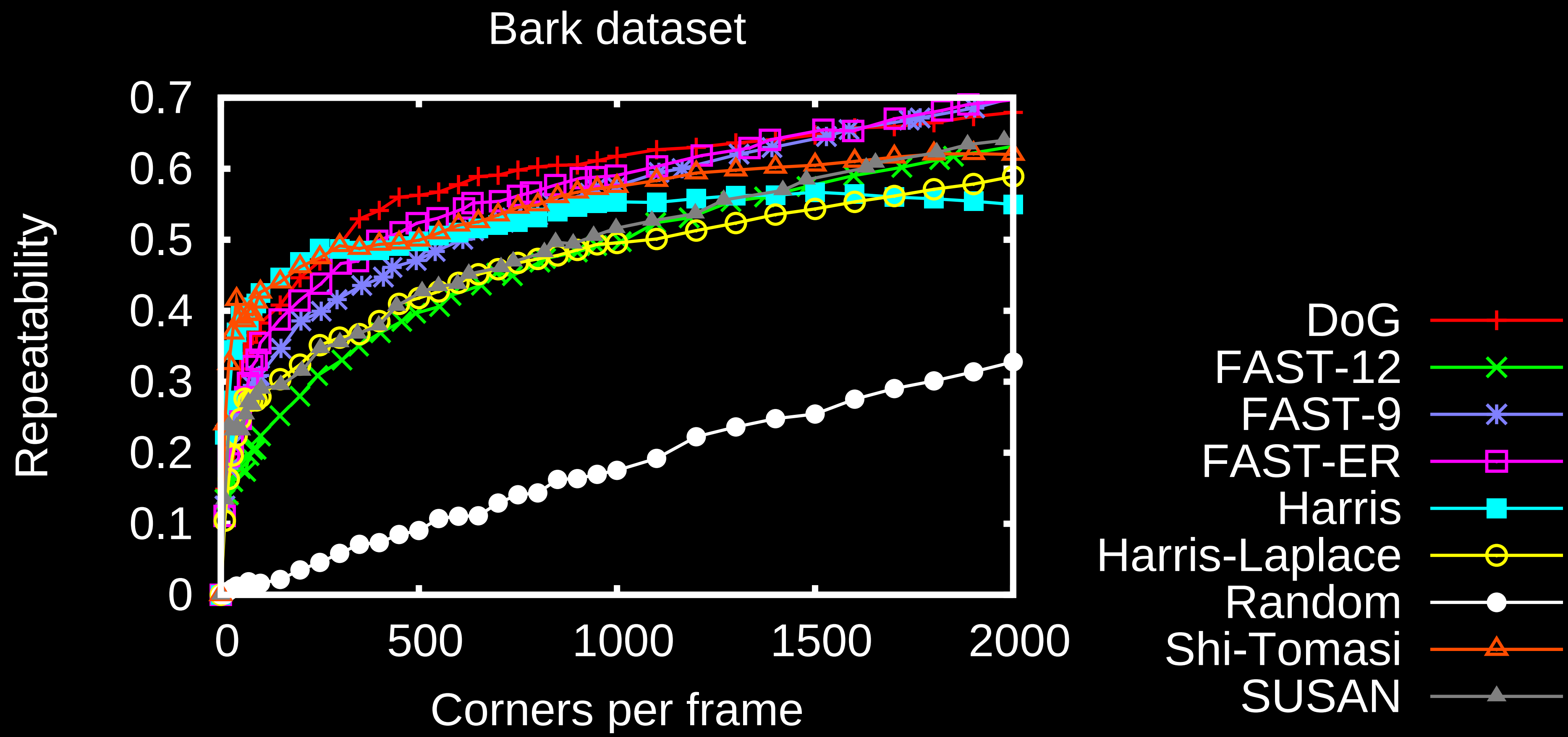
Results: Geometric dataset



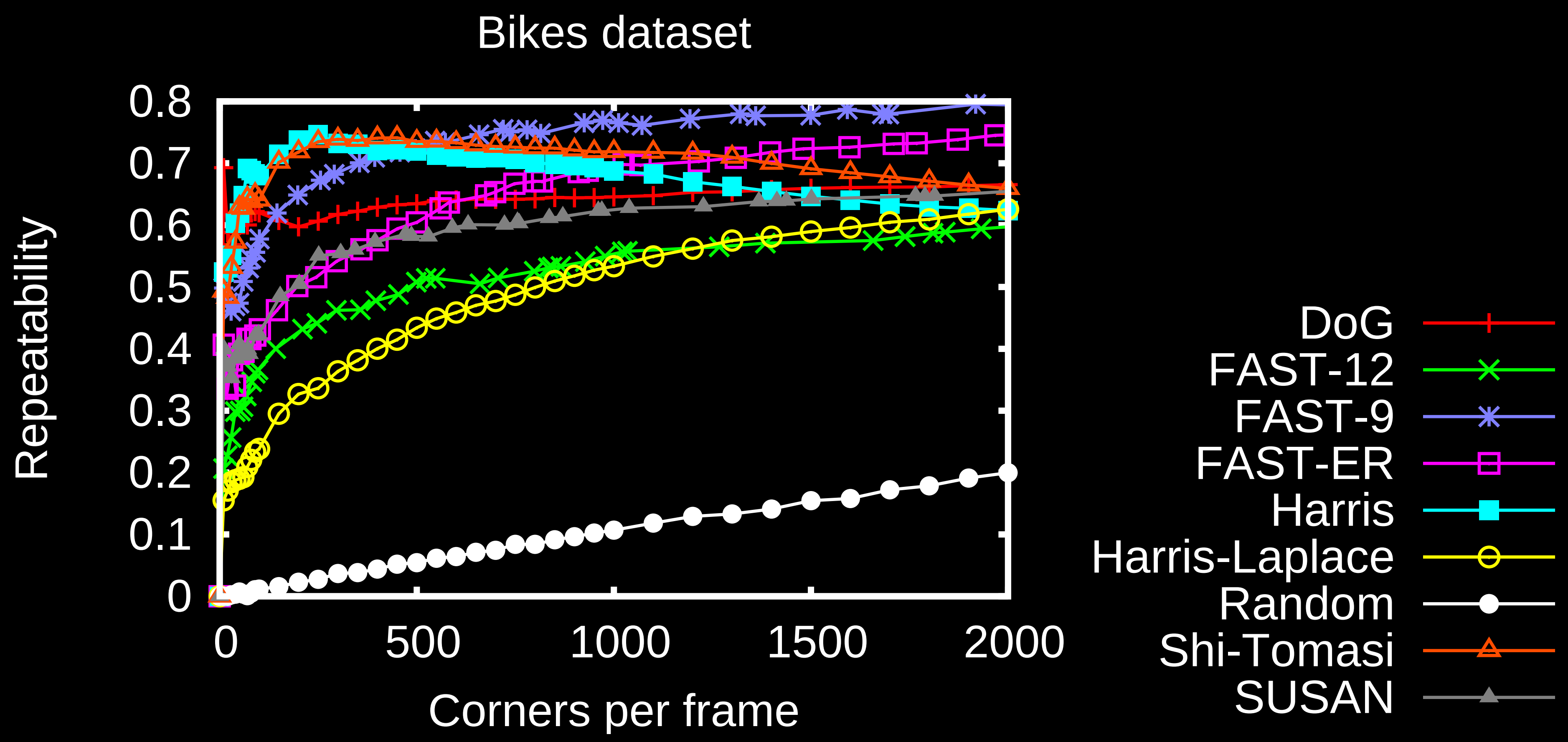
Results: Bas-relief dataset



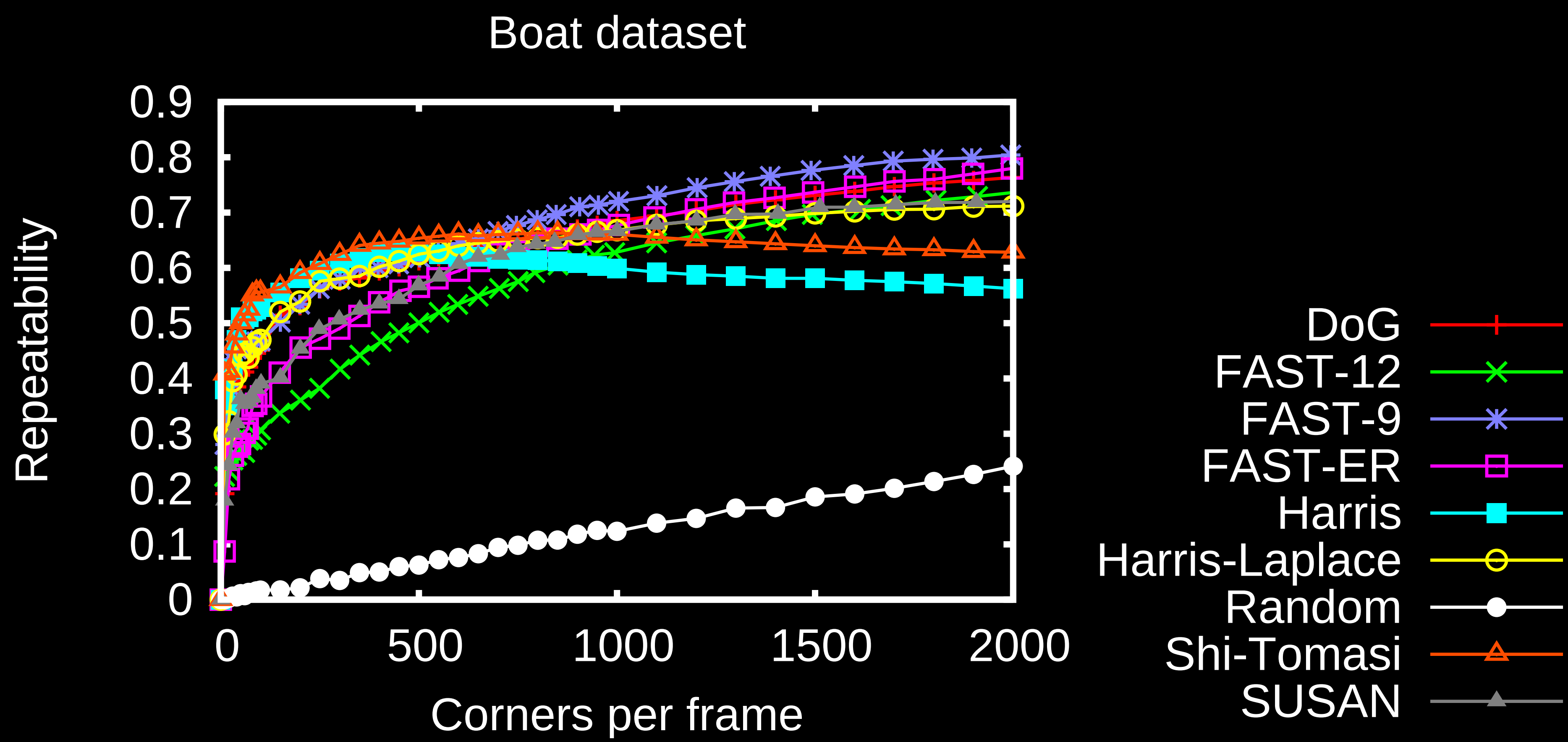
Results: Scale and rotation (bark) dataset



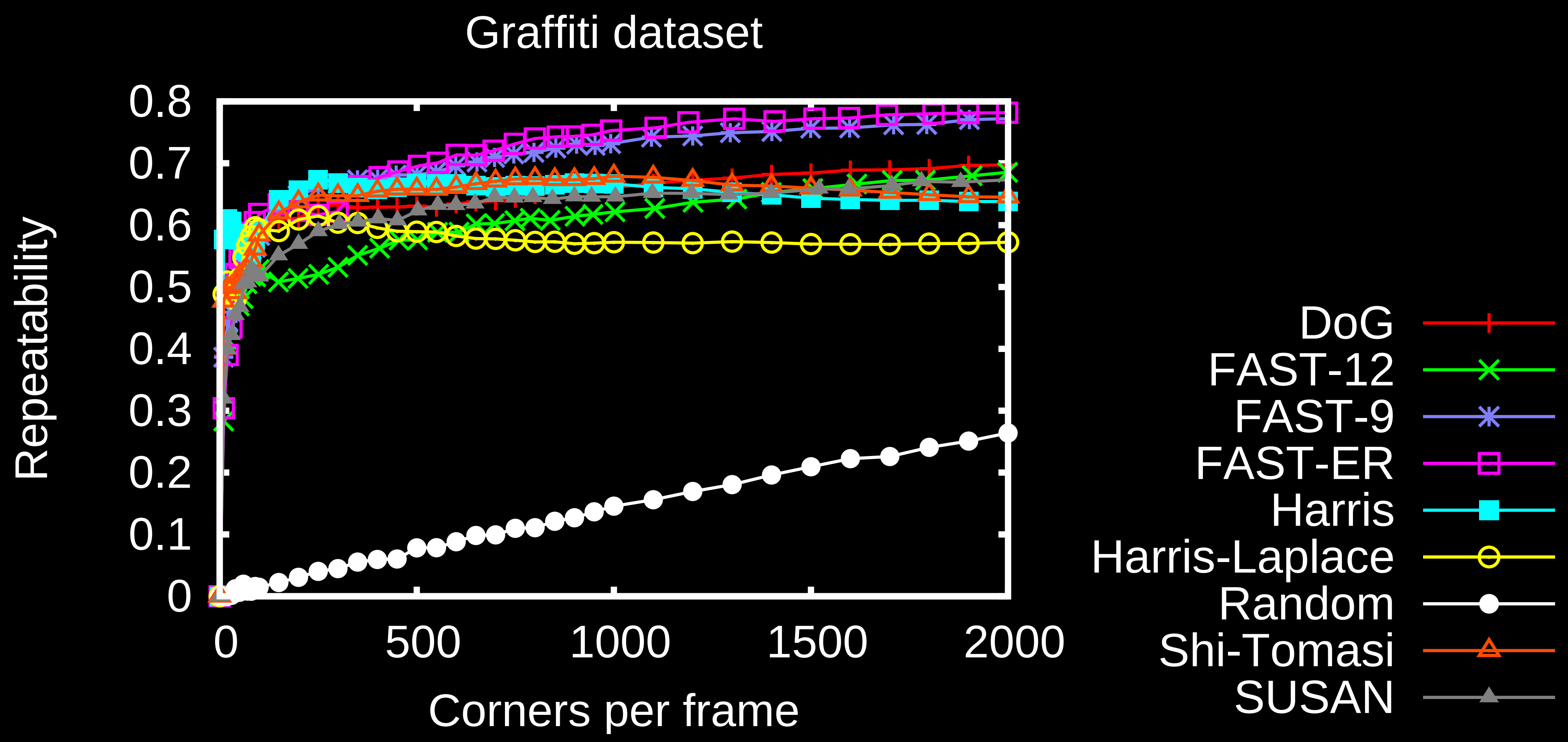
Results: Blur (bikes) dataset



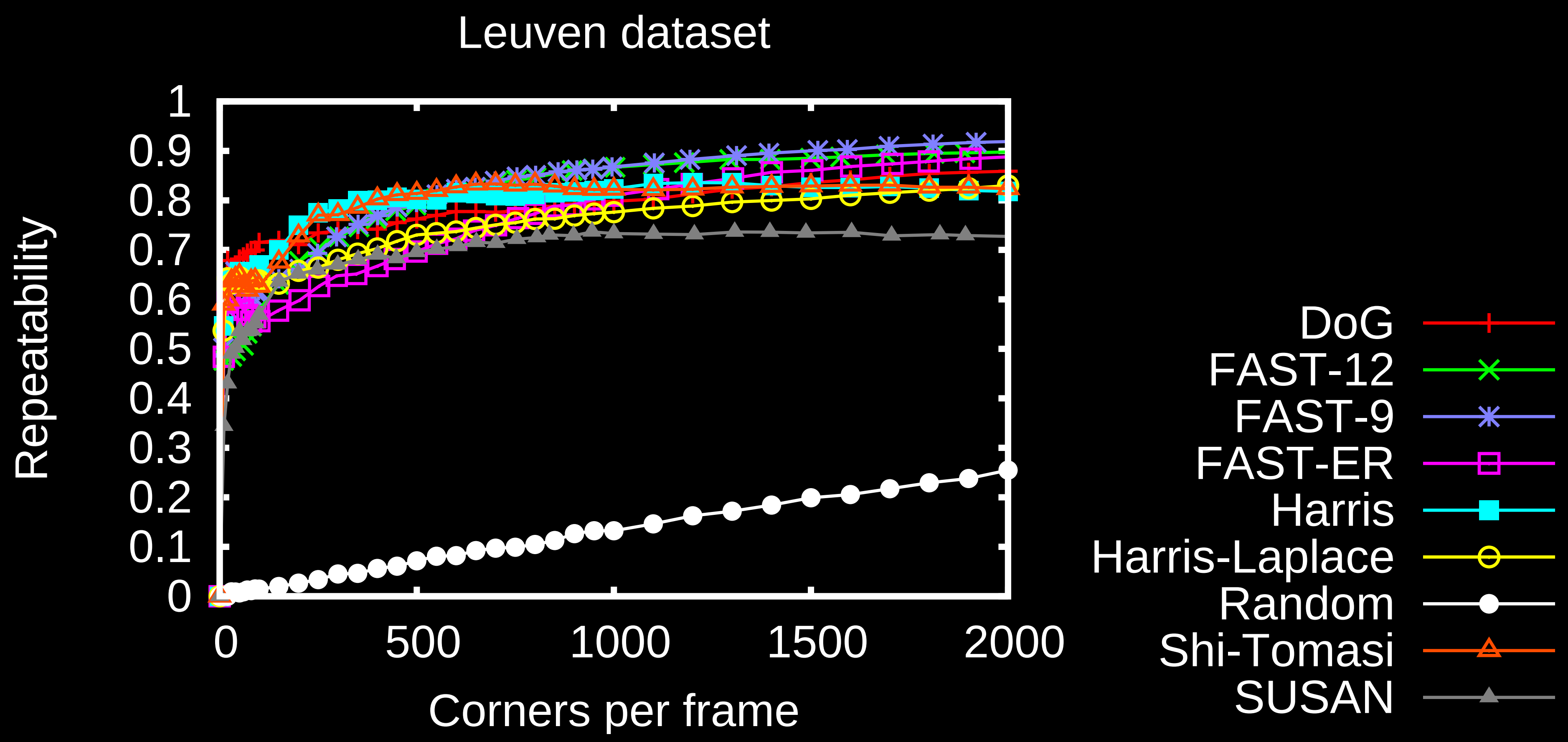
Results: Scale and rotation (boat) dataset



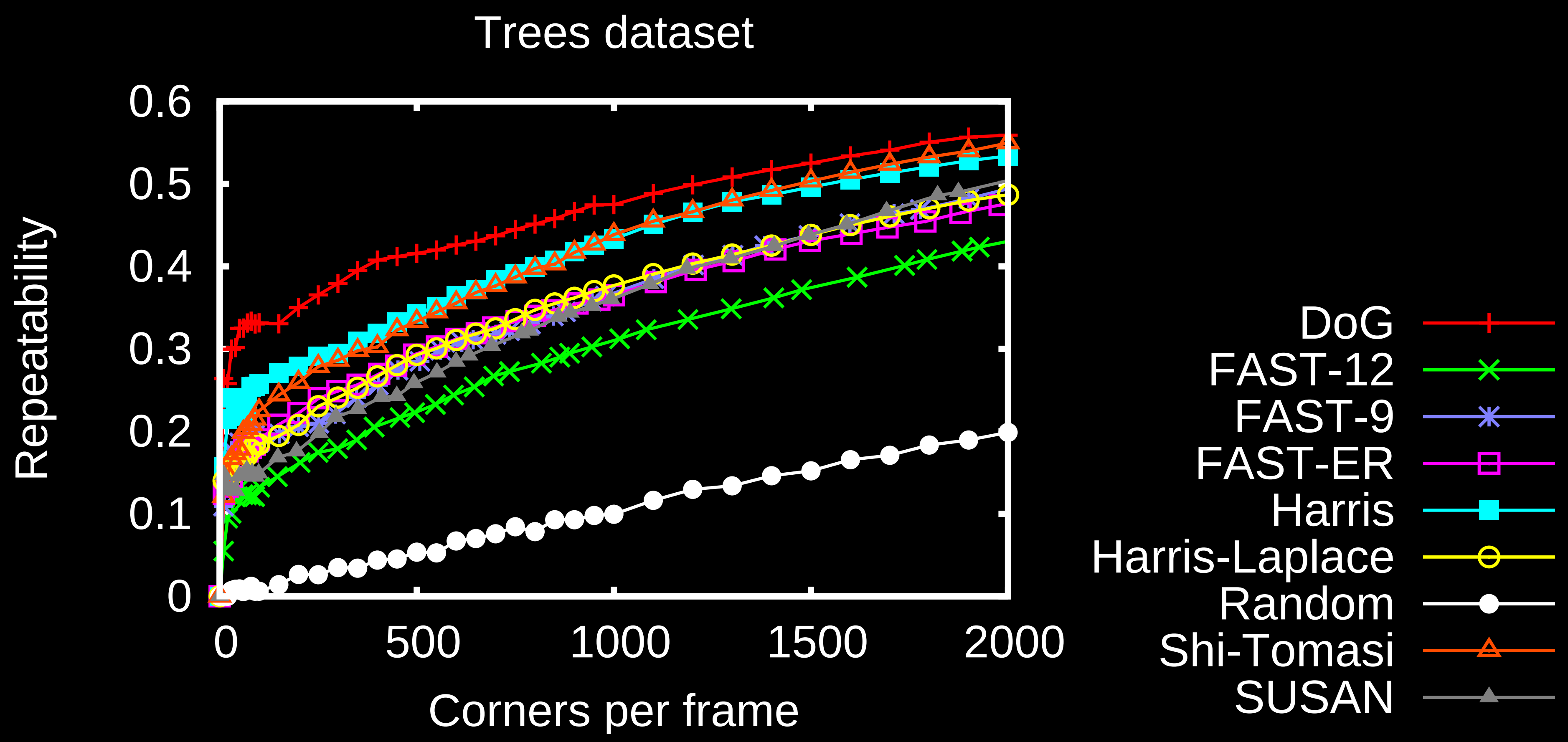
Results: Perspective (graffiti) dataset



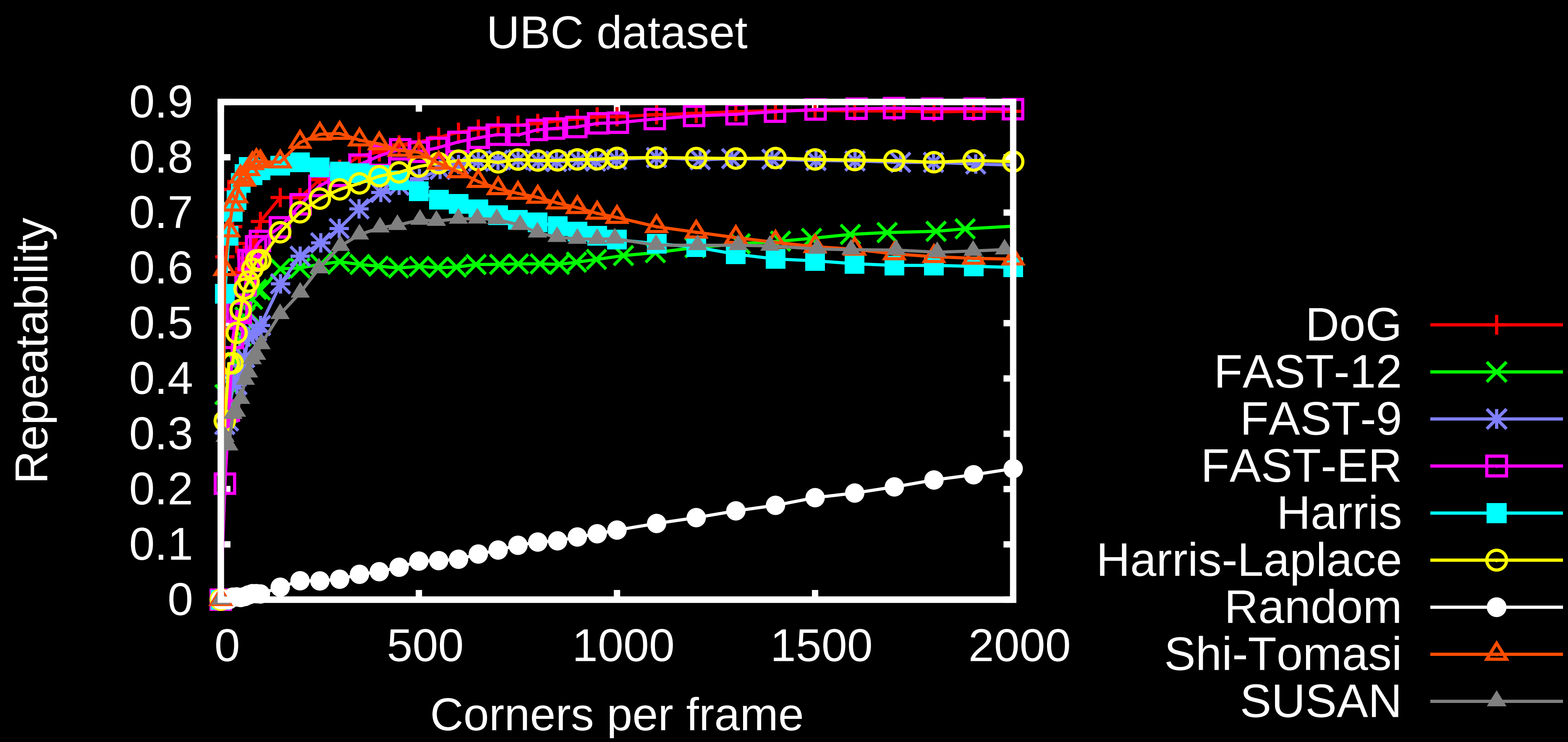
Results: Lighting dataset



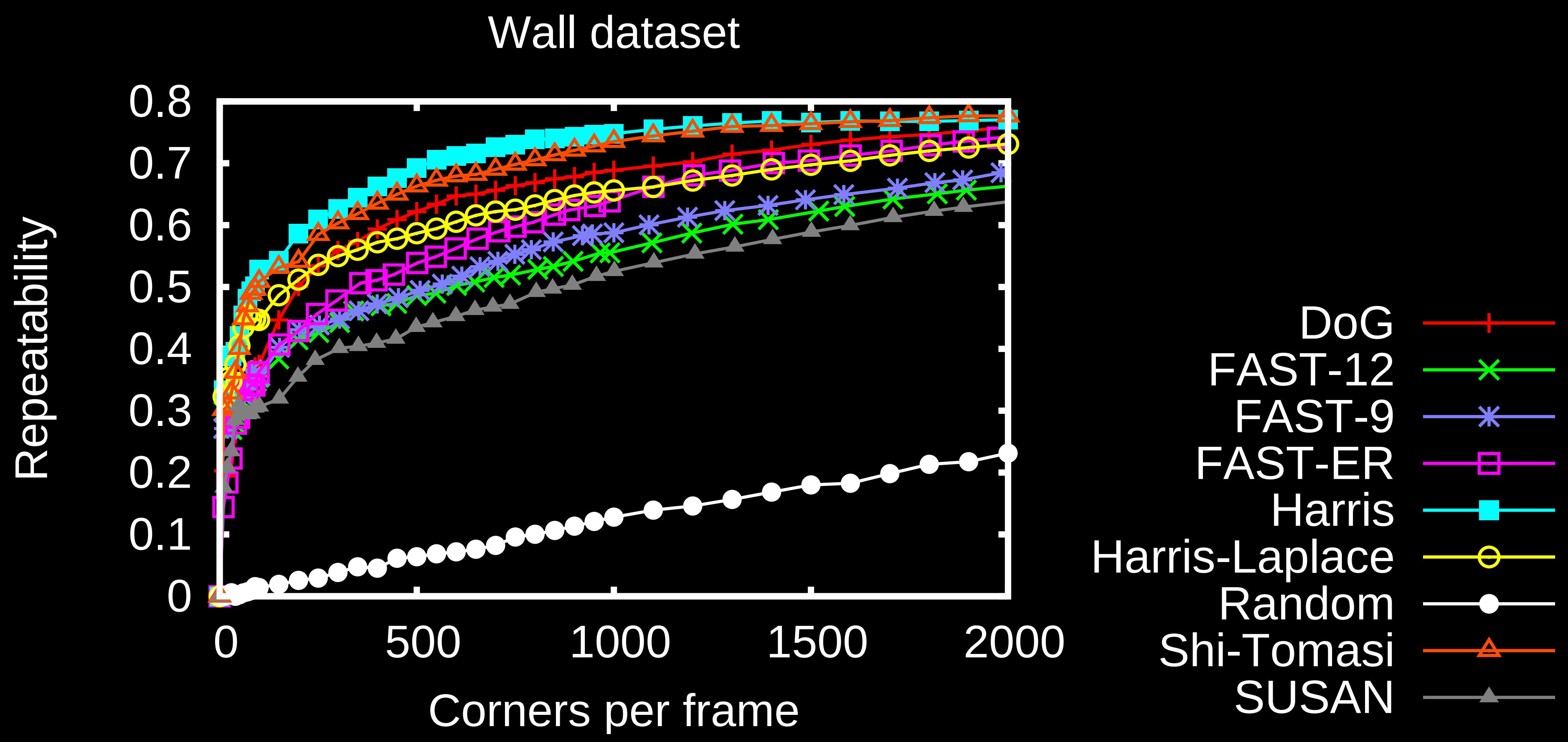
Results: Blur (trees) dataset



Results: JPEG compression dataset



Results: Perspective (wall) dataset

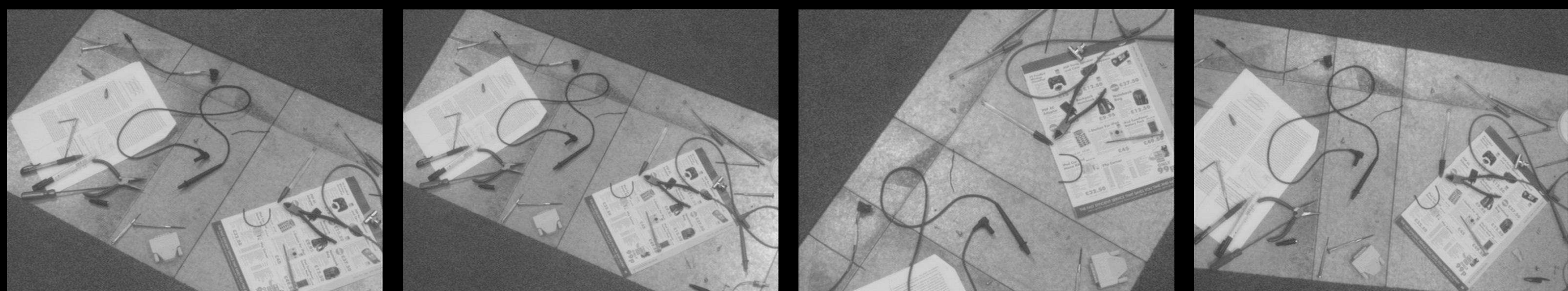


Evaluation: Datasets (3D Models)

14 images:

15 images:

8 images:



Evaluation: Homographies

6 images per set: