Faster and better: a machine learning approach to corner detection.

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What is interest point detection?

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

Useful for:

- 2D tracking, 3D tracking, SLAM, object recognition, …

Example: registration

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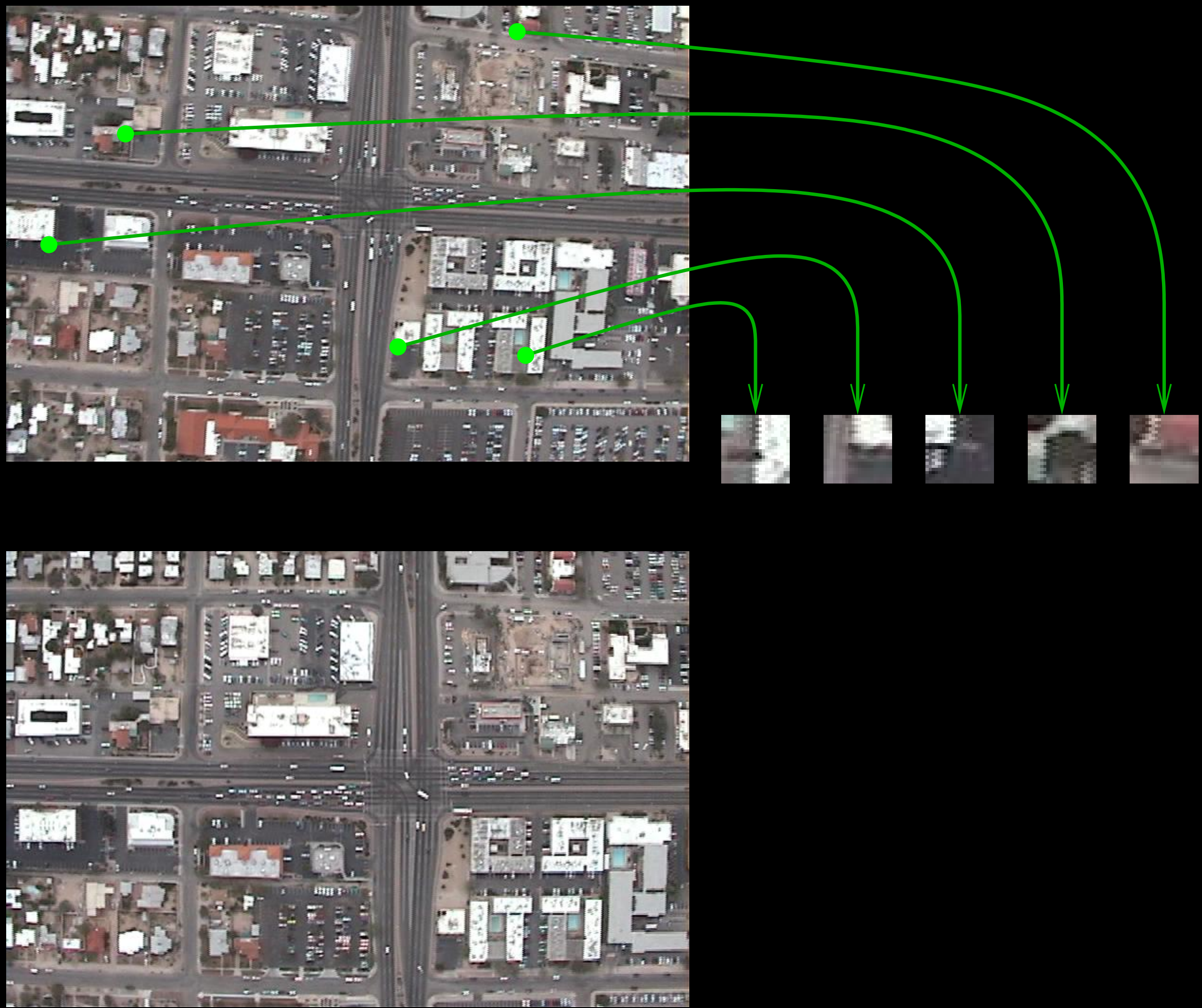
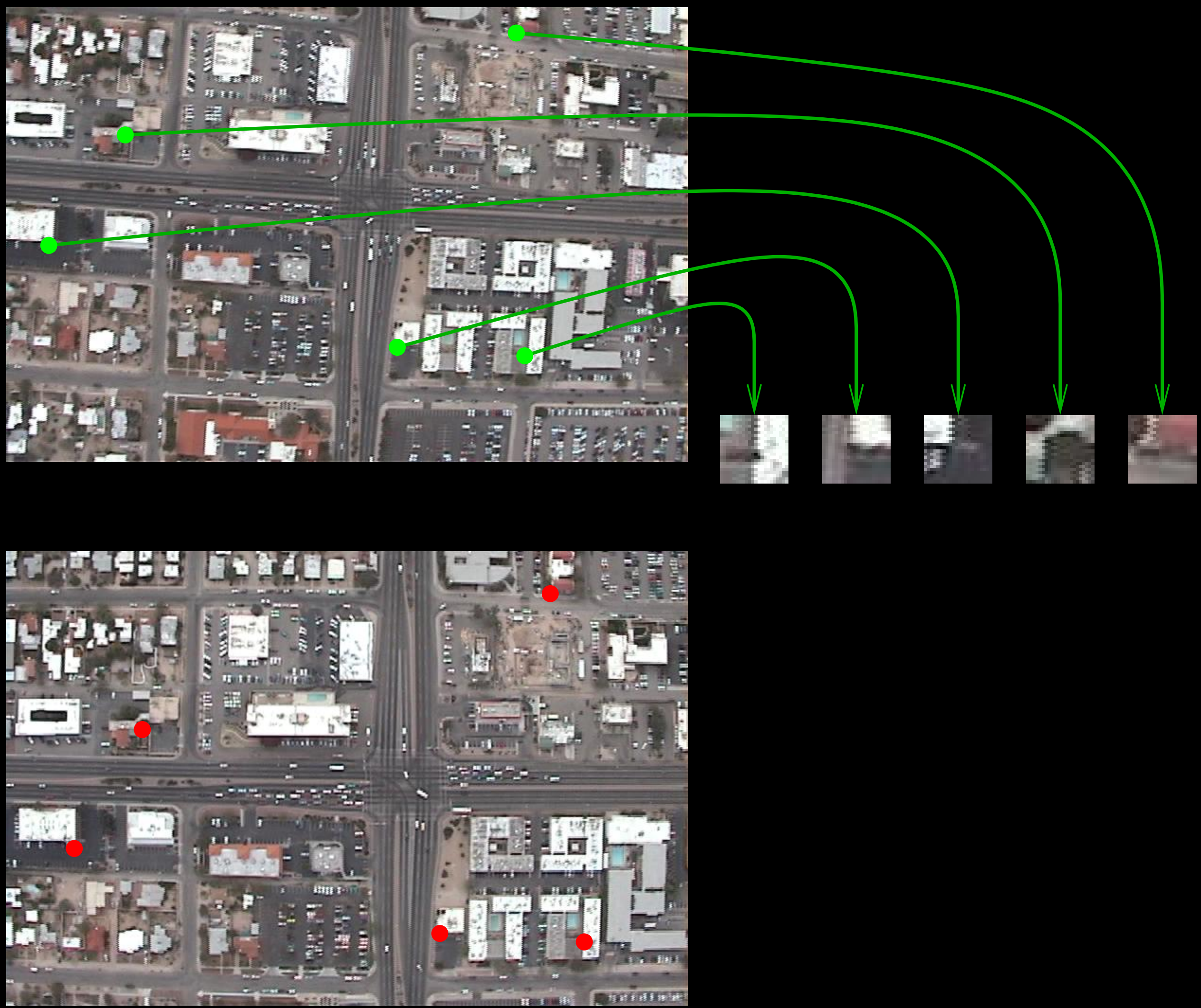


Example: registration



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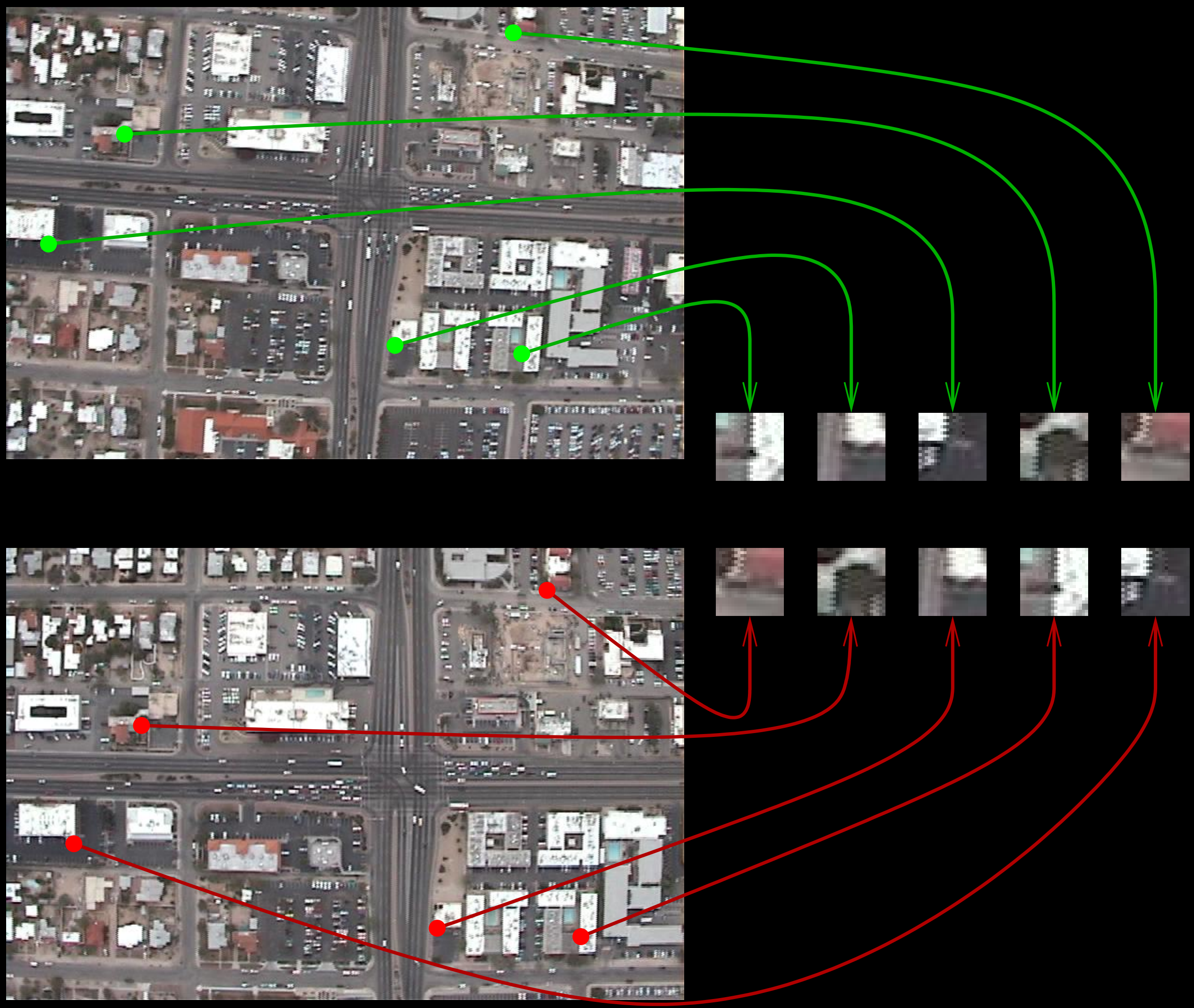

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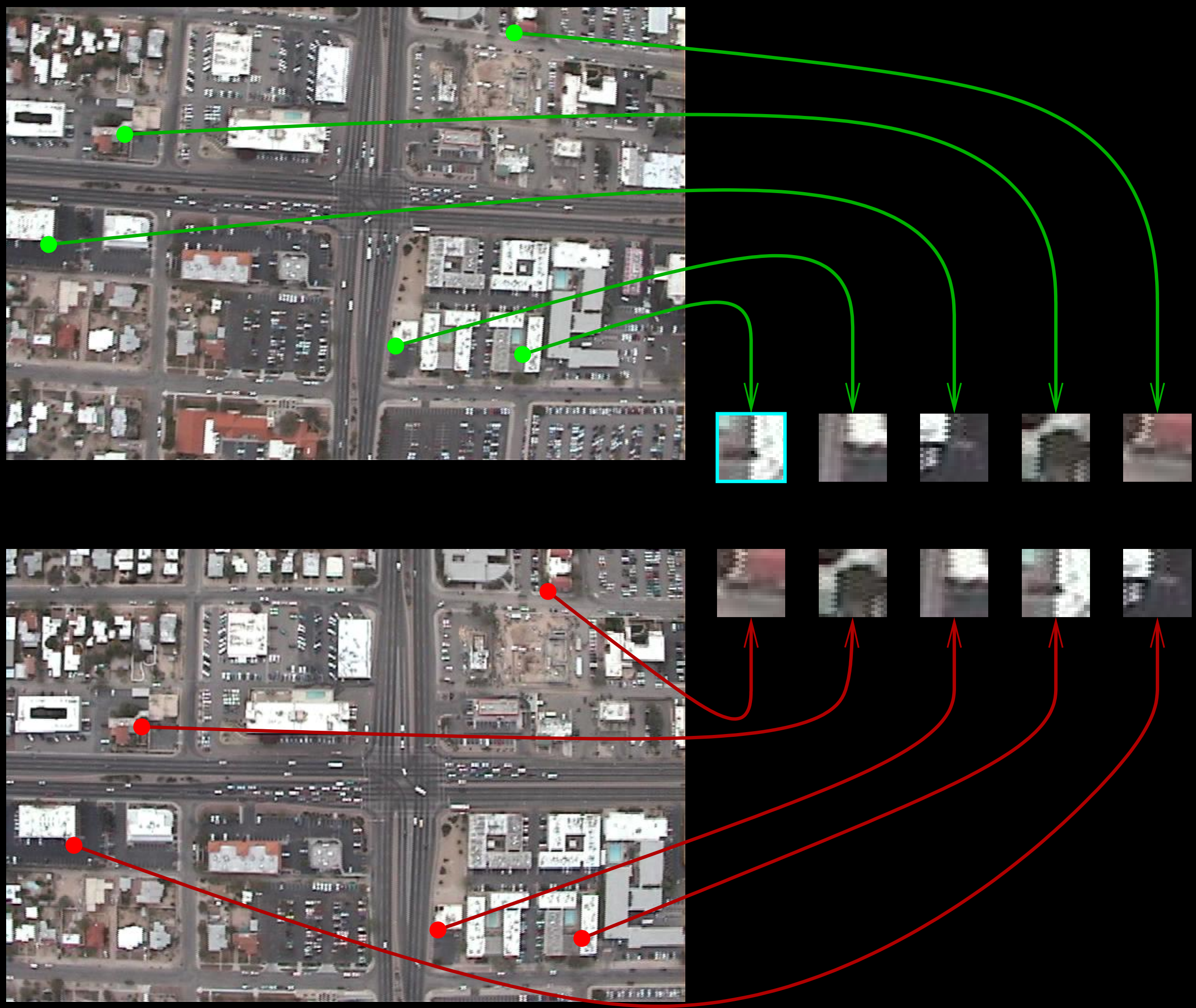

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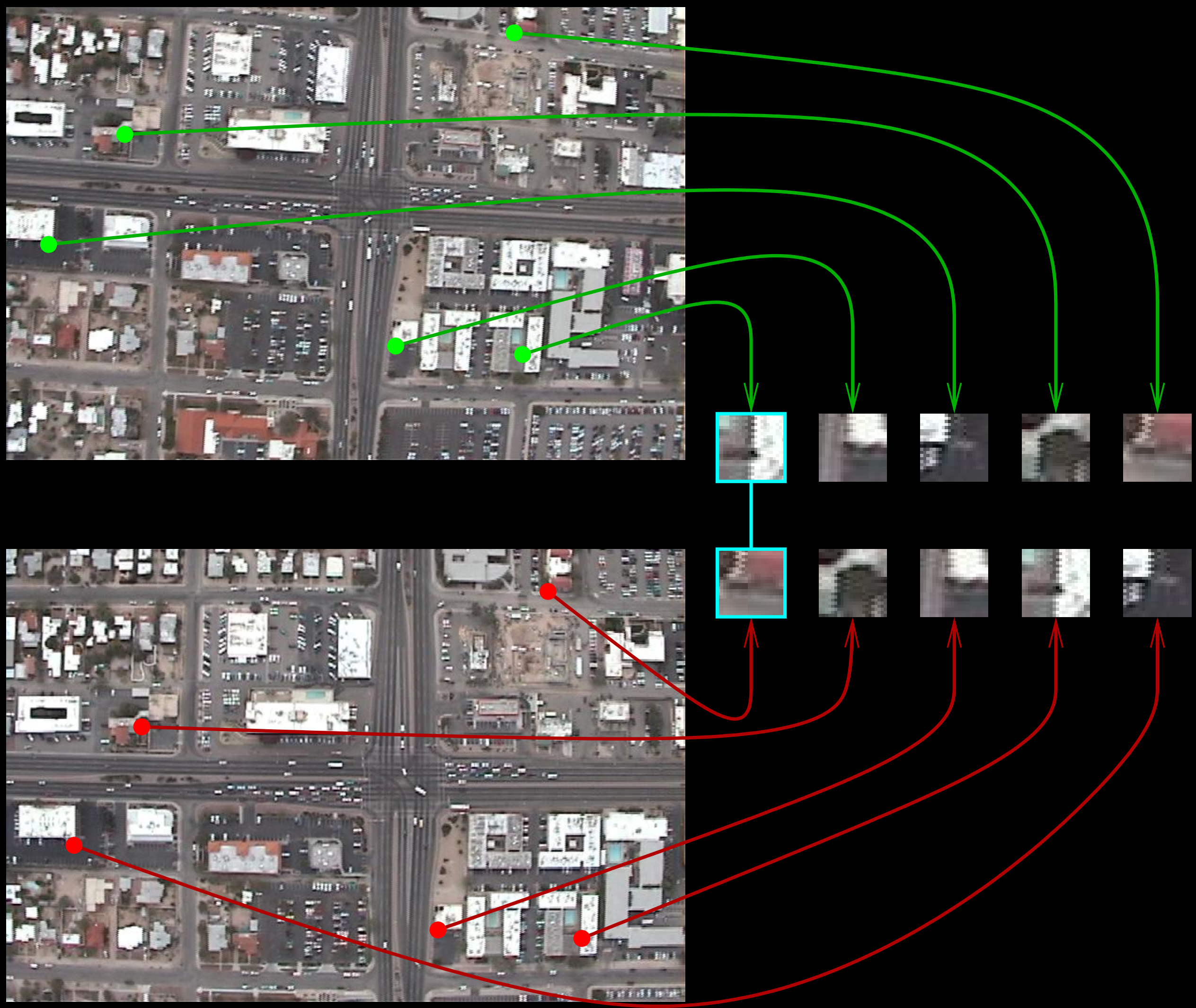

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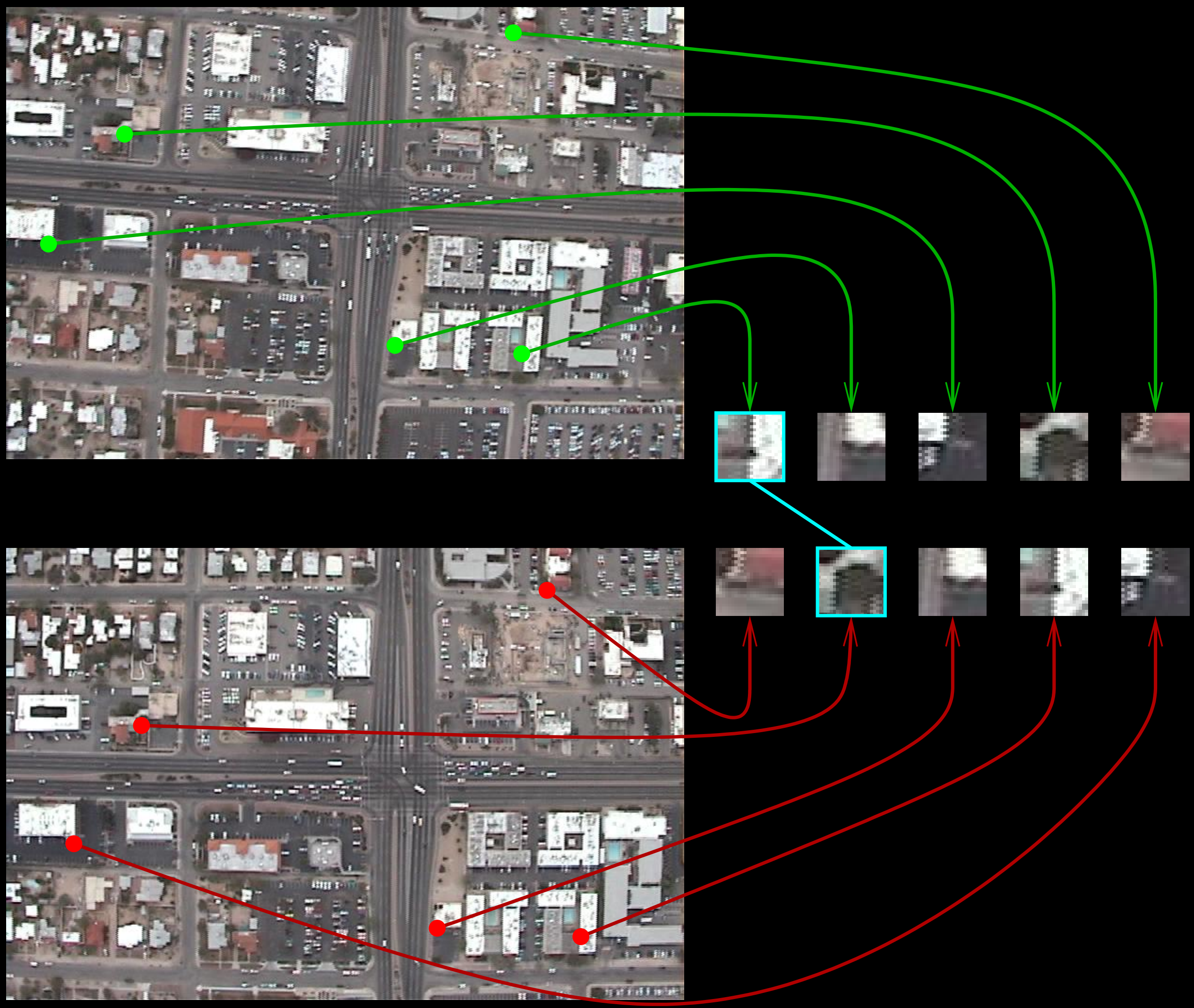
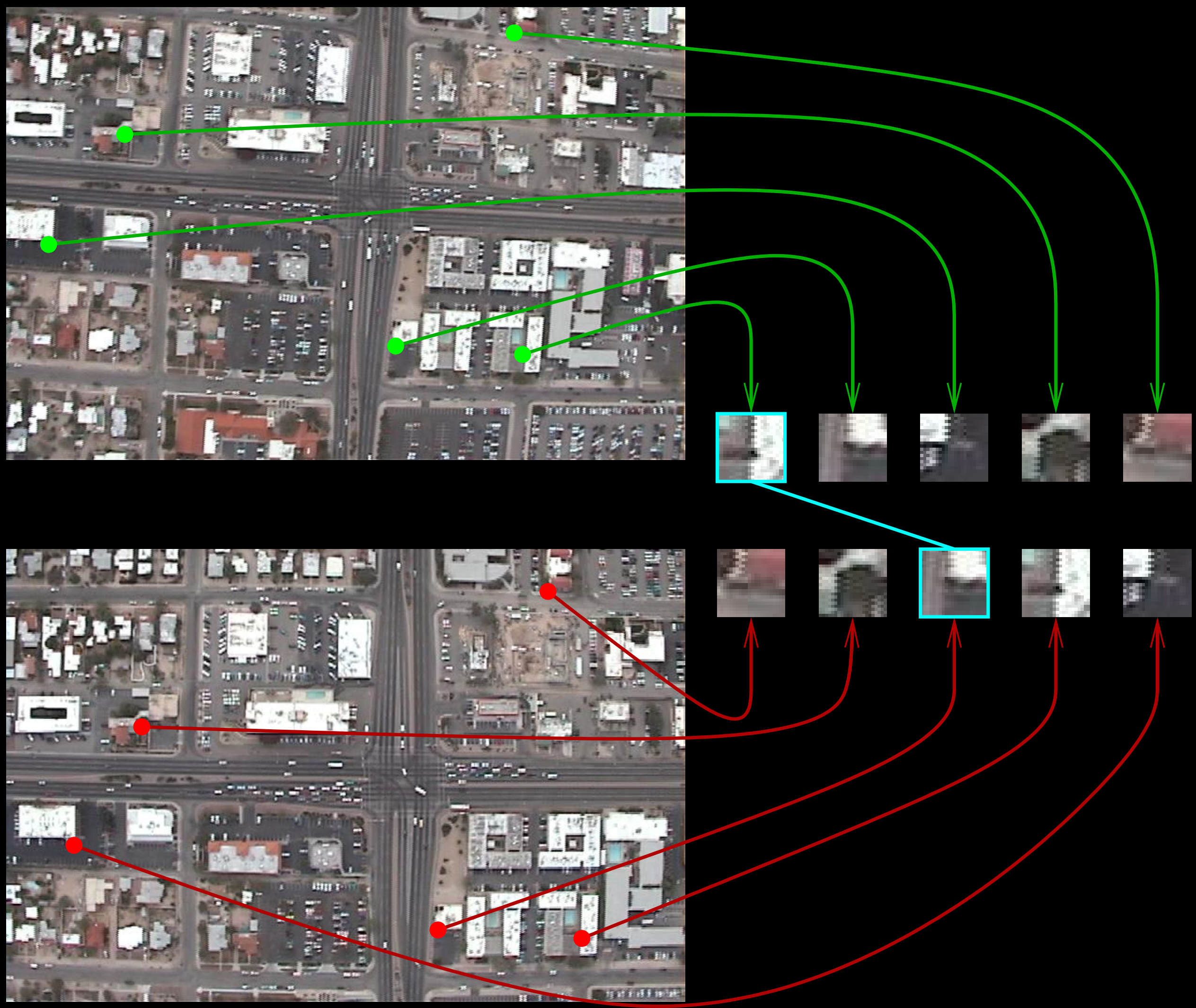


Example: registration



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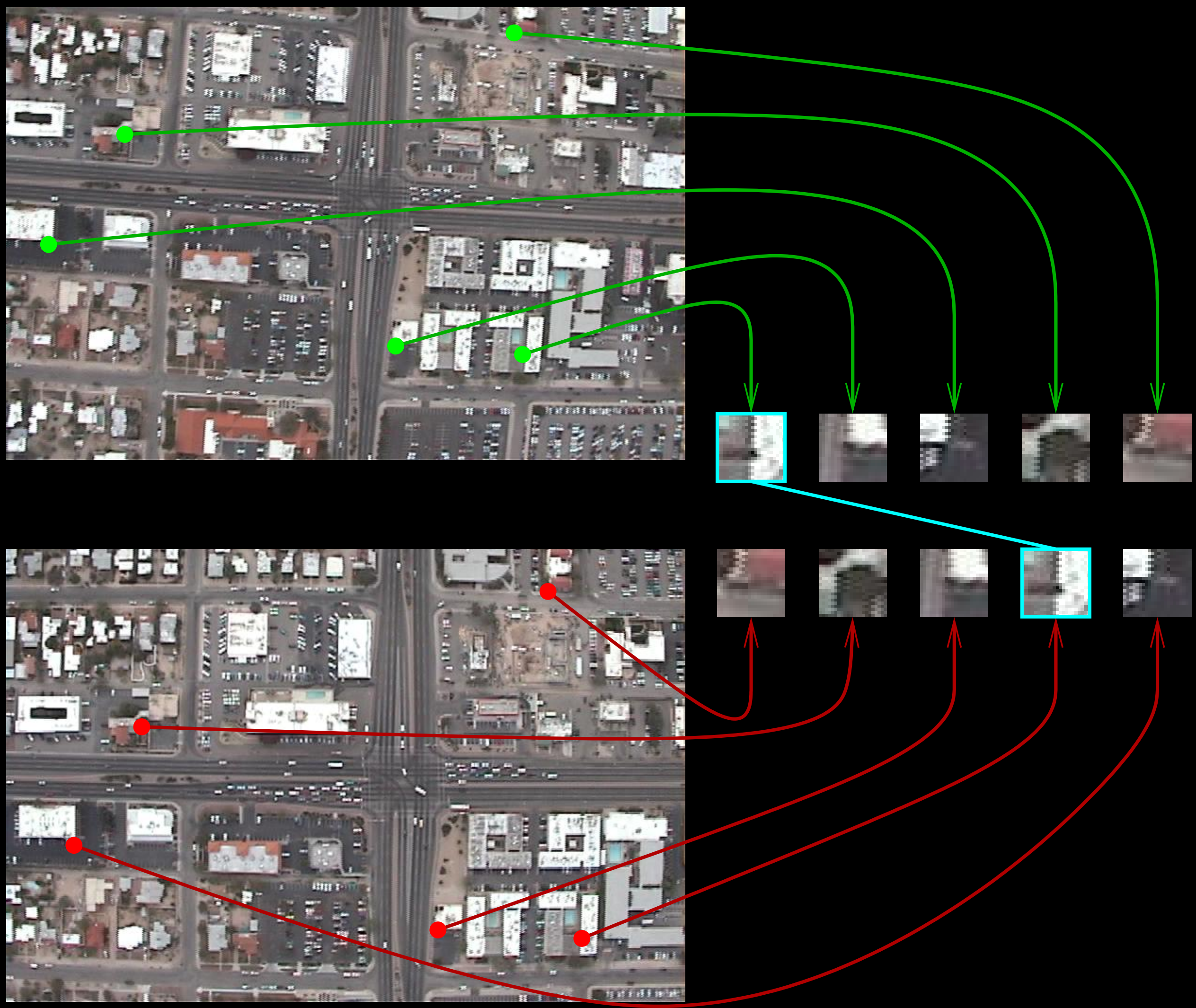
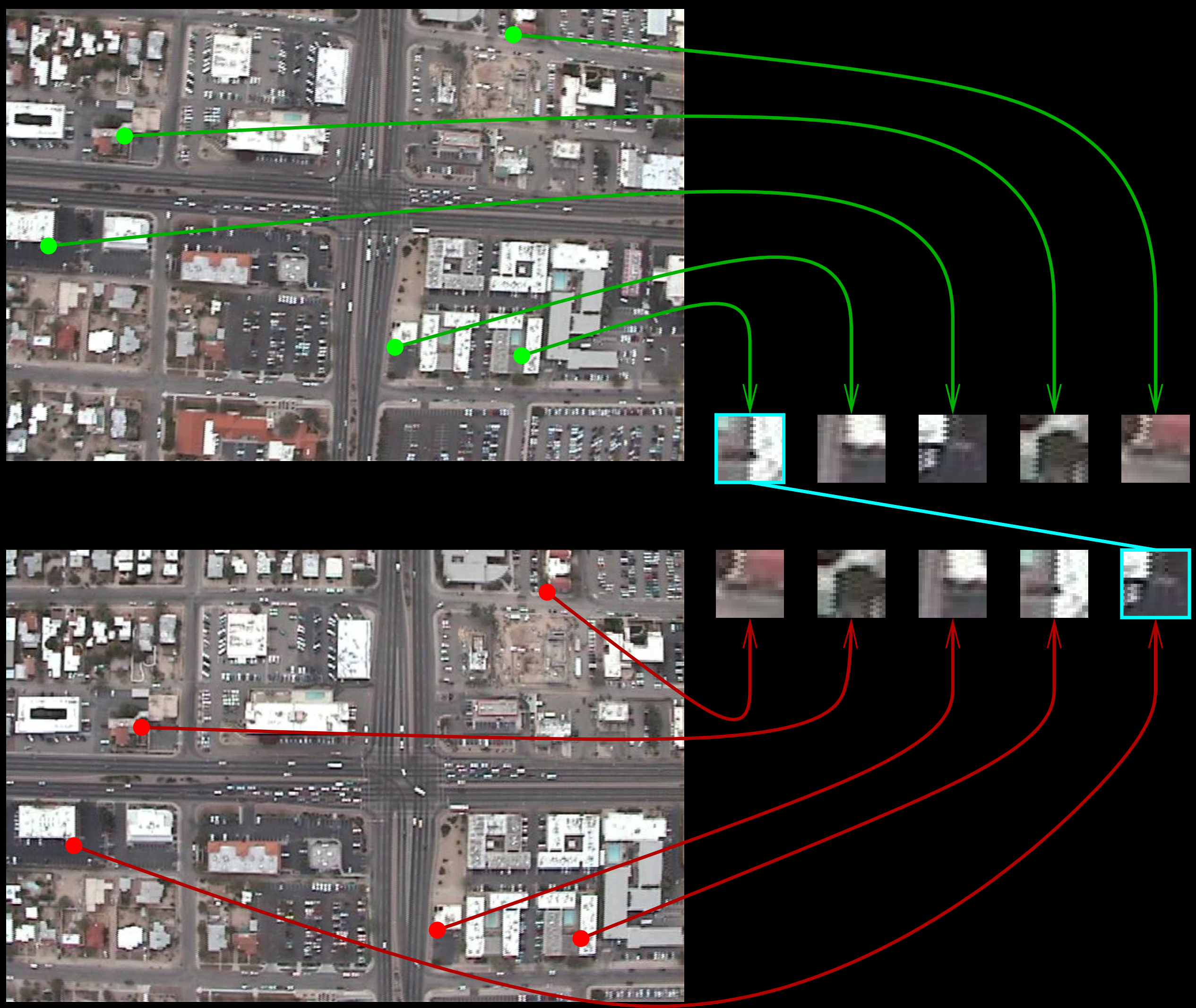
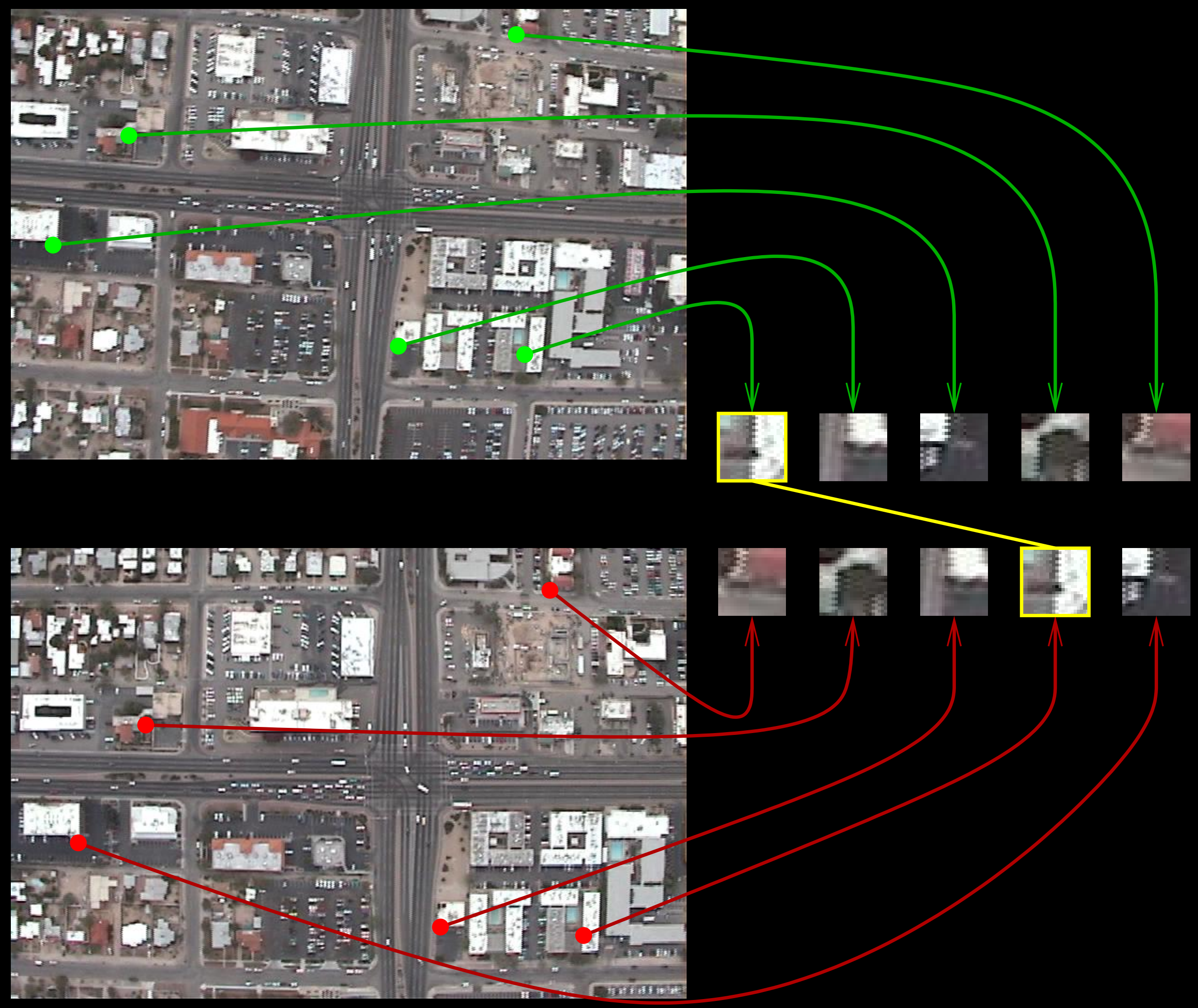


Example: registration



Example: registration



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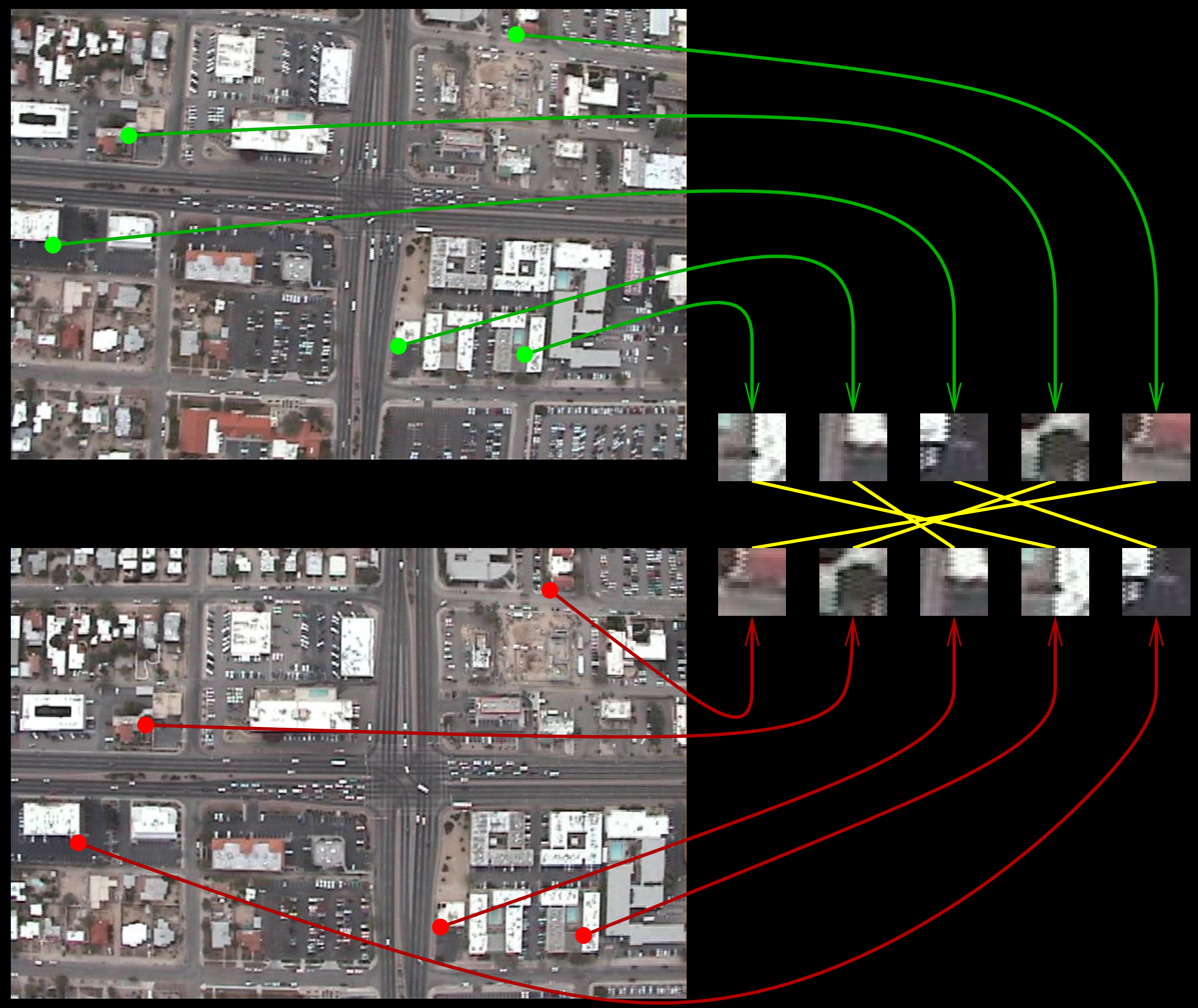

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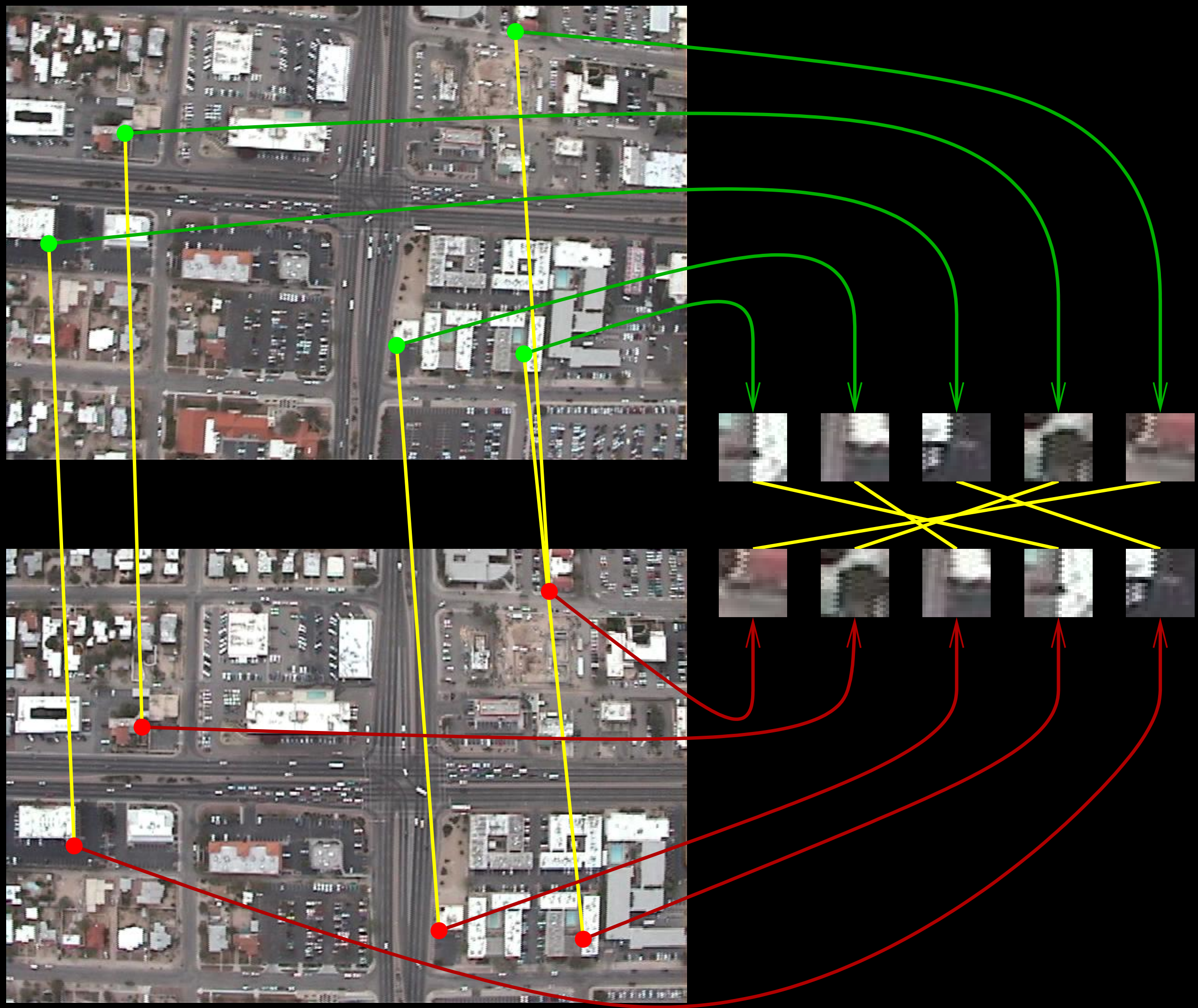


Example: registration

$$\begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ x_3 & y_3 \\ x_4 & y_4 \\ x_5 & y_5 \\ \vdots & \vdots \end{bmatrix} \begin{bmatrix} u_1 & v_1 \\ u_2 & v_2 \\ u_3 & v_3 \\ u_4 & v_4 \\ u_5 & v_5 \\ \vdots & \vdots \end{bmatrix}$$

Example: registration

$$\begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ x_3 & y_3 \\ x_4 & y_4 \\ x_5 & y_5 \\ \vdots & \vdots \end{bmatrix} \quad \begin{bmatrix} u_1 & v_1 \\ u_2 & v_2 \\ u_3 & v_3 \\ u_4 & v_4 \\ u_5 & v_5 \\ \vdots & \vdots \end{bmatrix}$$

$$\begin{bmatrix} u \\ v \end{bmatrix} \approx W\left(\begin{bmatrix} x \\ y \end{bmatrix}\right)$$

Typical processing pipeline

Typical processing pipeline

Saliency
function

Typical processing pipeline

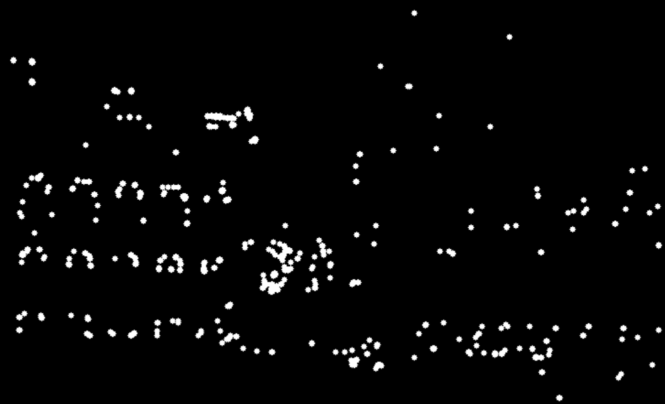
Saliency function →

Threshold ↓

Typical processing pipeline

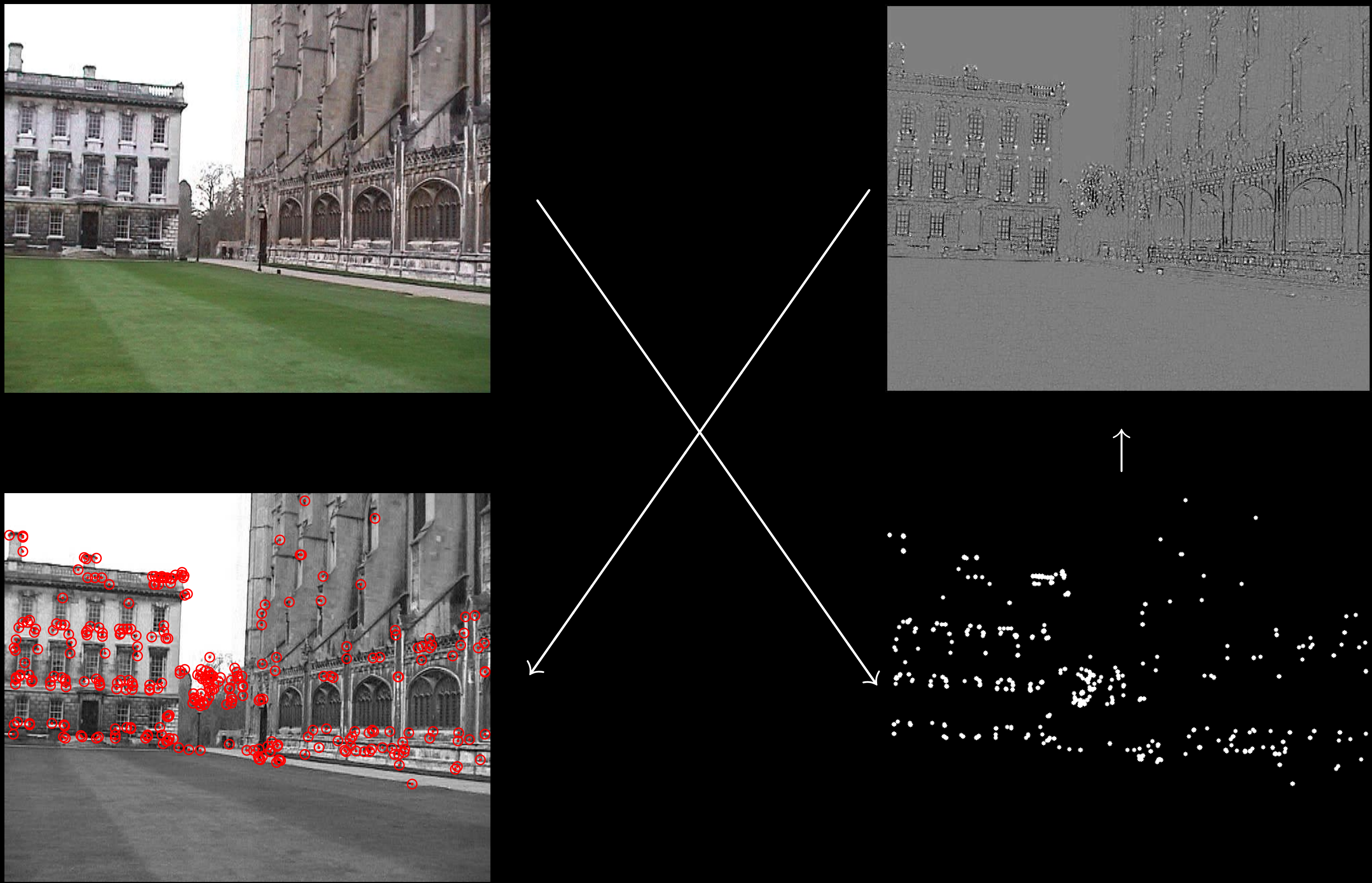
Saliency function →

Threshold ↓

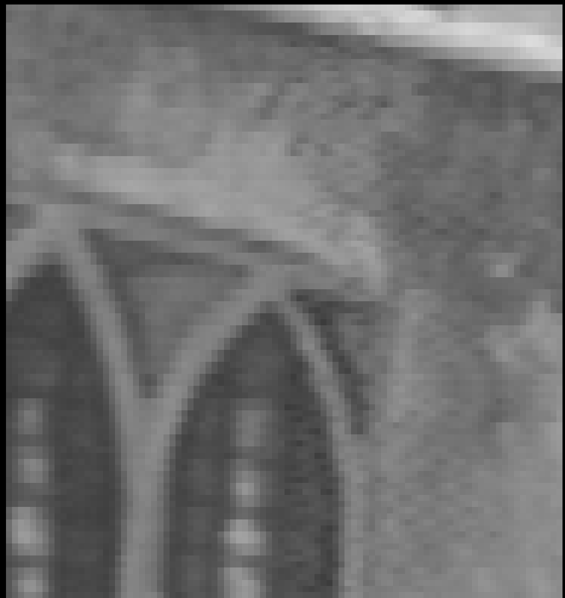


Local maxima ←

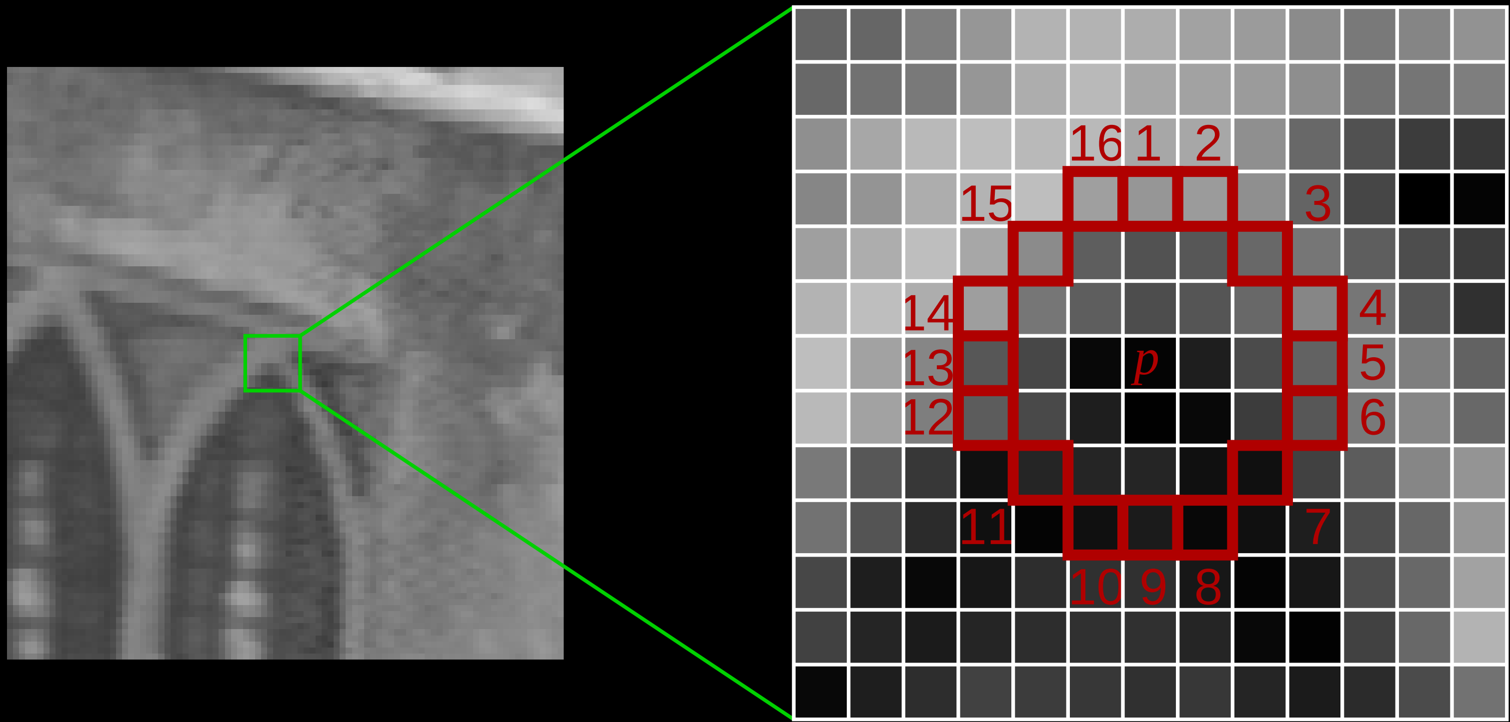
Typical processing pipeline



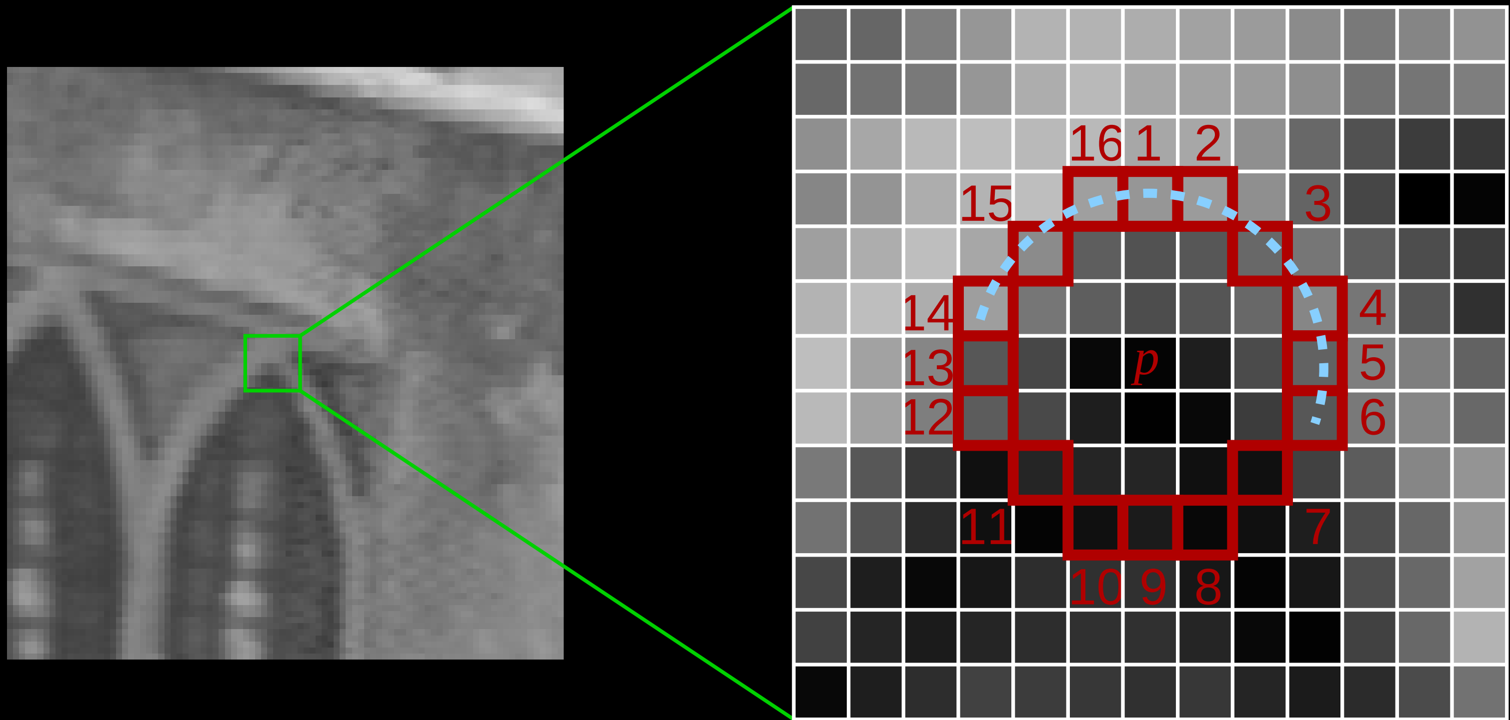
The segment-test detector



The segment-test detector



The segment-test detector



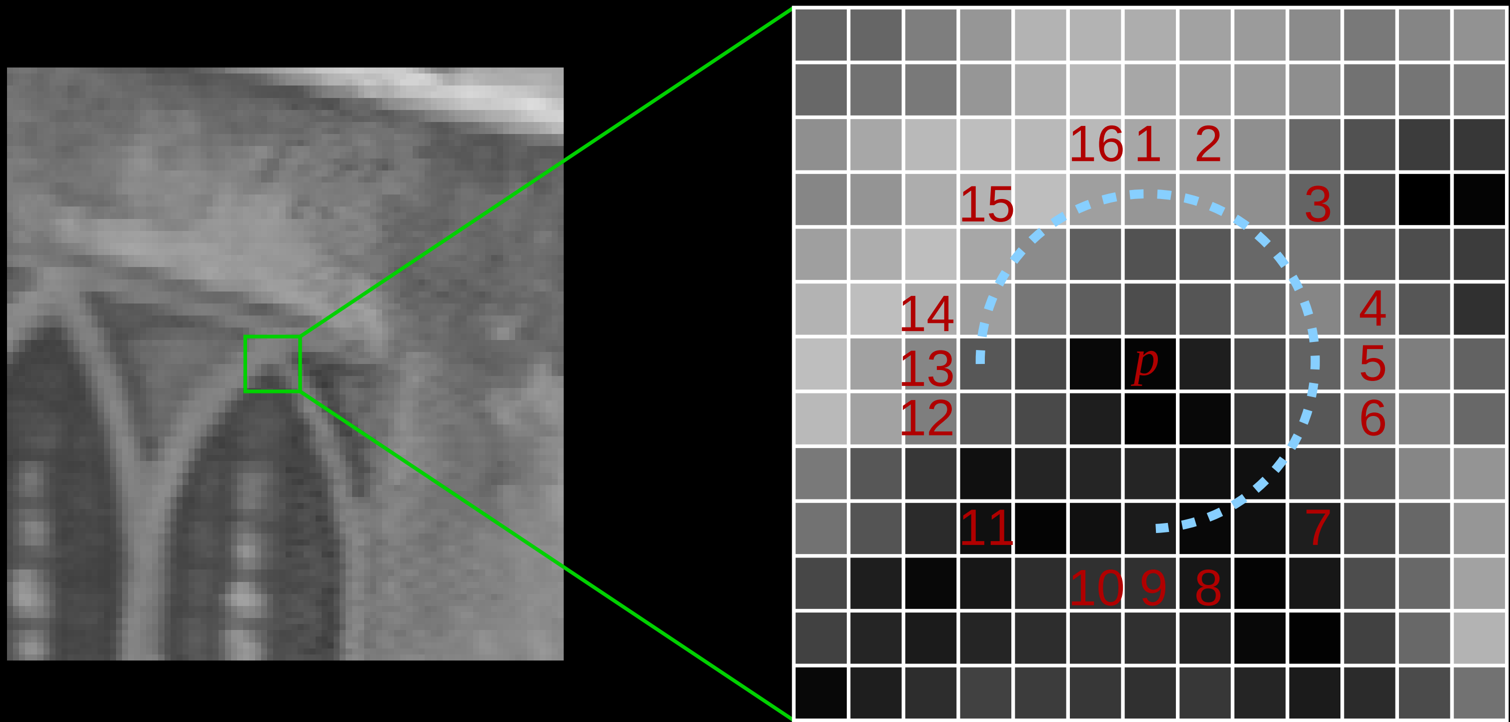
Contiguous arc of N or more pixels:

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

or

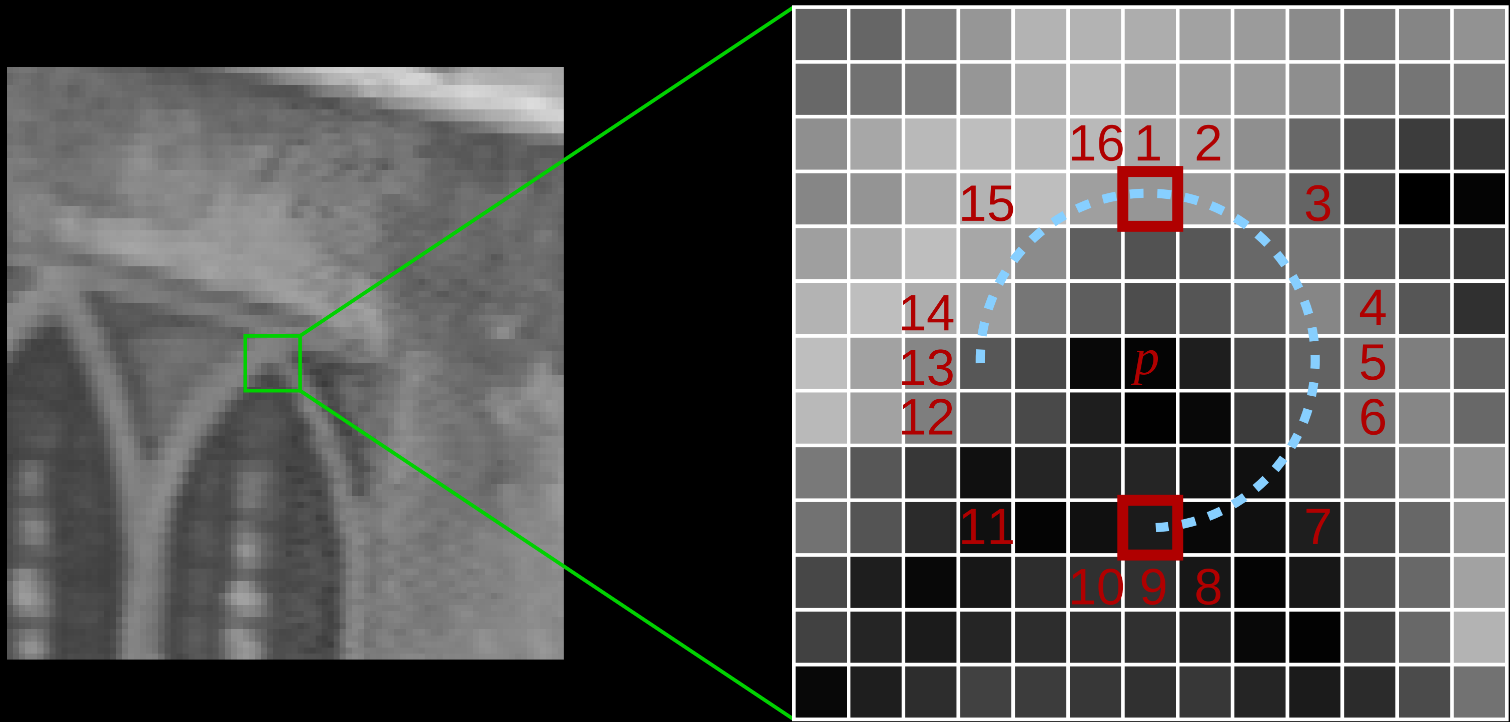
- All much darker than p (darker than $p - t$).

The FAST detector (version 1)



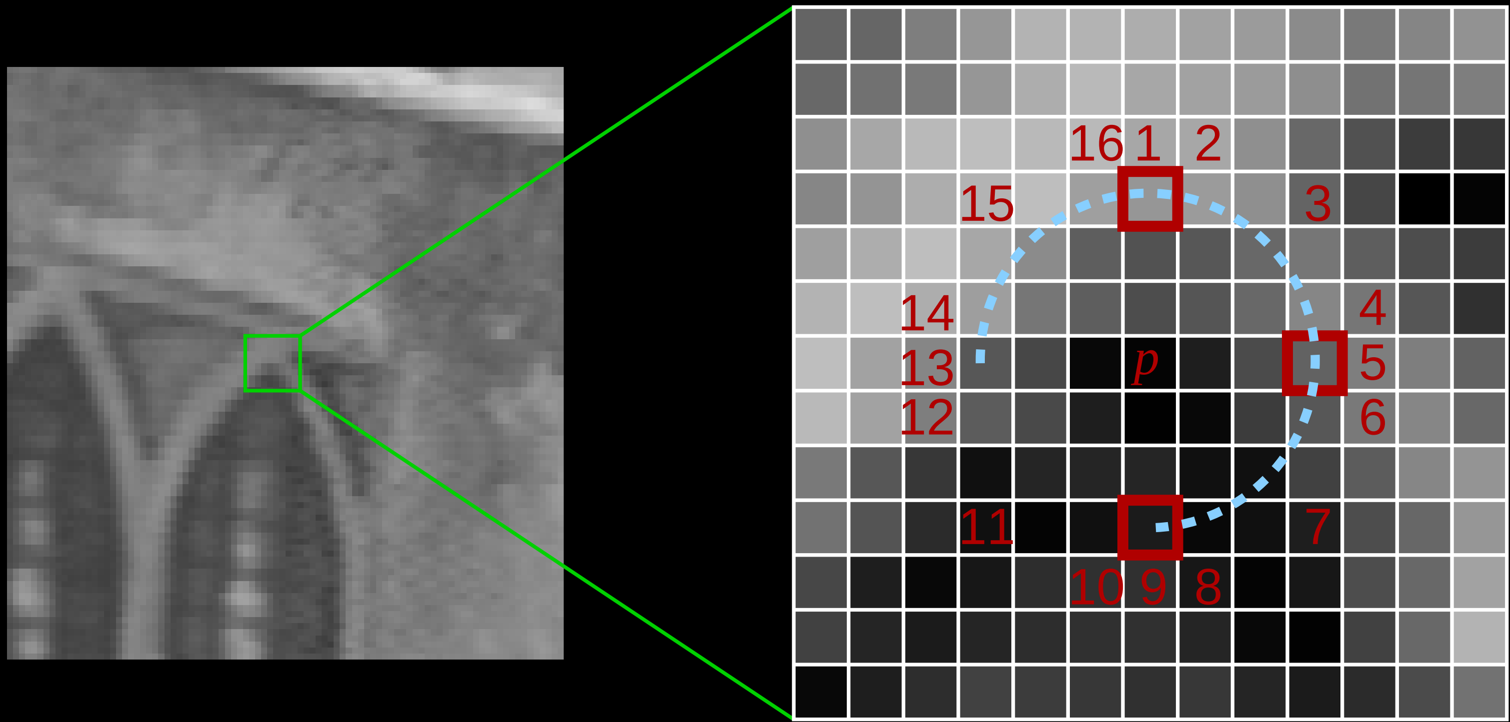
FAST—Features from Accelerated Segment Test

The FAST detector (version 1)



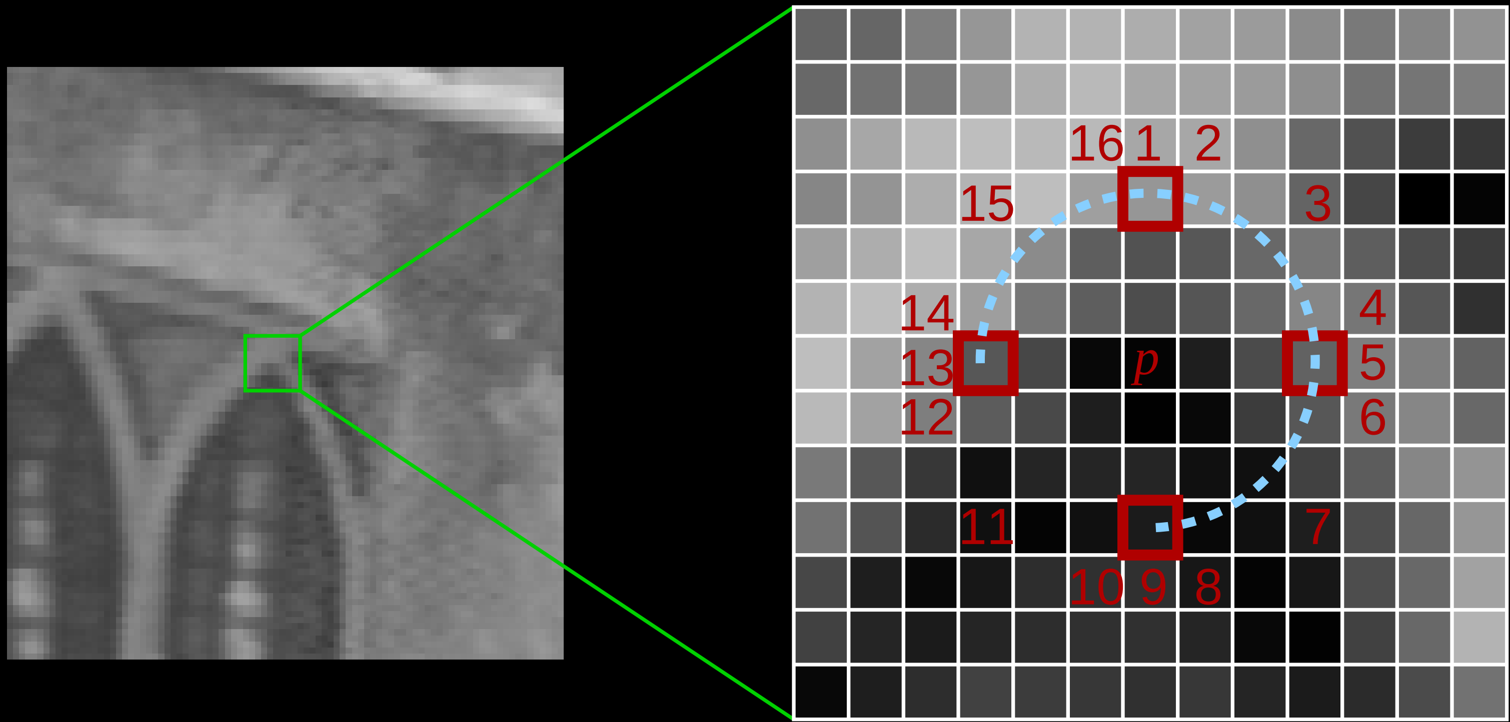
- Test pixels 1 and 9

The FAST detector (version 1)



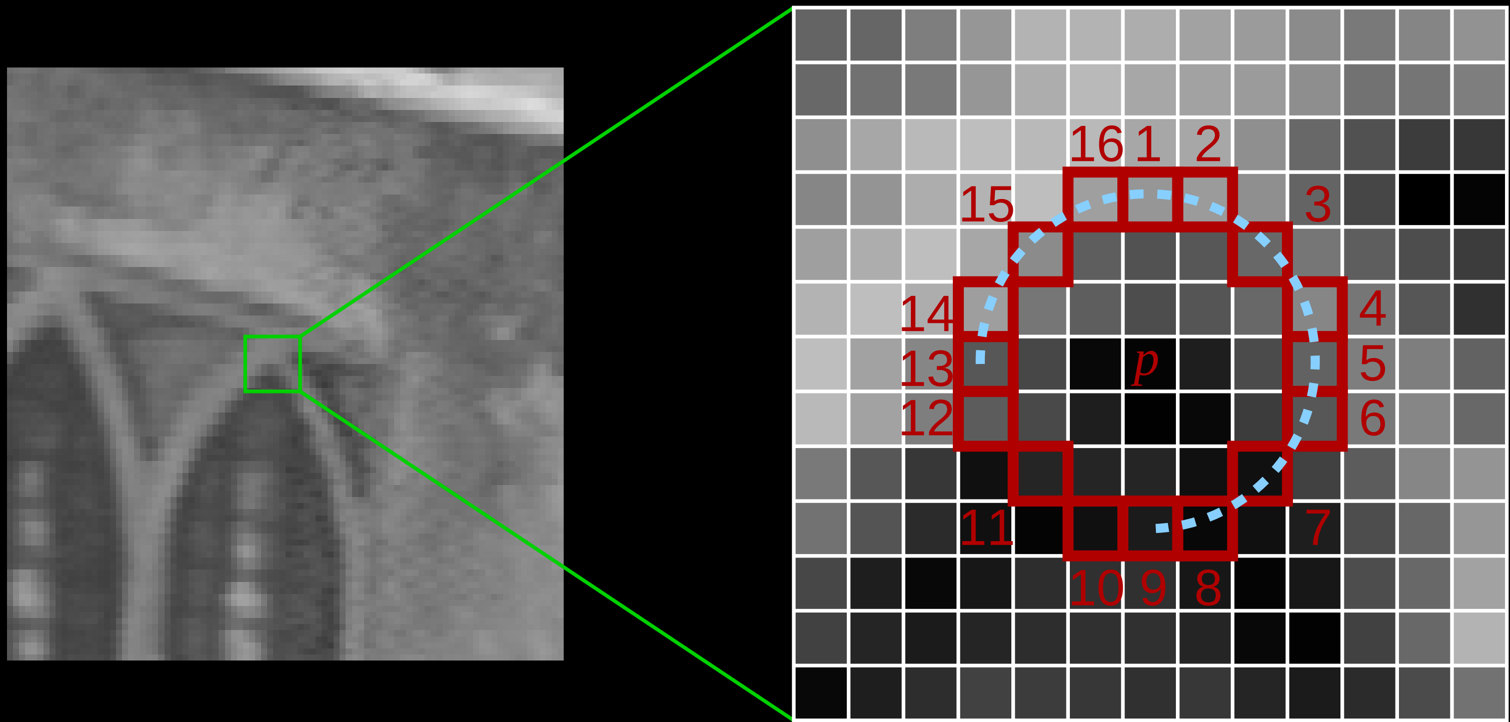
- Test pixels 1 and 9
- Test pixel 4

The FAST detector (version 1)



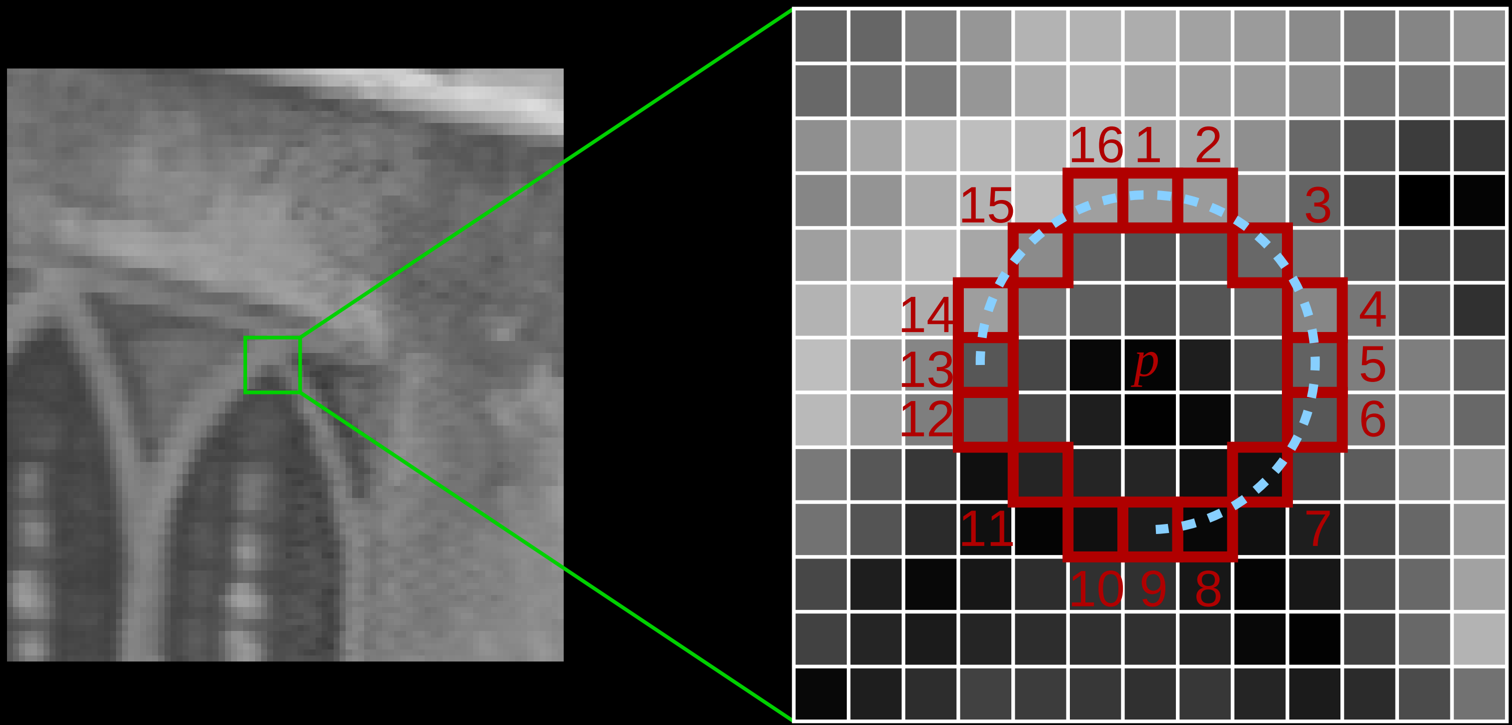
- Test pixels 1 and 9
- Test pixel 4
- Test pixel 12

The FAST detector (version 1)



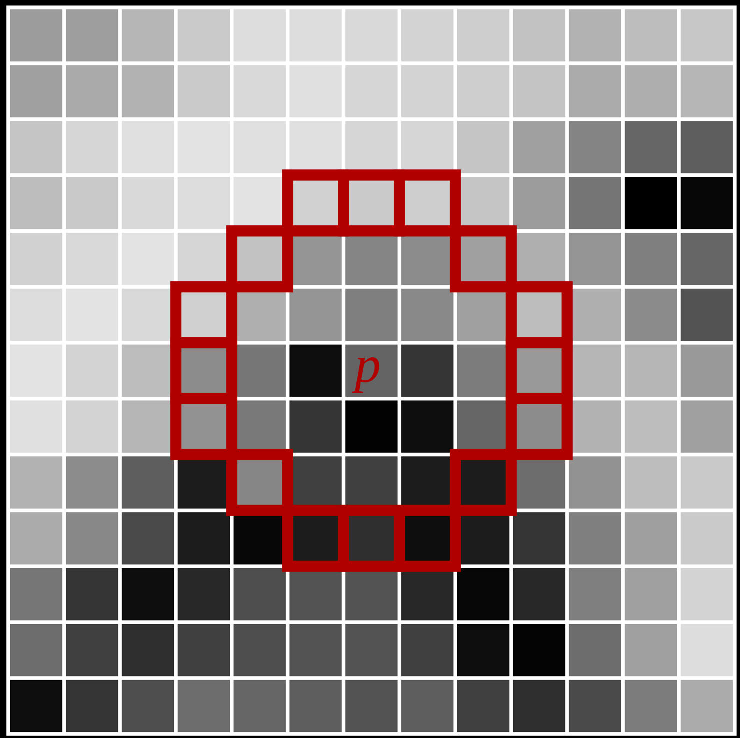
- Test pixels 1 and 9
- Test pixel 4
- Test pixel 12
- Perform complete segment test

FAST saliency

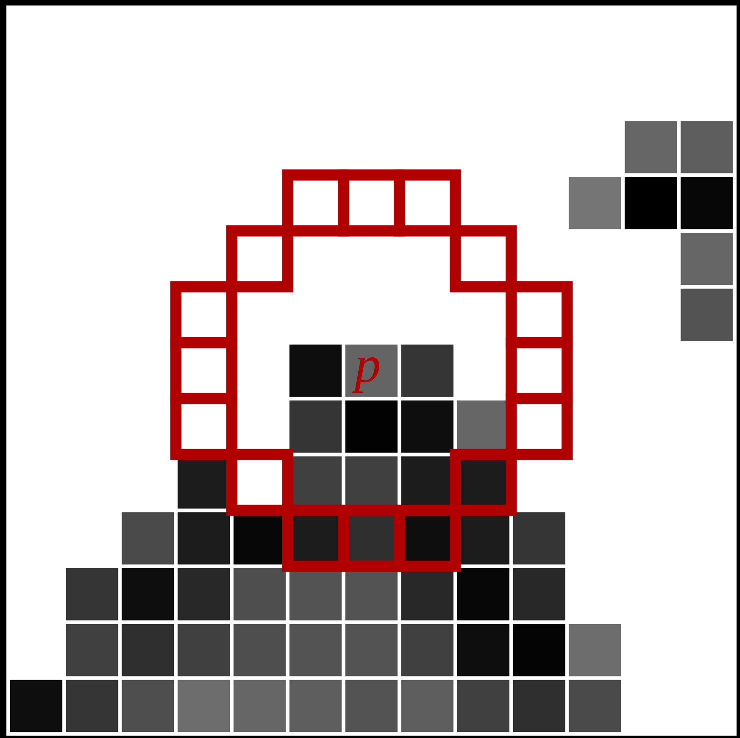


- Highest t for which point is a corner.
- Find using bisection over t.
  - 8 iterations required.
  - Very small subset of points.

FAST feature detection (version 2)

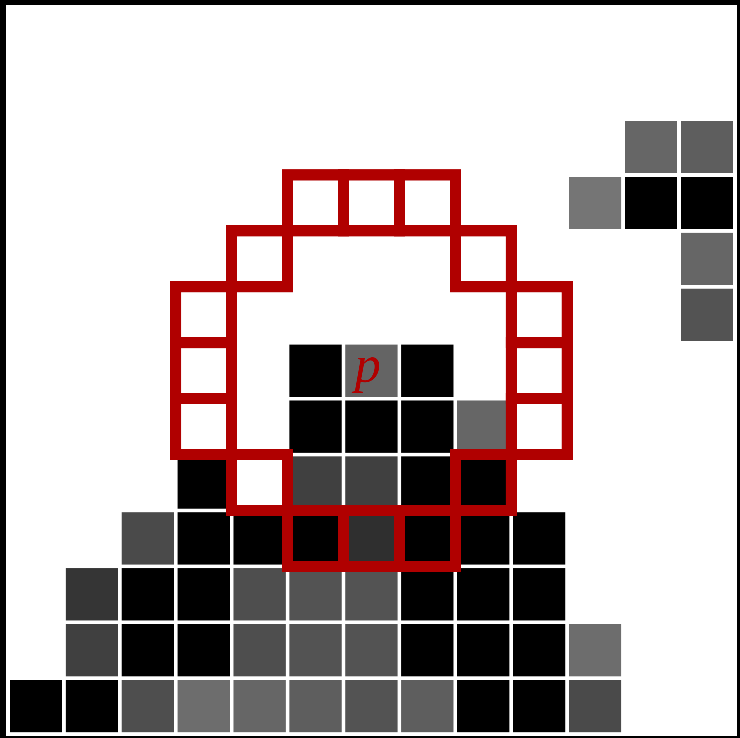


FAST feature detection (version 2)



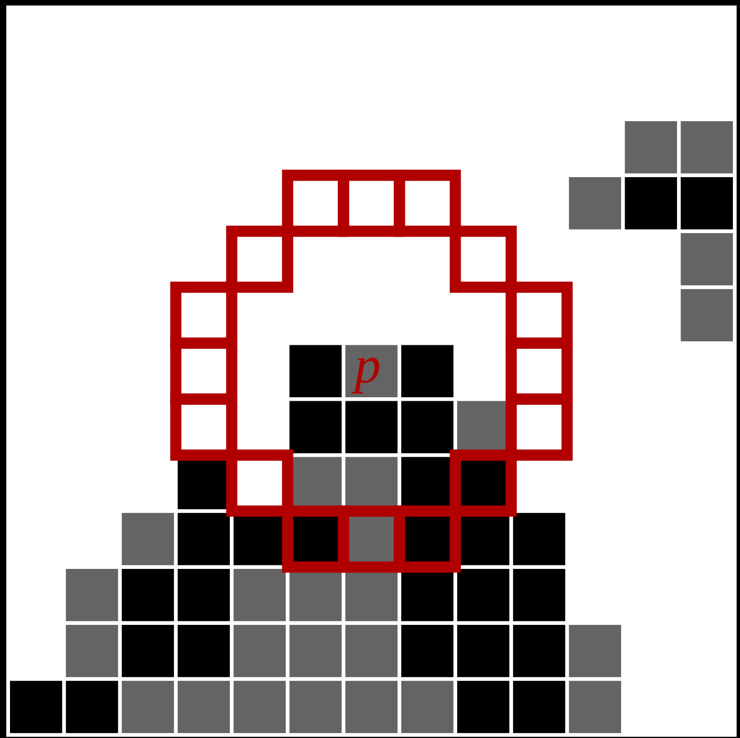
- Pixels are either:
  - Much brighter.

FAST feature detection (version 2)



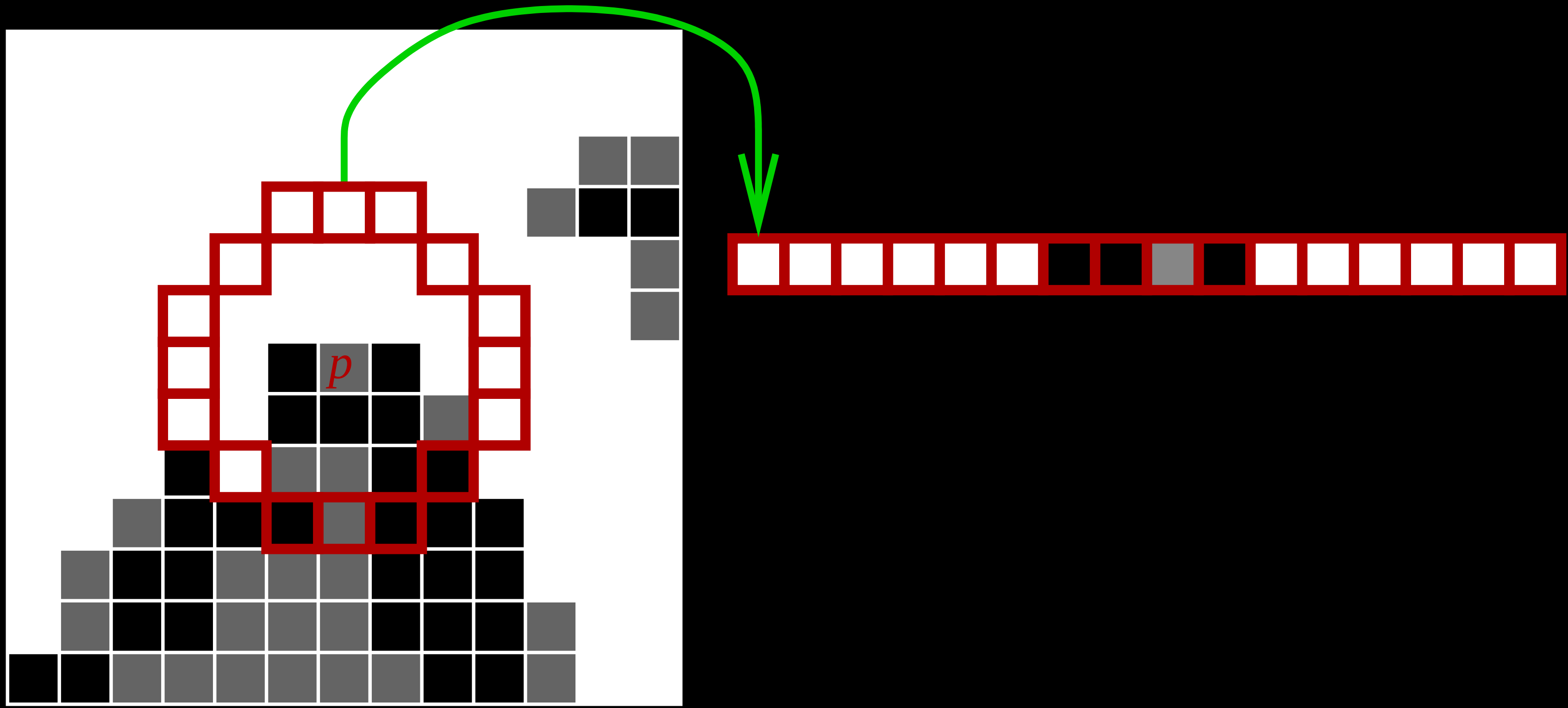
- Pixels are either:
  - Much brighter.
  - Much darker.

FAST feature detection (version 2)



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

FAST feature detection (version 2)



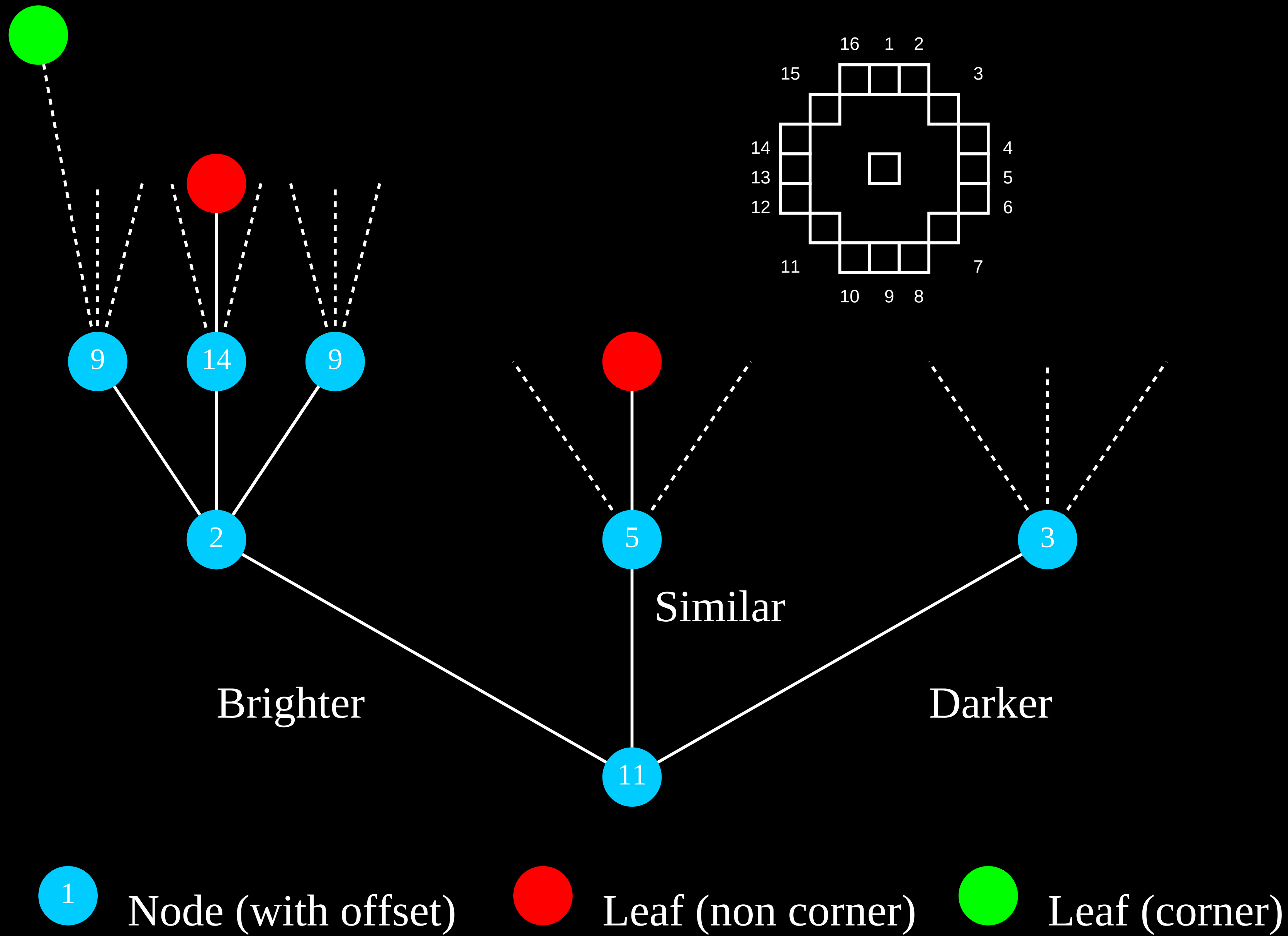
- Pixels are either:
  - Much brighter.
  - Much darker.
  - Similar.
- Represent ring as a ternary vector.
- Classify vectors using segment test.

Train a classifier

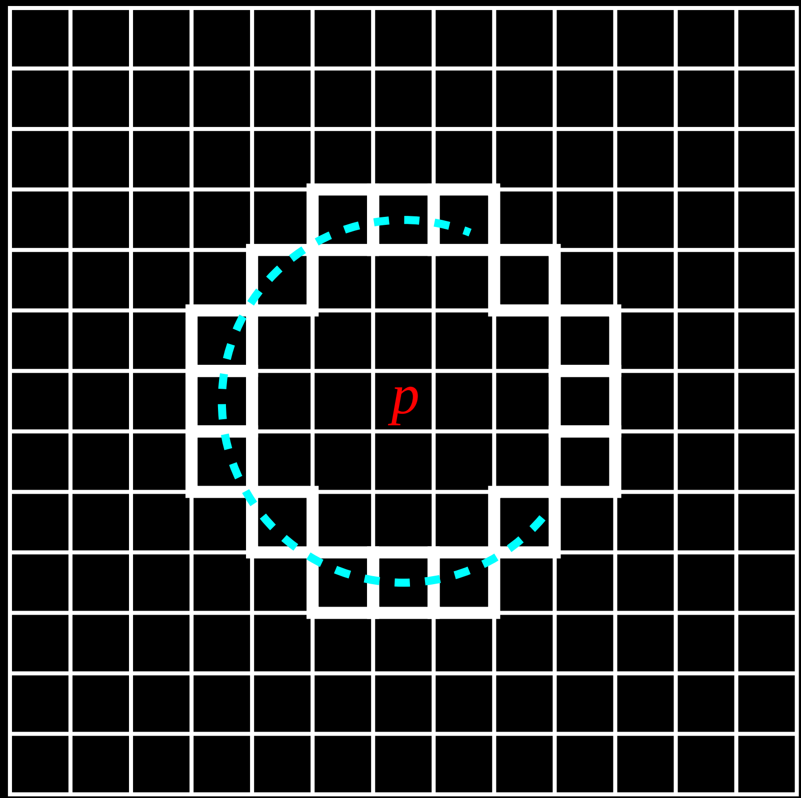
- Decision tree classifiers are very efficient.
- Ask: “What is the state of pixel x?”
- Question splits list in to 3 sublists.
- Query each sublist.
- Recurse until list contains all features or all non features.
- Choose questions to minimize entropy (ID3).

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

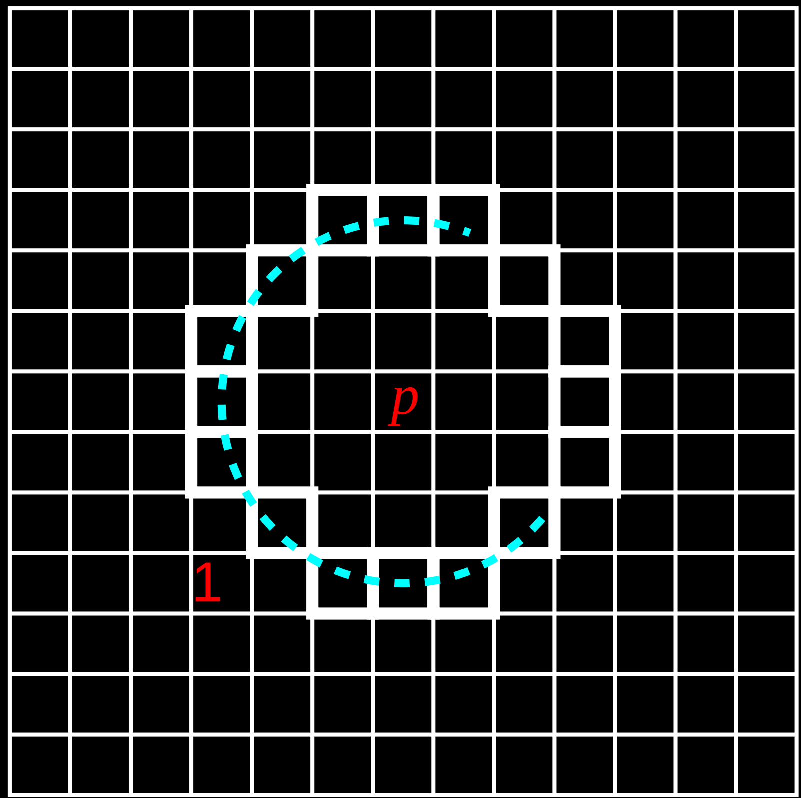
Example tree



Example tree



Example tree



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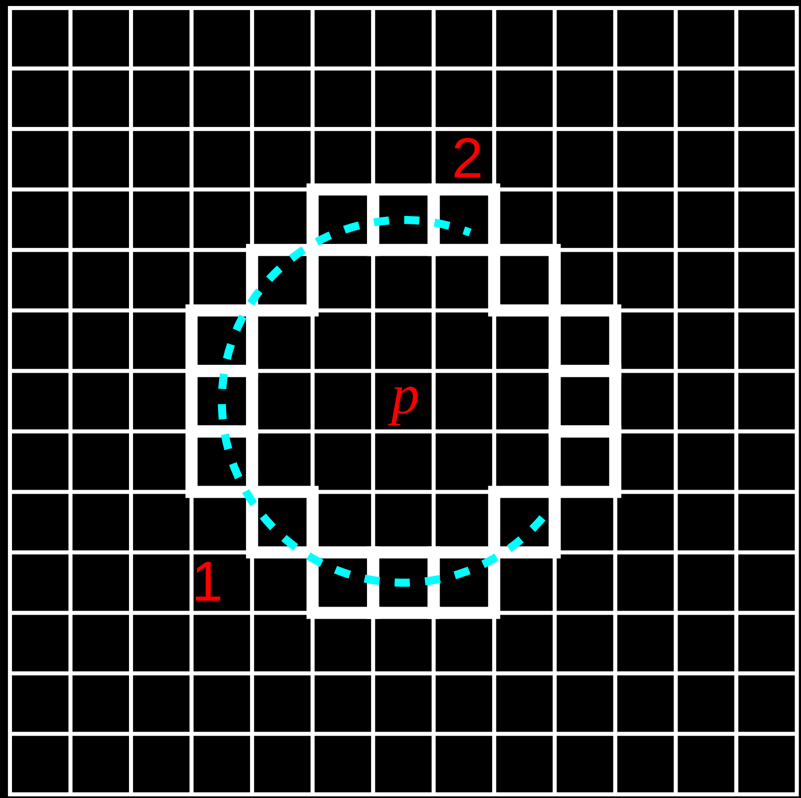

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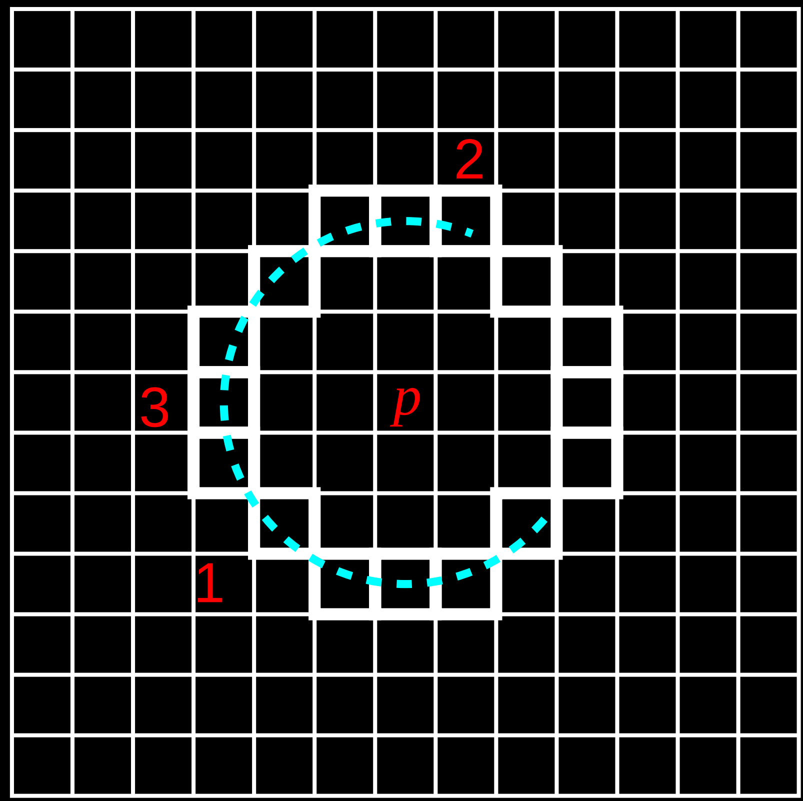
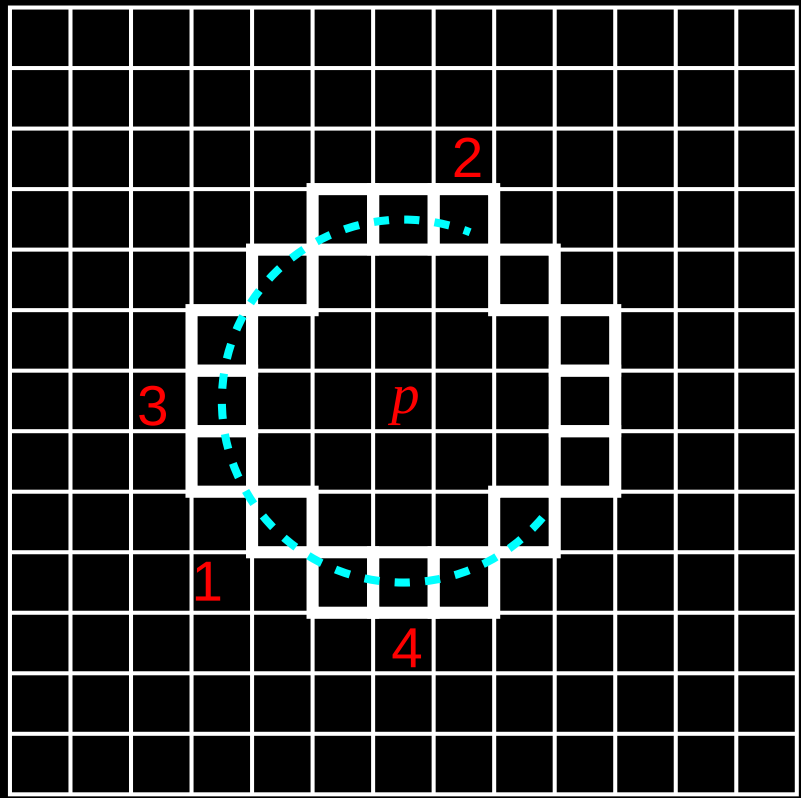


Example tree



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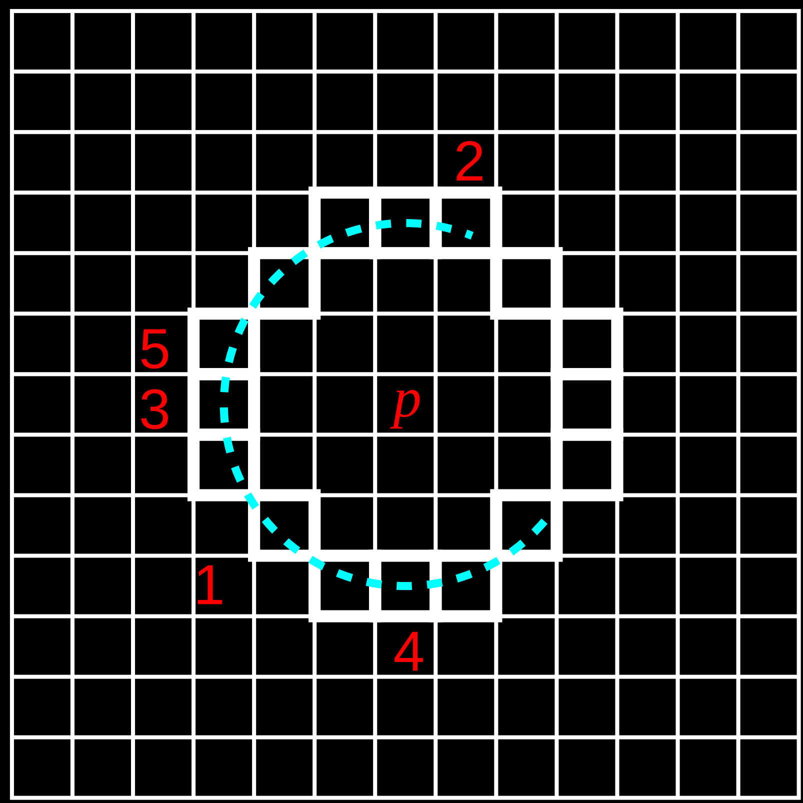

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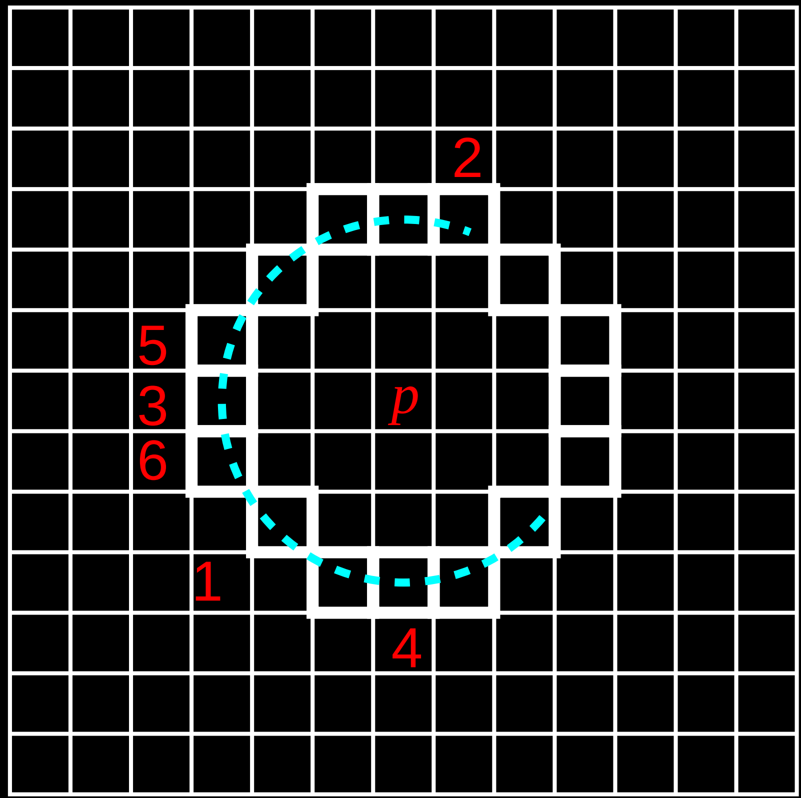

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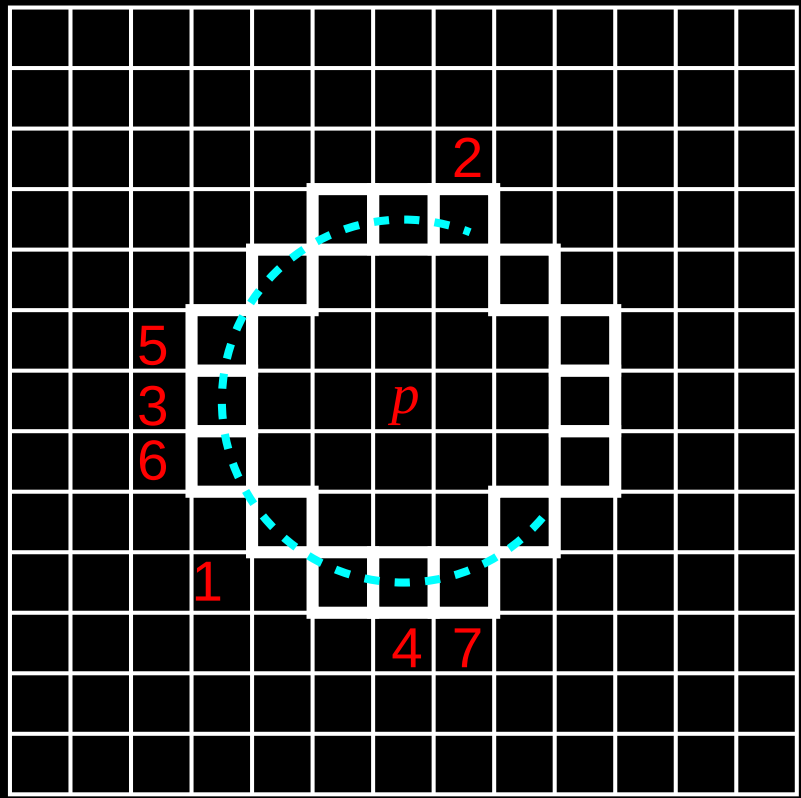
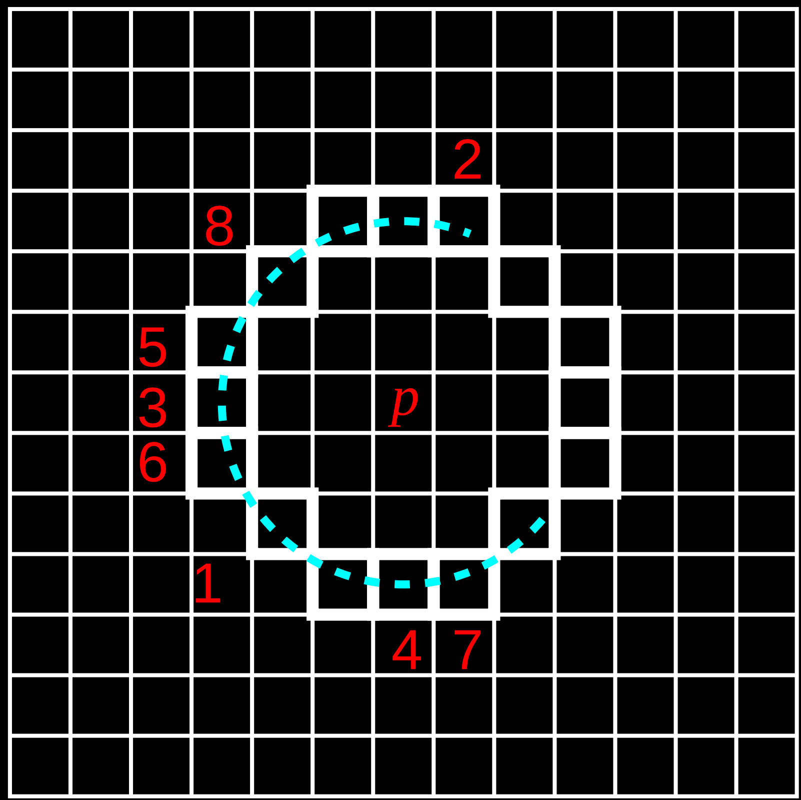
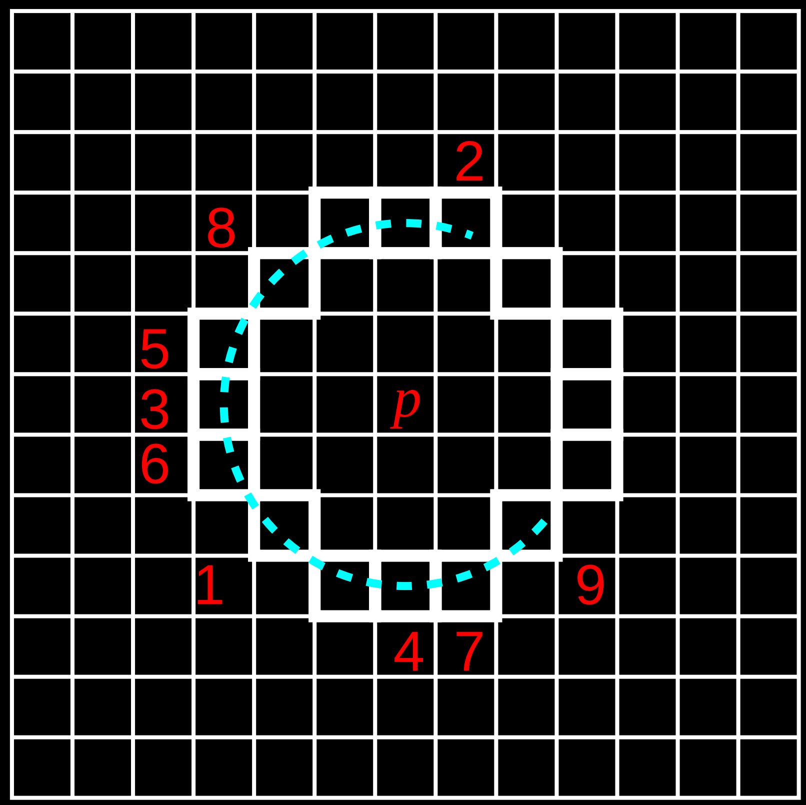


Example tree



Example tree



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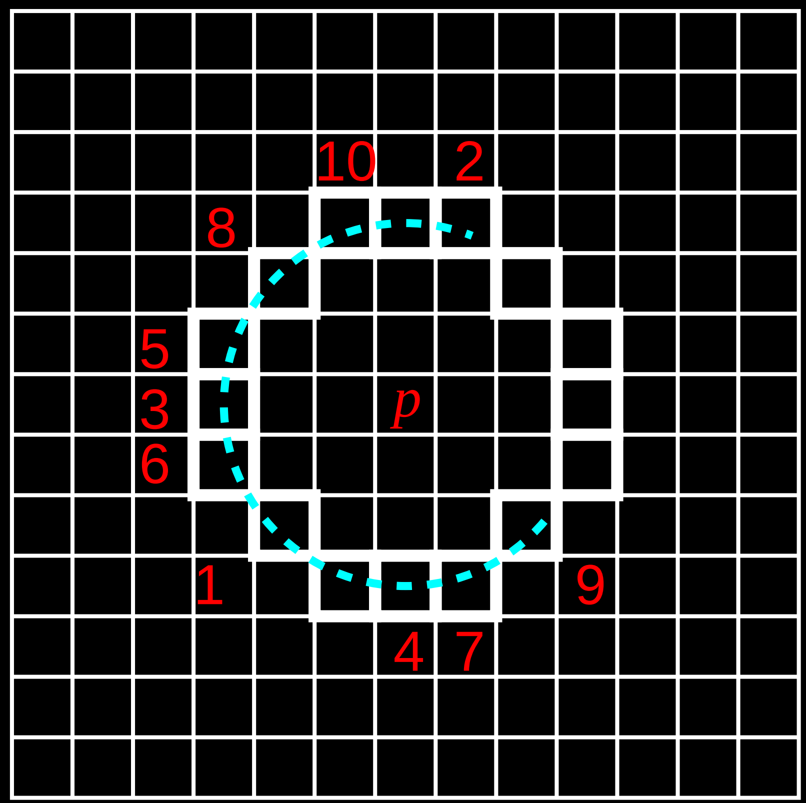

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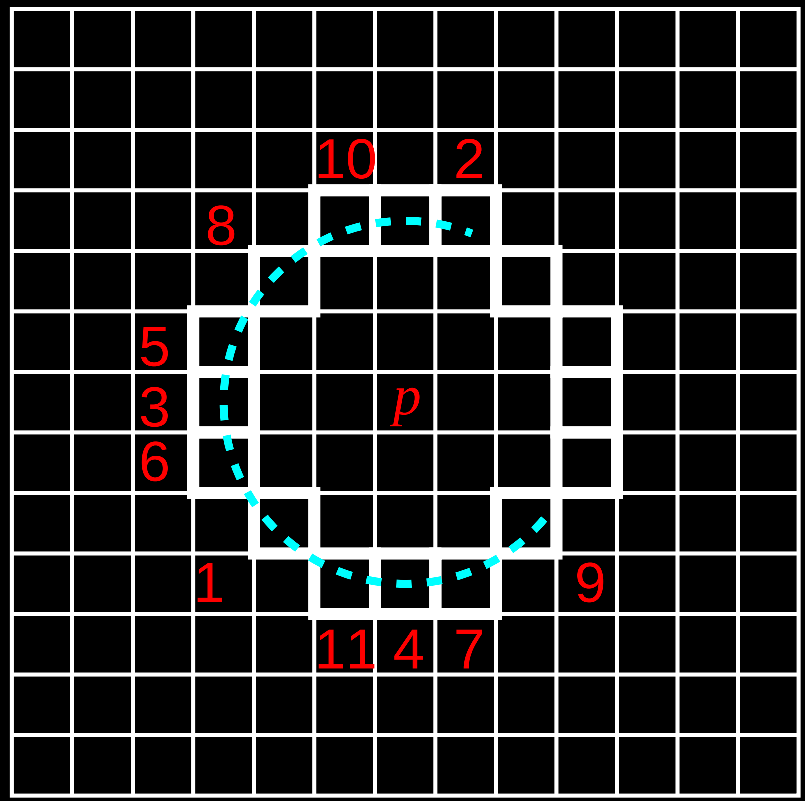

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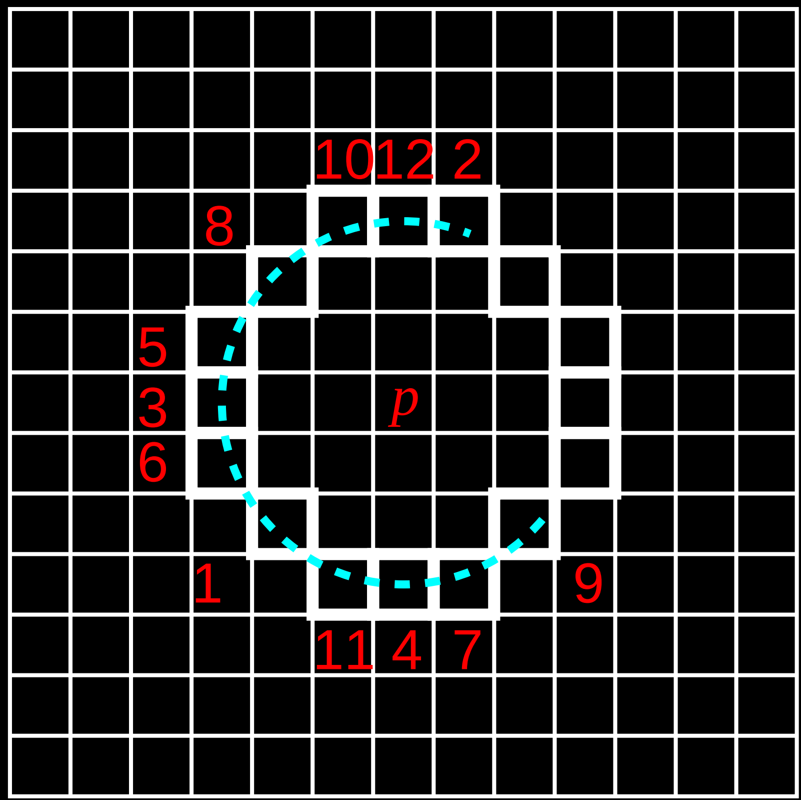

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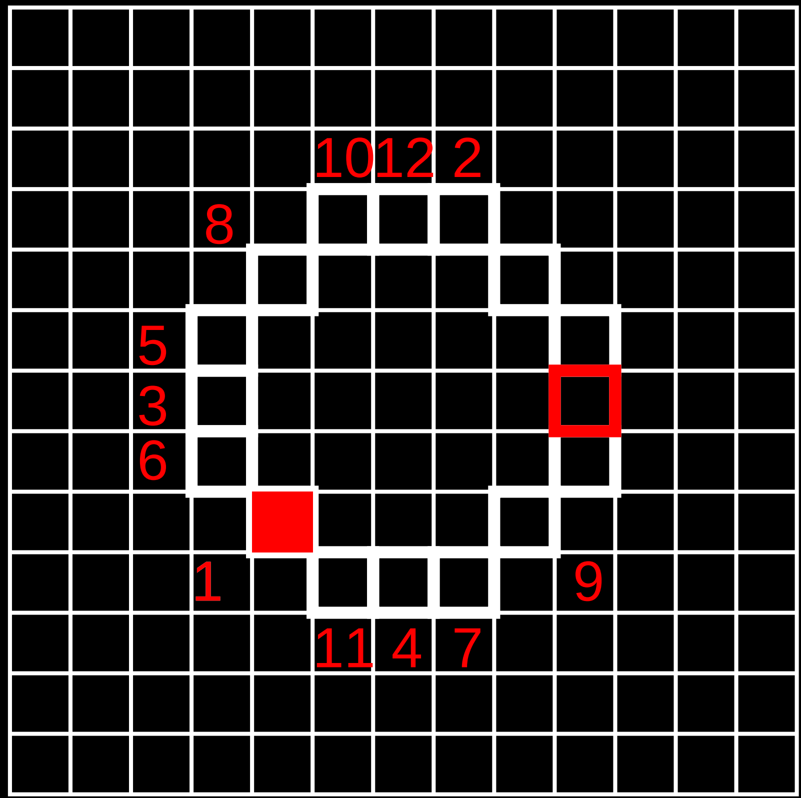

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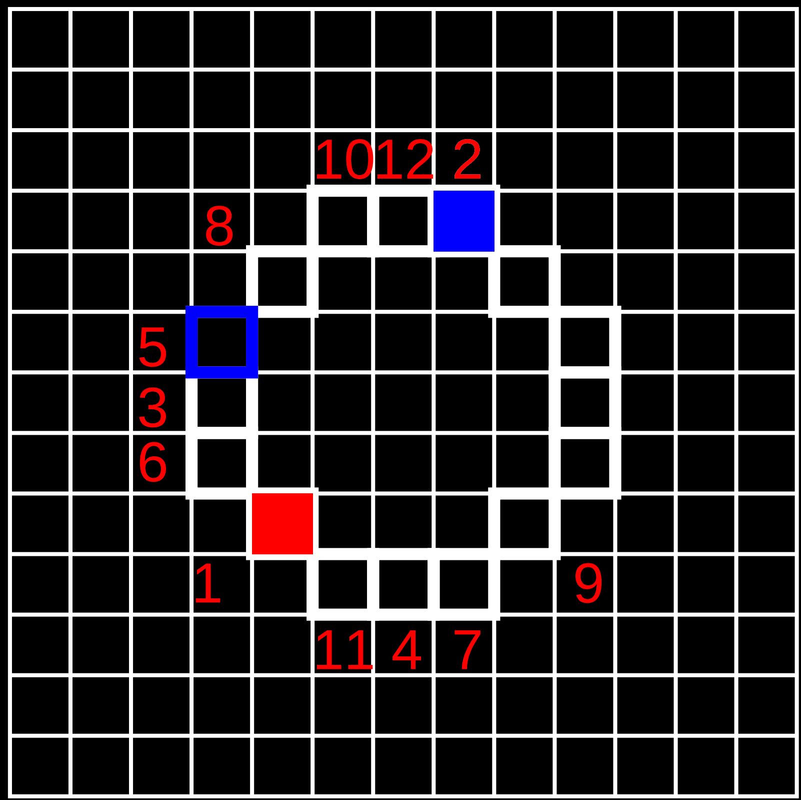

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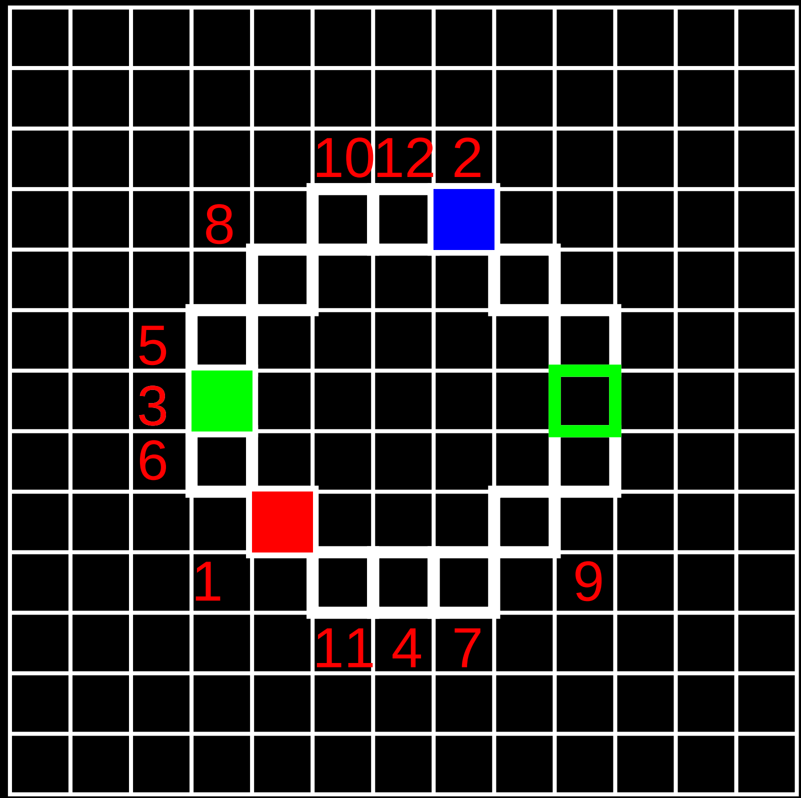

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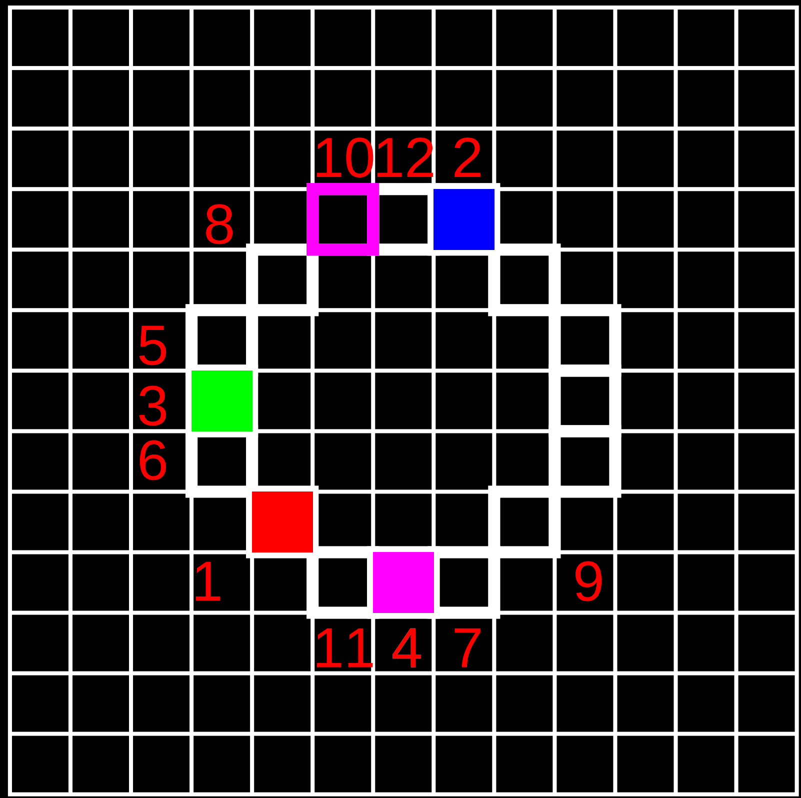
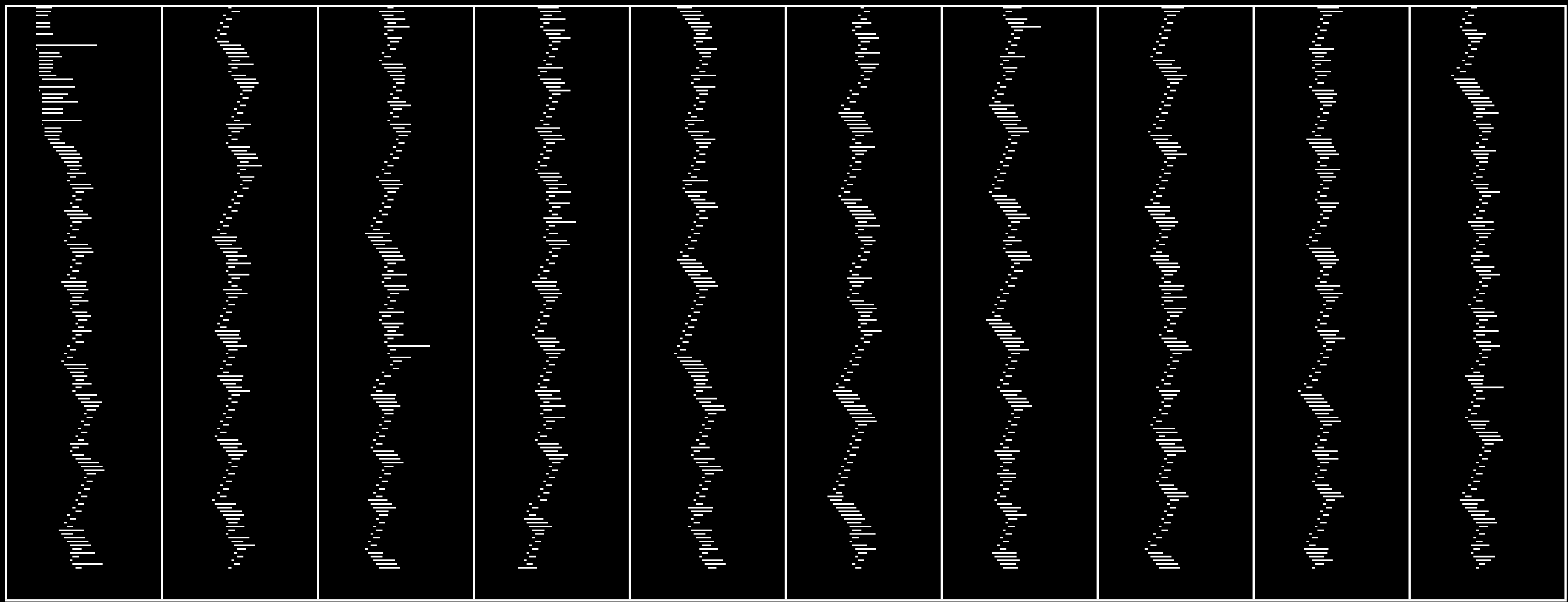


Output C++ code

A long string of nested if-else statements:



…which continues for 2 more pages.

How FAST? (very)

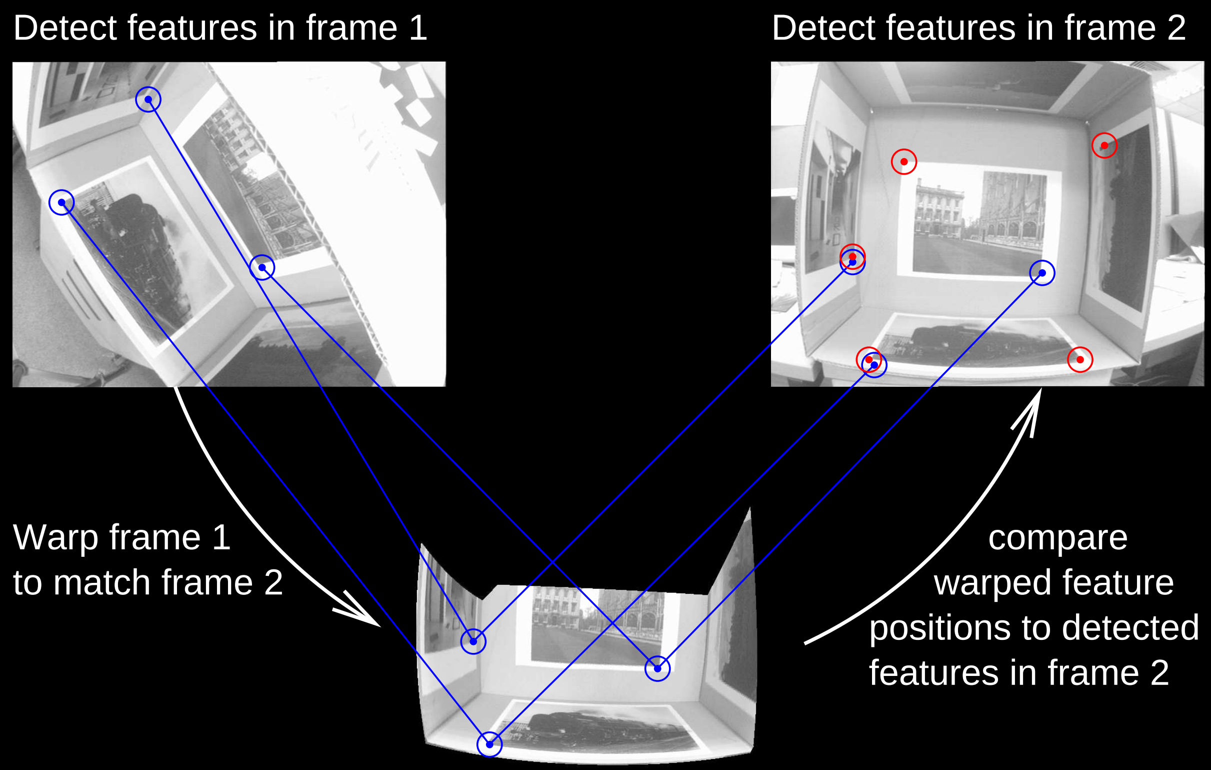
Detector	Set 1		Set 2	
	Pixel rate (MPix/s)	%	MPix/s	%
FAST $n = 9$	188	4.90	179	5.15
FAST $n = 12$	158	5.88	154	5.98
Original FAST ($n = 12$)	79.0	11.7	82.2	11.2
SUSAN	12.3	74.7	13.6	67.9
Harris	8.05	115	7.90	117
Shi-Tomasi	6.50	142	6.50	142
DoG	4.72	195	5.10	179

- 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

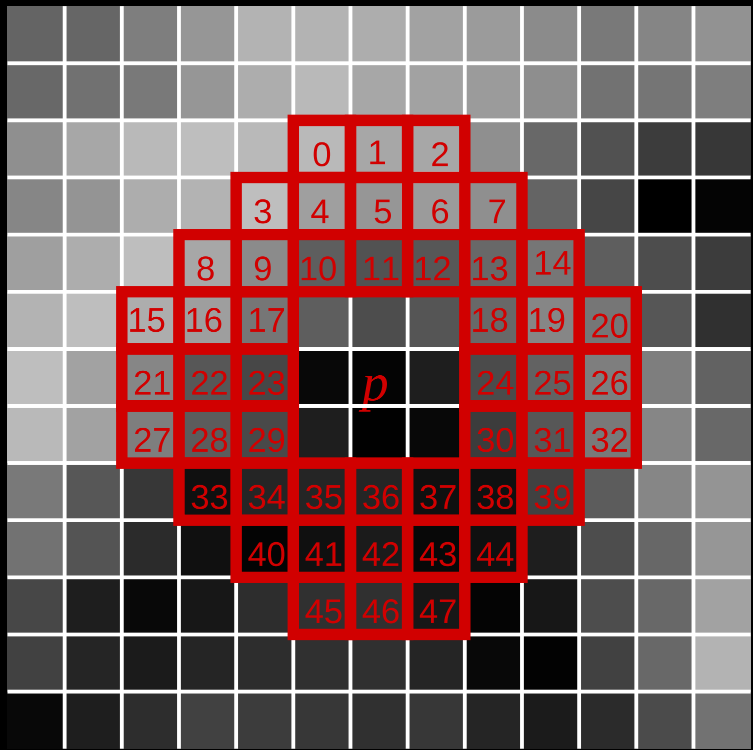
FAST-ER: Enhanced Repeatability

- Define feature detector as:

  A decision tree which detects points with a high repeatability.

- To evaluate repeatability:
  1. Detect features in all frames.
  2. Perform non-maximal suppression.
  3. Compute repeatability.
- Repeatability is a non-convex function of the tree configuration.
- Optimize tree using simulated-annealing.
- Use more offsets than FAST.

FAST-ER: Enhanced Repeatability



- Use more offsets 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:

$$cost = (k_R + R^{-2})(k_N + N^2)(k_S + S^{-2})$$

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

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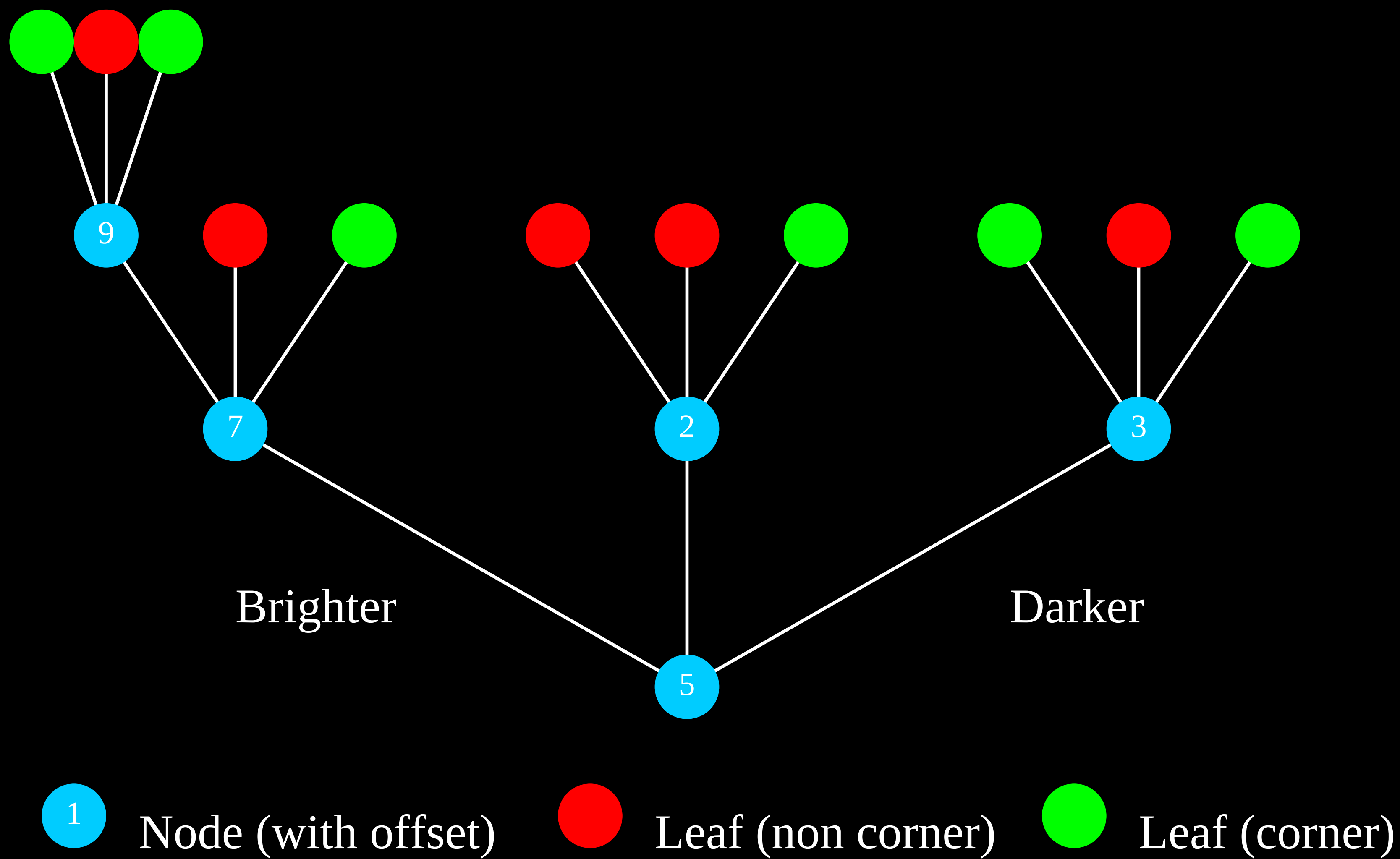
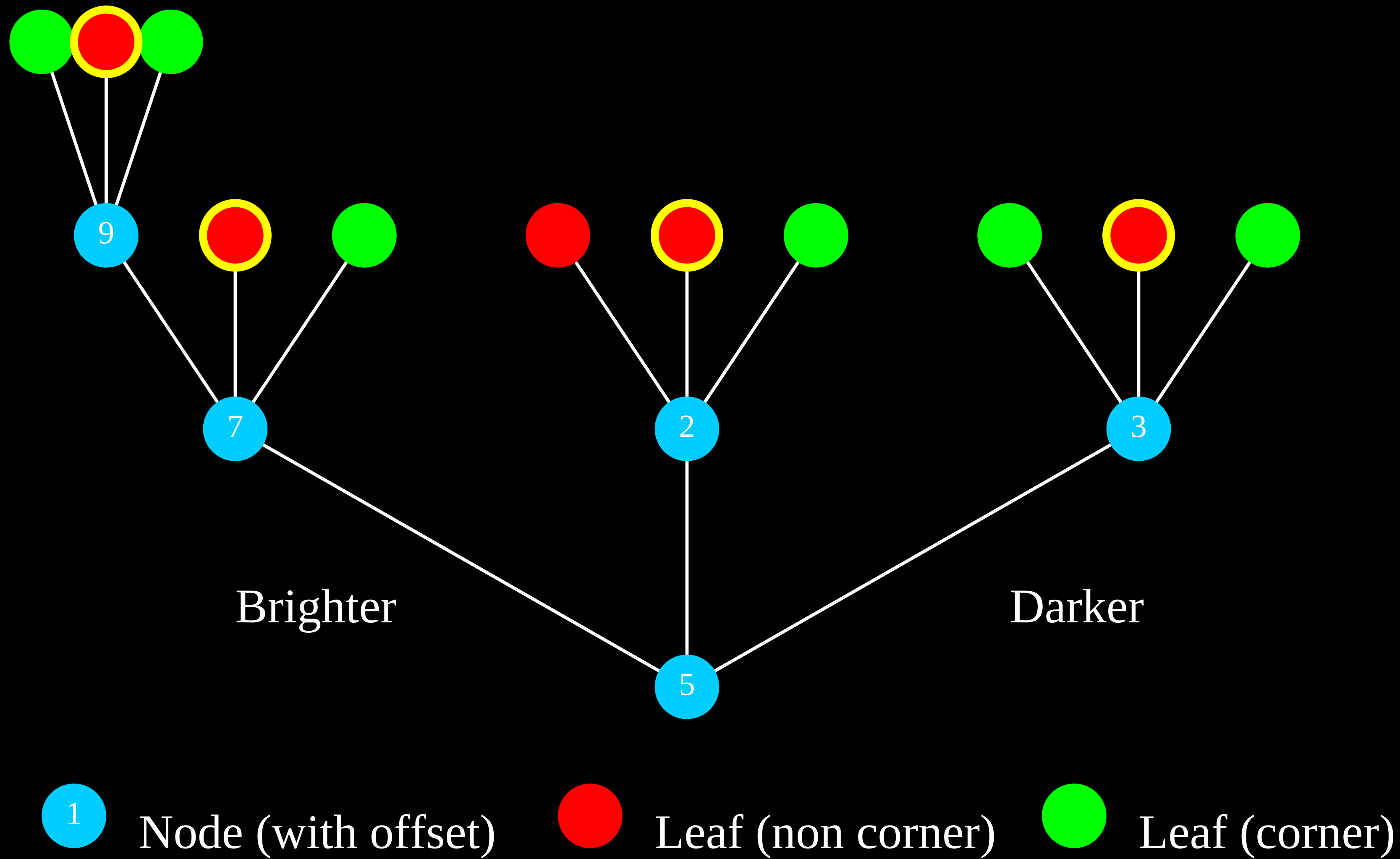
Operations

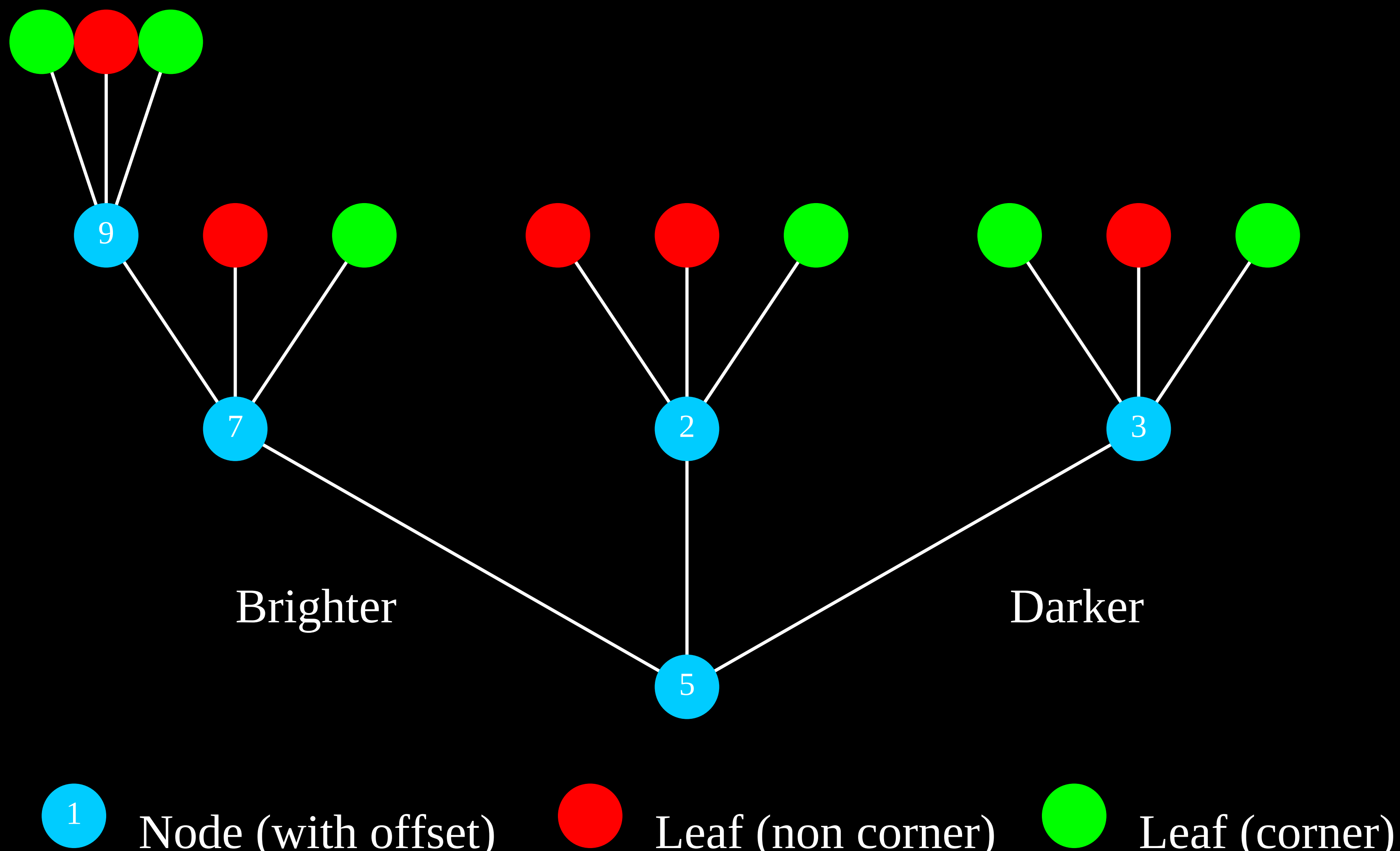

9
7
2
3
5
Brighter
Darker
1
Node (with offset)
Leaf (non corner)
Leaf (corner)

Operations

'Similar' lead nodes are constrained.

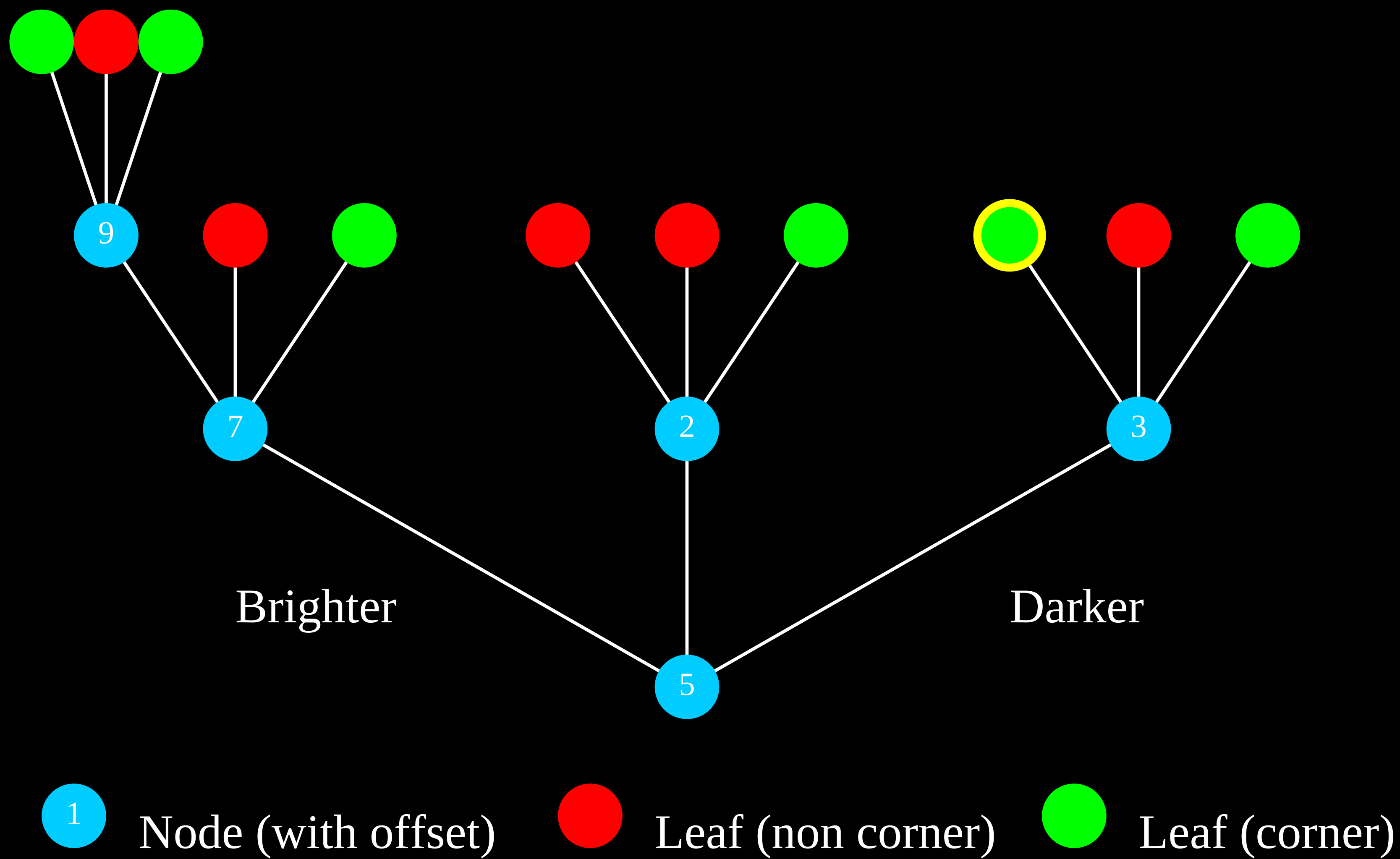


Operations


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

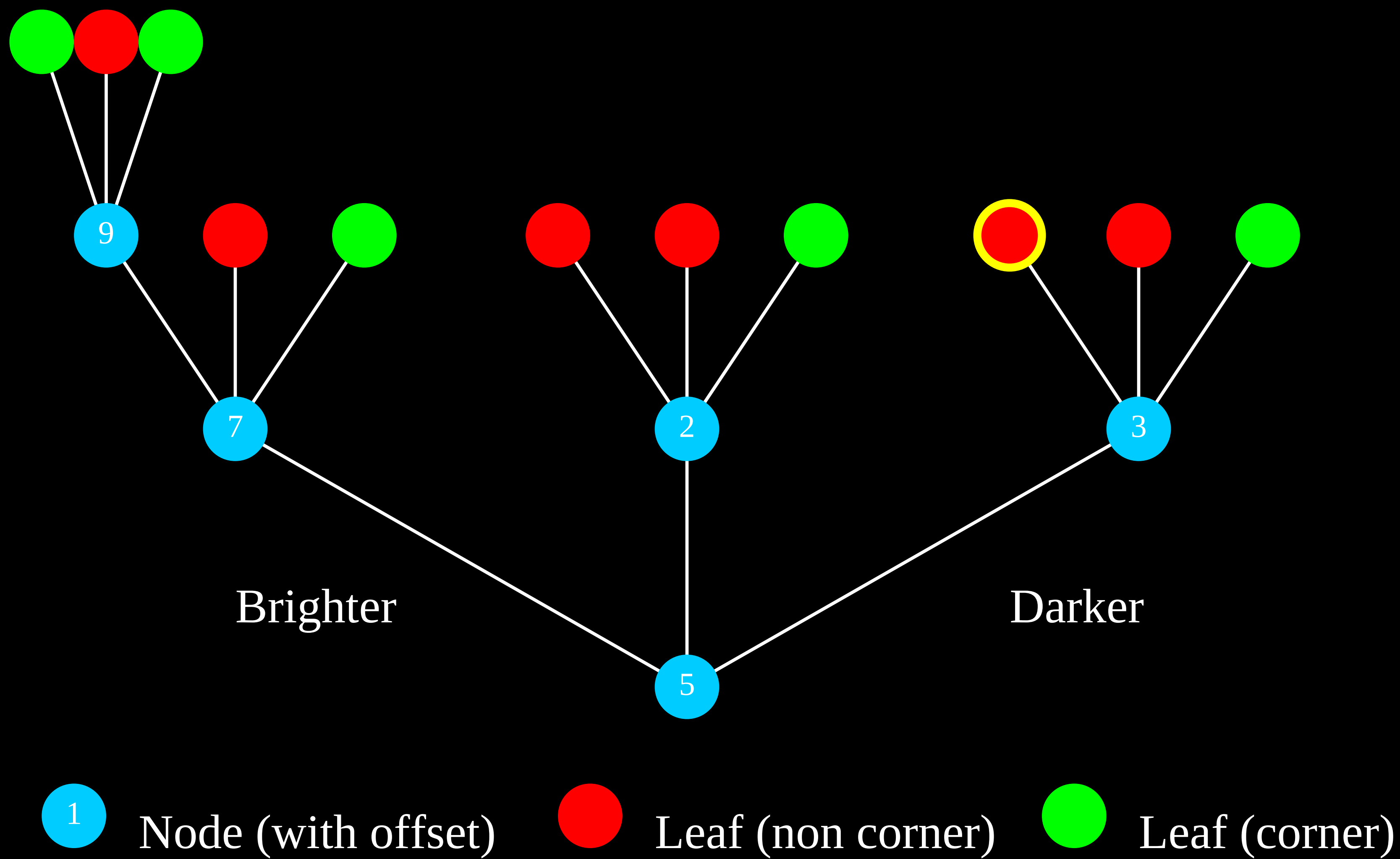
Operations

Select a random node. If node is a leaf:



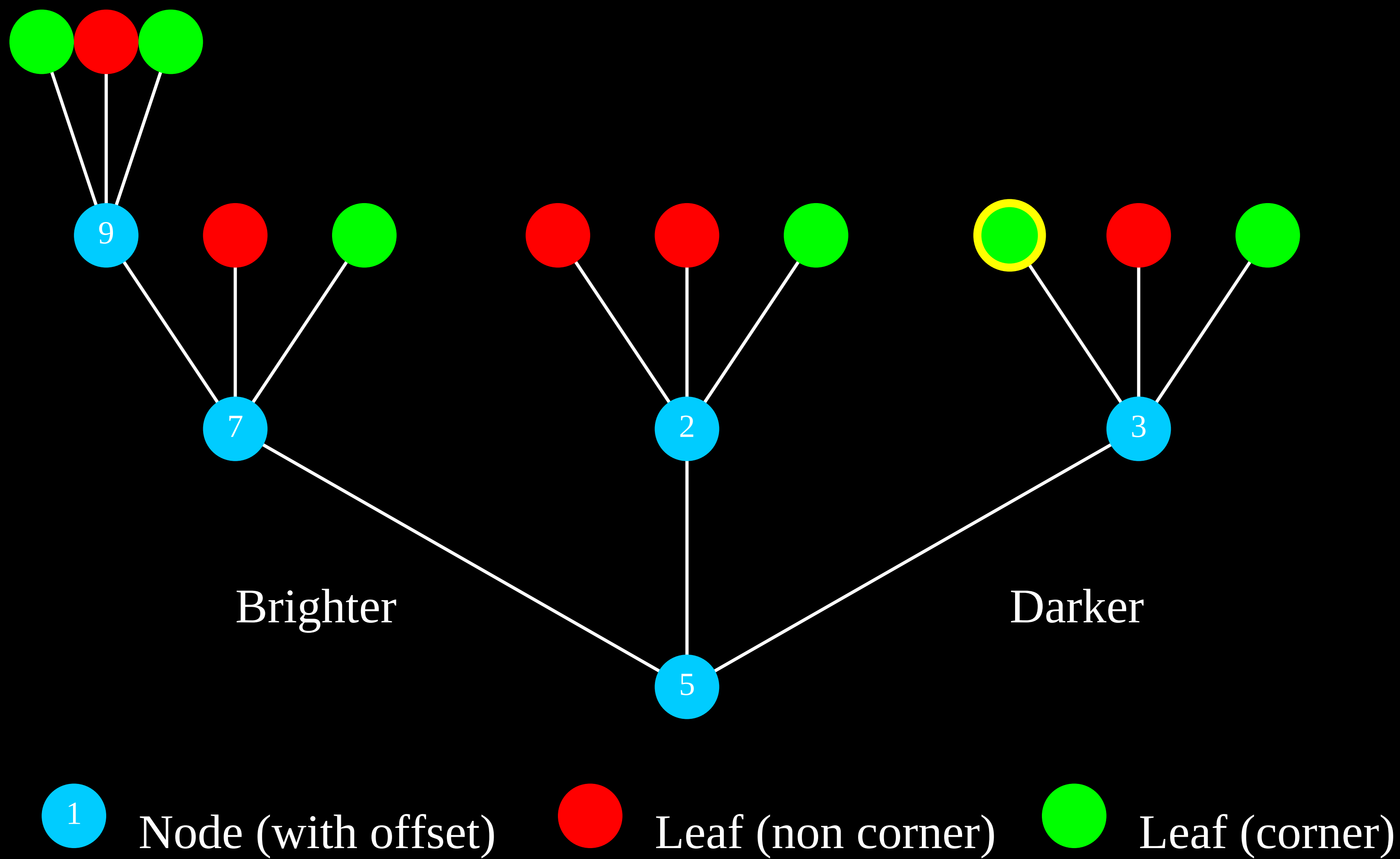
Operations

flip the class (if possible), . . .



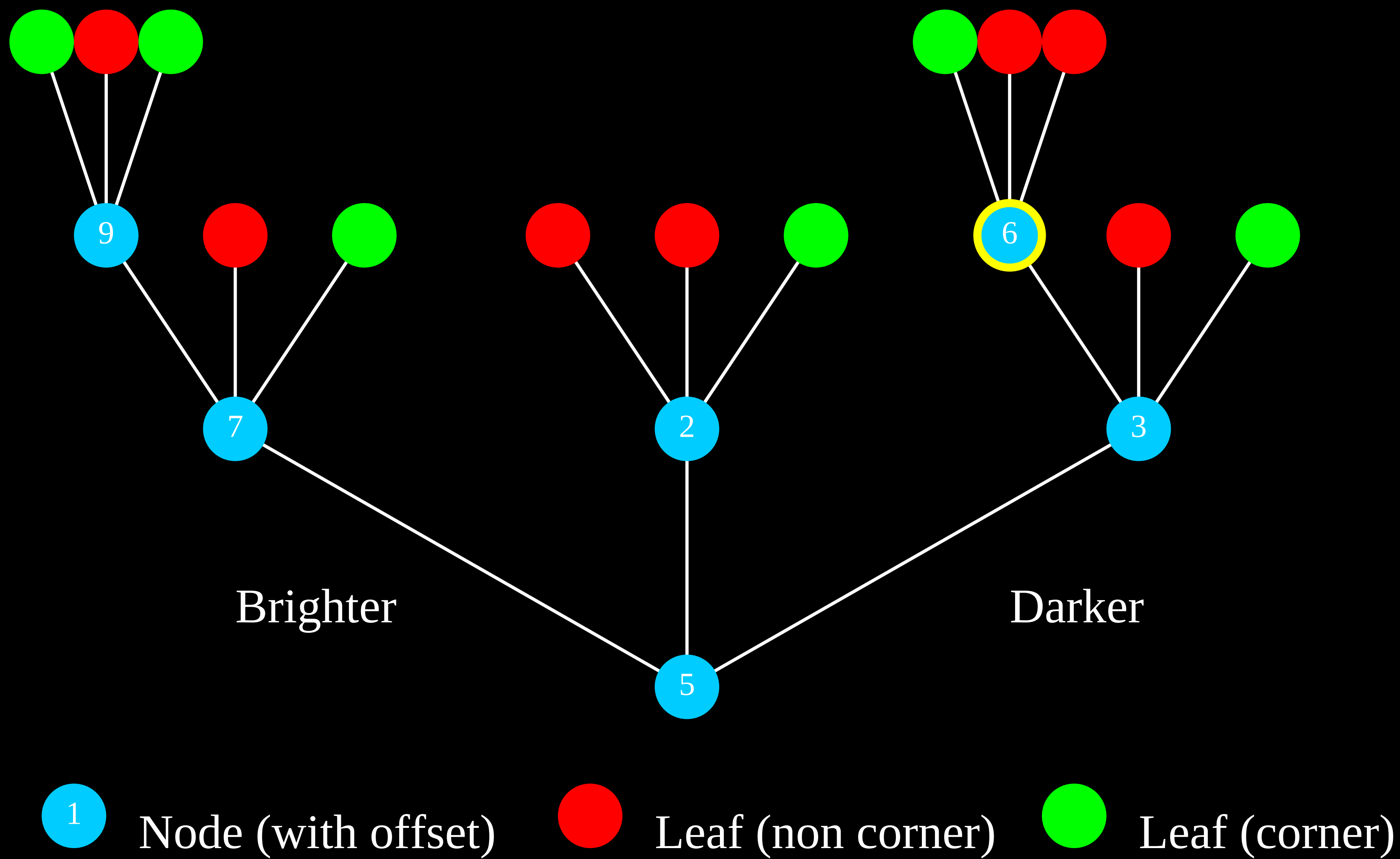
Operations

. . . or . . .



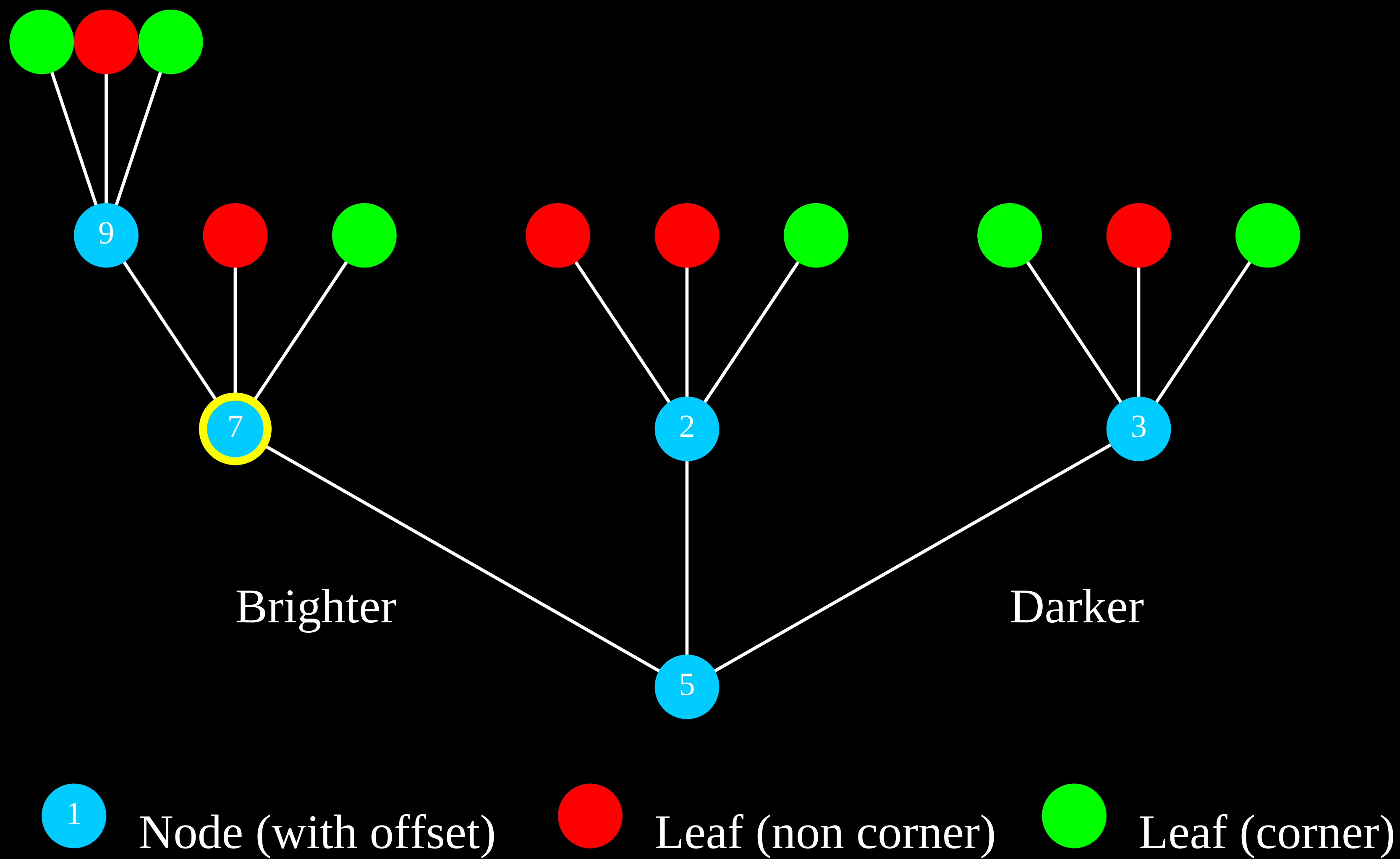
Operations

grow a random subtree.



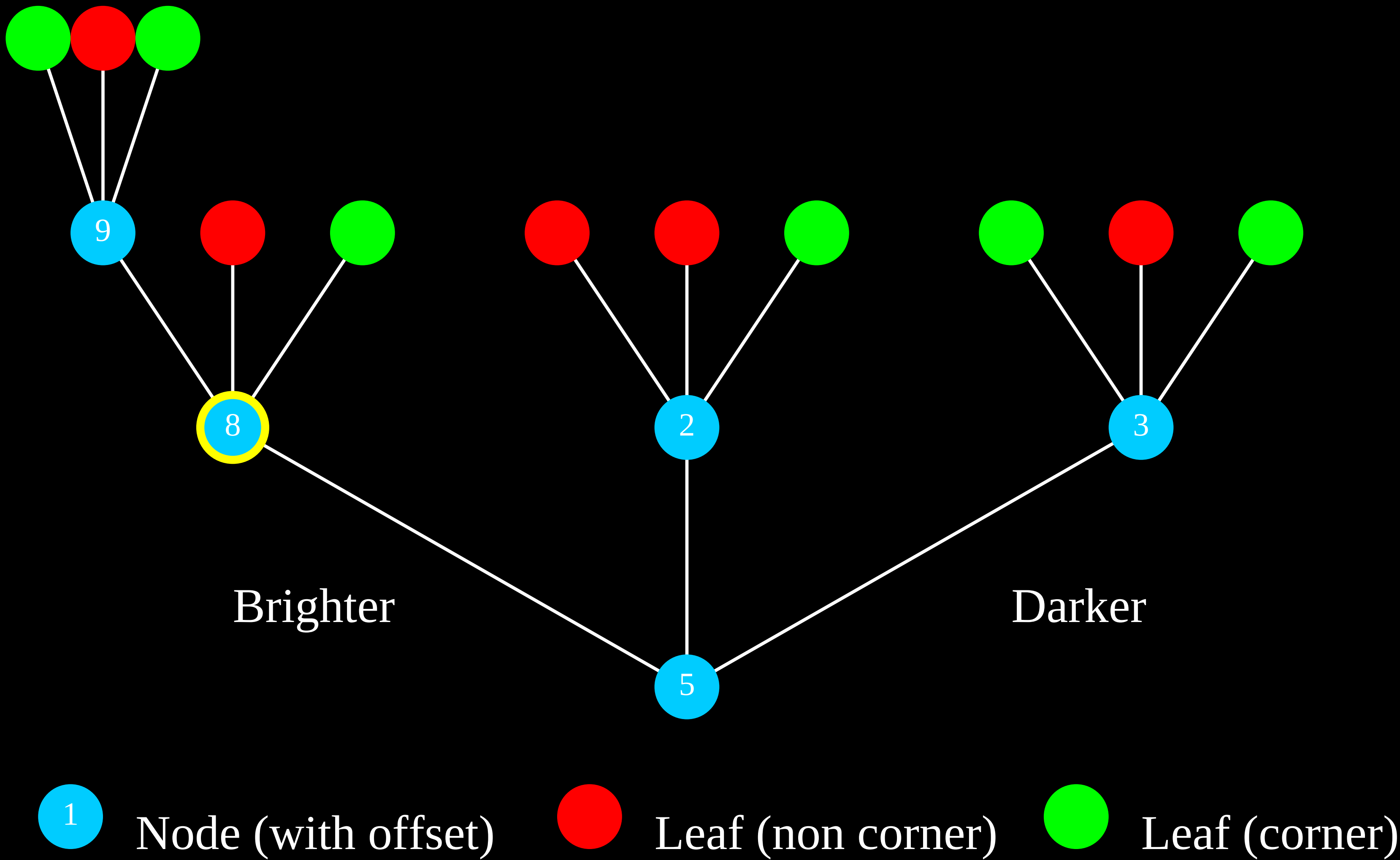
Operations

If node is a non-leaf:



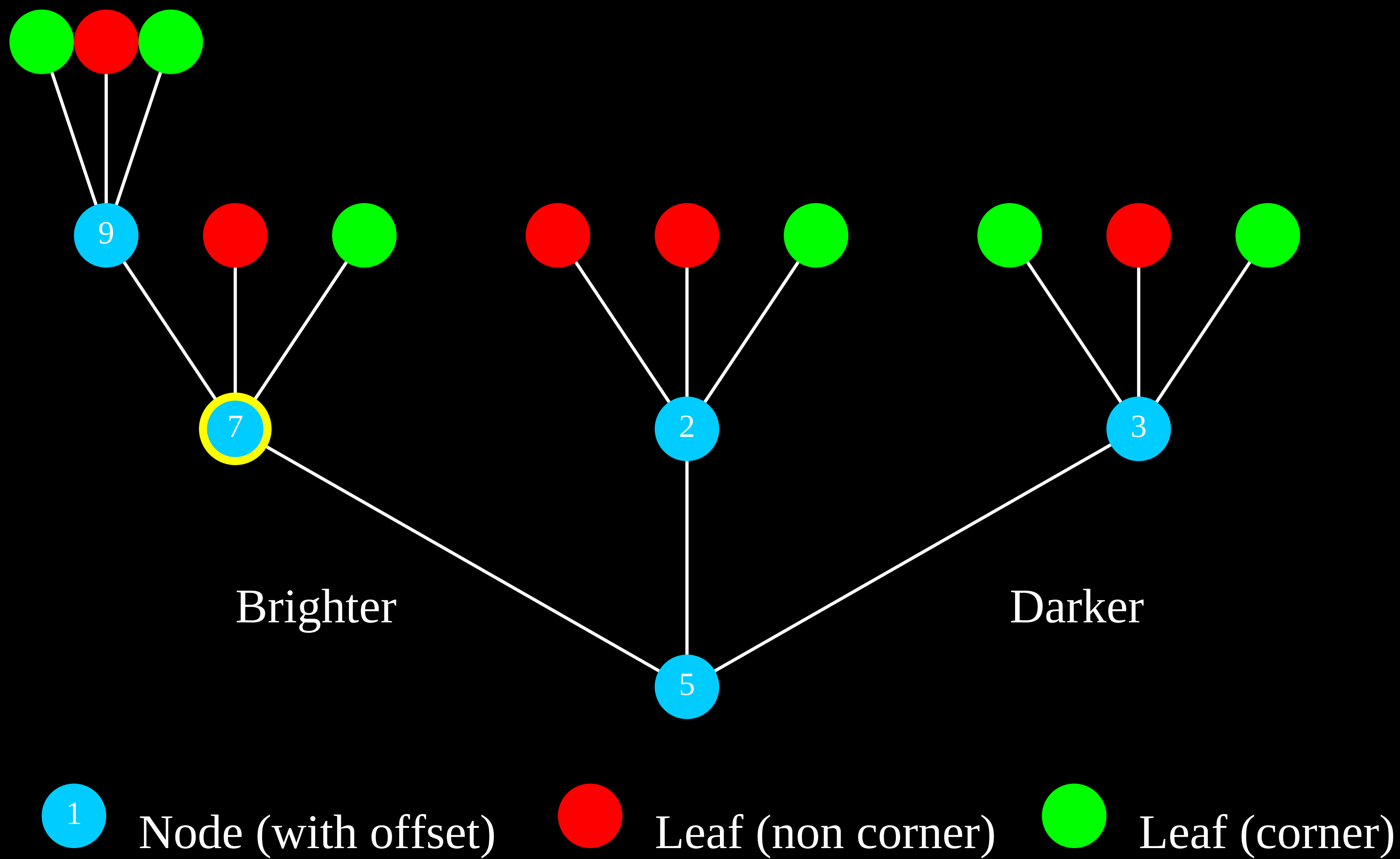
Operations

randomize the offset, . . .



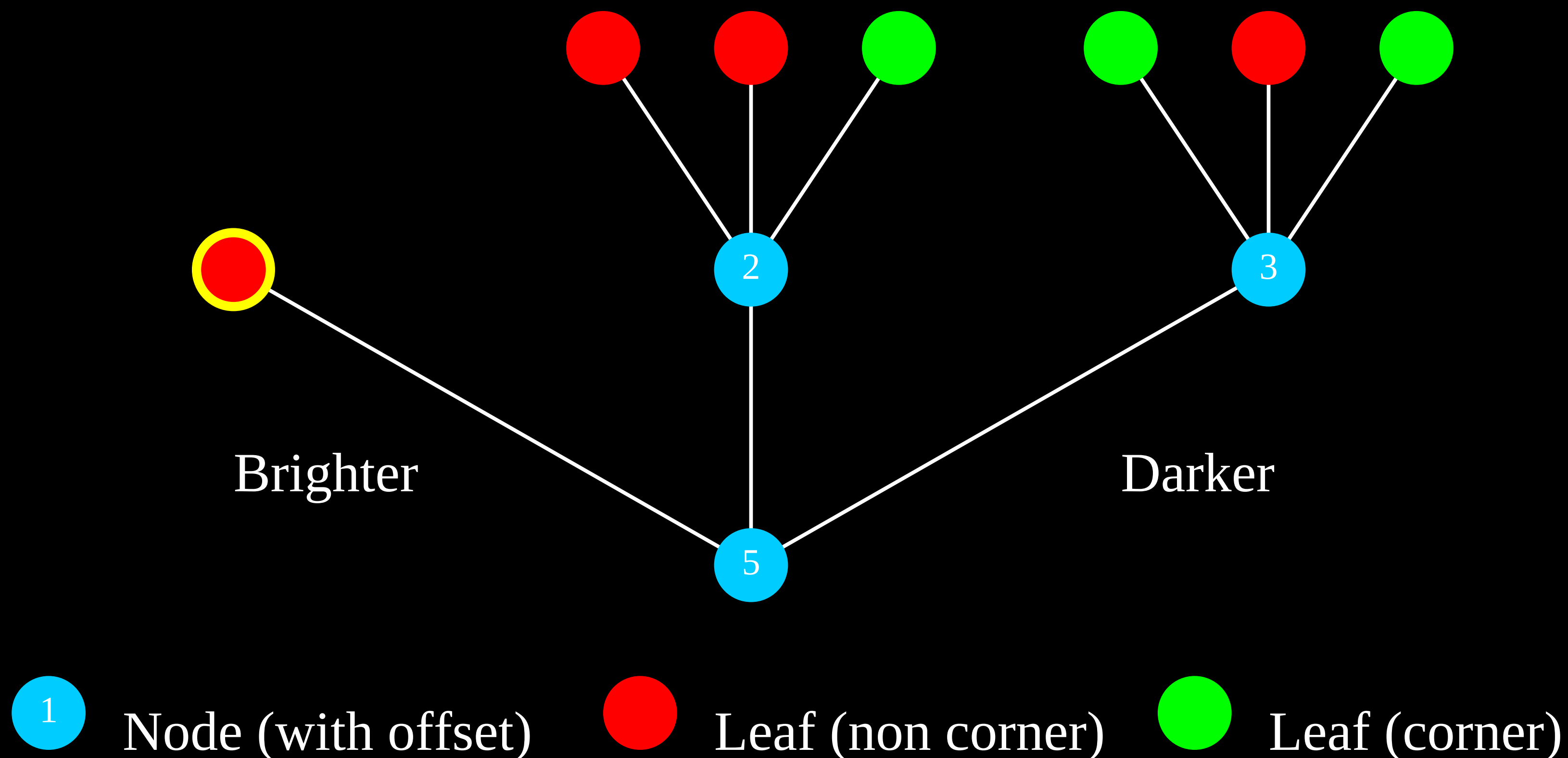
Operations

. . . or . . .



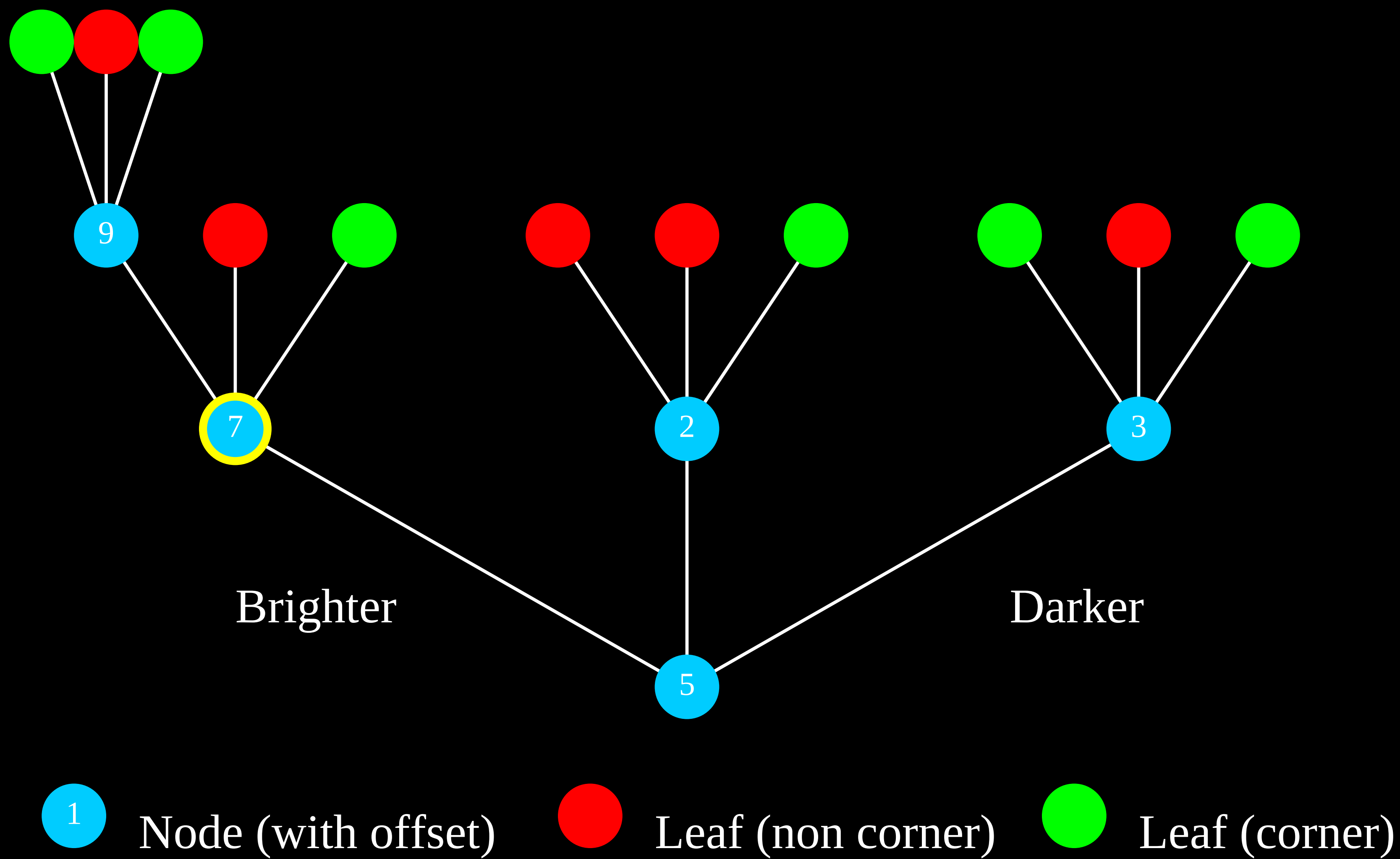
Operations

replace node with a leaf, . . .



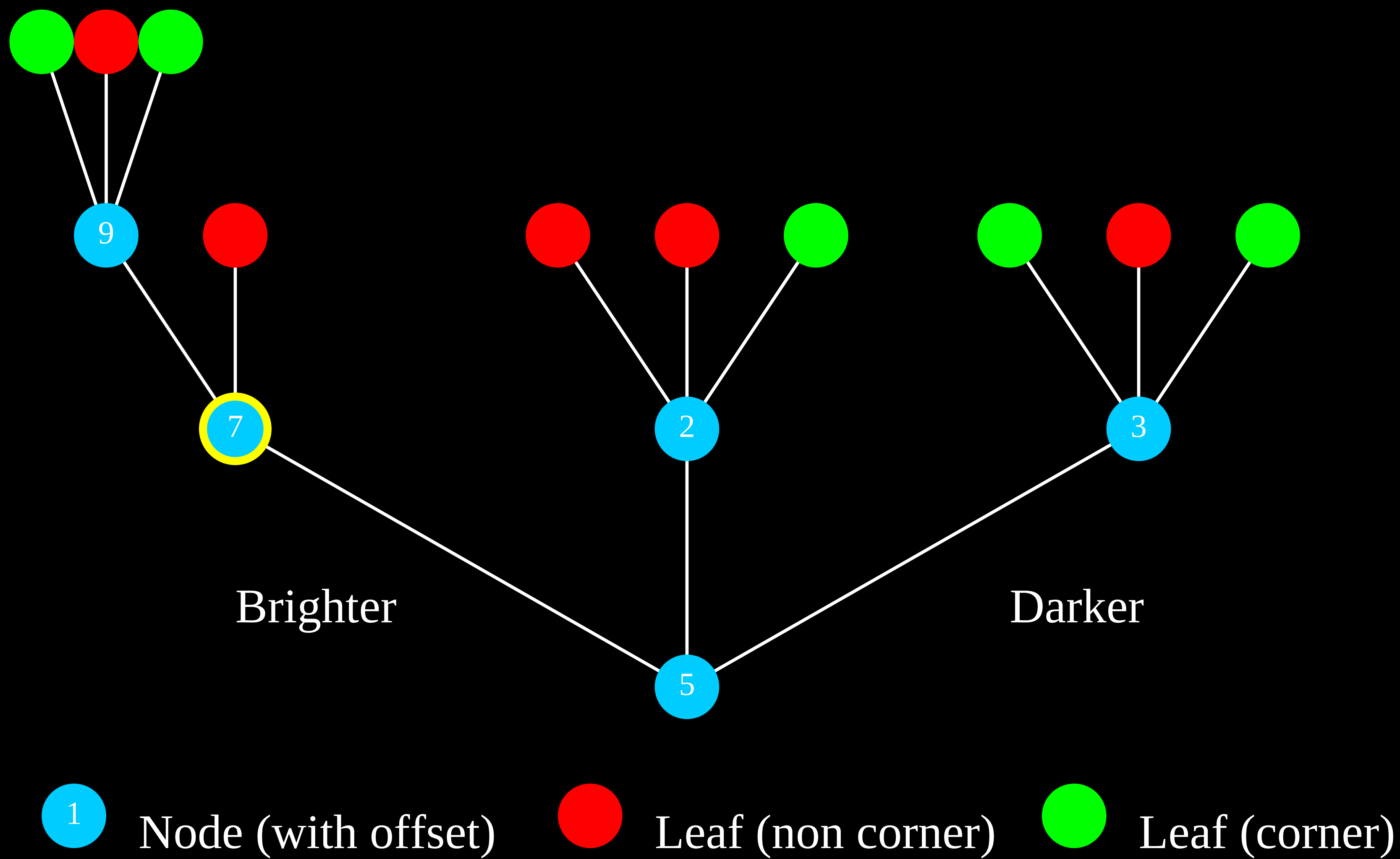
Operations

. . . or . . .



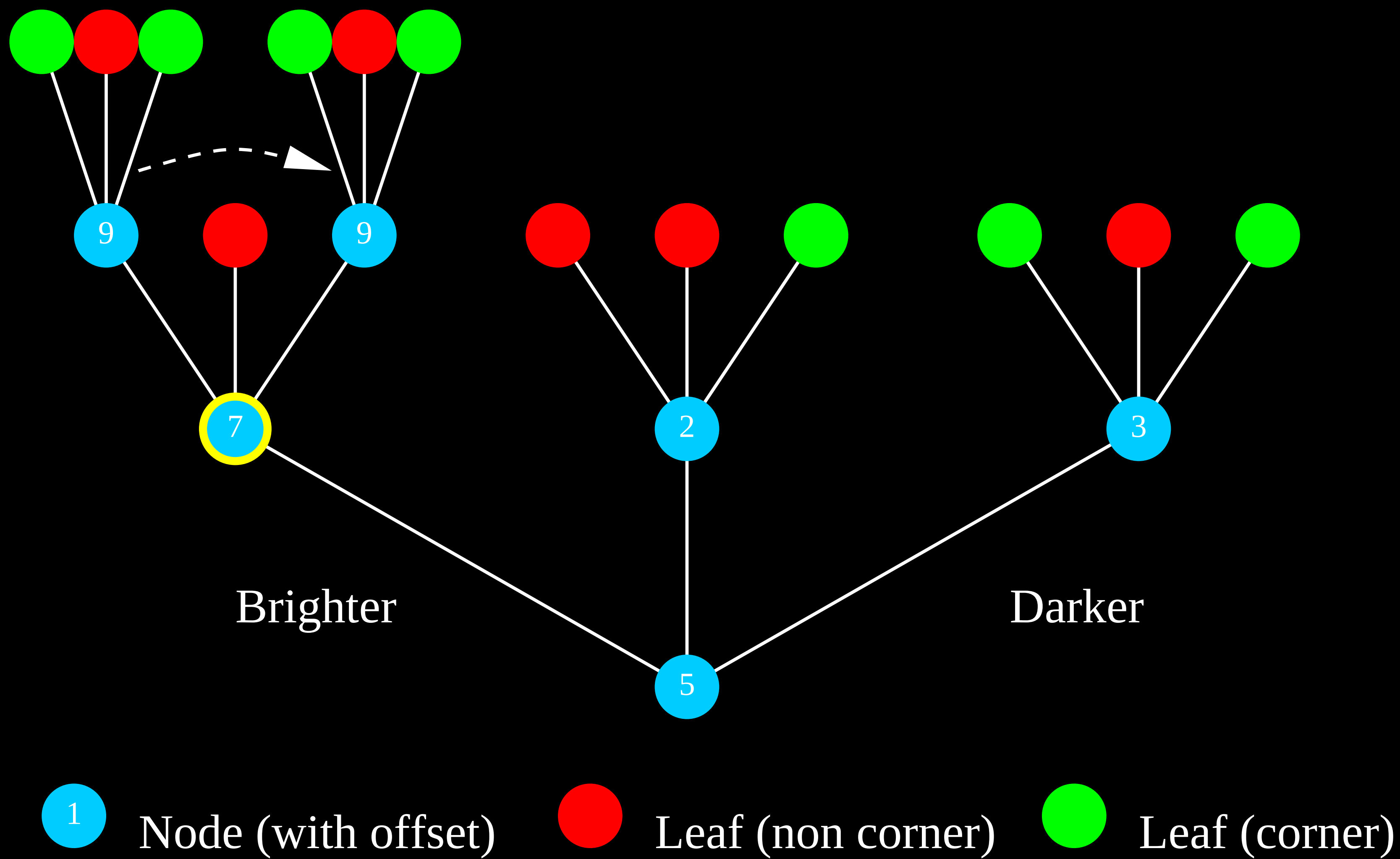
Operations

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. Output as code.
3. Detect features and perform nonmax suppression.
4. Compute repeatability.
5. Evaluate cost.
6. Keep the modification if:

$$e^{\frac{\text{oldcost}-\text{cost}}{\text{temp}}} > \text{rand}$$

7. Reduce the temperature.

Now repeat that 100 times (200 Hours required).

Training data for repeatability



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

Optimizing FAST-ER for speed

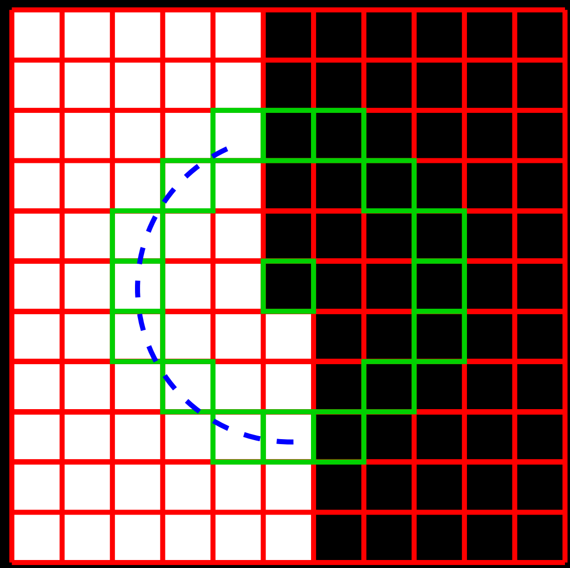
- Tree is applied 16 times at each pixel
- Use repeatability optimized FAST-ER to gather training data:
  1. Detect points in images.
  2. Extract ternary vector of surrounding pixels available to FAST-ER.
- Train single decision tree using ID3.
- Output tree as C code.

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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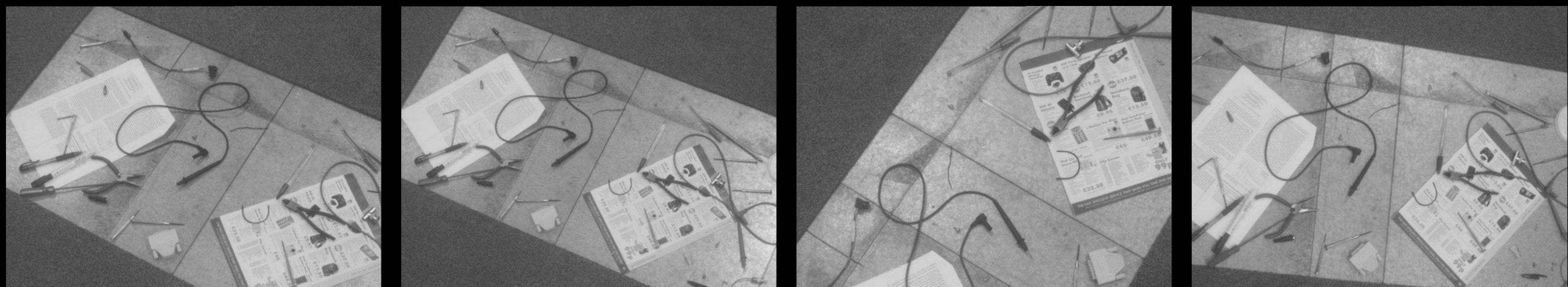
  - SUSAN
- What parameters should these detectors use?

Evaluation: Datasets (3D Models)

14 images:

15 images:

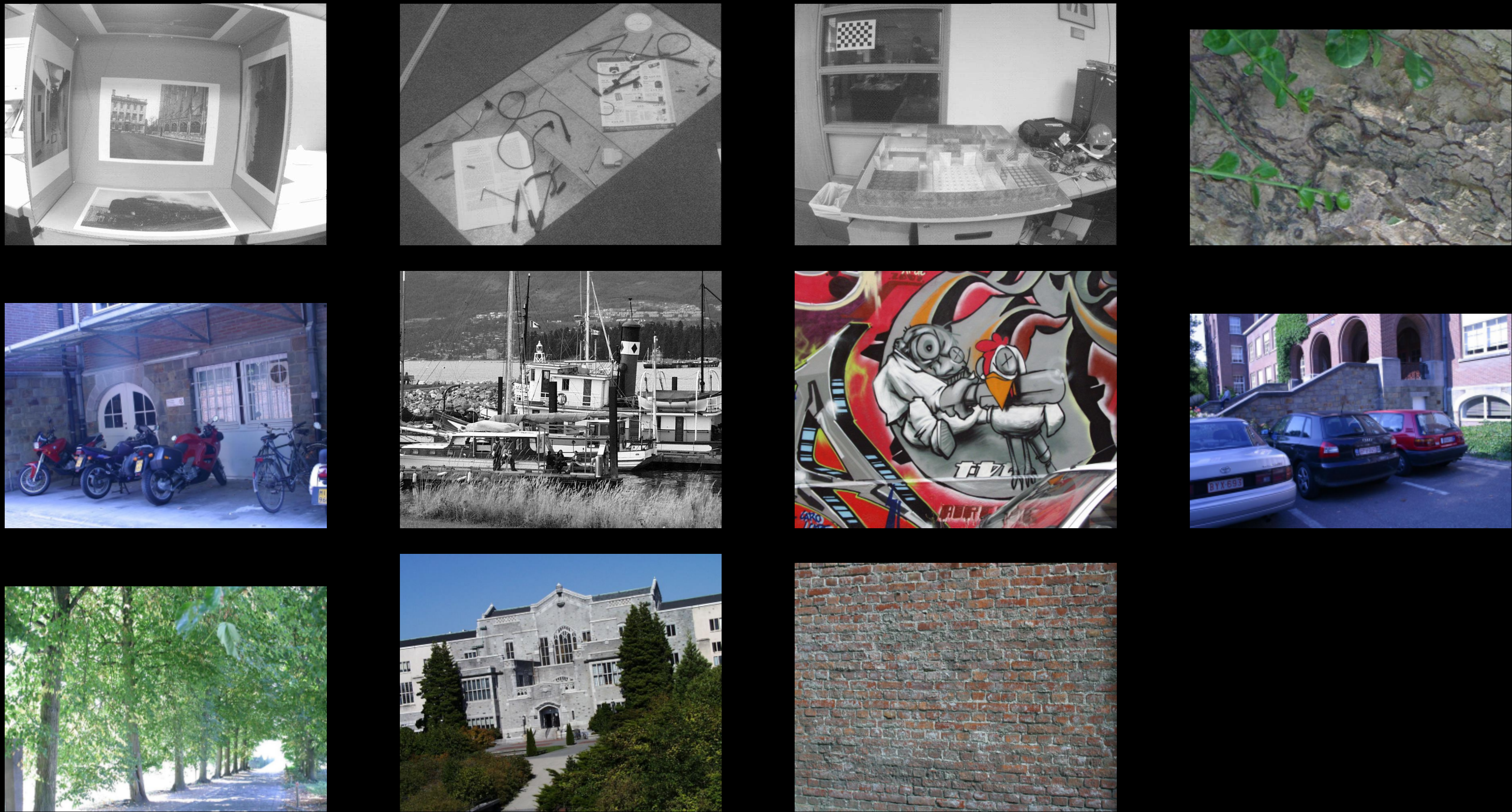
8 images:



Evaluation: Homographies

6 images per set:

Results: repeatability curves



Aggregate results

Detector	A
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

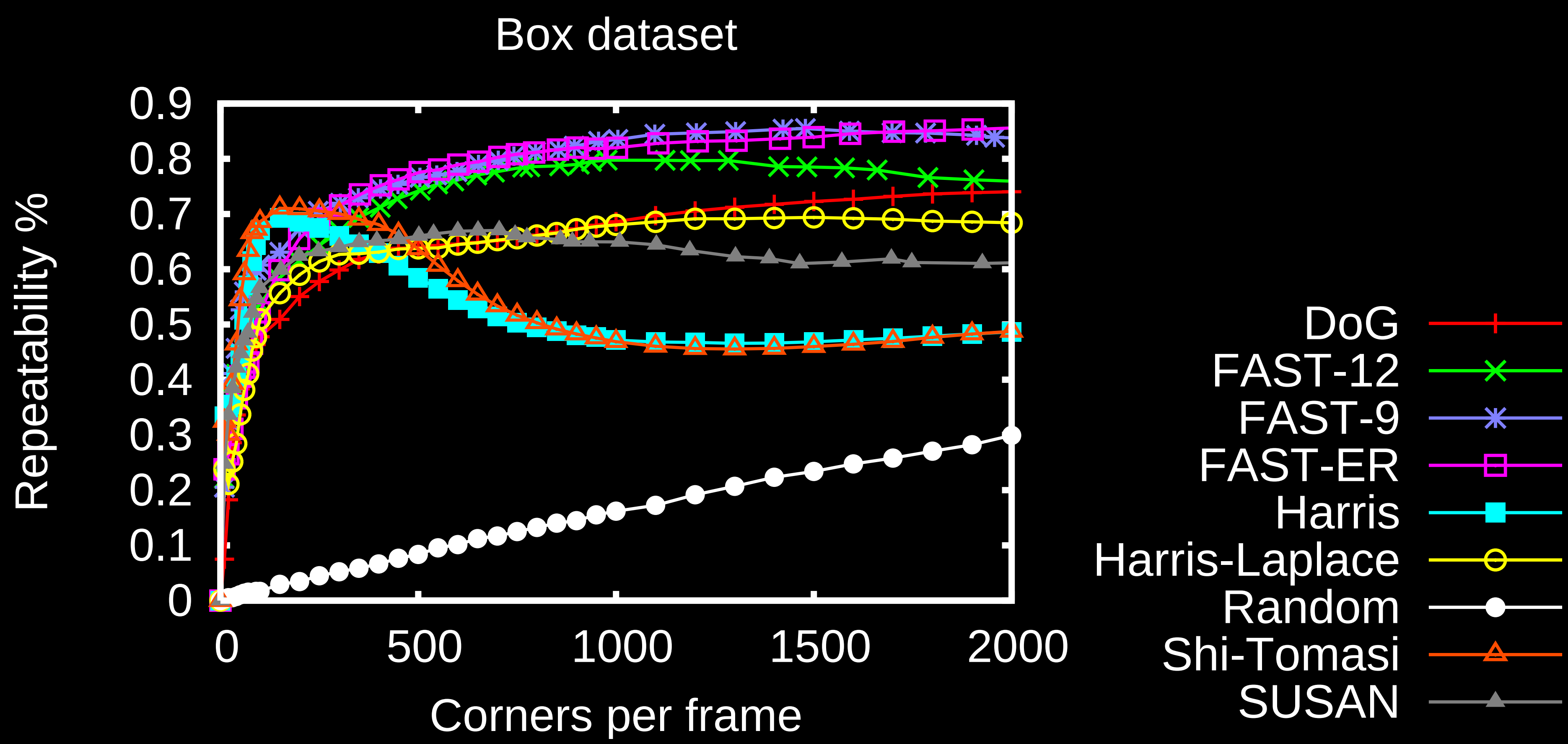
Conclusions

What do the results say?

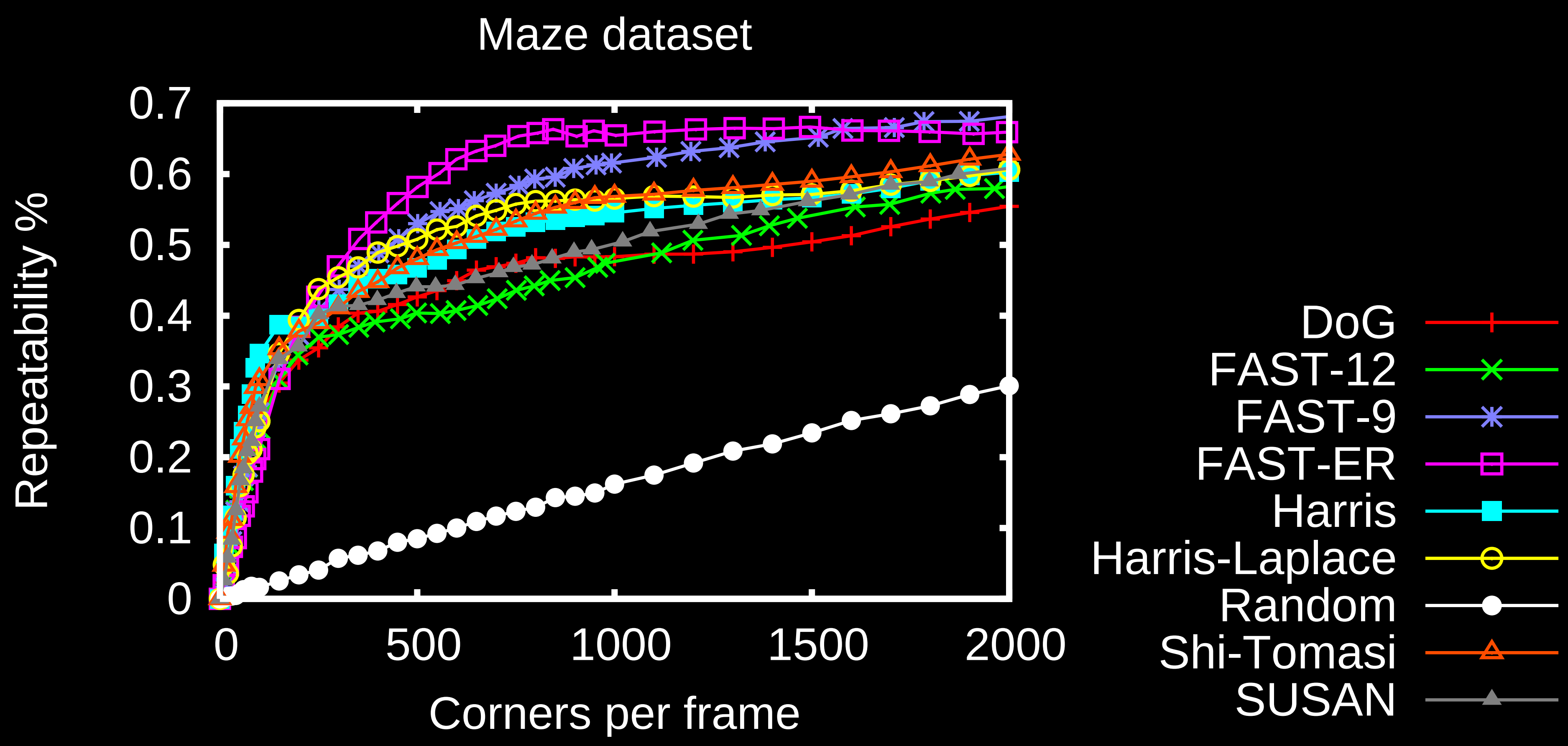
- FAST is suprisingly good.
- FAST-ER is better but slower.

More results

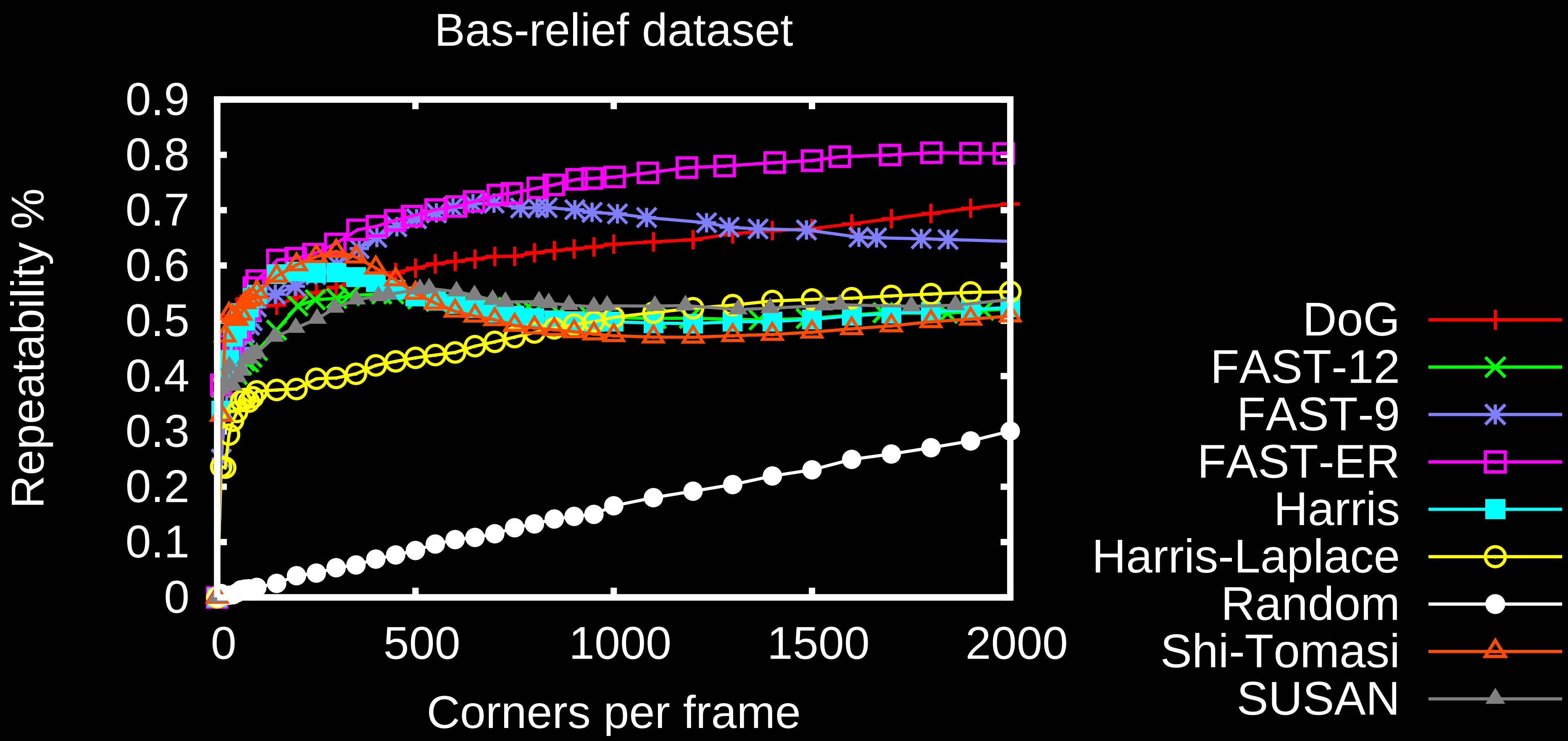
Results: Perspective (box) dataset



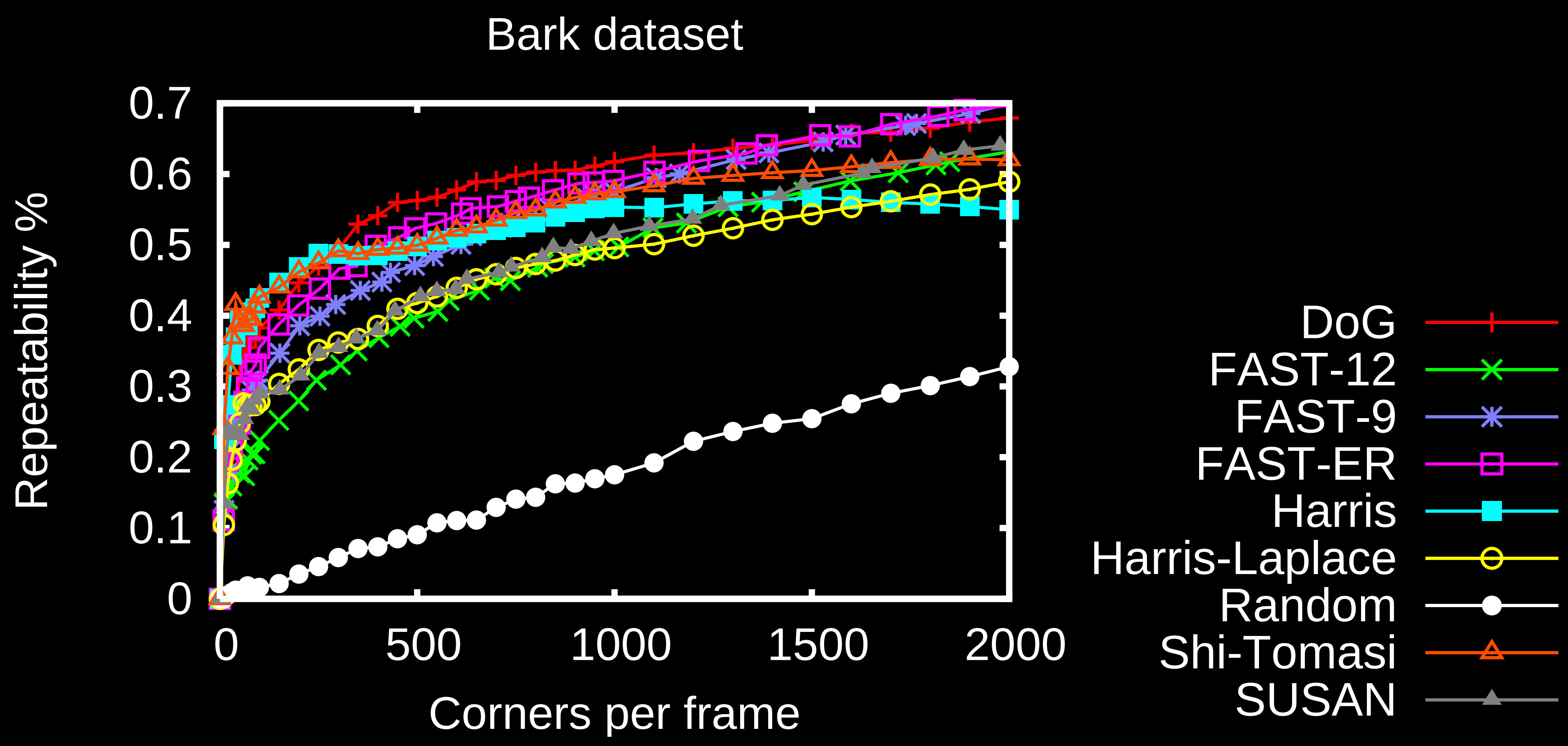
Results: Geometric dataset



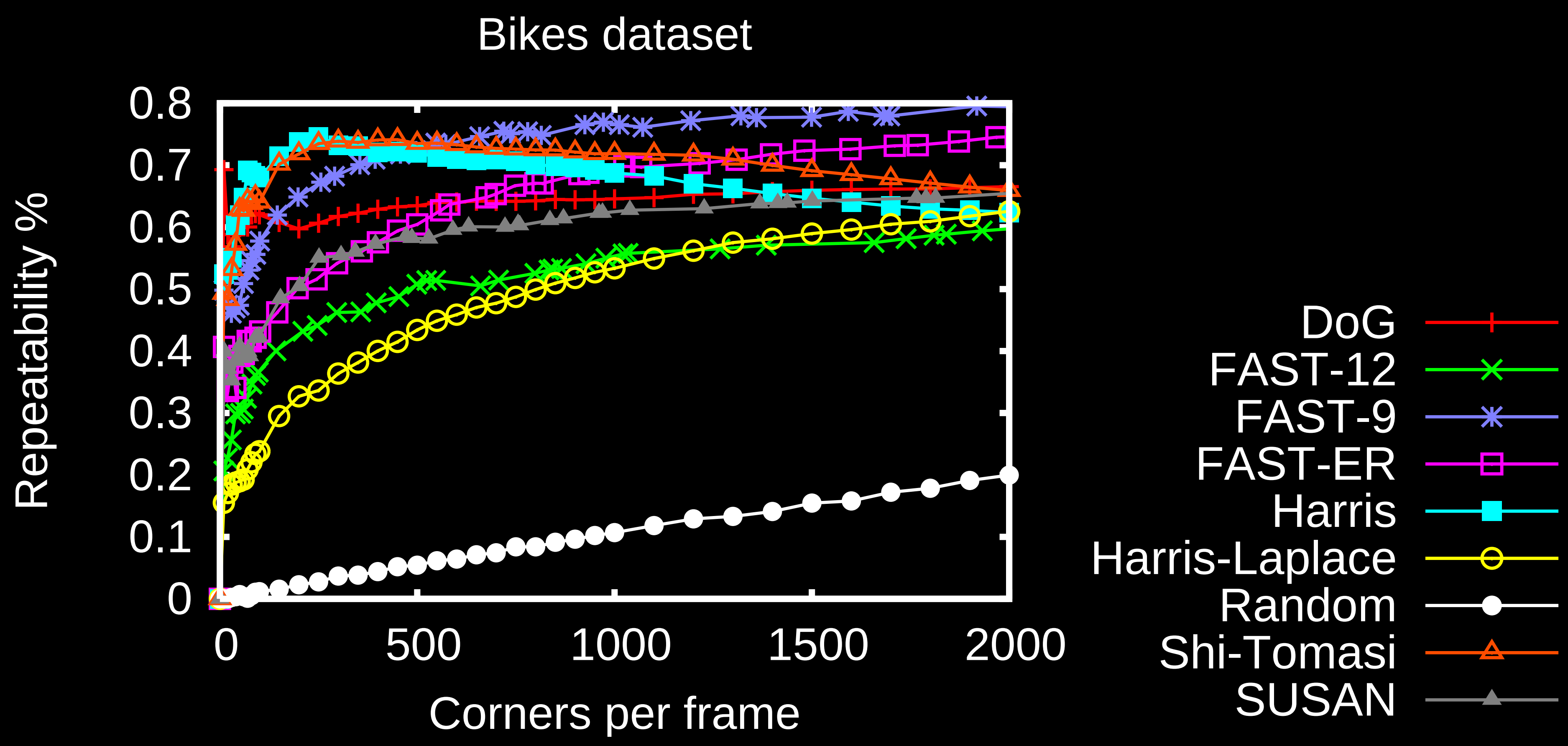
Results: Bas-relief dataset



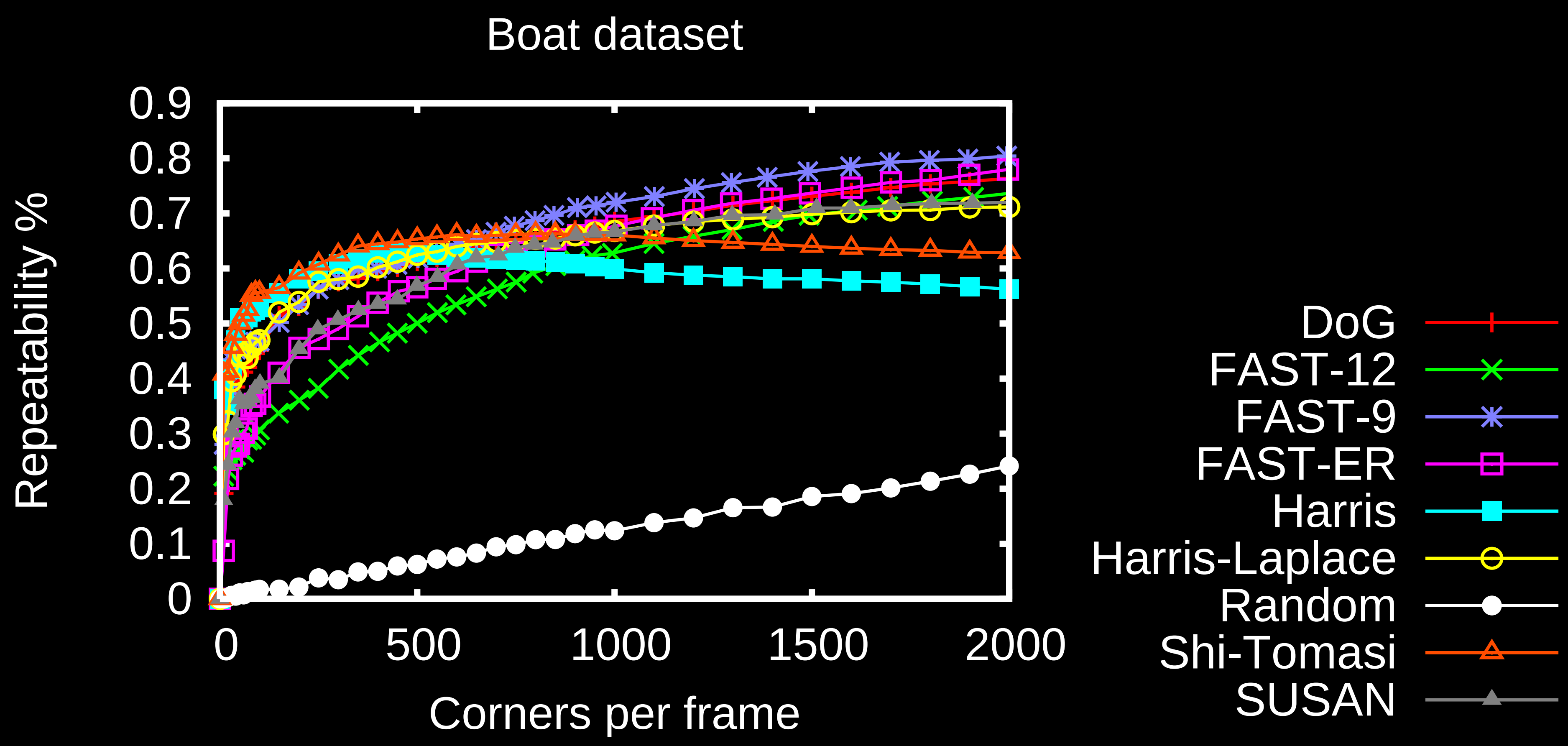
Results: Scale and rotation (bark) dataset



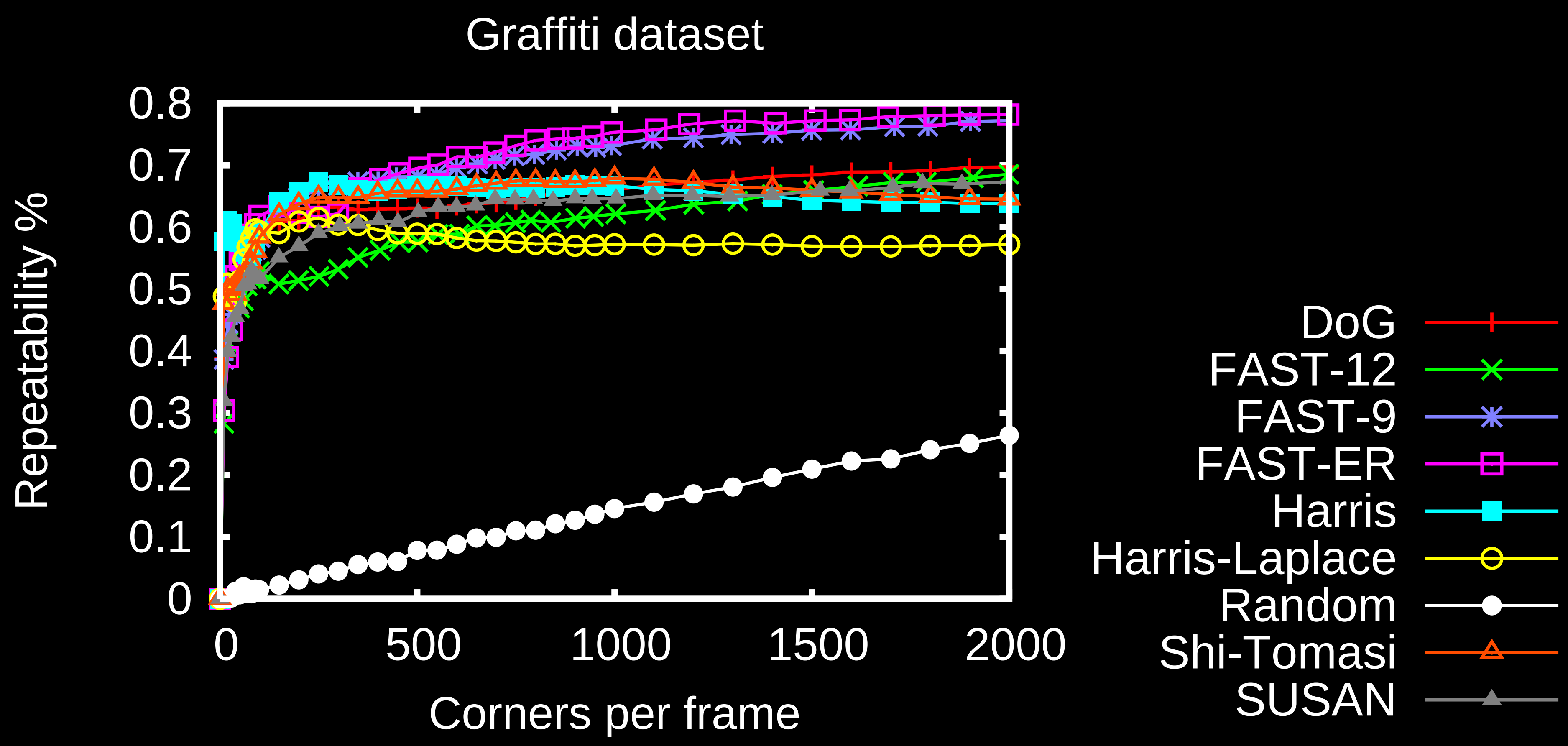
Results: Blur (bikes) dataset



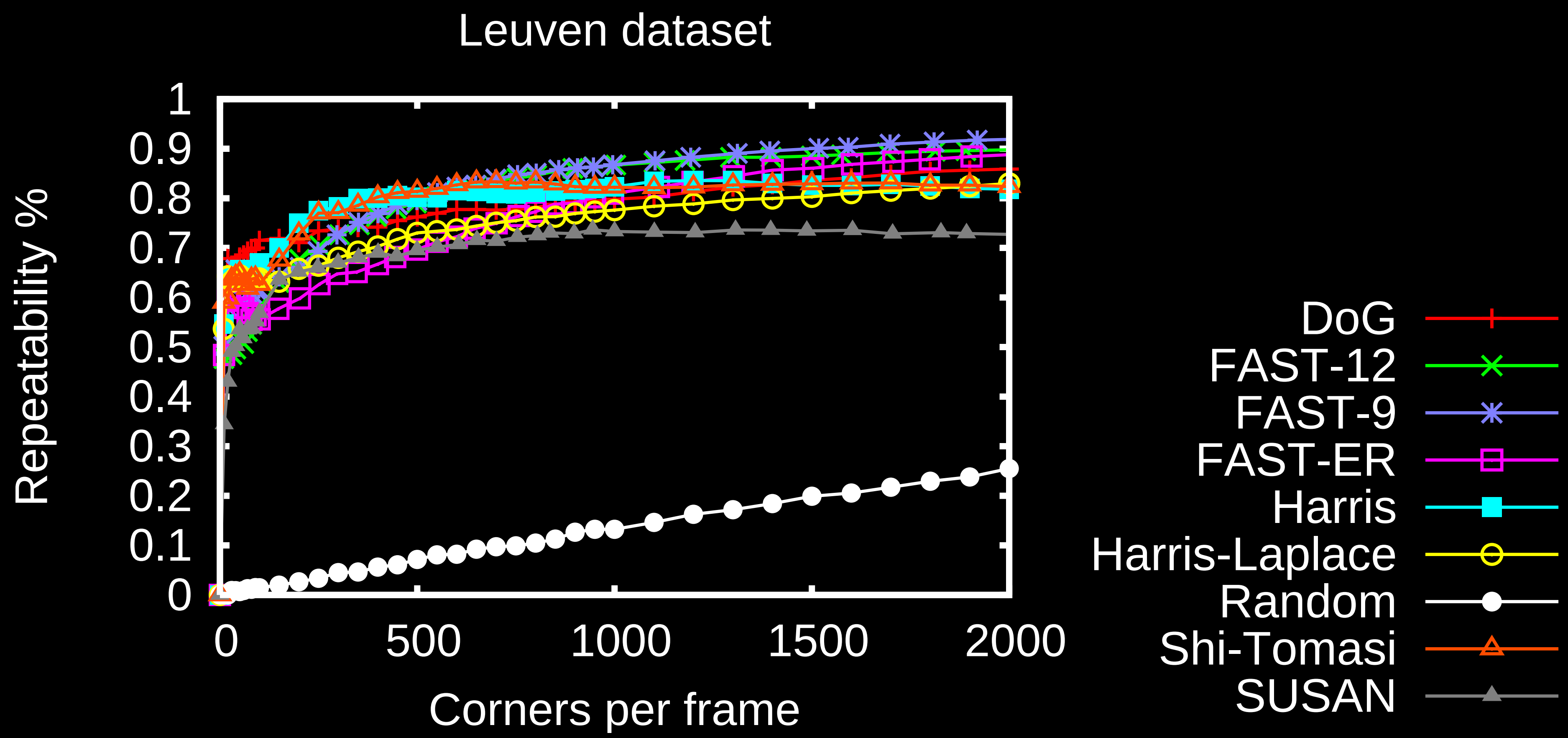
Results: Scale and rotation (boat) dataset



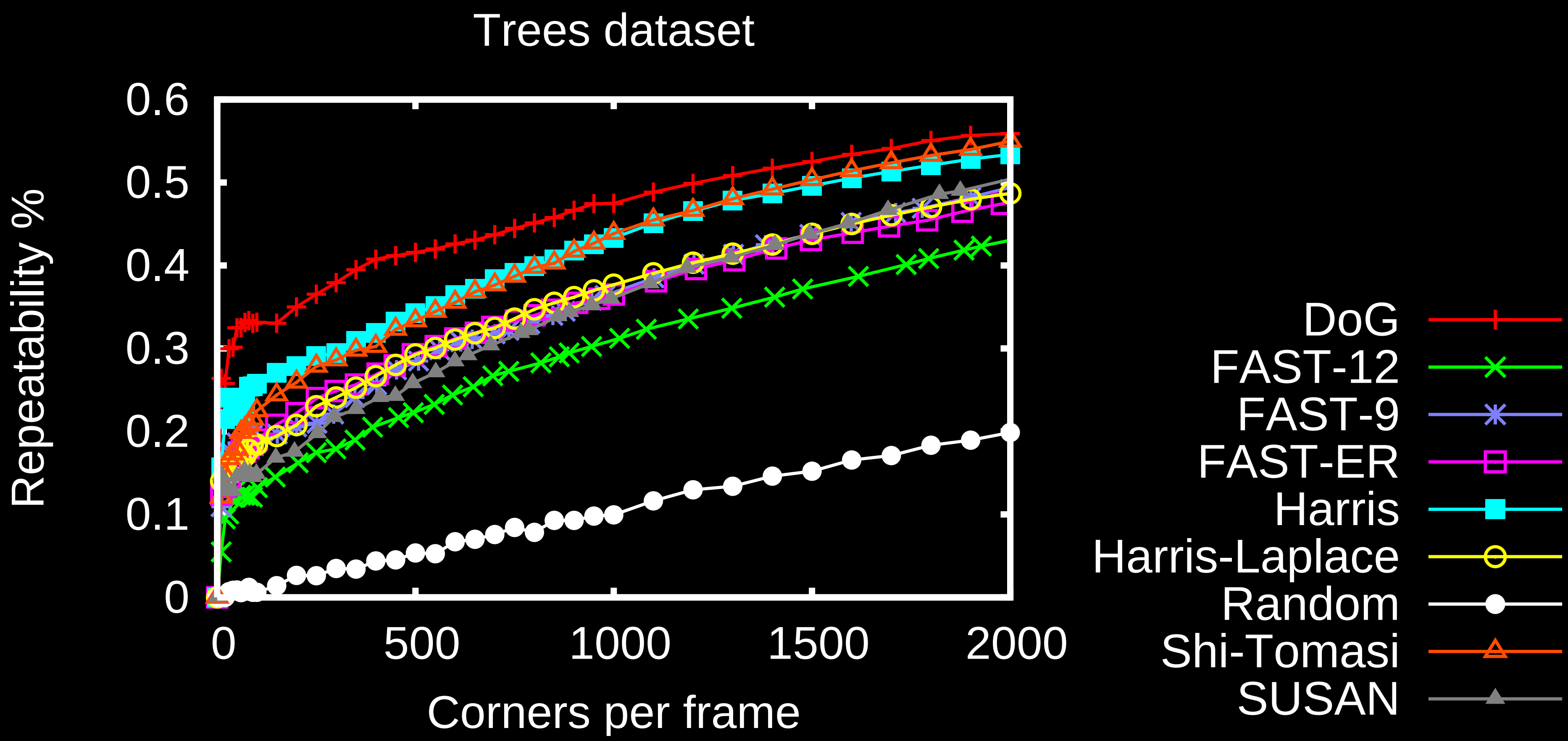
Results: Perspective (graffiti) dataset



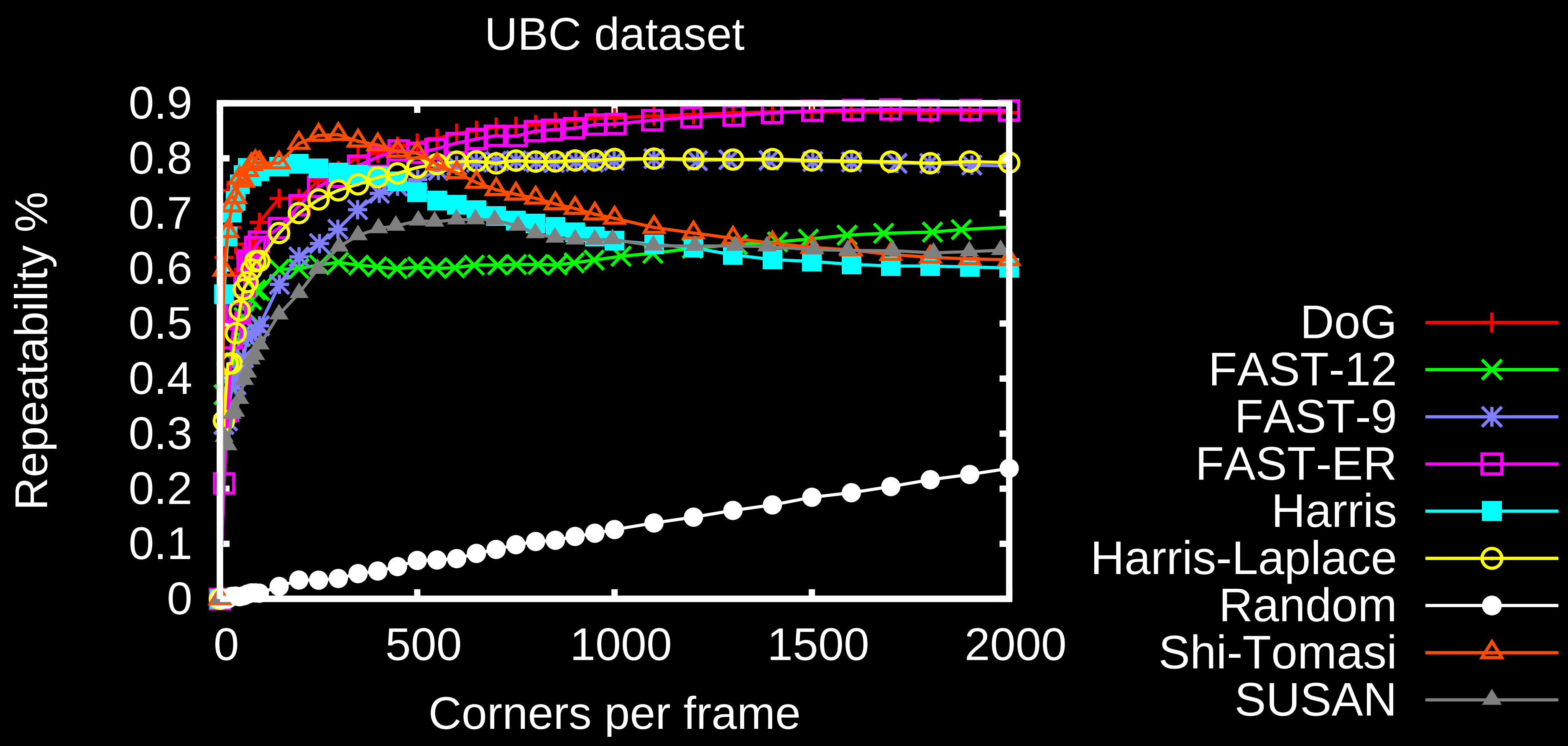
Results: Lighting dataset



Results: Blur (trees) dataset



Results: JPEG compression dataset



Results: Perspective (wall) dataset