Dictionary Methods for Micrograph Analysis

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Agenda

Problem Setting

Workflow

Algorithm

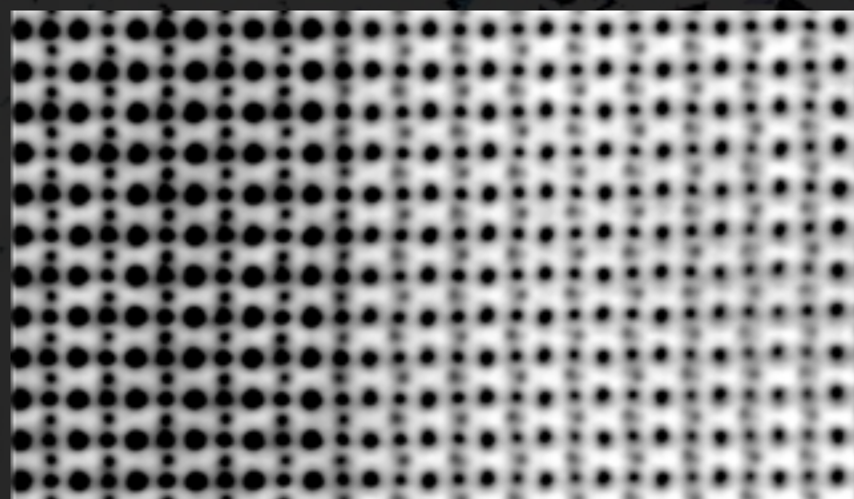
Current Outcome

Improvements

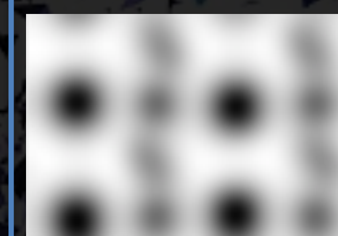
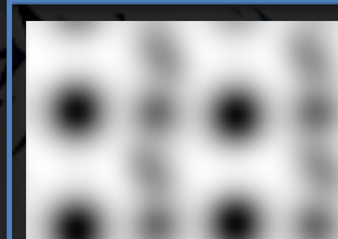
Future Work

Problem Setting

Micrograph Image



Dictionary

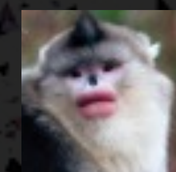
	mode 1
	mode 2
	mode 3
	mode 4

1. Every atom associated with a specific ‘**mode**’
2. The dictionary **exhausts** all possible modes
3. Goal: **identify** each atom in the micrograph with a specific mode in the dictionary

Problem Setting

Dictionary

Micrograph Image

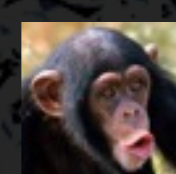


Colobus Guerezas

Golden Lion Tamarin

Spectacled Langur

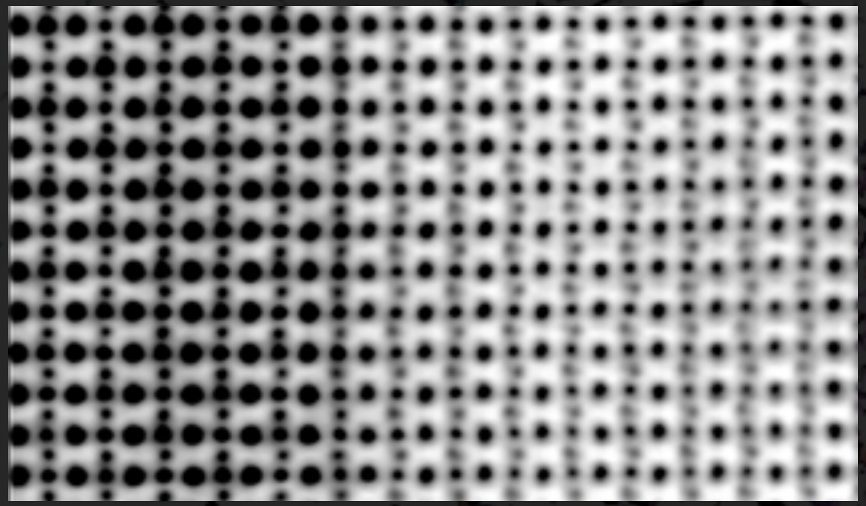
Whatever-kind-of monkey



Chimp

Problem Setting

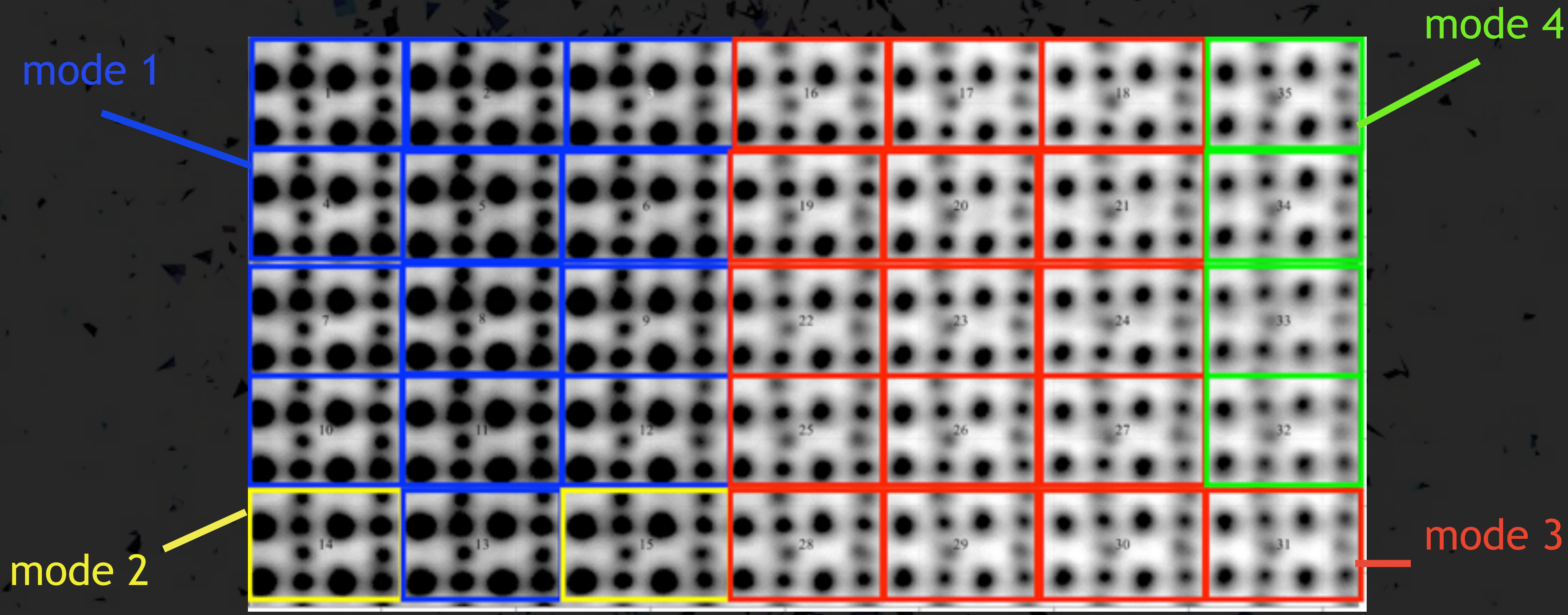
Micrograph Image



Dictionary

1. **Less** features to depend on
2. Extremely **similar** dictionary items

Problem Setting

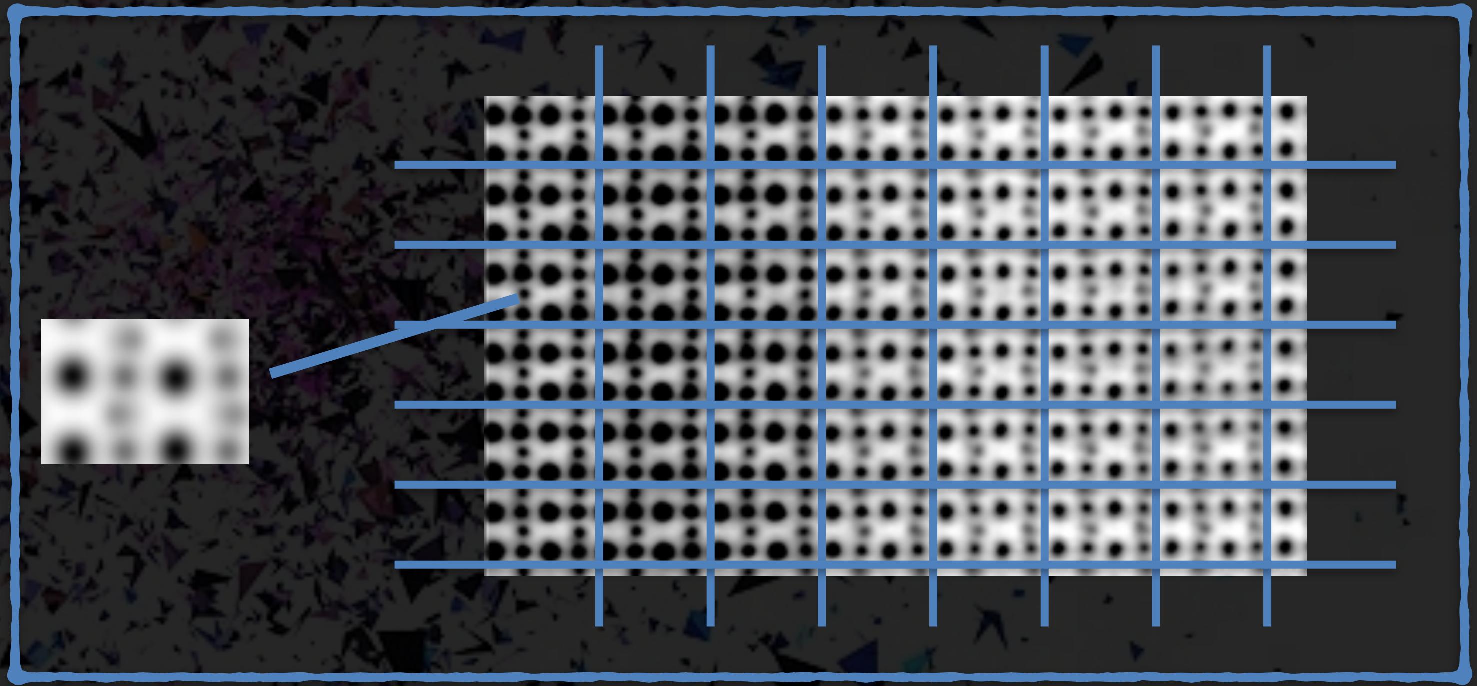


Ideal Output

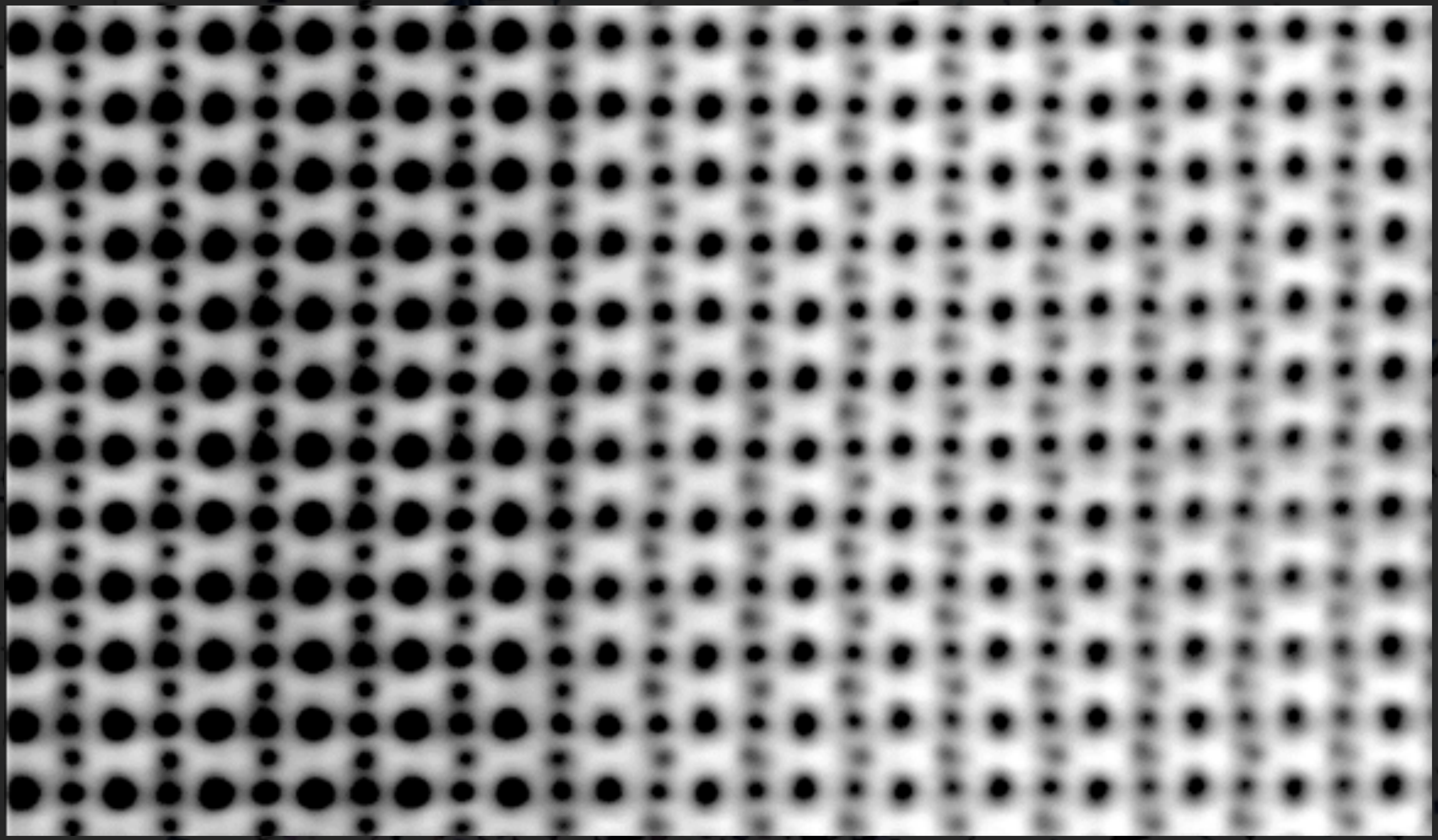
Workflow - Scale, Locate and Slice

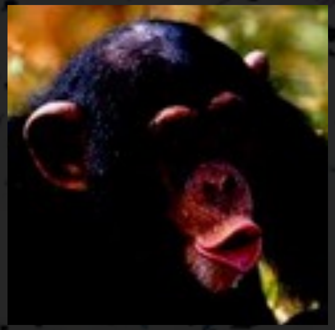
Workflow - Scale, Locate and Slice

Workflow



Workflow - Normalization



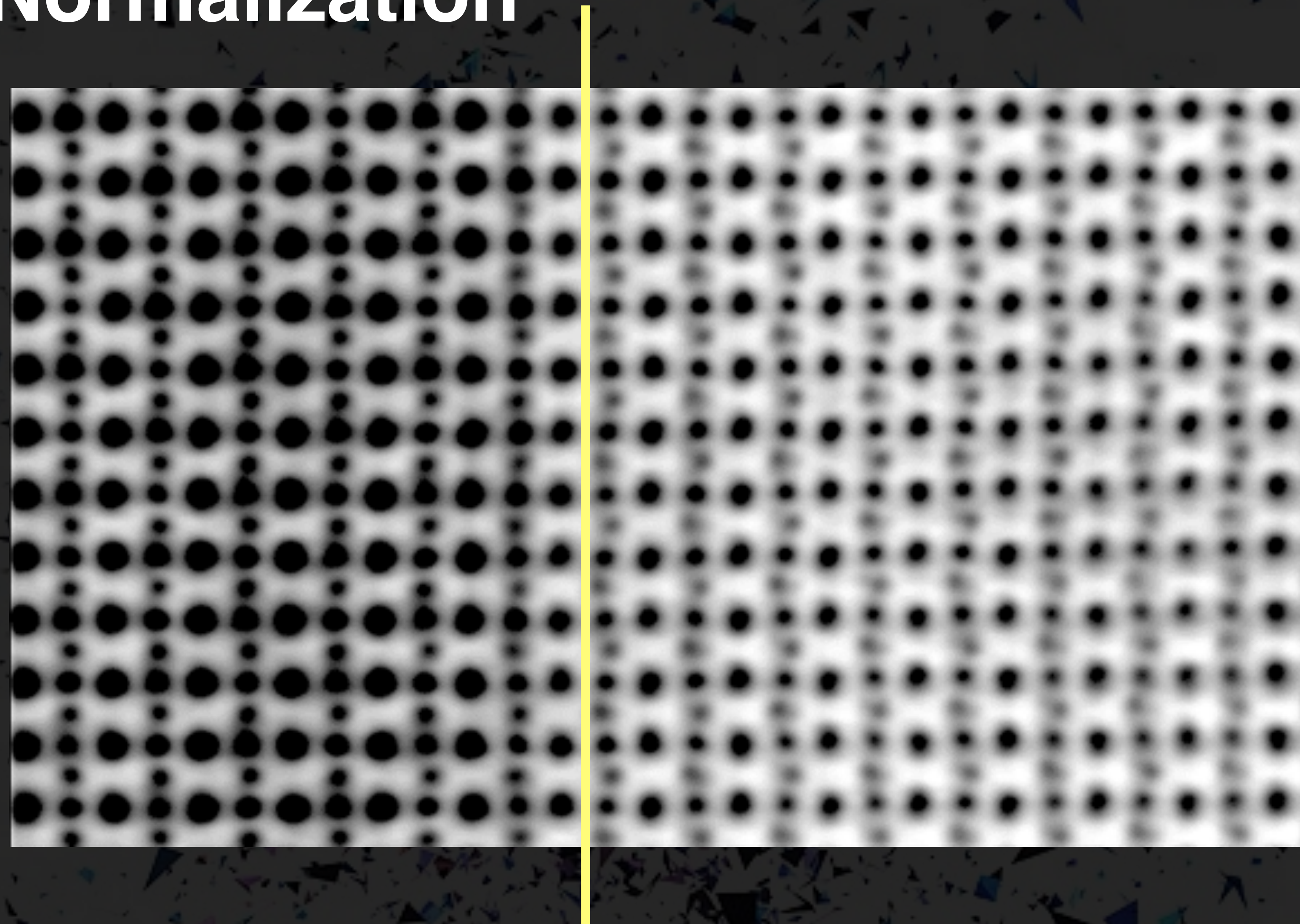


dark Chimp

normal Chimp

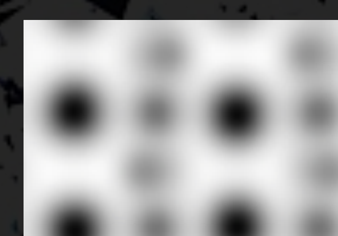
Workflow - Normalization

dark



bright

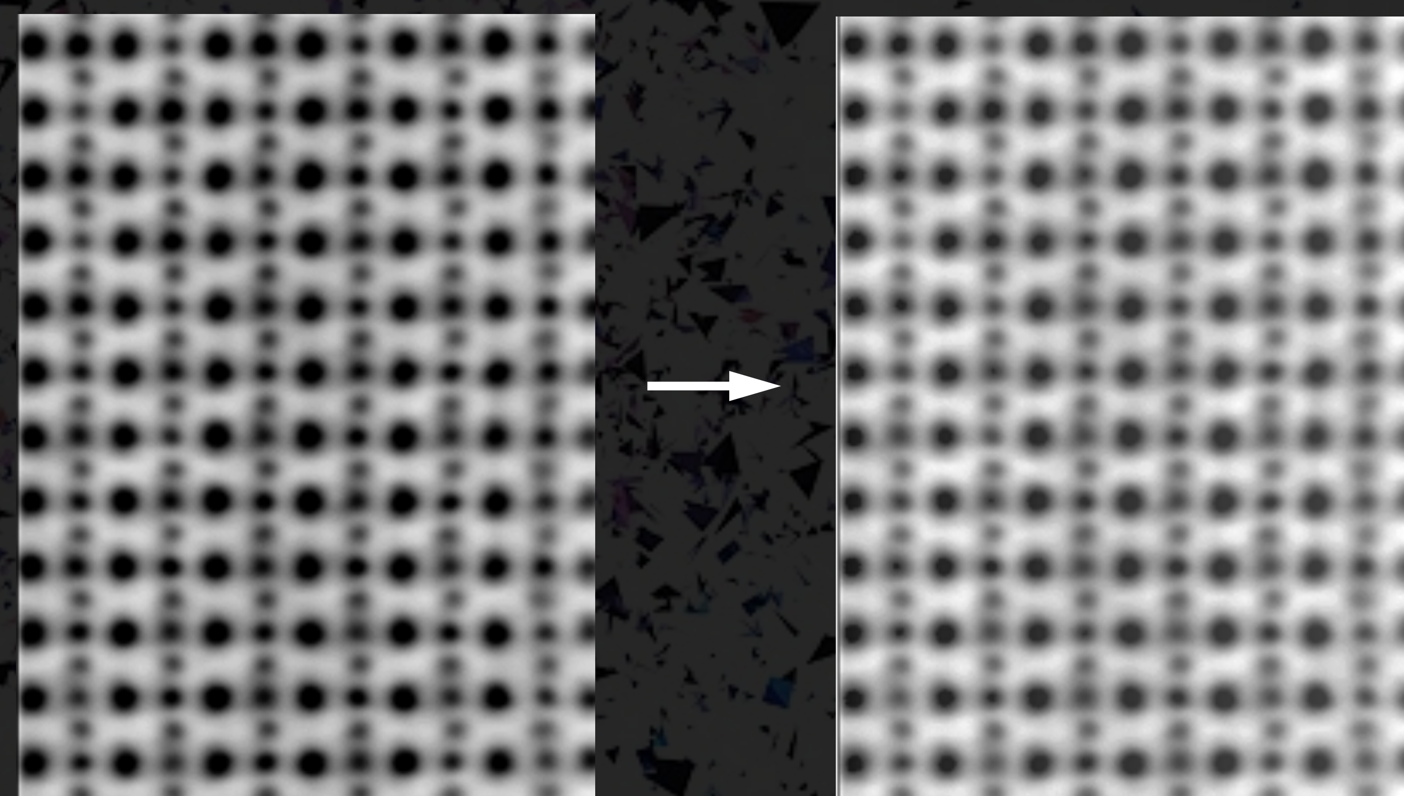
dark atom



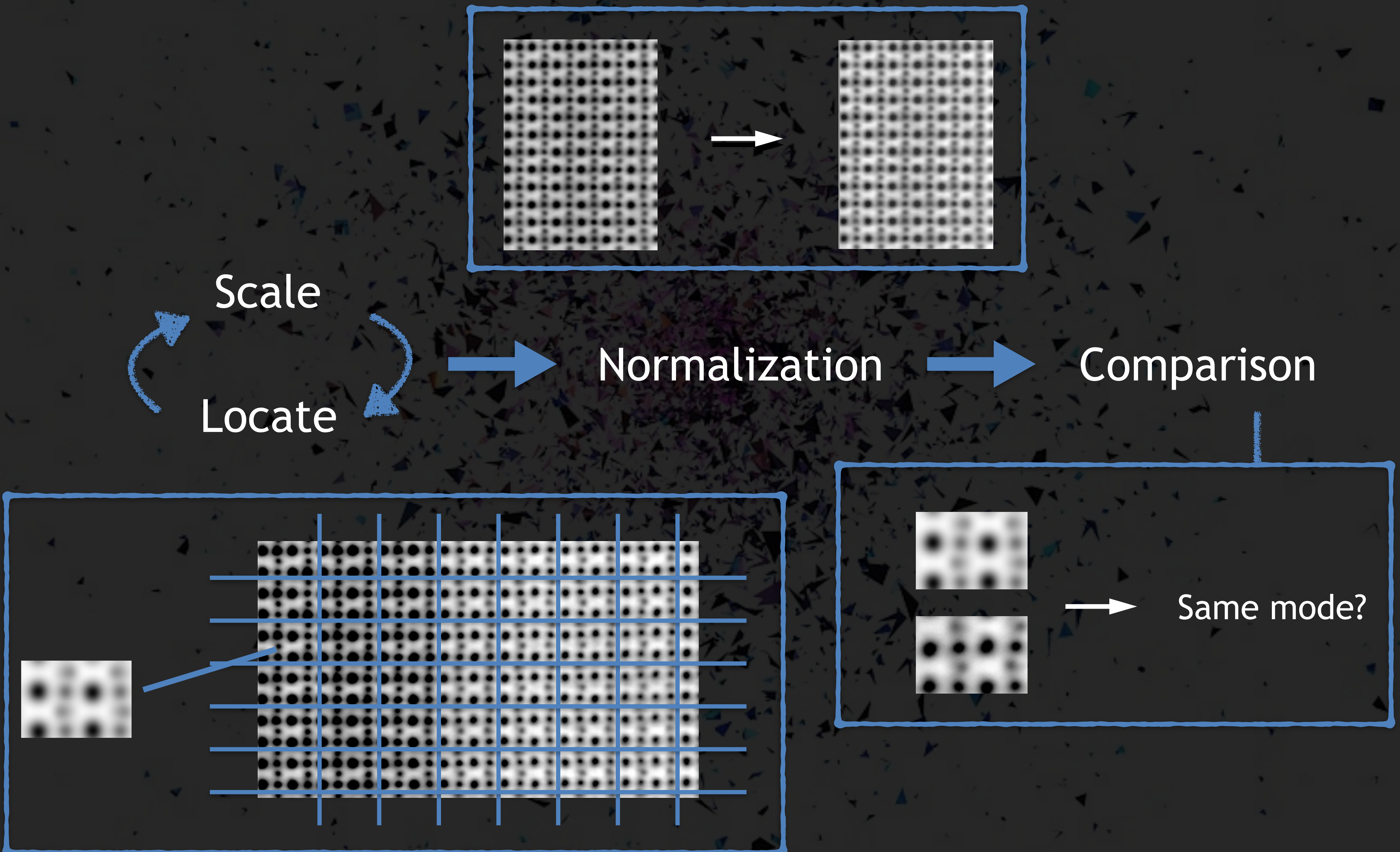
normal atom

Workflow

Normalization

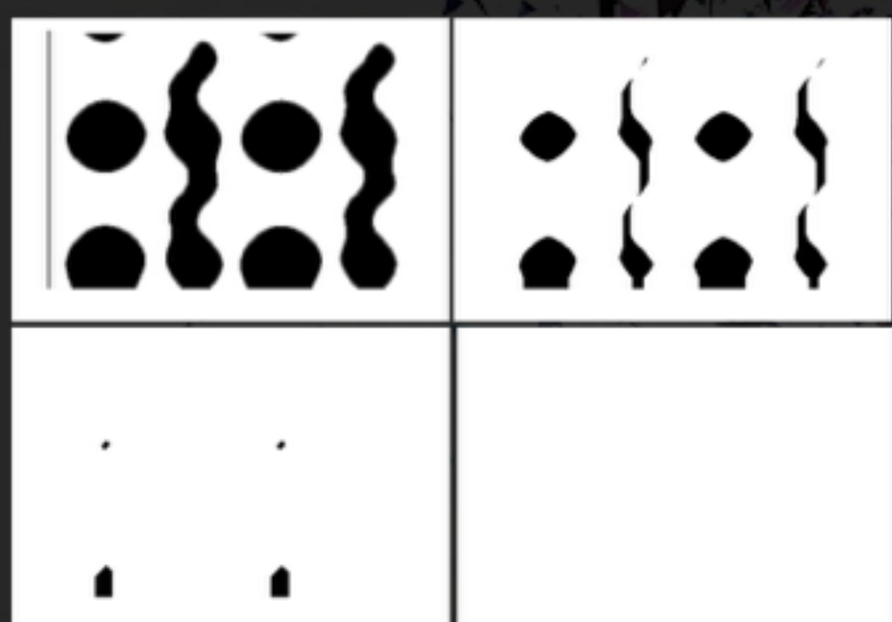


Workflow

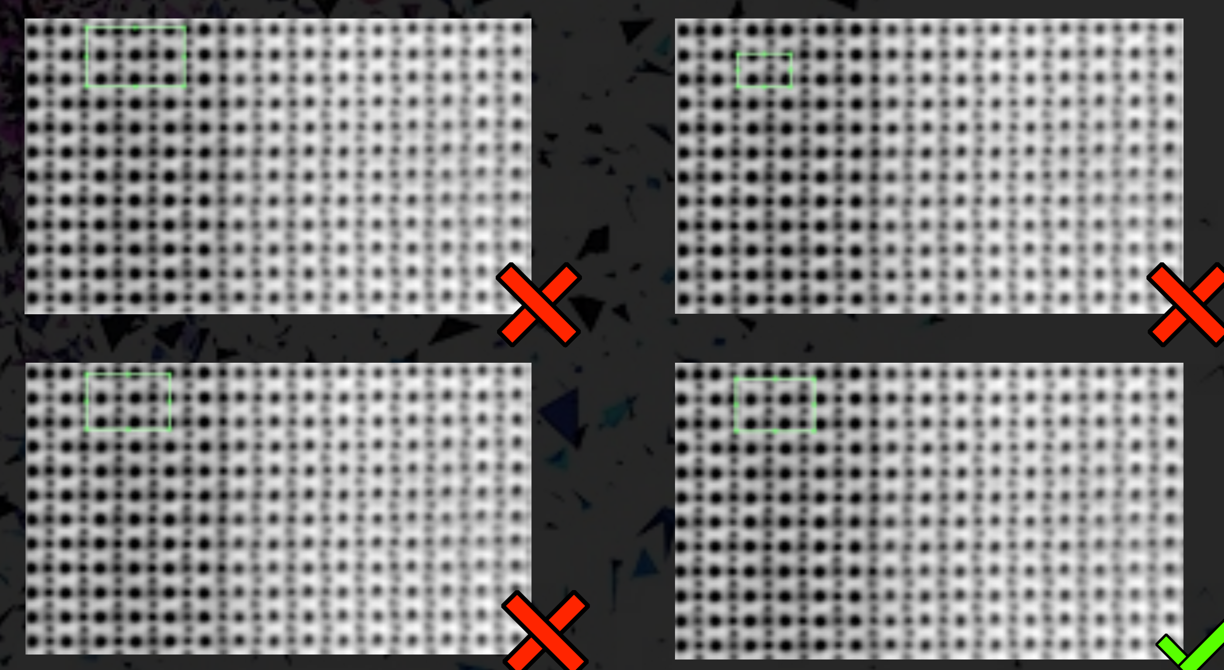


Algorithm

Scale + Locate



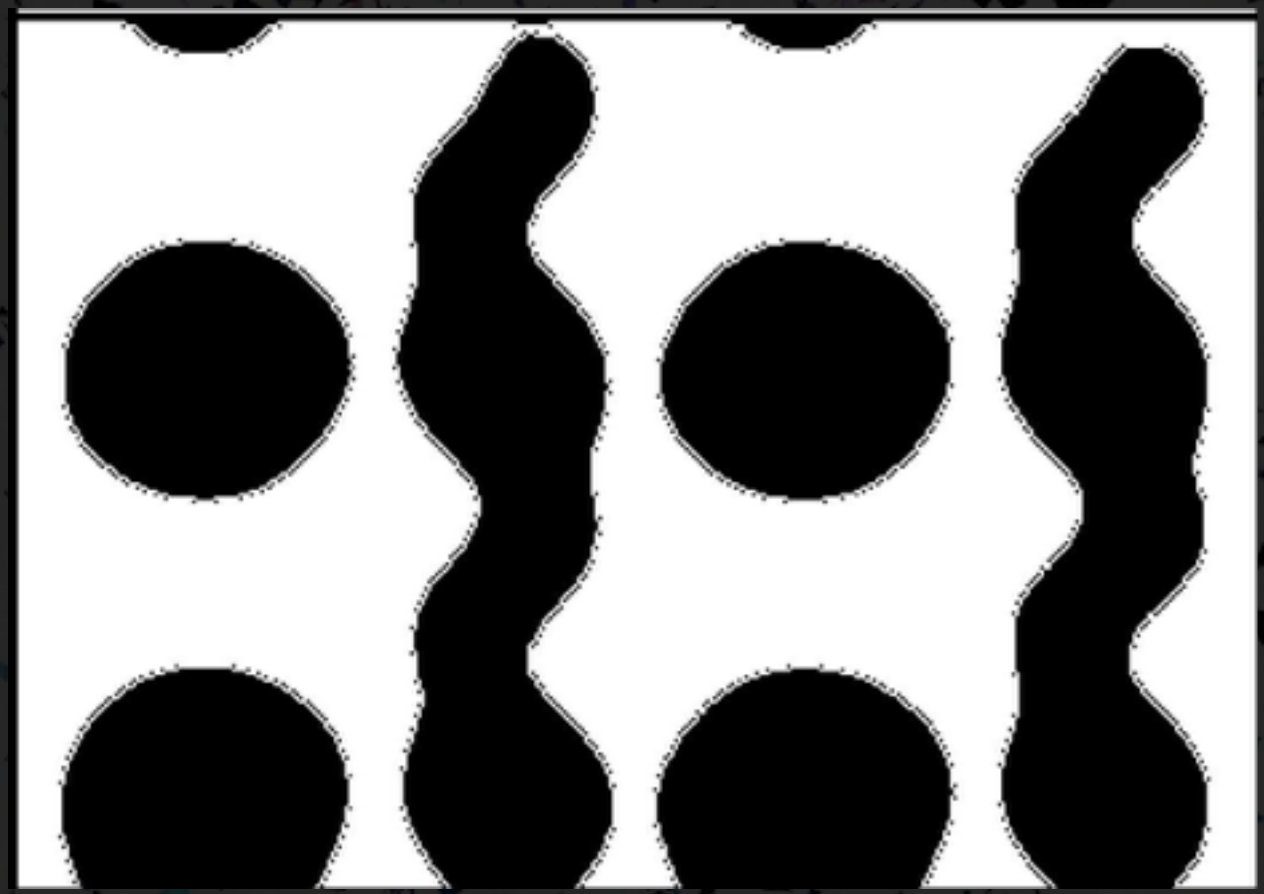
‘Eating from Outside’



‘Brute Force Search’

Algorithm

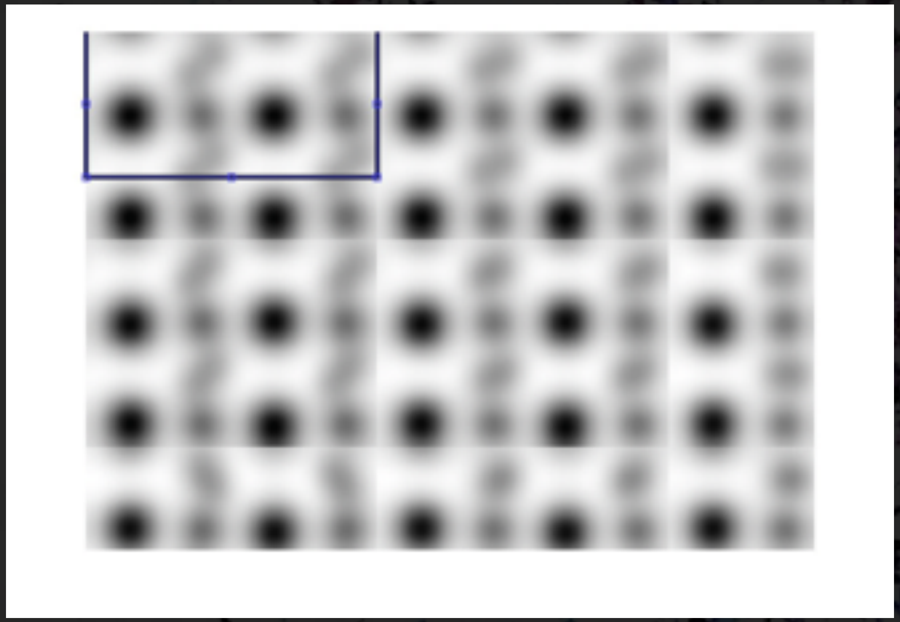
Step 1 : Eating from outside

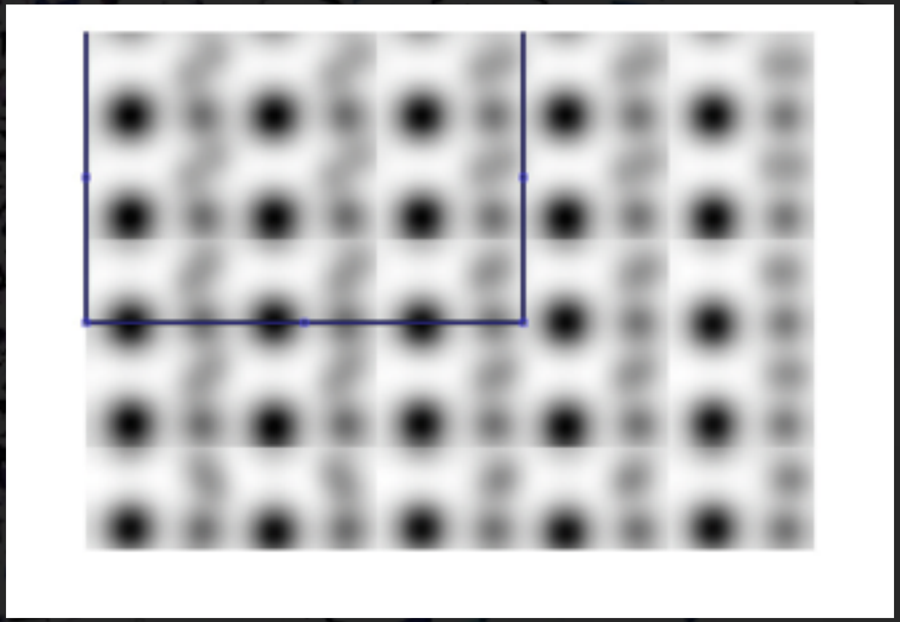


When we do this to both the dictionary item and microscopy image, we get an approximated ‘time’

Algorithm

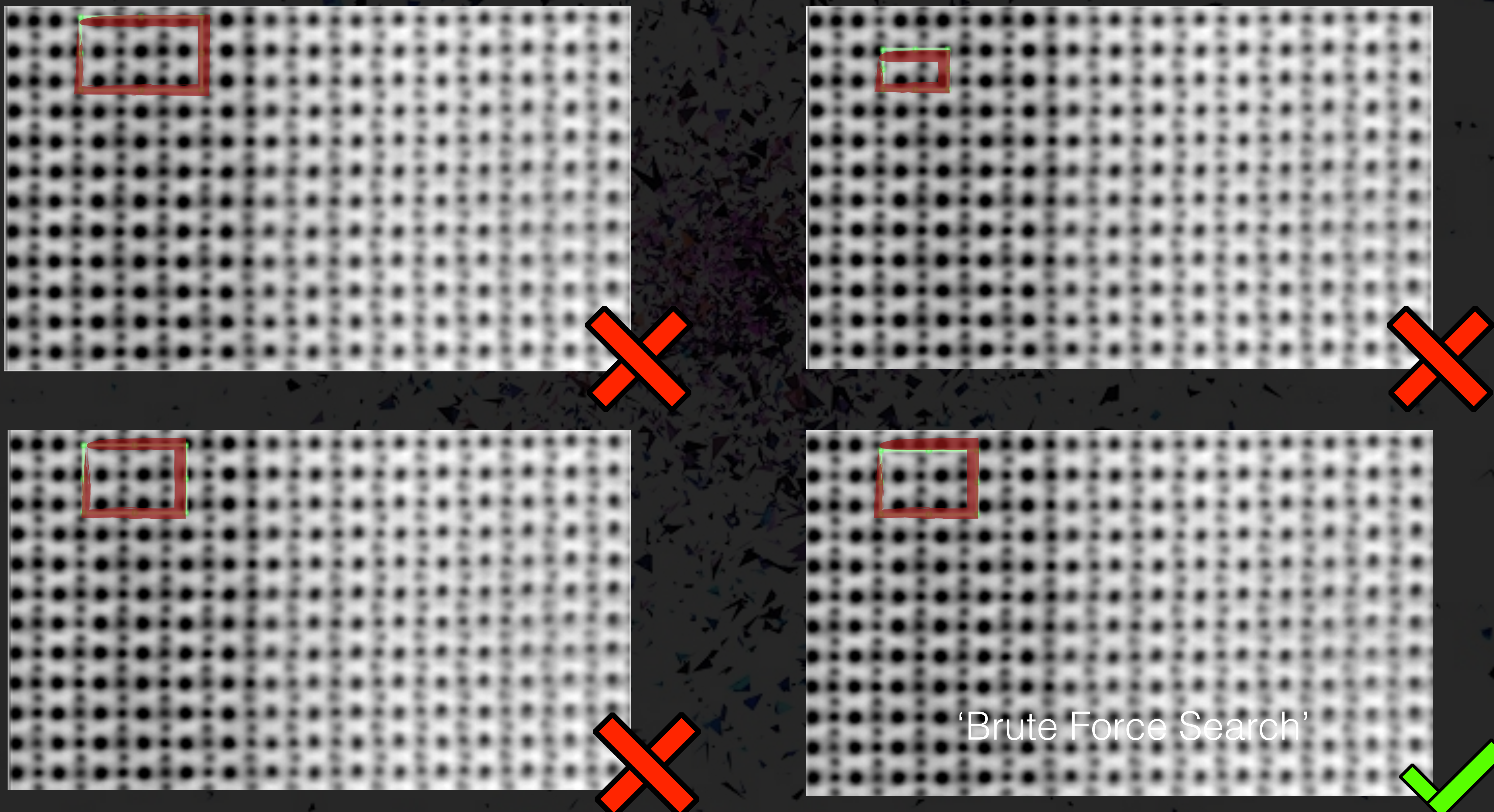
Step 2 : Brute force search





Algorithm

Step 2 : Brute force search



Algorithm

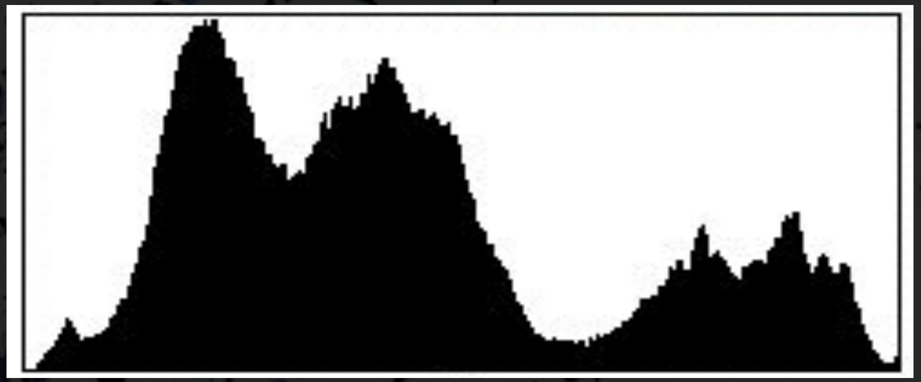
Normalization

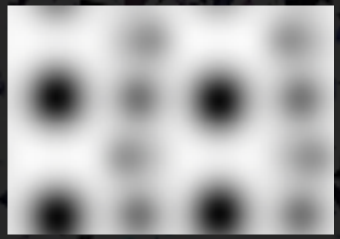
In grayscale images, ‘colors’ are represented by ‘intensity’, from 0 (white) to 255 (black), thus each grayscale image has an **intensity distribution**.

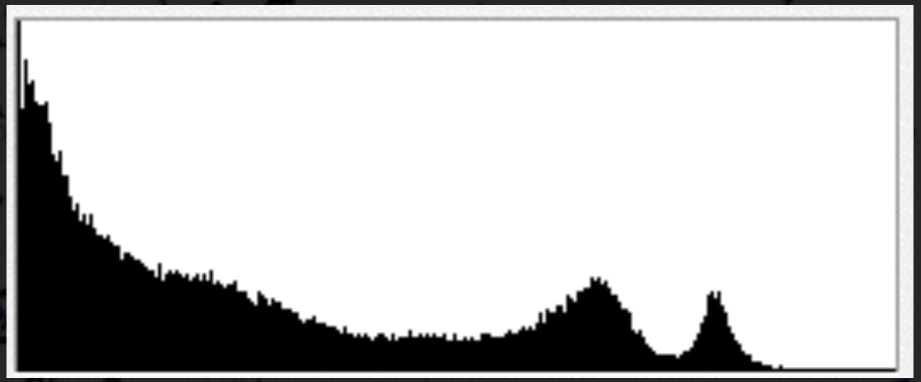
Algorithm

Normalization

The differences in **contrast and brightness** are actually differences in the **intensity distribution**!

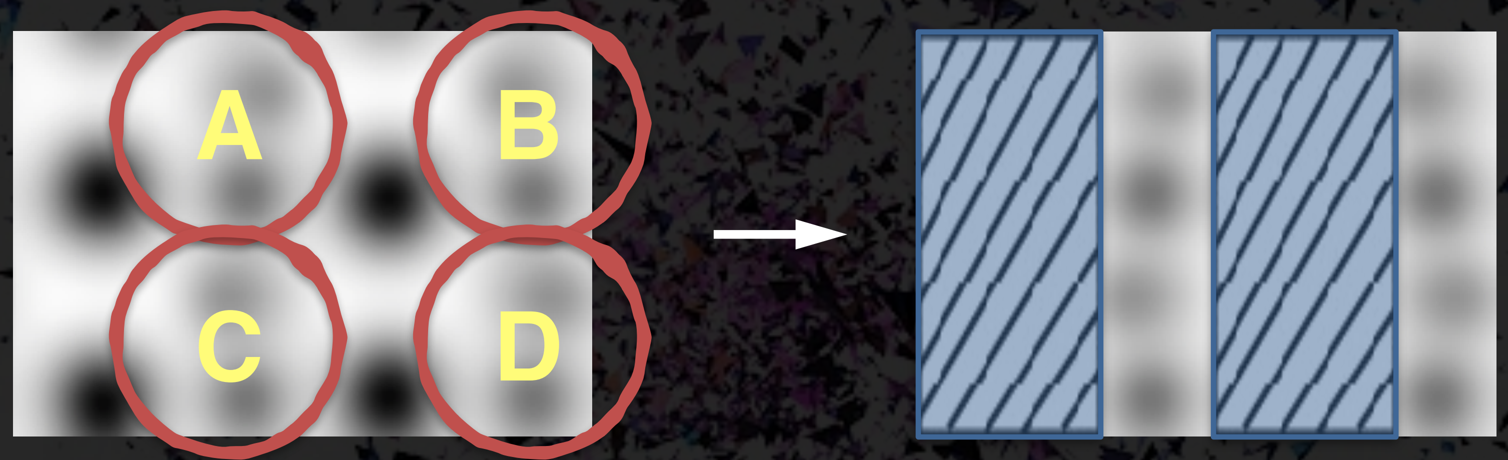






Algorithm

Comparison



Since we are **only concerned** about the subtle differences in the **circled area**, we use a **mask** to shade the cores and will **NOT** take them into consideration for final comparison.

Algorithm

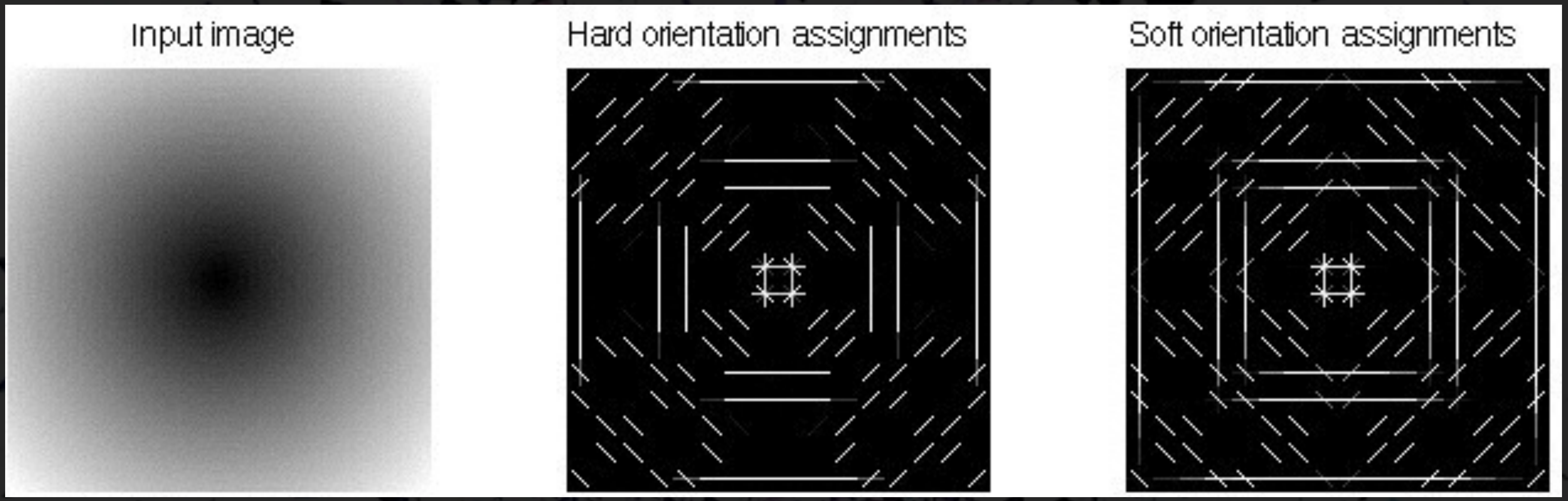
Comparison

How to **summarize** the concerned images with effective **features**?

HOG (Histogram of Oriented Gradients) comes in.

Algorithm

Comparison



HOG:

1. **Divide** an image into smaller patches
2. Calculate the **gradients** at each pixel
3. Generate a **feature vector** of gradients distribution for each small patch

Algorithm

Comparison

$$r_{xy} = \frac{\sum_{i=1}^{n}(x(i)-\bar{x})(y(i)-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x(i)-\bar{x})^2 \sum_{i=1}^{n}(y(i)-\bar{y})^2}}$$

Cross Correlation

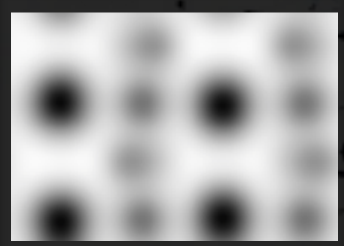
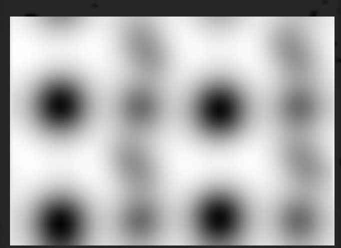
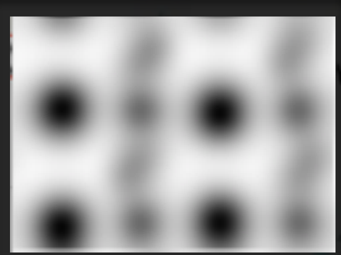
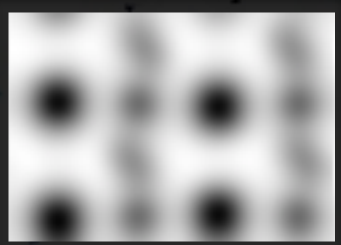
Use the cross correlation of HOG feature vectors to **represent** the **similarity** between two images.

PROBLEM: **'gap'** too small between **'similar'** and **'dissimilar'!**

Algorithm

Comparison

Dictionary

	mode 1
	mode 2
	mode 3
	mode 4

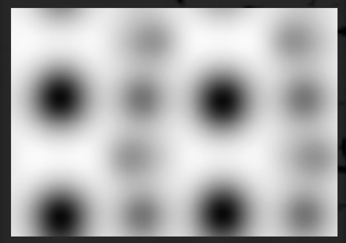
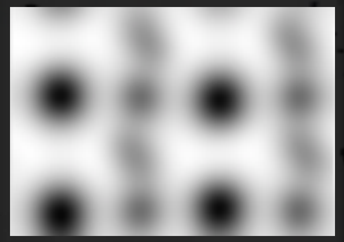
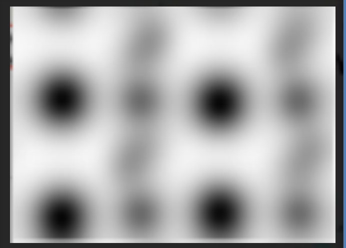
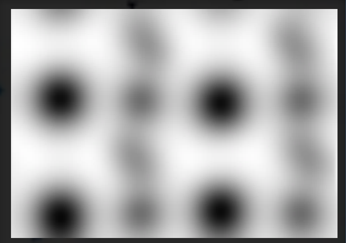
Items are **so similar** that the cross correlations nearly all **above 0.75**. Items from **different** modes can even have cross correlation as high as **0.88**.

distance = 1- cc

Algorithm

Comparison

Dictionary

	mode 1
	mode 2
	mode 3
	mode 4

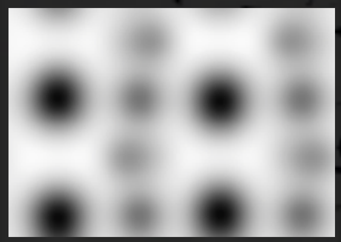
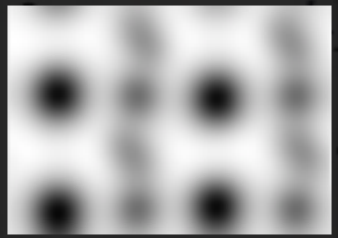
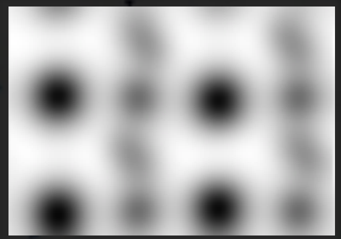
Items are **so similar** that the cross correlation nearly all **above 0.75**. Items from **different** modes can even have cross correlation as high as **0.88**.

cc:
Same mode: 0.92
Different modes: 0.88

Algorithm

Comparison

Dictionary

	mode 1
	mode 2
	mode 3
	mode 4

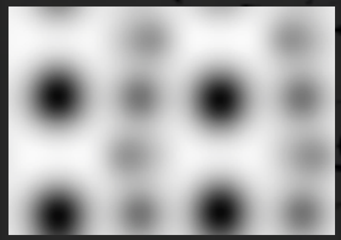
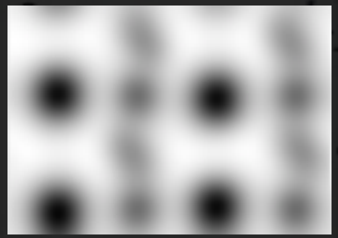
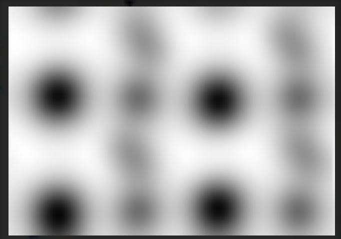
Items are **so similar** that the cross correlation nearly all **above 0.75**. Items from **different** modes can even have cross correlation as high as **0.88**.

distance:
Same mode: 0.08
Different modes: 0.12

Algorithm

Comparison

Dictionary

	mode 1
	mode 2
	mode 3
	mode 4

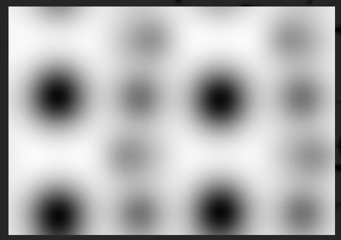
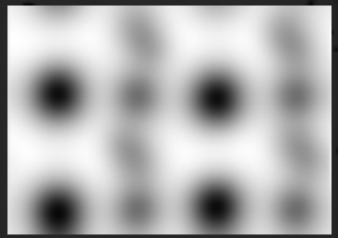
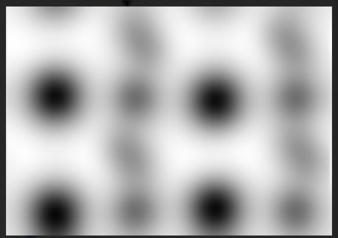
Items are **so similar** that the cross correlation nearly all **above 0.75**. Items from **different** modes can even have cross correlation as high as **0.88**.

$$1 - 0.92*0.92 = 0.154$$
$$1 - 0.88*0.88 = 0.226$$

Algorithm

Comparison

Dictionary

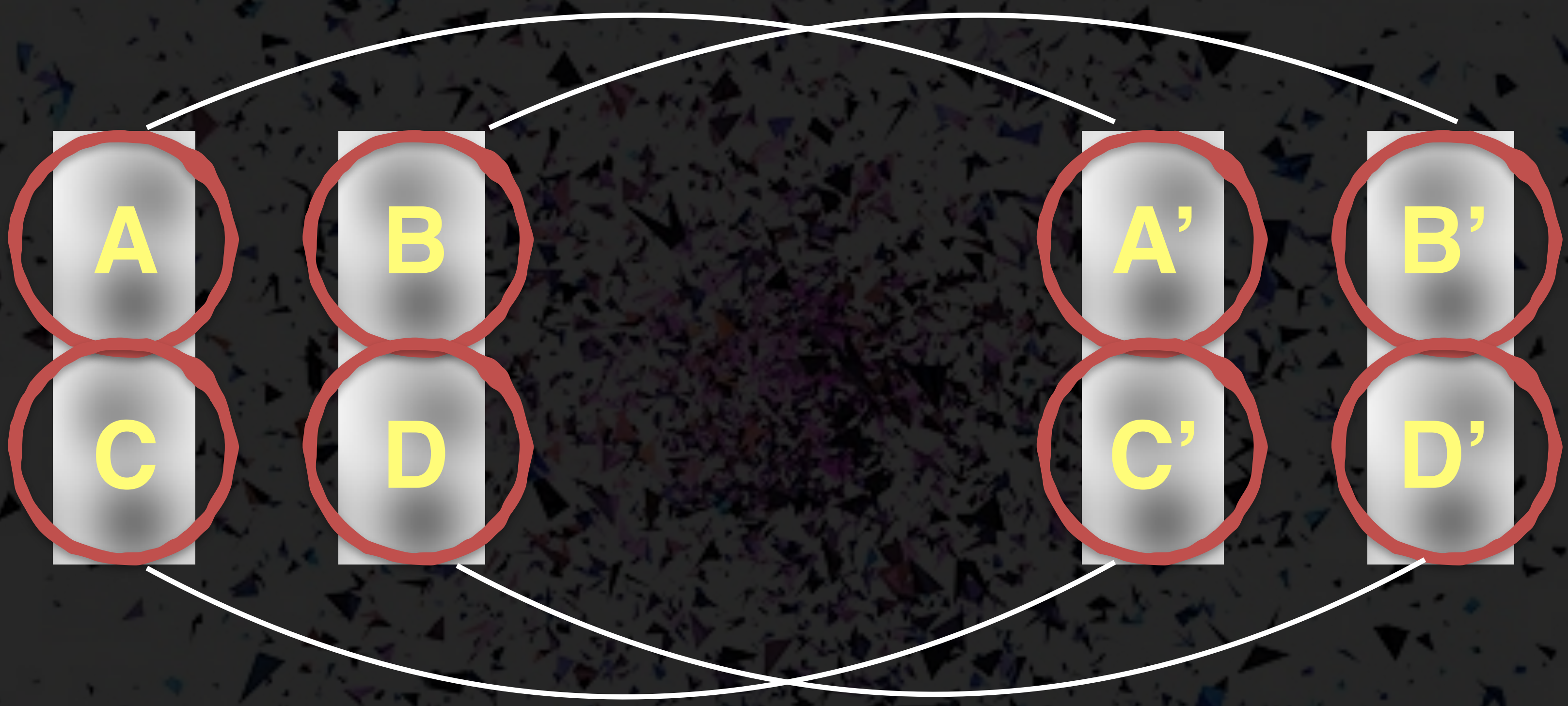
	mode 1
	mode 2
	mode 3
	mode 4

Items are **so similar** that the cross correlation nearly all **above 0.75**. Items from **different** modes can even have cross correlation as high as **0.88**.

$$(1 - 0.92)^2 = 0.0064$$
$$(1 - 0.88)^2 = 0.0144$$

Algorithm

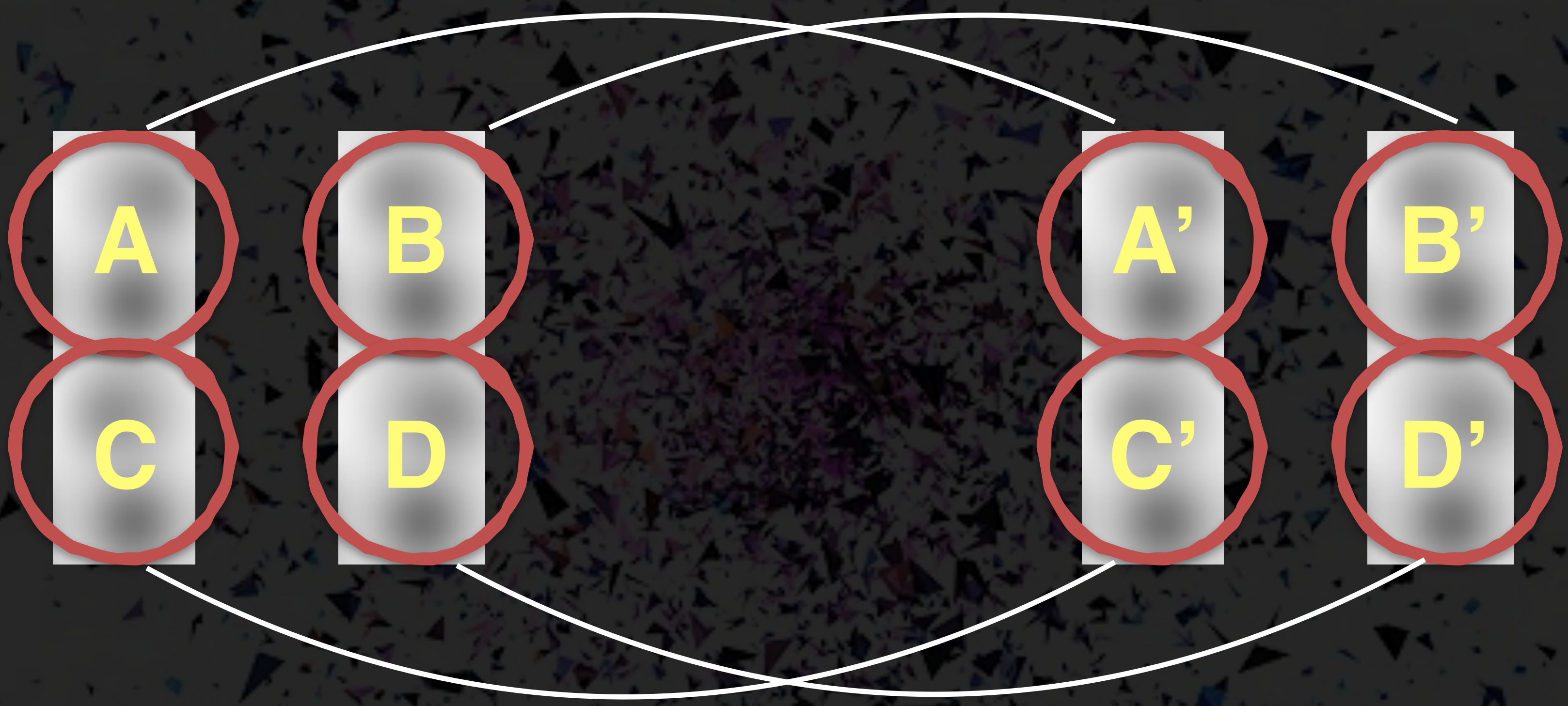
Comparison



$$10000 \times (1 - cc(A, A'))(1 - cc(B, B'))(1 - cc(C, C'))(1 - cc(D, D'))(1 - cc(A, A')cc(B, B')cc(C, C')cc(D, D'))$$

Algorithm

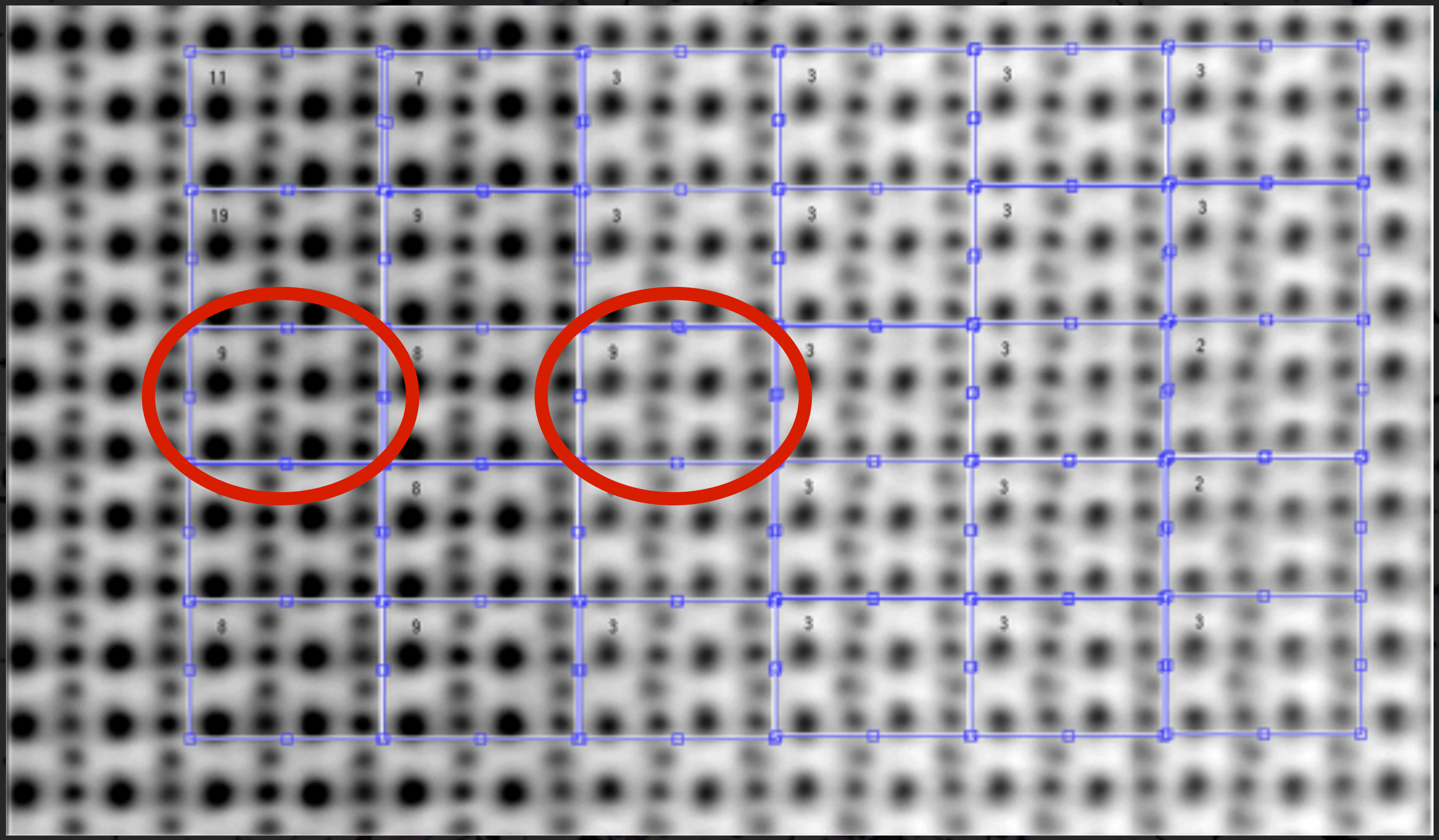
Comparison



Assume cc = **0.92** and **0.88** for all parts.

Using cc only once we get distances: **0.08** and **0.12**
Using our formula we get distances: **0.12** and **0.83**

Current Outcome



The numbers at the corner of each unit stands for the dictionary item it is matched to.

On average our algorithm takes 110s to run on a MacBook Air (1.8 GHz Intel Core i5, 4 GB 1600 MHz DDR3) for a dictionary of size 25 and a microscopy of size 30 (items). A more detailed complexity analysis will be included in our final

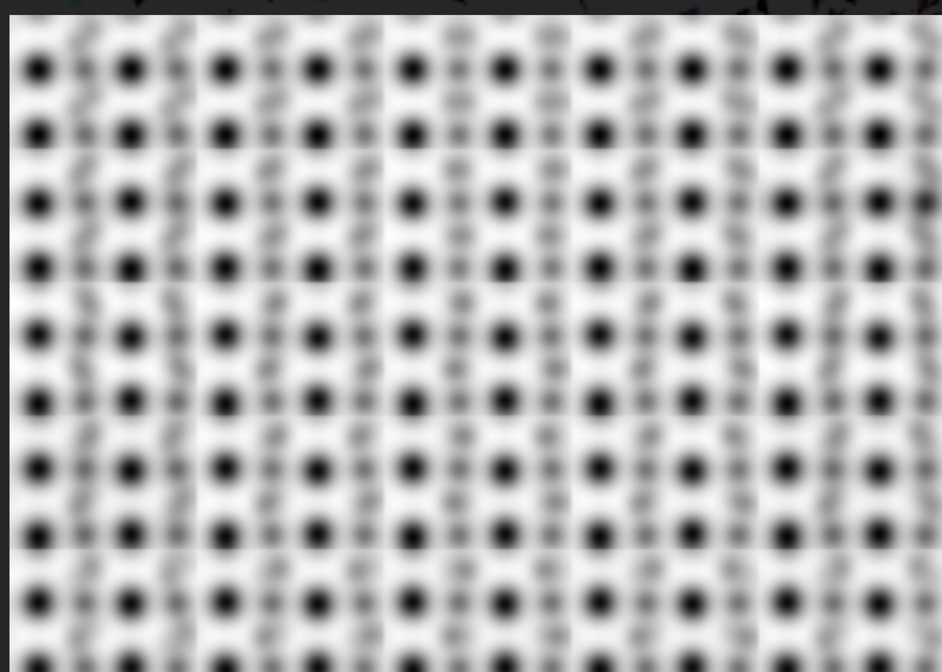
Improvements

Divide the dictionary into subgroups

Divide the dictionary into **subgroups** using **k-means**, and label each atom with a **signature** of the group; then just pick the best group match first

Improvements

Original Dictionary



Categorized Dictionary
(Partial)

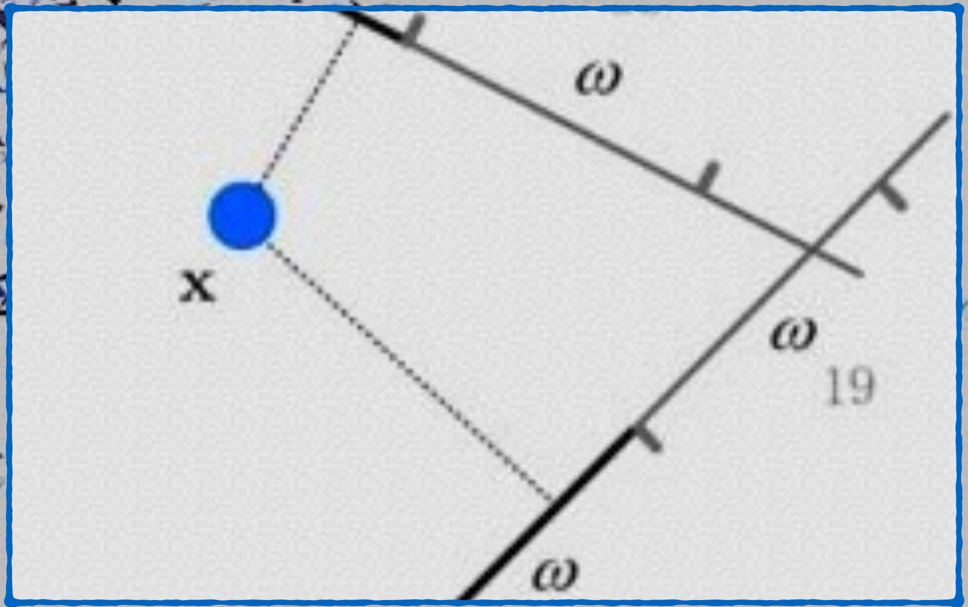
k-means + sampling

Future Work

- Accuracy: Machine Learning

- Compatibility: C/C++ platform

- Performance: LSH (Locality-Sensitive Hashing)



Q & A