

## Geometric Pattern Mining using the MDL Principle

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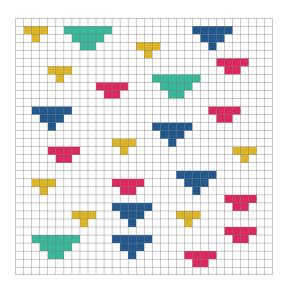
LIACS, Leiden University, Leiden, the Netherlands

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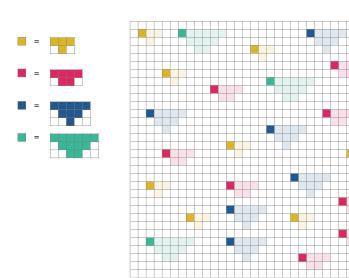


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# Minimum Description Lengtl



Idea: the best solution is a balance of model and instantiation complexity, given by:

$$L(H) + L(A|H)$$
Model Data given model

In this case:



### Model and Instantiation Matrix



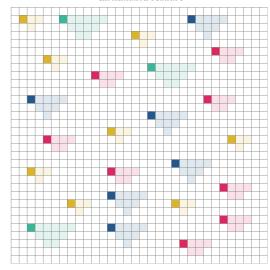


$$L(H) = 887$$

L(I) = 30

Compression: 89.5%

#### Instantiation Matrix I



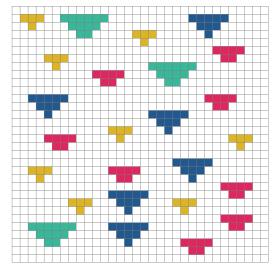






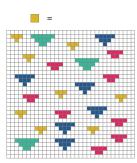
L(H) = 4 L(I) = 1024Ratio: 100.4%

#### Instantiation Matrix I



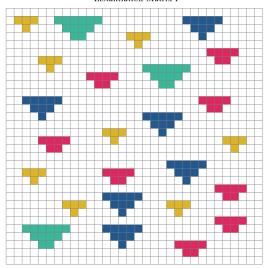


#### Model H

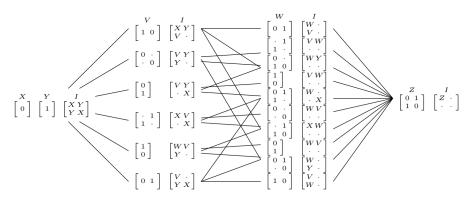


L(H) = 1024 L(I) = 1Ratio: 100.1%

#### Instantiation Matrix I



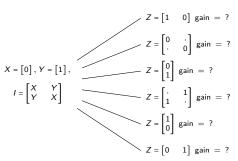




Model space lattice for a 2  $\times$  2 Boolean matrix. The V, W, and Z columns show which pattern is added in each step, while I depicts the current instantiation.



Candidates are generated by enumerating all combinations of two adjacent patterns that occur in the instantiation matrix.





$$\underbrace{\Delta L(A',c)}_{\text{Gain}} = \underbrace{\left(L_1(H') + L_2(I')\right)}_{\text{New Lengths}} - \underbrace{\left(L_1(H) + L_2(I)\right)}_{\text{Old Lengths}}$$

 $L_1$  and  $L_2$  are independent length functions that compute the length of the model and the instantiation, respectively.

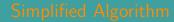
Please see the paper for more information on the encoding scheme.



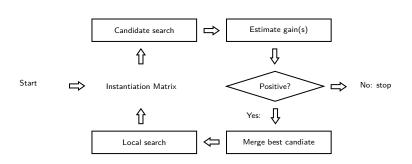
We can construct complex patterns by repeatedly combining simpler ones. We use instances for this as they encode the position of one pattern relative to another.

$$X = \begin{bmatrix} 0 \end{bmatrix} \qquad \qquad \bar{X} = \begin{bmatrix} \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{bmatrix} \longrightarrow \bar{X} + \bar{Y} = \begin{bmatrix} \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot \\ \cdot & 1 & \cdot \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & \cdot \\ \cdot & 1 & \cdot \\ \cdot & 1 & \cdot \end{bmatrix}$$
Candidate patterns
$$\bar{X} = \begin{bmatrix} \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot \\ \cdot & 1 & \cdot \end{bmatrix} \longrightarrow \bar{X} + \bar{Y} = \begin{bmatrix} \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot \\ \cdot & 1 & \cdot \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & \cdot \\ \cdot & 1 \end{bmatrix}$$
New pattern

Instances









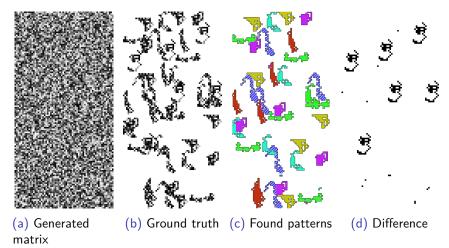
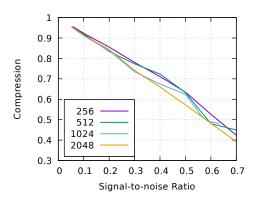


Figure: Synthetic patterns are added to a matrix filled with noise. The difference between the ground truth and the matrix reconstructed by the algorithm is used to compute precision and recall.





Results for different square matrices (256  $\times$  256 to 1024  $\times$  1024). Signal-to-noise ratio is computed as  $\frac{\text{signal}}{\text{signal+noise}}.$ 

### Geometric Pattern Mining using the MDL principle

The article was published at the Symposium on Intelligent Data Analysis (IDA) 2020

Archive link: http://arxiv.org/abs/1911.09587

Code repository: https://github.com/mickymuis/libvouw

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Thank you for watching!