# Boolean Matrix Decomposition by Formal Concept Sampling 

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## Boolean Matrix Decomposition

:: method for analysis of Boolean data
:: general aim: for a given matrix $I \in\{0,1\}^{n \times m}$ find matrices $A \in\{0,1\}^{n \times k}$ and $B \in$ $\{0,1\}^{k \times m}$ for which $I$ (approximately) equals $A \circ B$
:: ○ is the Boolean matrix product

$$
(A \circ B)_{i j}=\max _{l=1}^{k} \min \left(A_{i l}, B_{l j}\right) .
$$

$$
\left(\begin{array}{l}
10111 \\
01101 \\
01001 \\
10110
\end{array}\right)=\left(\begin{array}{l}
110 \\
011 \\
001 \\
100
\end{array}\right) \circ\left(\begin{array}{l}
10110 \\
00101 \\
01001
\end{array}\right)
$$

:: discovery of $k$ factors that exactly or approximately explain the data
:: factors $=$ interesting patterns (rectangles) in data

## Formal Concept Analysis

:: $n \times m$ matrix $I \rightarrow$ formal context $(\{1, \ldots, n\},\{1, \ldots, m\}, J)$ with $(x, y) \in J$ iff $I_{x y}=1$
:: formal context induces a pair of operators ${ }^{\uparrow}: 2^{X} \rightarrow 2^{Y}$ and ${ }^{\downarrow}: 2^{Y} \rightarrow 2^{X}$ defined by

$$
\begin{aligned}
& D^{\uparrow}=\{y \in\{1, \ldots, m\} \mid \text { for all } x \in D:(x, y) \in J\} \\
& E^{\downarrow}=\{x \in\{1, \ldots, n\} \mid \text { for all } y \in E:(x, y) \in J\}
\end{aligned}
$$

:: formal concept $\langle D, E\rangle$, where $D \subseteq\{1, \ldots, n\}, E \subseteq\{1, \ldots, m\}, D^{\uparrow}=E, E^{\downarrow}=D$
:: set of all formal concepts $\mathcal{B}(I)$ can be ordered by $\preceq$ defined by $\langle D, E\rangle \preceq\left\langle D^{\prime}, E^{\prime}\right\rangle$ iff $D \subseteq D^{\prime}$ (or equivalently $E^{\prime} \subseteq E$ ), moreover forms complete lattice

Formal Concepts as Factors

| $a$ | $b$ | $c$ | $d$ | $e$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 |  |  |  |  |
| 2 |  |  |  |  |
| 3 |  |  |  |  |
| 4 |  |  |  |  |
| 5 | $\left(\begin{array}{llllll}1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1\end{array}\right)$ |  |  |  |



## GreCon Algorithm

:: the simplest algorithm for BMD
:: Belohlavek, R., Vychodil, V.: Discovery of optimal factors in binary data via a novel method of matrix decomposition. J. Comput. Syst. Sci. 76, 1 (2010), 3-20.
:: reduction BMD to Set-Cover problem.

```
procedure GRECON(I)
```

    \(U \leftarrow I\)
    \(\mathcal{F} \leftarrow \emptyset\)
    Compute the set \(\mathcal{B}(I)\) of all formal concepts of \(I\)
    while there is a 1 in \(U\) do
            find \(\langle D, E\rangle \in \mathcal{B}(I)\) that covers the most 1 s in \(U\)
            add \(\langle D, E\rangle\) to \(\mathcal{F}\)
            for \((i, j) \in D \times E\) do
            \(U_{i j} \leftarrow 0\)
        \(t \leftarrow 1\)
        for \(\langle D, E\rangle \in F\) do
            set \(A_{t}\) to the characteristic vector of \(D\)
            set \(B_{t_{-}}\)to the characteristic vector of \(E\)
            \(t \leftarrow t+1\)
    return \(A, B\)
    
## Formal Concept Sampling

:: Metropolis-Hastings algorithm
:: Boley, M., Gartner, T., Grosskreutz, H.: Formal Concept Sampling for Counting and Threshold-Free Local Pattern Mining. In Proceedings of the SIAM International Conference on Data Mining, SDM 2010, 1770-188, 2010.
:: algorithm moves from one formal concept to another formal concept in $\mathcal{B}(I)$
:: $f$ assigning to a formal concept a nonzero value
:: formal concept $\langle D, E\rangle$ is drawn with probability $\frac{f(\langle D, E\rangle)}{\sum f\left(\left\langle D^{\prime}, E^{\prime}\right\rangle\right)}$
:: the logarithmic number iterations is sufficient

## New Algorithm

:: modification of GreCon
:: $f$ takes into account the number covered 1 s

## Experimental evaluation

:: sets of $1000 \times 500$ matrices with various properties
:: real-world data
:: GreCon is outperformed by the probabilistic algorithm
:: increase in the number trials increases the coverage quality
:: sparser data usually require less trials

Synthetic Data (Selected Results)

| 5 | 10 | 15 | 20 | 25 | 30 | 35 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |

GreCon 0.2990 .5110 .6860 .8220 .9231 .0001 .000 25 trials $\begin{array}{llllllll} & 0.283 & 0.499 & 0.675 & 0.813 & 0.921 & 0.990 & 1.000\end{array}$ 50 trials $\begin{array}{lllllllll}0.293 & 0.510 & 0.685 & 0.824 & 0.932 & 0.999 & 1.000\end{array}$ 75 trials $\quad 0.2960 .5100 .686 \quad 0.825 \quad 0.9320 .9991 .000$ 100 trials 0.2990 .5110 .6870 .8260 .9331 .0001 .000
Table 1: Coverage quality of the first $l$ rectangles on Set A

| 5 | 10 | 15 | 20 | 25 | 30 | 35 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |

GreCon $0.2620 .4620 .620 \quad 0.7550 .8771 .0001 .000$
25 trials $\begin{array}{llllllll}0.198 & 0.363 & 0.509 & 0.646 & 0.751 & 0.827 & 0.896\end{array}$ $\begin{array}{llllllllll}50 \text { trials } & 0.240 & 0.434 & 0.598 & 0.729 & 0.837 & 0.921 & 0.980\end{array}$ 75 trials $\quad 0.2530 .4400 .614 \quad 0.7530 .8720 .9540 .996$ $\begin{array}{llllllll}100 \text { trials } & 0.254 & 0.460 & 0.630 & 0.771 & 0.889 & 0.977 & 1.000\end{array}$

## Real Data (Selected Results)



Figure 1: Coverage quality of the first $l$ factors on DNA dataset

## Conclusion

:: new (probabilistic) BMD algorithm
:: new directions in BMD algorithm design

