

Generalized Matrix Factorizations

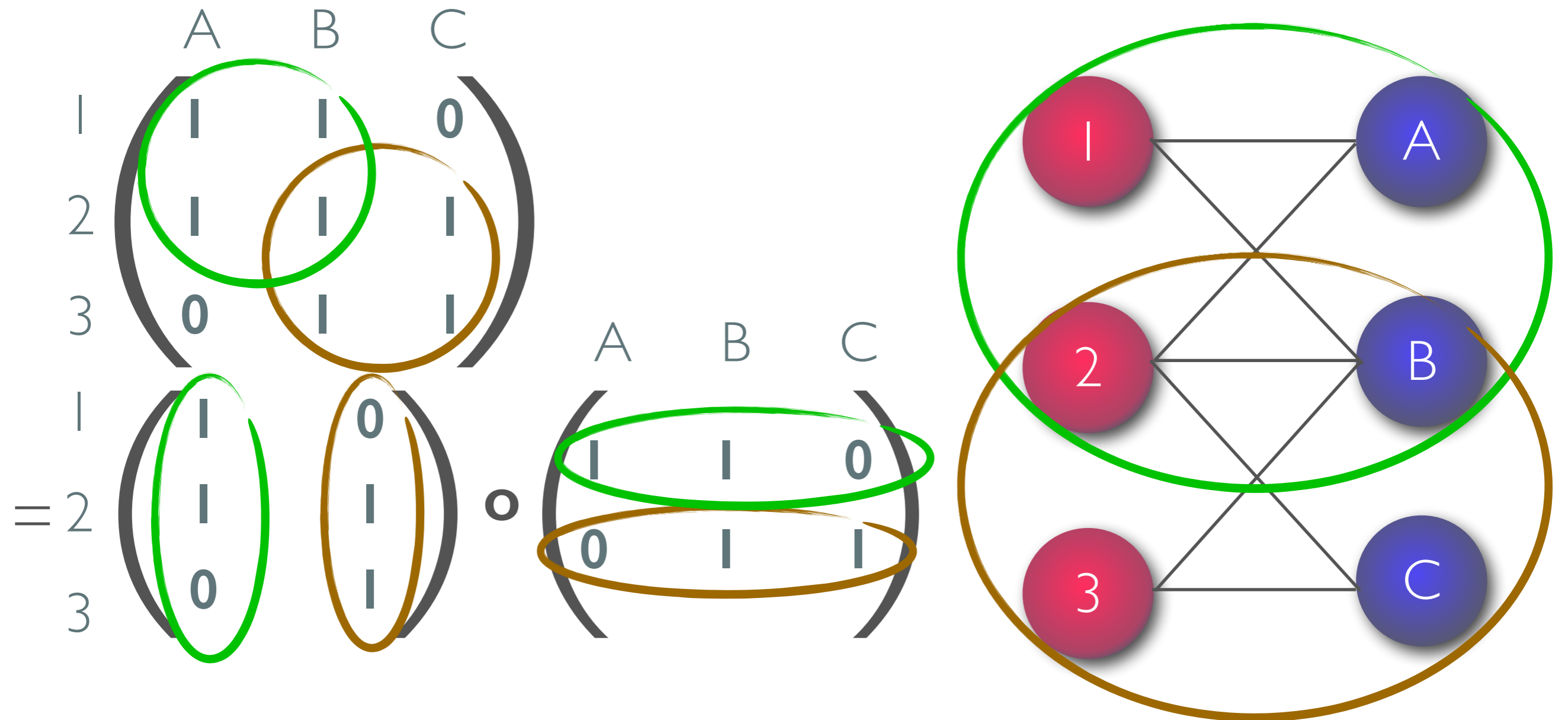
as a
Unifying Framework
for
Pattern Set Mining
Complexity Beyond Blocks

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10 September 2015



Community detection



Rank-1 matrices

- (Bi-)cliques are rank-1 submatrices
 - Collection of rank-1 submatrices summarizes the graph using its cliques
- Matrix factorizations express the (complex) input as a sum of rank-1 matrices

$$\bullet \mathbf{AB} = \mathbf{a}_1 \mathbf{b}_1^T + \mathbf{a}_2 \mathbf{b}_2^T + \cdots + \mathbf{a}_k \mathbf{b}_k^T$$

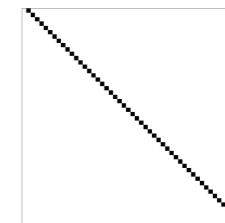
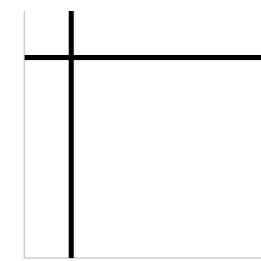
- Matrix factorizations summarize complex data using simple patterns

Beyond blocks

- Cliques are not the only (graph) patterns

- Biclique cores, stars, chains

- Koutra et al., SDM '14.



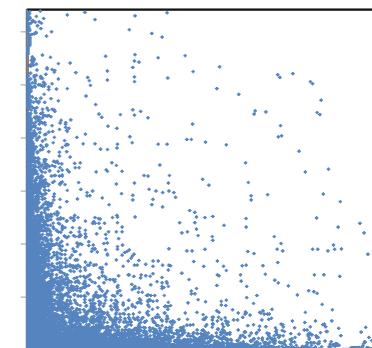
- Nested graphs

- e.g. Junttila '11, Kötter et al., WWW '15



- Hyperbolic communities

- Araujo et al., ECML PKDD '14

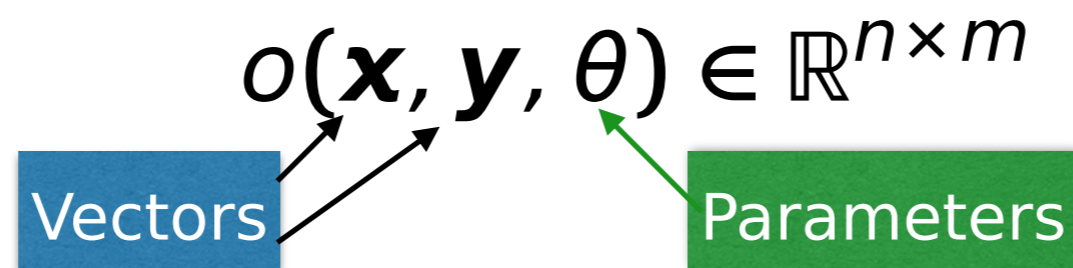


Limitations of matrix factorization

- The matrix-factorization language is useful
 - Recycle ideas, approaches, and results
- But the other patterns are not rank-1 matrices
 - It is not easy to express a collection of nested matrices as a matrix factorization

Generalized outer products

- Rank-1 matrix = outer product of two vectors
 - $\mathbf{A} = \mathbf{xy}^T$
- Define **generalized outer product**



- $o(\mathbf{x}, \mathbf{y}, \theta)_{ij} = x_i y_j$ or 0

Example: biclique core

$$O \left(\begin{matrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, [1 \ 1 \ 1 \ 1 \ 1], \{1, 2\} \end{matrix} \right) = \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Rows that belong
to the pattern

Columns that belong
to the pattern

The core

Example: nested matrix

$$o \left(\begin{array}{c} [1] \\ [1] \\ [1] \\ [0] \\ [1] \end{array}, [1\ 1\ 1\ 1\ 1], [1\ 2\ 2\ 5\ 6] \right) \stackrel{\text{Step function}}{=} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Generalized decompositions

- Recall, $\mathbf{X} \approx \mathbf{AB} = \mathbf{a}_1 \mathbf{b}_1^T + \mathbf{a}_2 \mathbf{b}_2^T + \cdots + \mathbf{a}_k \mathbf{b}_k^T$ is a decomposition of \mathbf{X}

- The **generalized decomposition** of \mathbf{X} is

$$\mathbf{X} \approx \mathbf{F}_1 \boxplus \mathbf{F}_2 \boxplus \cdots \boxplus \mathbf{F}_k, \quad \mathbf{F}_i = o(\mathbf{x}_i, \mathbf{y}_i, \theta_i)$$

- \boxplus is the addition in the underlying algebra
 - sum, AND, OR, XOR, ...

***o*-induced rank**

- The smallest k s.t. $\mathbf{X} = \mathbf{F}_1 \boxplus \dots \boxplus \mathbf{F}_k$ is the ***o*-induced rank** of \mathbf{X}
 - Analogous to the standard (Schein) rank
- Can be infinite if the matrix cannot be expressed (exactly) with that kind of outer products
 - If the outer product can generate a matrix that has exactly one nonzero at arbitrary position, it's induced rank is always bounded

Decomposability

- Outer product o is **decomposable** (to f) if, for some f , $o(\mathbf{x}, \mathbf{y}, \theta)_{ij} = f(x_i, y_j, i, j, \theta)$
- Then we have

$$x_{ij} = \bigoplus_{l=1}^k f(x_{il}, y_{lj}, i, j, \theta)$$

as in standard matrix multiplication

Nice work, but ... why?

- So, we can express complex patterns using some weird functions
- What's the advantage?
- Using the common language, it's easy to see how some results (and techniques) can be generalized as well

How hard can it be...

- ...to find the maximum-circumference pattern?
- I.e. given \mathbf{A} , find \mathbf{x} , \mathbf{y} , and θ s.t. $o(\mathbf{x}, \mathbf{y}, \theta) \in \mathbf{A}$ and you maximize $|\mathbf{x}| + |\mathbf{y}|$
 - If o is hereditary and the pattern can have infinitely many distinct rows and columns, NP-hard
 - If there's only fixed number of distinct rows or columns, the problem is in P
 - If $\mathbf{x} = \mathbf{y}$ is required, then it's almost always NP-hard

How hard can it be...

- ...to select the smallest subset that gives an exact summarization?
- I.e. given a set $S = \{\mathbf{F}_i : \text{rank}(\mathbf{F}_i) = 1\}$,
 $\boxplus_{\mathbf{F} \in S} \mathbf{F} = \mathbf{X}$, find the the smallest $C \subseteq S$ s.t.
 $\boxplus_{\mathbf{F} \in C} \mathbf{F} = \mathbf{X}$
 - NP-hard for $\boxplus \in \{\text{AND}, \text{OR}, \text{XOR}\}$
 - hard to approximate within $\ln(n)$ for OR and within superpolylogarithmic for XOR

How hard can it be...

- ...to compute the rank?
- Well, that depends... (on the underlying algebra)
- Doesn't depend (only) on the outer product
 - E.g. normal outer product is NP-hard for OR but in P for XOR

How hard can it be...

- ...to find the decomposition of fixed size that minimizes the error?
- NP-hard if computing the rank is
- NP-hard to approximate to within superpolylogarithmic factors for OR and XOR

Conclusions

- Matrix factorizations are sort-of mixture models
 - Present complex data as an aggregate of simpler parts
- Generalized outer products let us represent more than just cliques as "rank-1" matrices
 - And allow to generalize many results from cliques

Future

- More work is needed to see what is the correct level of generality for the outer products
- Results for numerical data?
- Framework with no users isn't very useful...

Thank You!

Questions?