Hands-on `scikit-network`
A Python Package for Graph Analysis

Thomas Bonald, Tiphaine Viard

Graph Embedding and Mining workshop @ ECML-PKDD
September 2021

Tutorial outline

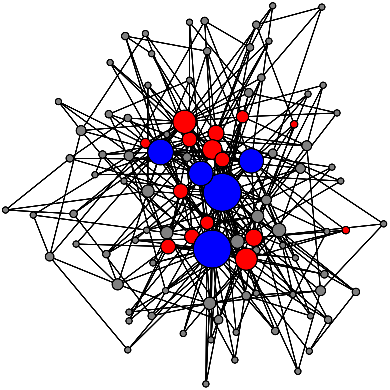
09:50 - 10:00	Opening
10:00 - 11:30	**Data structures, manipulation, simple tasks** *Tiphaine Viard*
11:30 - 11:45	Coffee break
11:45 - 12:45	**Analysis of the Wikipedia "vital articles" graph** *Thomas Bonald*
12:45 - 13:00	Concluding Remarks

All material on
`https://gem-ecmlpkdd.github.io/program/`

Graph data

Graphs
Social networks
Web graphs
Knowledge graphs

Bipartite graphs
User $\leftrightarrow$ Product
Actor $\leftrightarrow$ Movie
Deputy $\leftrightarrow$ Bill
Document $\leftrightarrow$ Word
Patient $\leftrightarrow$ Med



(Bi-)adjacency matrix

Graphs
Social networks
Web graphs
Knowledge graphs

Bipartite graphs
User ↔ Product
Actor ↔ Movie
Deputy ↔ Bill
Document ↔ Word
Patient ↔ Med

$$A = \begin{bmatrix} & 1 & & & 1 \\ 1 & & & & \\ & & & 1 & \\ & & 1 & & \\ 1 & & & & \end{bmatrix}$$

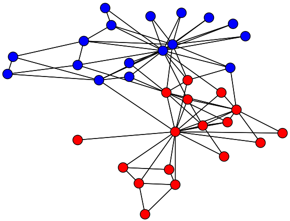
$$B = \begin{bmatrix} & 1 & & & 1 & & 1 & & \\ 1 & & & & & & & 1 & \\ 1 & & & & 1 & & & & \end{bmatrix}$$

Sparse data

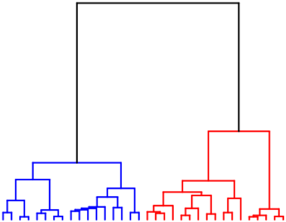
Graph	#nodes	#edges	Density
Openflights	2,939	30,500	$\approx 10^{-3}$
WordNet	146k	657k	$\approx 10^{-5}$
Wikipedia	12M	378M	$\approx 10^{-6}$
Twitter	42M	1.5G	$\approx 10^{-6}$
Friendster	68M	2.5G	$\approx 10^{-7}$

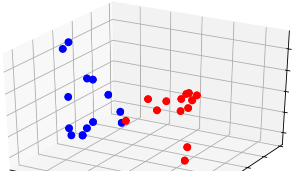
Bipartite graph	#nodes	#edges	Density
Message-Word	11k; 56k	1M	$\approx 10^{-3}$
Movie-Actor	88k; 45k	304k	$\approx 10^{-4}$
User-Product	21M; 10M	83M	$\approx 10^{-7}$

Graph analysis



Key tasks
Clustering
Hierarchy
Ranking
Classification
Embedding
Link prediction





Scikit-network

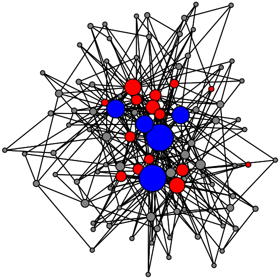
A Python library for graph analysis

- **easy** to install `pip install scikit-network`
- **easy** to use `algorithm.fit(data)`
- **fast** and **memory-efficient**

Relies on **NumPy** and **SciPy** only
BSD license

Data format

Graph = **adjacency** matrix or **biadjacency** matrix
Represented in the **CSR** (Compressed Sparse Row) format of SciPy



$$A = \begin{bmatrix} & 1 & & & 1 \\ 1 & & & & \\ & & & 1 & \\ & & 1 & & \\ 1 & & & & \end{bmatrix}$$

Fast matrix-vector products

The COOrdinate format

A sparse matrix (in dense format):

$$\begin{bmatrix} 3 & 0 & 5 & 0 & 0 & 0 & 4 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 0 & 2 & 4 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 3 & 5 & 3 & 0 & 0 \\ 0 & 2 & 0 & 4 & 1 & 5 & 0 & 0 & 1 & 0 \\ 5 & 0 & 3 & 0 & 4 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The COOrdinate format

A sparse matrix (in dense format):

$$\begin{bmatrix} 3 & 0 & 5 & 0 & 0 & 0 & 4 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 0 & 2 & 4 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 3 & 5 & 3 & 0 & 0 \\ 0 & 2 & 0 & 4 & 1 & 5 & 0 & 0 & 1 & 0 \\ 5 & 0 & 3 & 0 & 4 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The same matrix in COO (COOrdinate) format:

$$(0,0,3),(0,2,5),(0,6,4),\ldots$$

or equivalently,

$$\begin{aligned} \text{row} &= 0,0,0,0,1,1,\ldots \\ \text{col} &= 0,2,6,7,4,6,7,\ldots \\ \text{data} &= 3,5,4,4,4,2,4,\ldots \end{aligned}$$

The CSR (Compressed Sparse Row) format

A (not so) sparse matrix (in dense format):

$$\begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$$

The CSR (Compressed Sparse Row) format

A (not so) sparse matrix (in dense format):

$$\begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$$

The same matrix in coordinates:

$$(0,0,2),(1,1,3)$$

or equivalently, in CSR format:

$$\text{indices} = 0,1$$
$$\text{indptr} = 0,1,2$$
$$\text{data} = 2,3$$

Dense = 4 values, sparse = 7 values

The CSR (Compressed Sparse Row) format

A sparse matrix (in dense format):

$$\begin{bmatrix} 3 & 0 & 5 & 0 & 0 & 0 & 4 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 0 & 2 & 4 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 3 & 5 & 3 & 0 & 0 \\ 0 & 2 & 0 & 4 & 1 & 5 & 0 & 0 & 1 & 0 \\ 5 & 0 & 3 & 0 & 4 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Coordinates:

$$(0,0,3),(0,2,5),(0,6,4),\ldots$$

The same matrix in CSR (Compressed Sparse Row) format:

$$\begin{aligned} \text{indices} &= 0,2,6,7,4,6,7,0,\ldots \\ \text{indptr} &= 0,4,7,12,17,20 \\ \text{data} &= 3,5,4,4,4,2,4,\ldots \end{aligned}$$

Dense = 50 values, sparse = 46 values (*20 + 6 +20*)

Properties of the CSR format

Pros

- Efficient storage
- Fast row slicing
- Fast matrix-vector product

Cons

- Slow column slicing
- Slow modification (e.g., add an entry)
- Slow transpose

Properties of the CSR format

Pros

- Efficient storage
- Fast row slicing
- Fast matrix-vector product

Cons

- Slow column slicing
- Slow modification (e.g., add an entry)
- Slow transpose

For efficient column slicing, use the CSC (Compressed Sparse Column) format (= CSR of the transpose matrix)

Other Python libraries for graphs

NetworkX	**iGraph**	**graph-tool**
Python only	Core in C/C++	Core in C/C++

	NetworkX	iGraph	graph-tool	**scikit-network**
Data	✓	✗	✓	✓
Topology	✓	✓	✓	✓
Clustering	✓	✓	✗	✓
Hierarchy	✗	✓	✓	✓
Ranking	✓	✓	✓	✓
Classification	✓	✗	✗	✓
Embedding	✓	✗	✓	✓
Visualization	✓	✓	✓	✓

✓ Available

✓ Partially available or not scalable

✗ Not available

Performance

Test on the Orkut graph (3M nodes, 117M edges)

RAM usage

NetworkX	iGraph	graph-tool	**scikit-network**
	18G	10G	1G

Running times

	iGraph	graph-tool	**scikit-network**
Louvain	33 min	✗	2 min
PageRank	3 min 56 s	45 s	48 s
HITS	1 min 20 s	2 min 24 s	1 min 49 s

Perspectives

New tasks

- Graph generation (e.g., with prescribed degrees)
- Community detection (e.g., with Leiden)
- Anomaly detection

New types of graphs

- Dynamic graphs
- Multilayer graphs
- Labeled graphs

Credits

Development lead

- Thomas Bonald
- Marc Jeanmougin
- Nathan de Lara
- Quentin Lutz
- Tiphaine Viard

Institutions

- Institut Polytechnique de Paris
- Sorbonne Université
- Technical University of Munich (TUM)
- Nokia
- Inria

+ **External contributors**