ERCIM SNA WG *Algorithmic Aspects of Social Network Analysis*

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Distributed community detection over dynamic networks using neighborhood similarity

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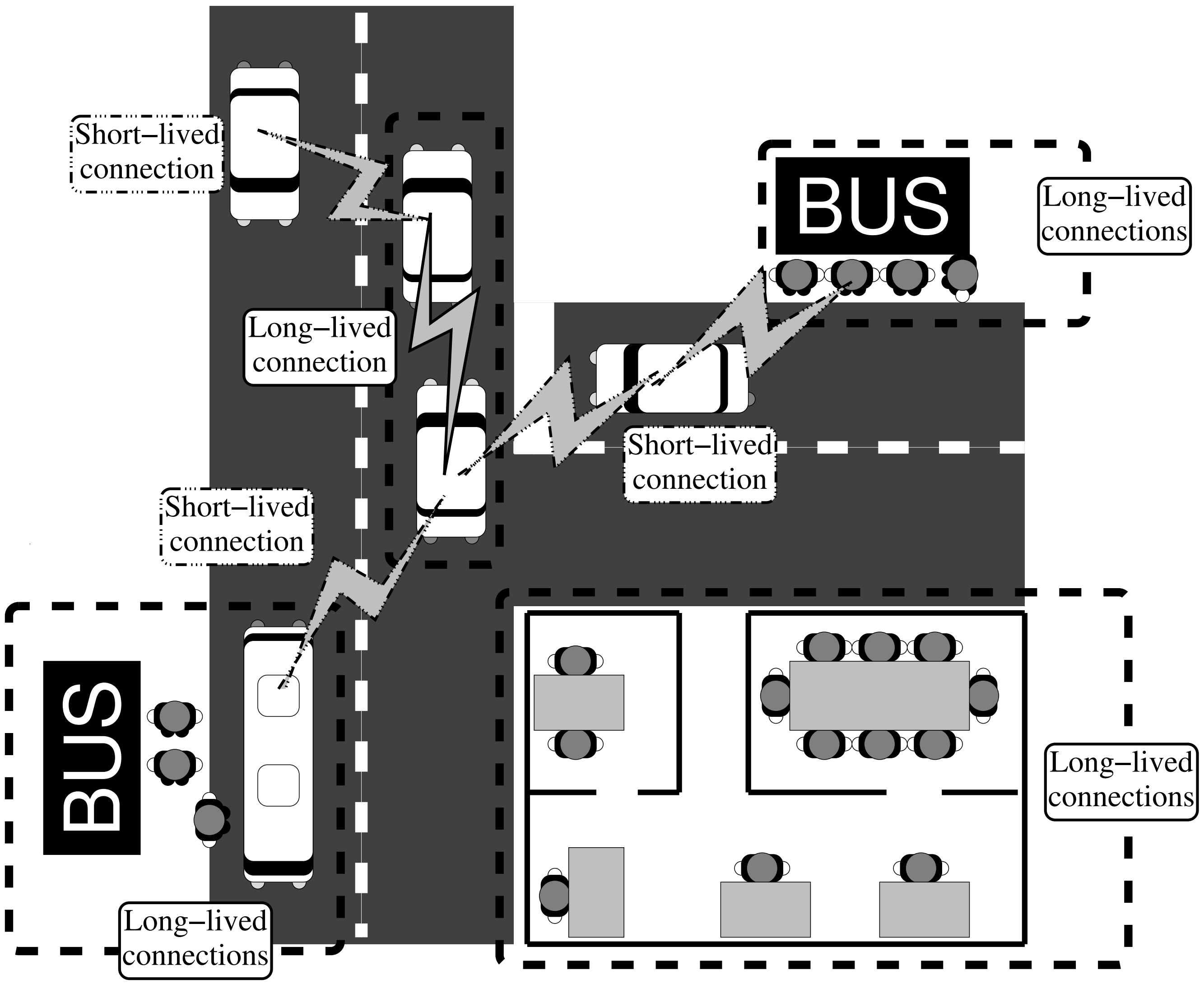
  - Propagation/environment
  - Human (i.e. social) mobility patterns
  - Mutual or group shared interest



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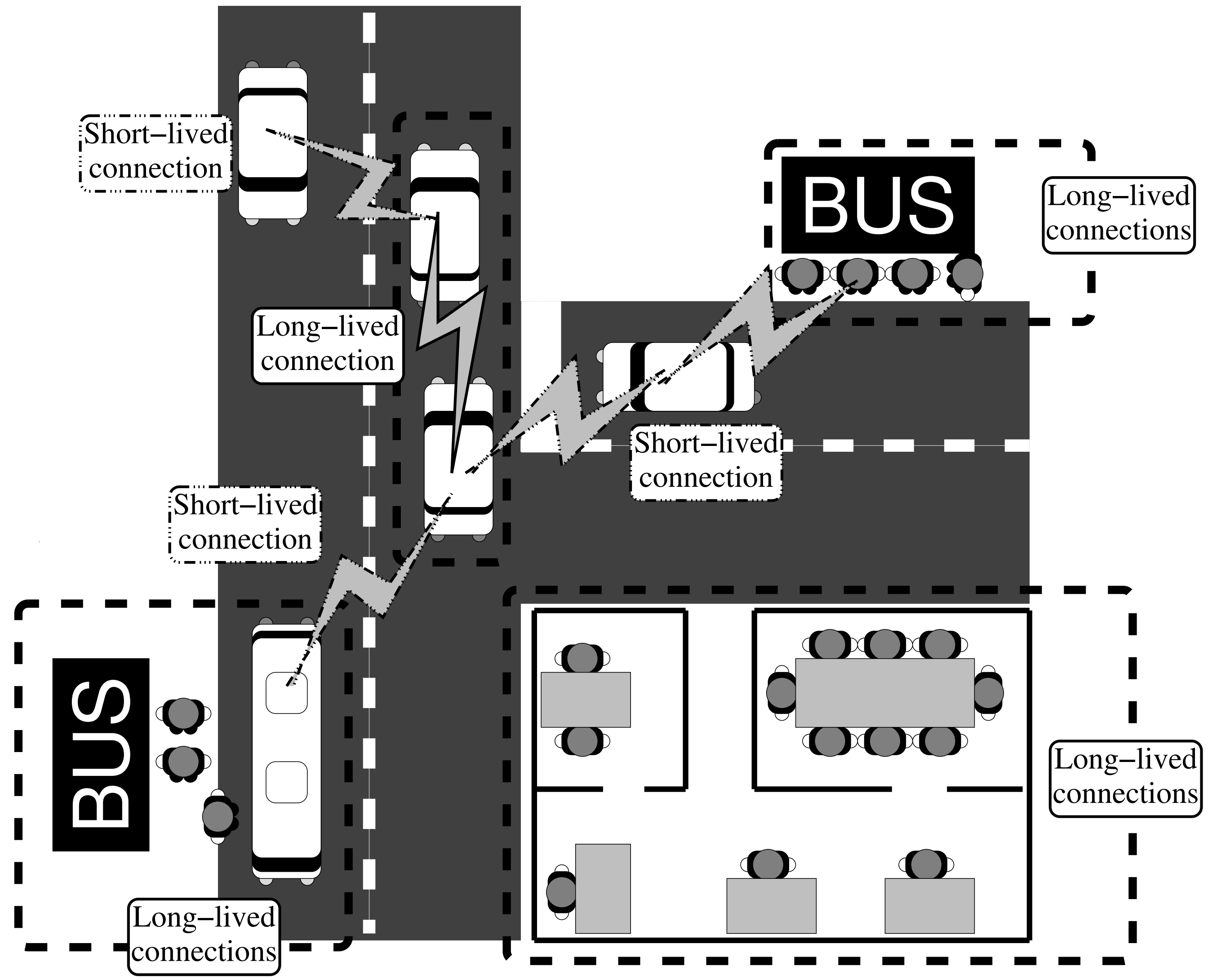

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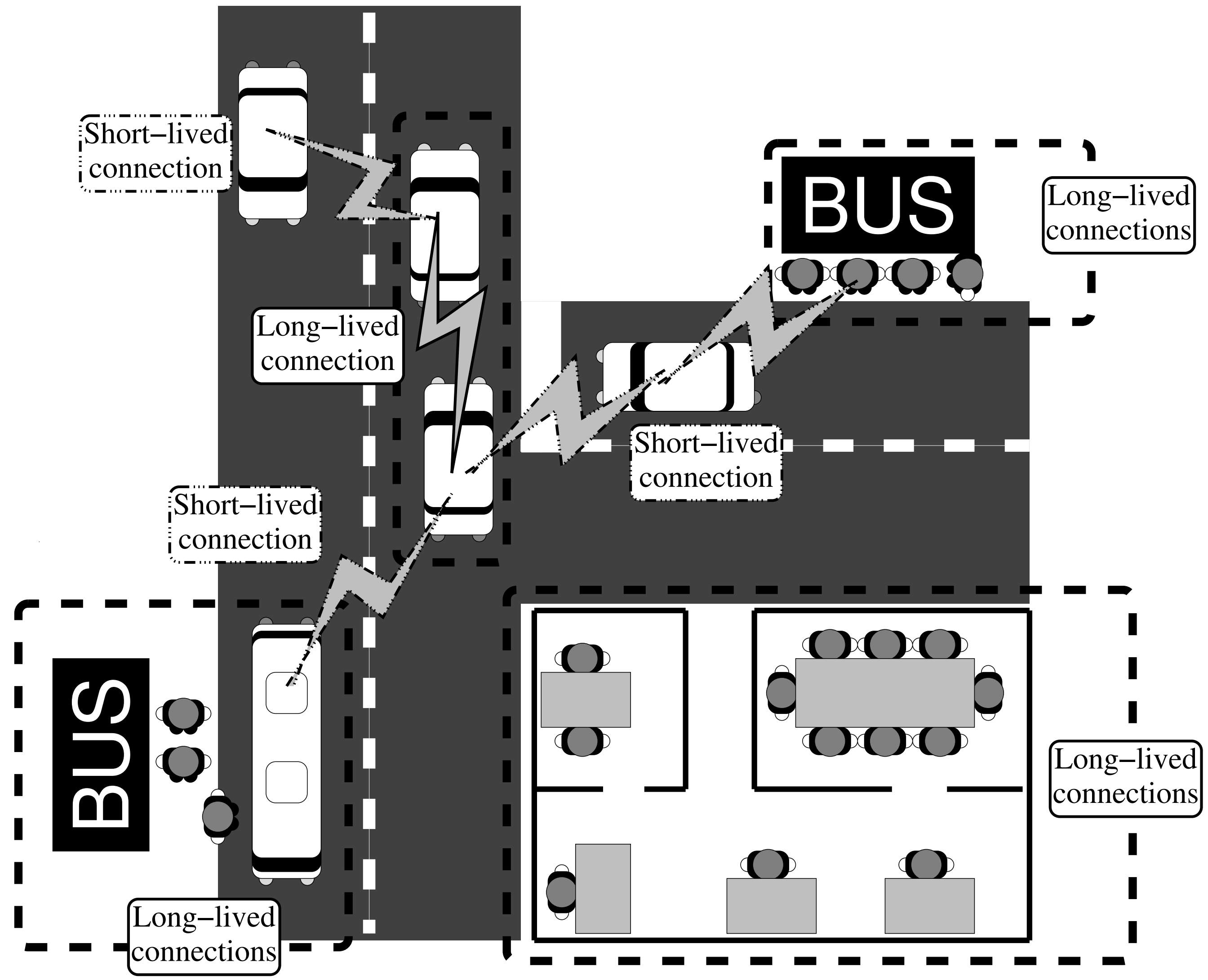
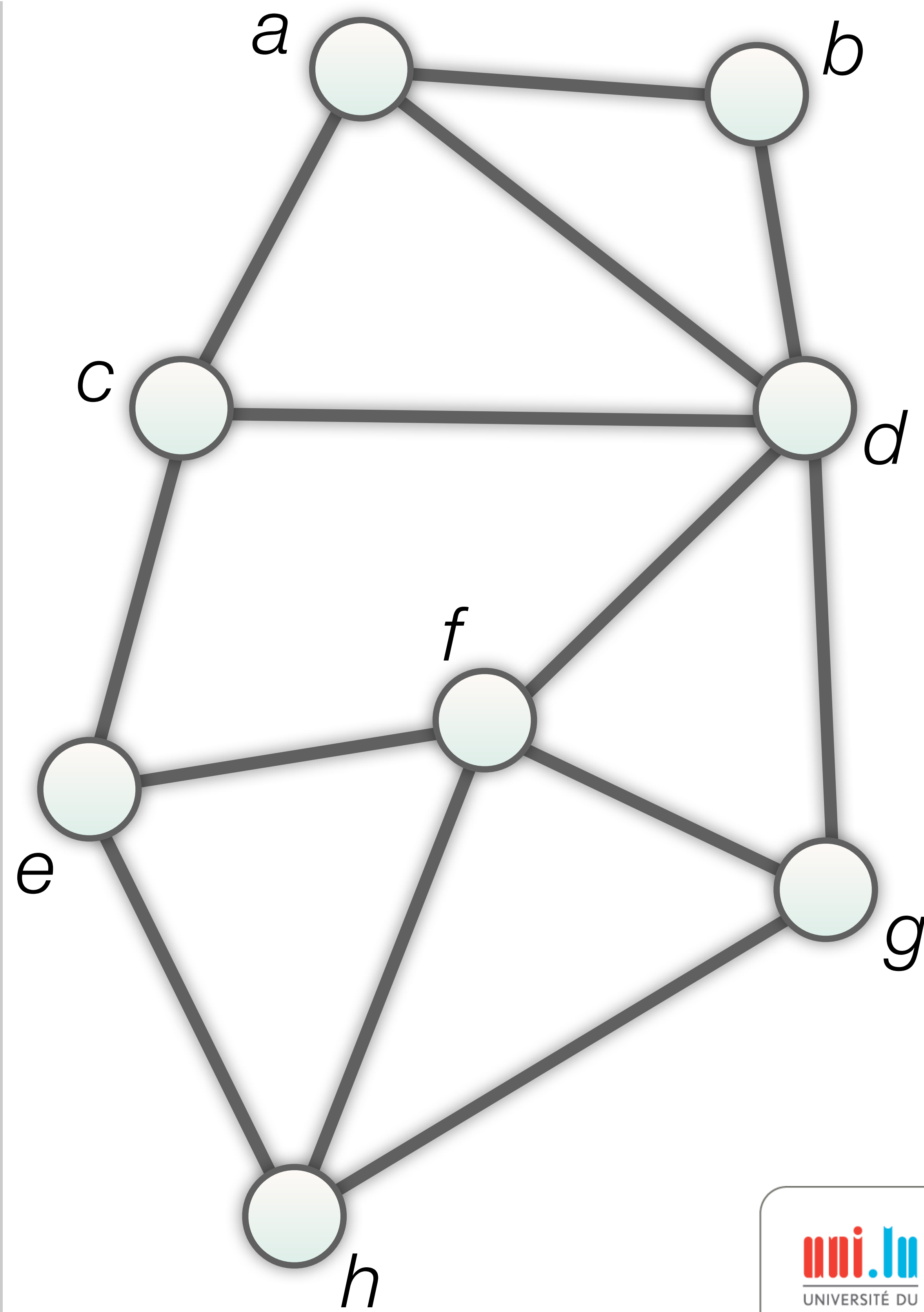
- **Challenges:**
  - Dynamic network
  - Distributed approach



Principle and limitation of distributed algorithms



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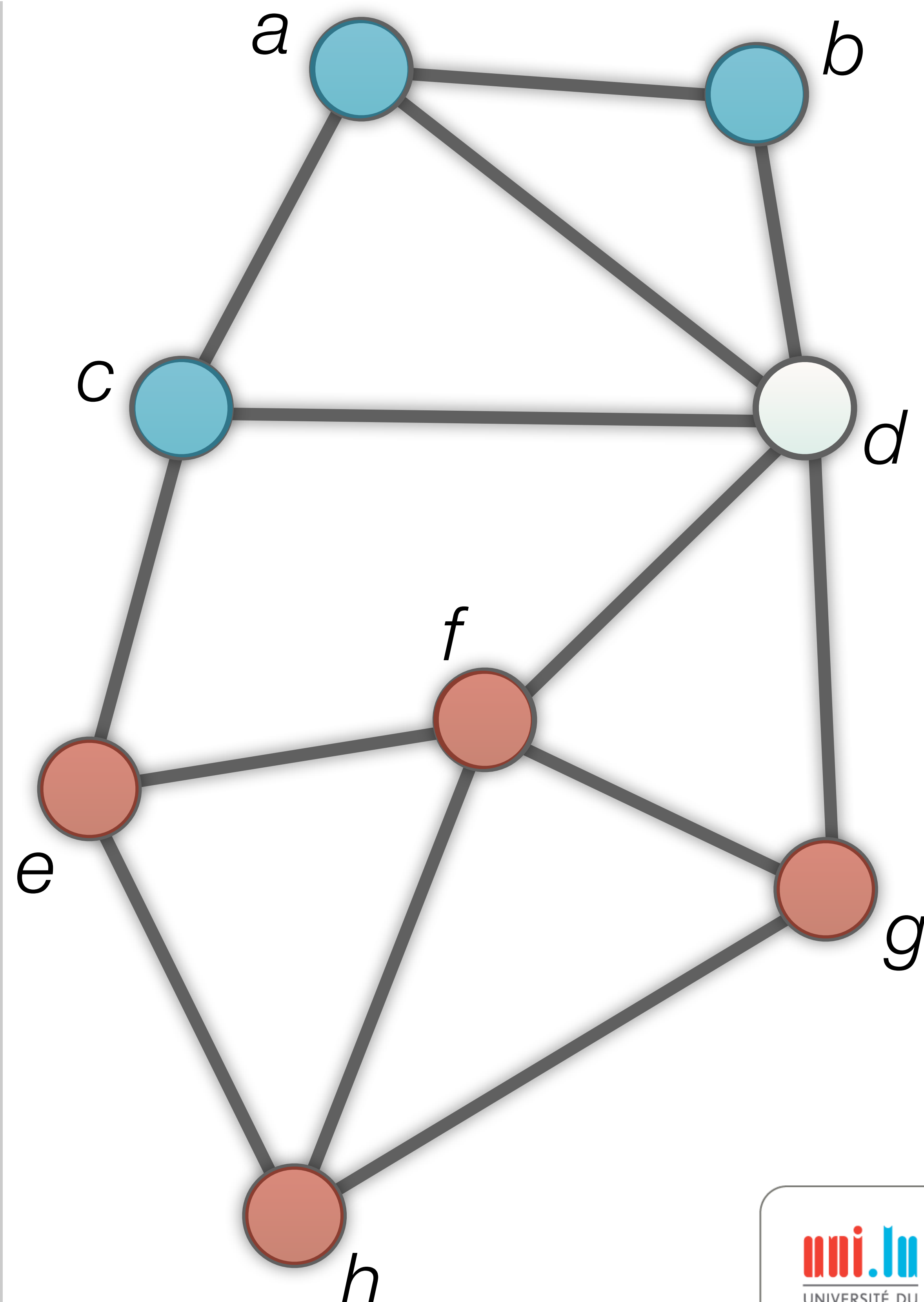

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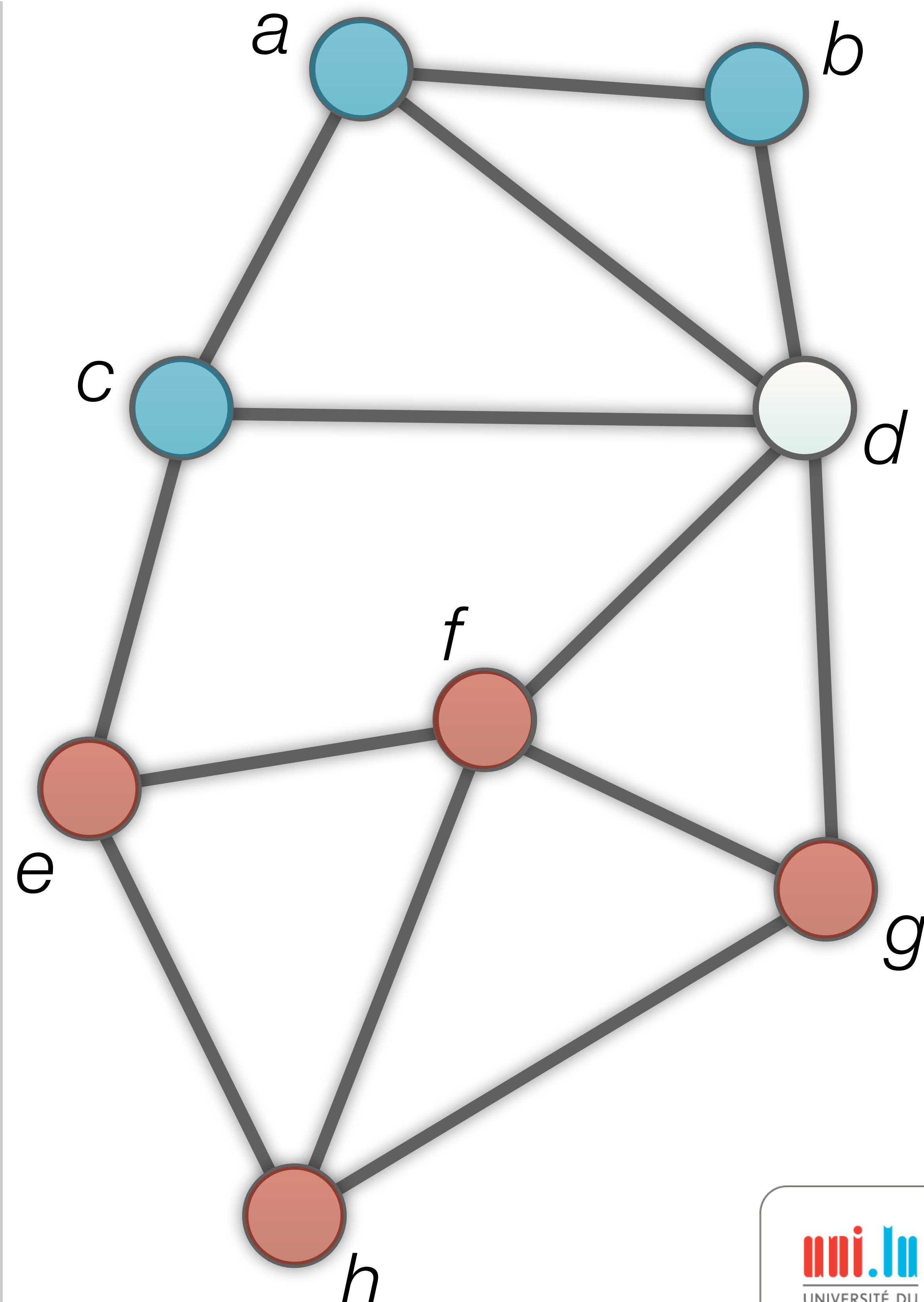

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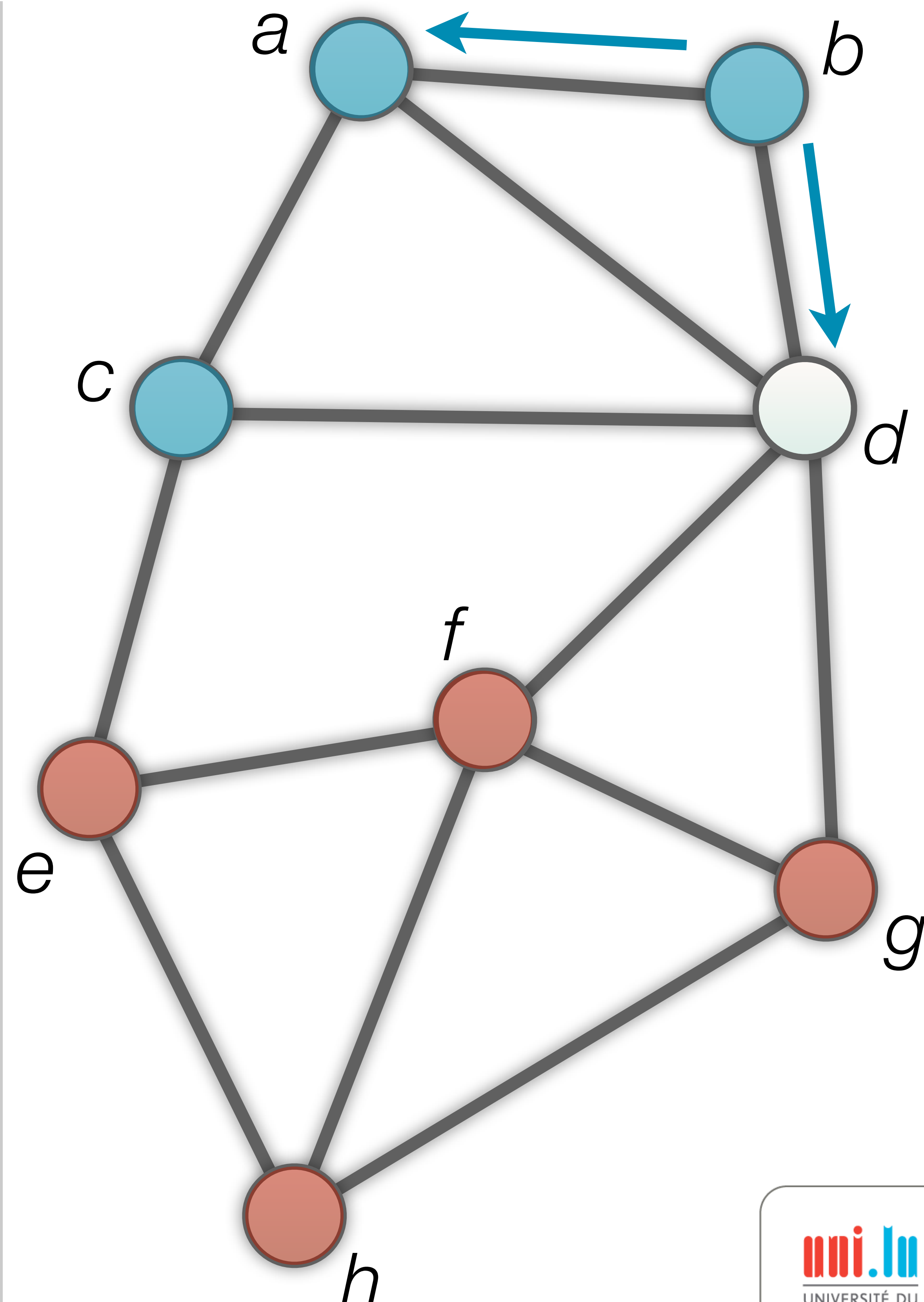

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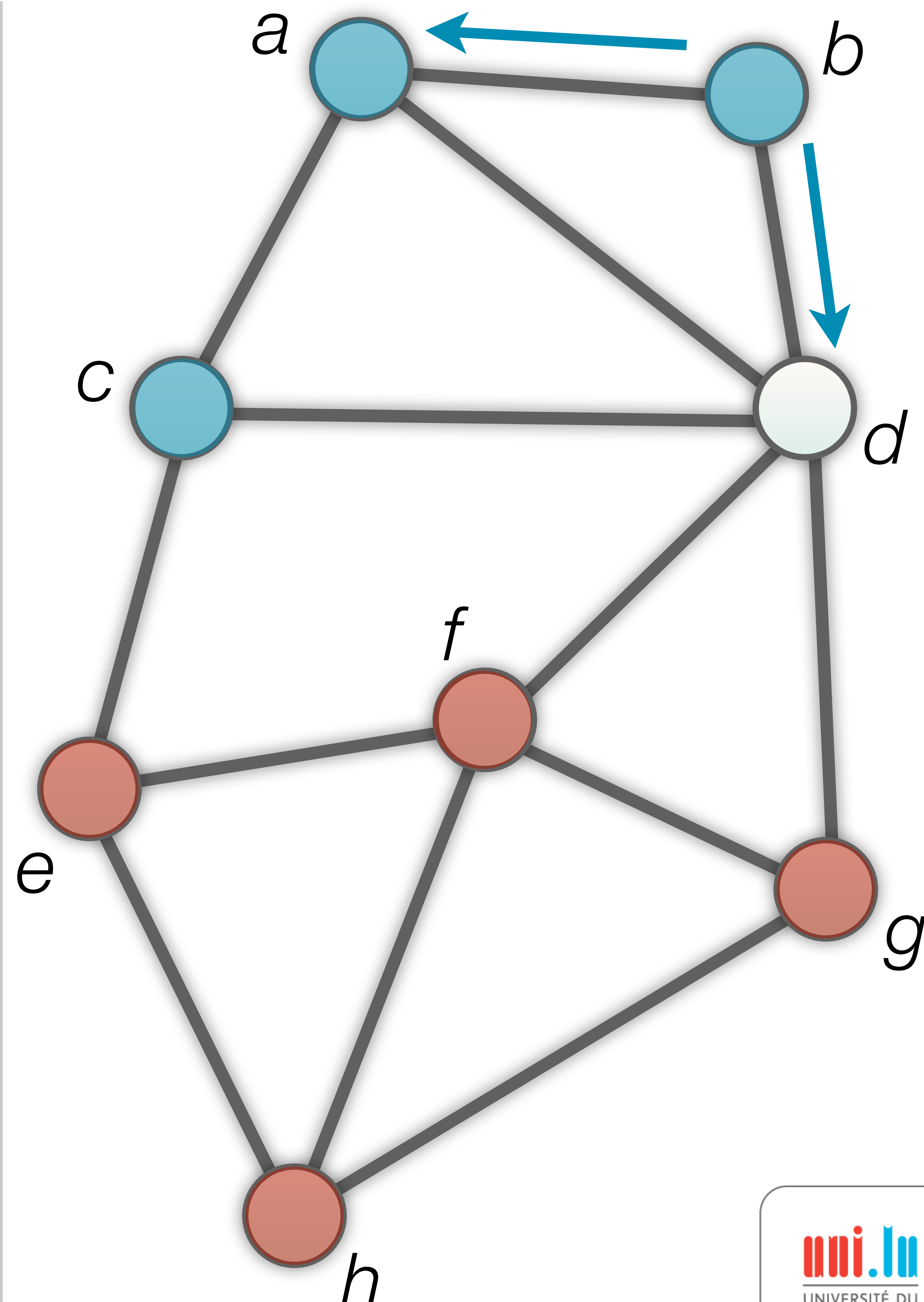

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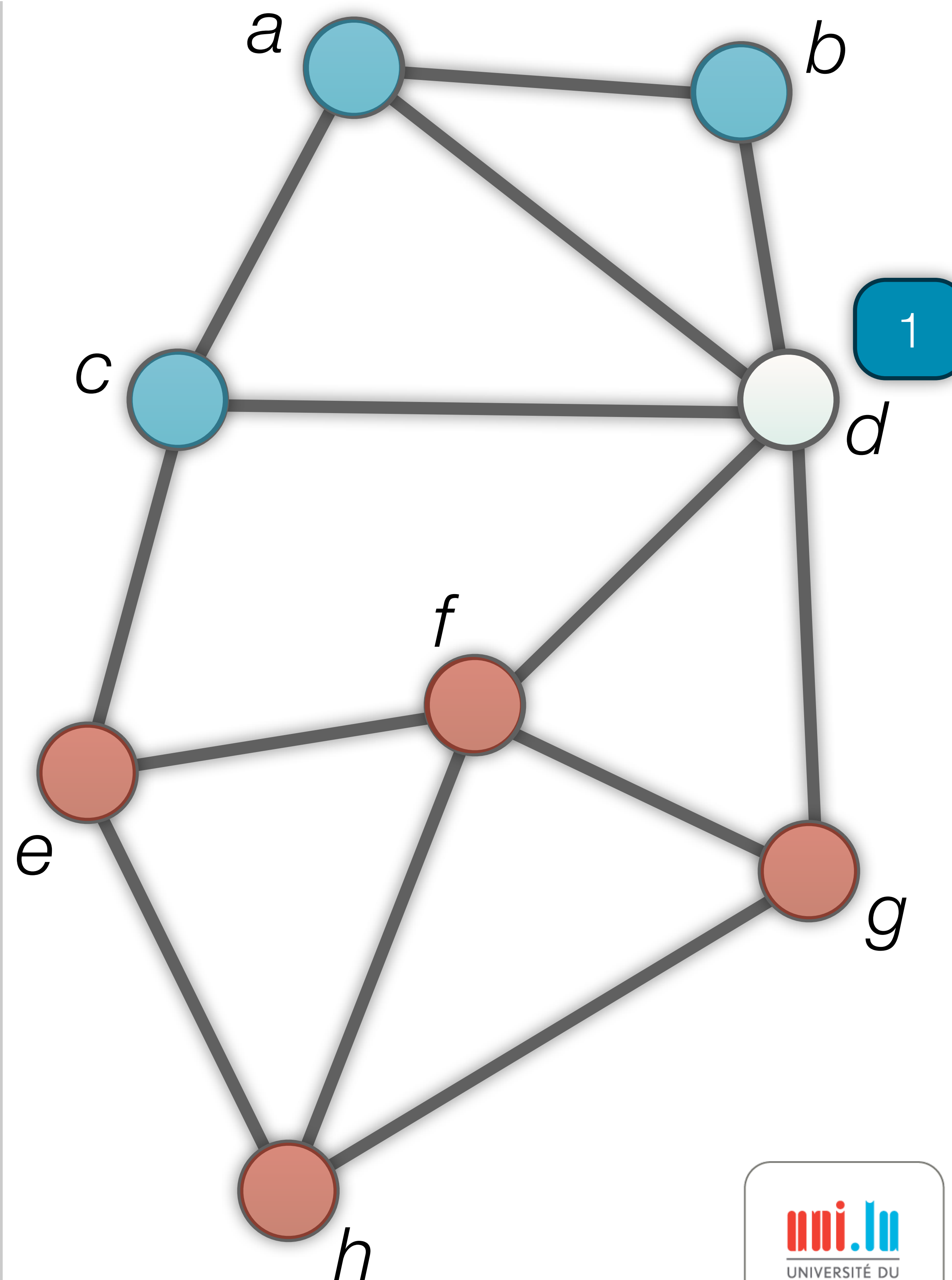

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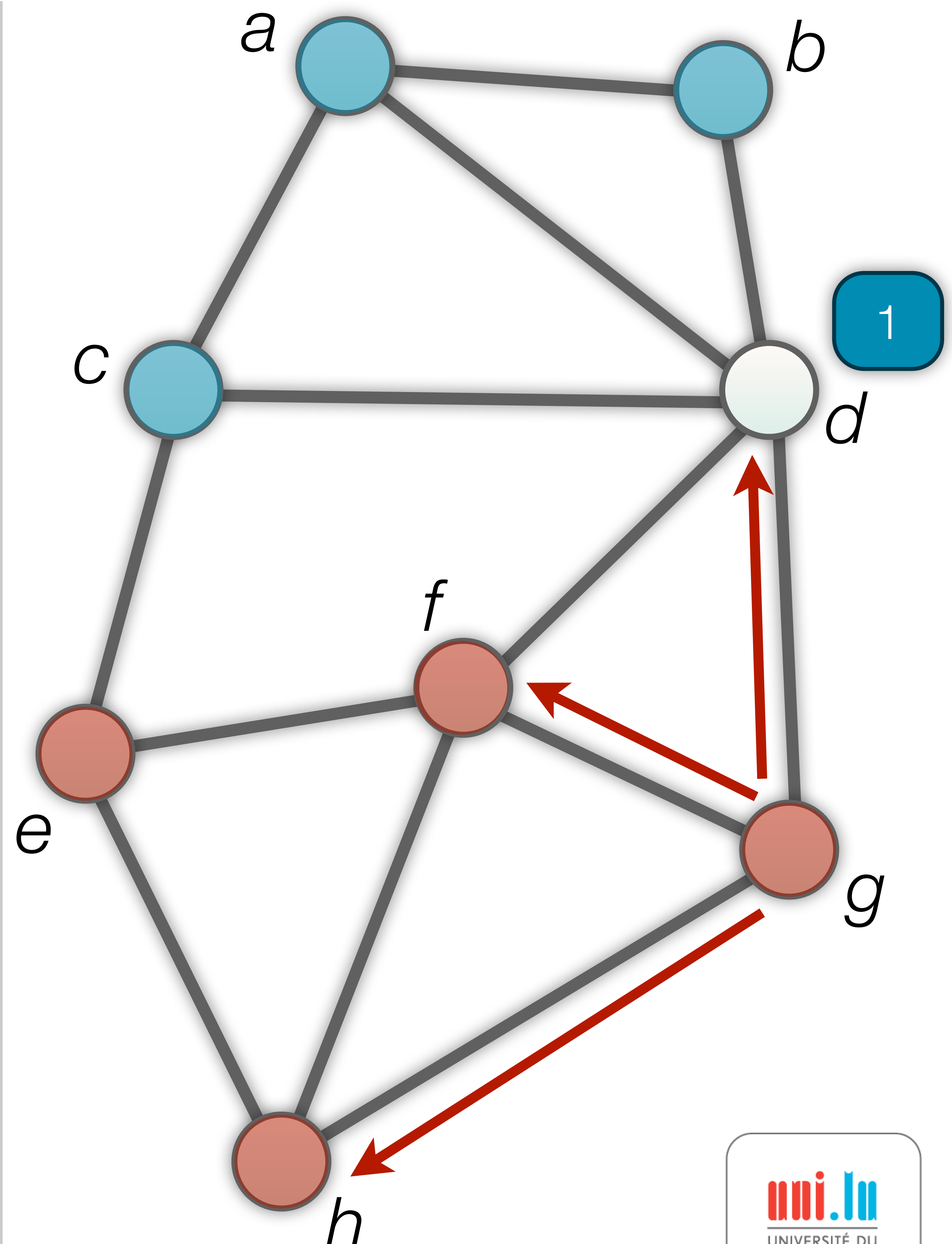

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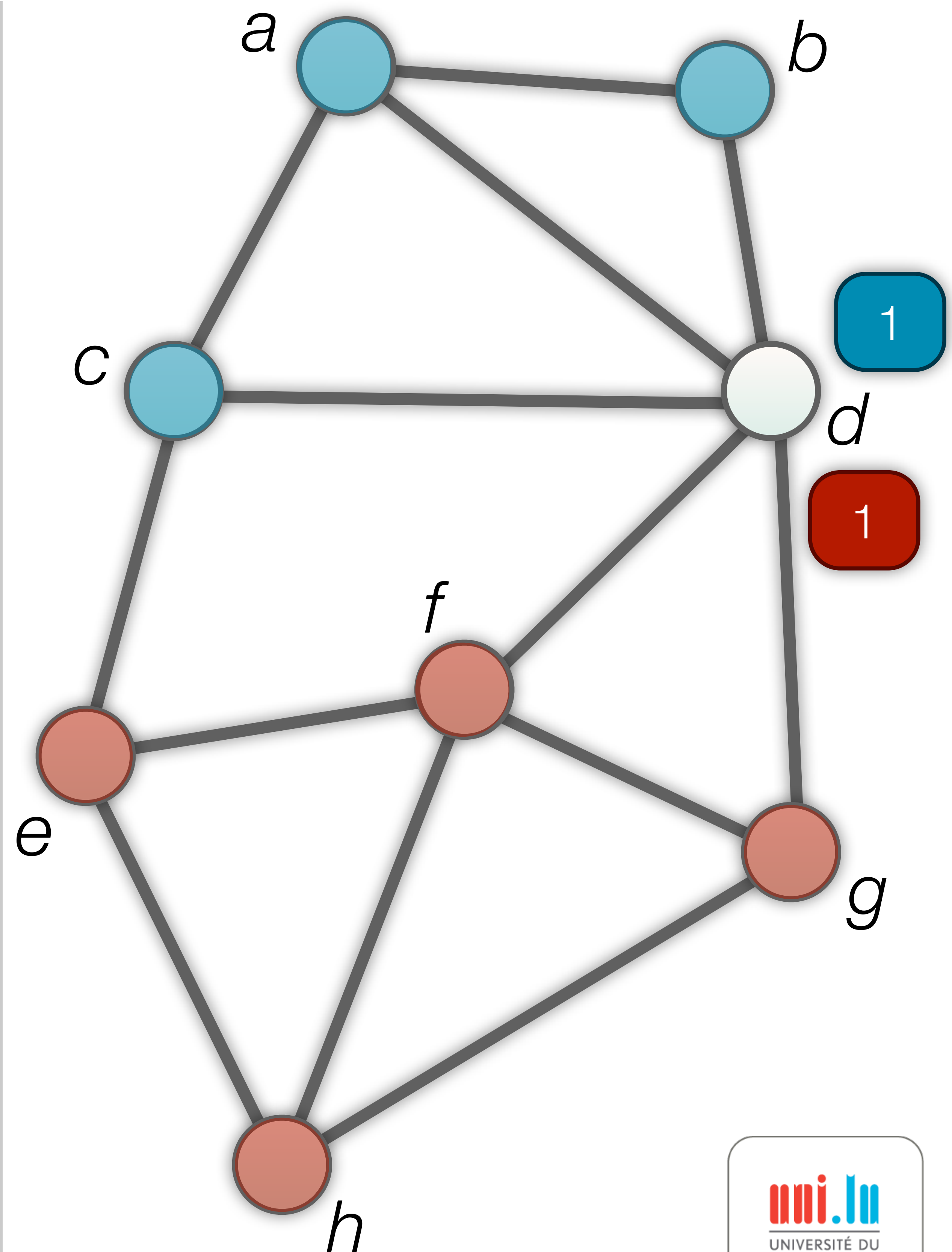

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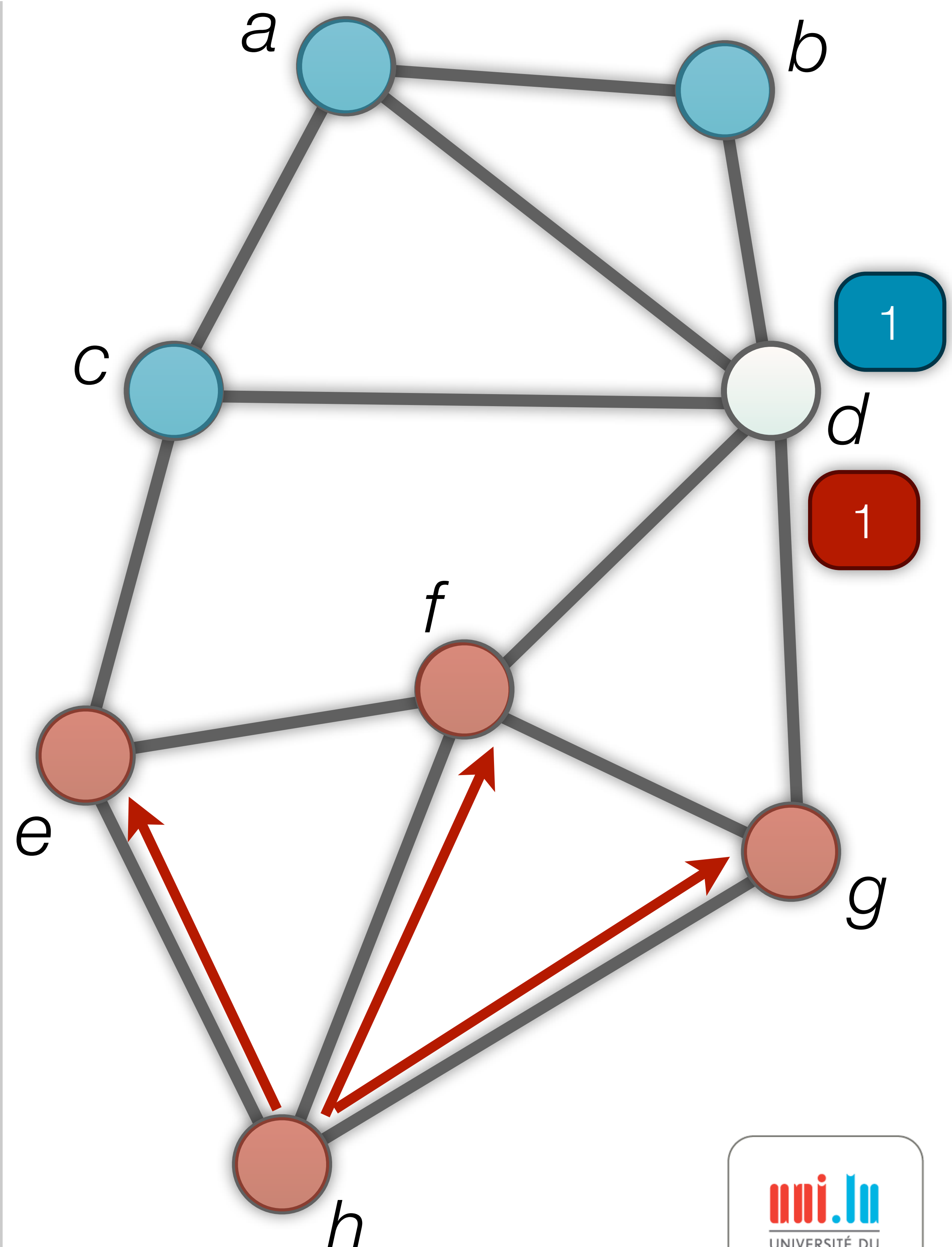

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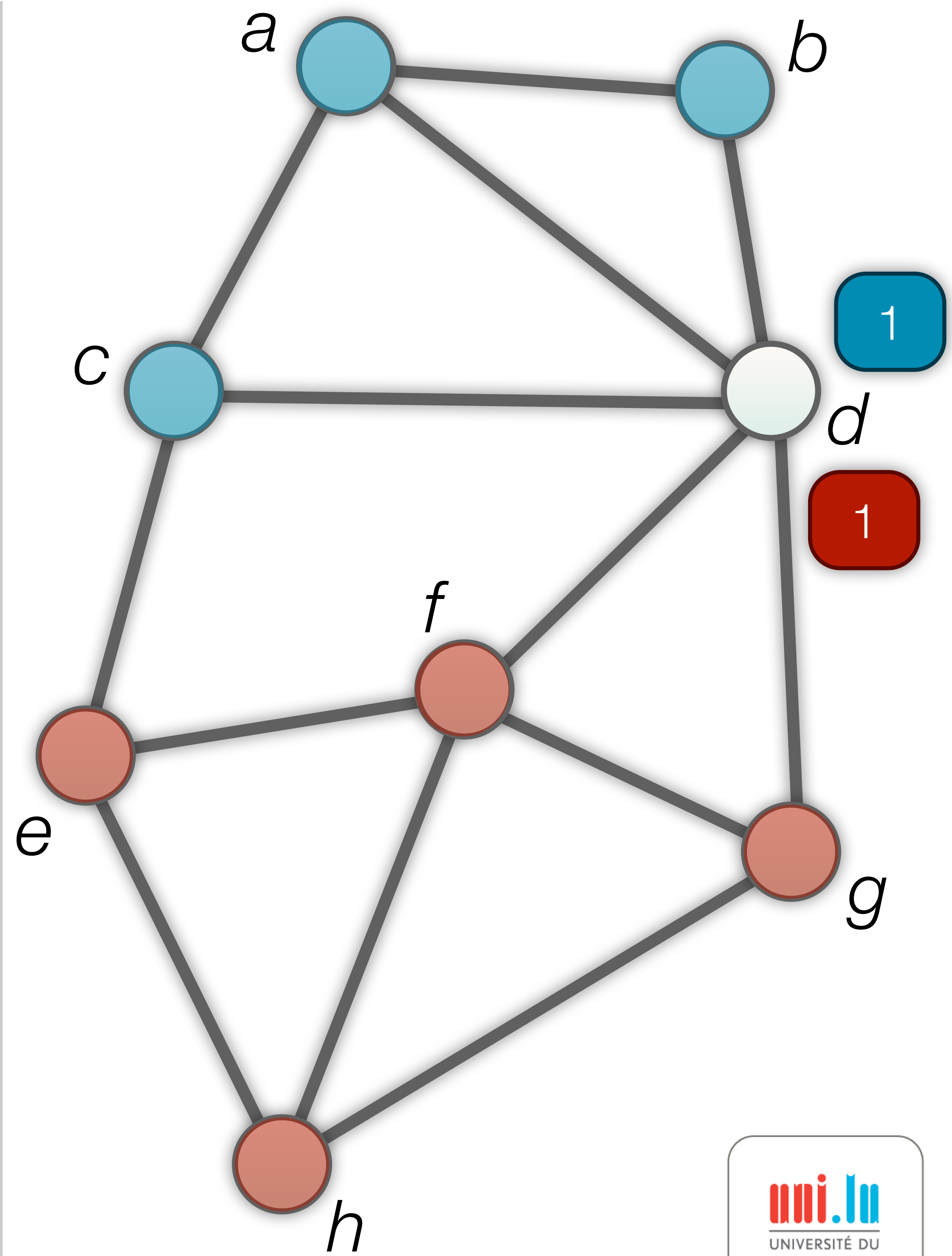

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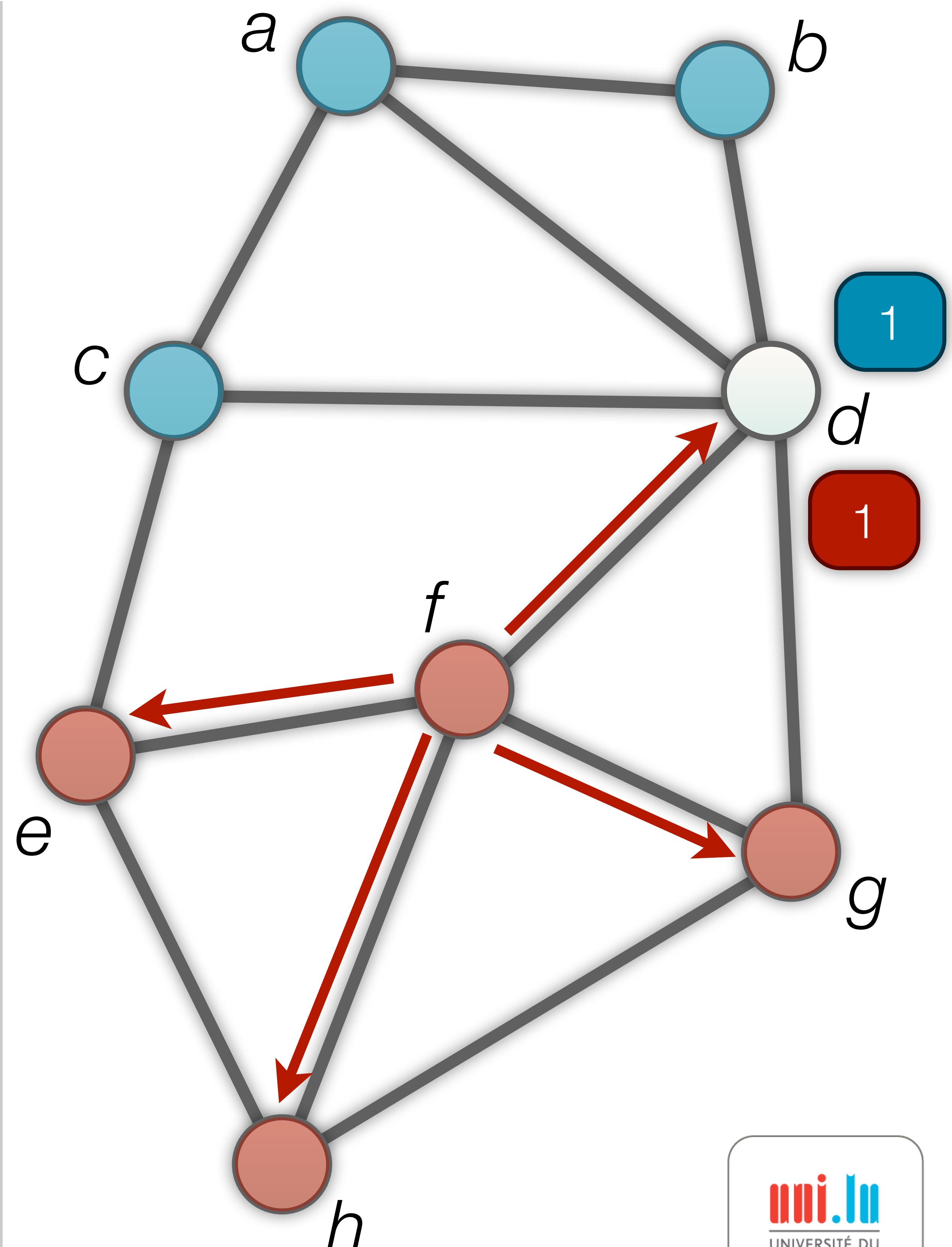

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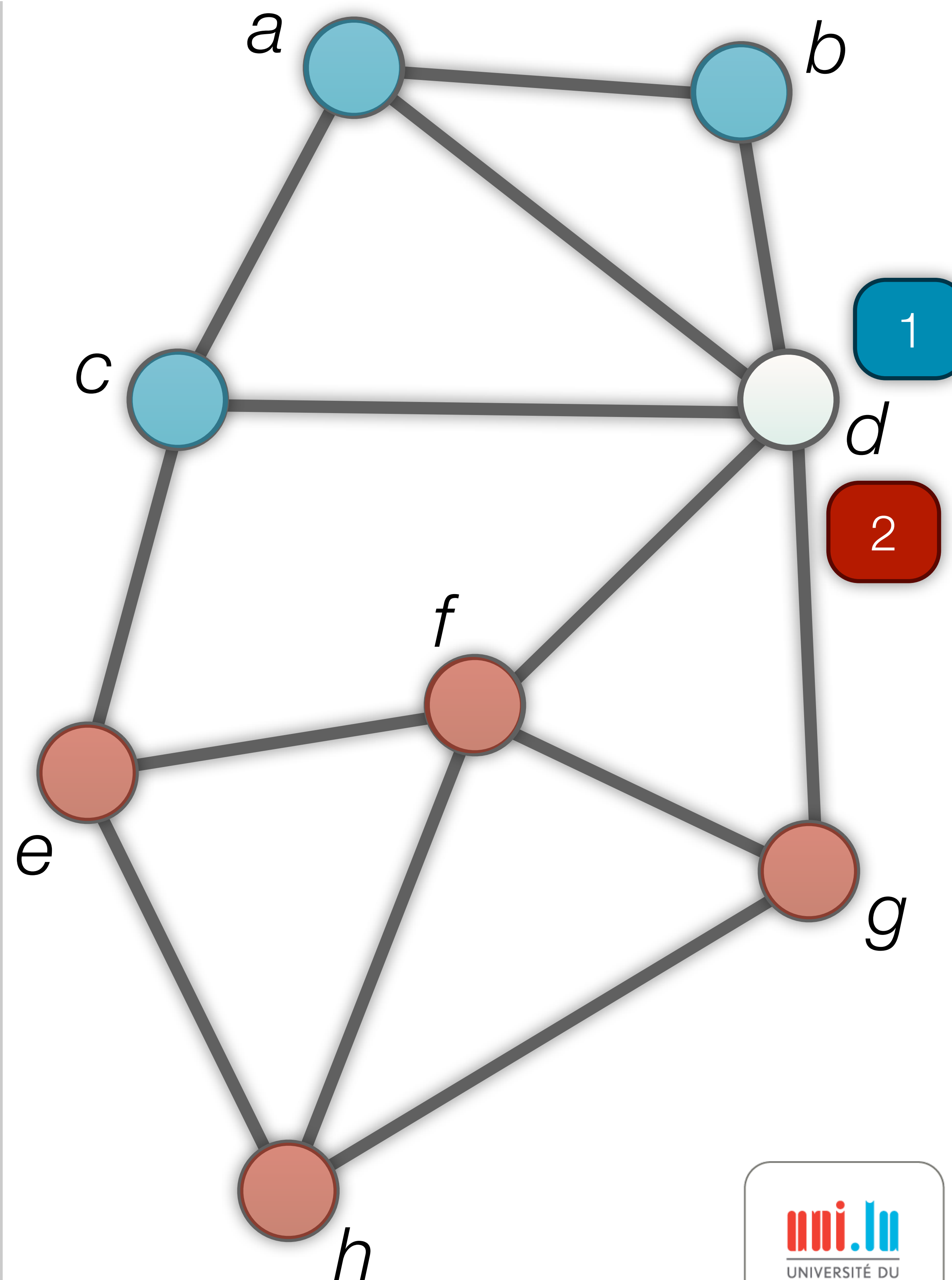

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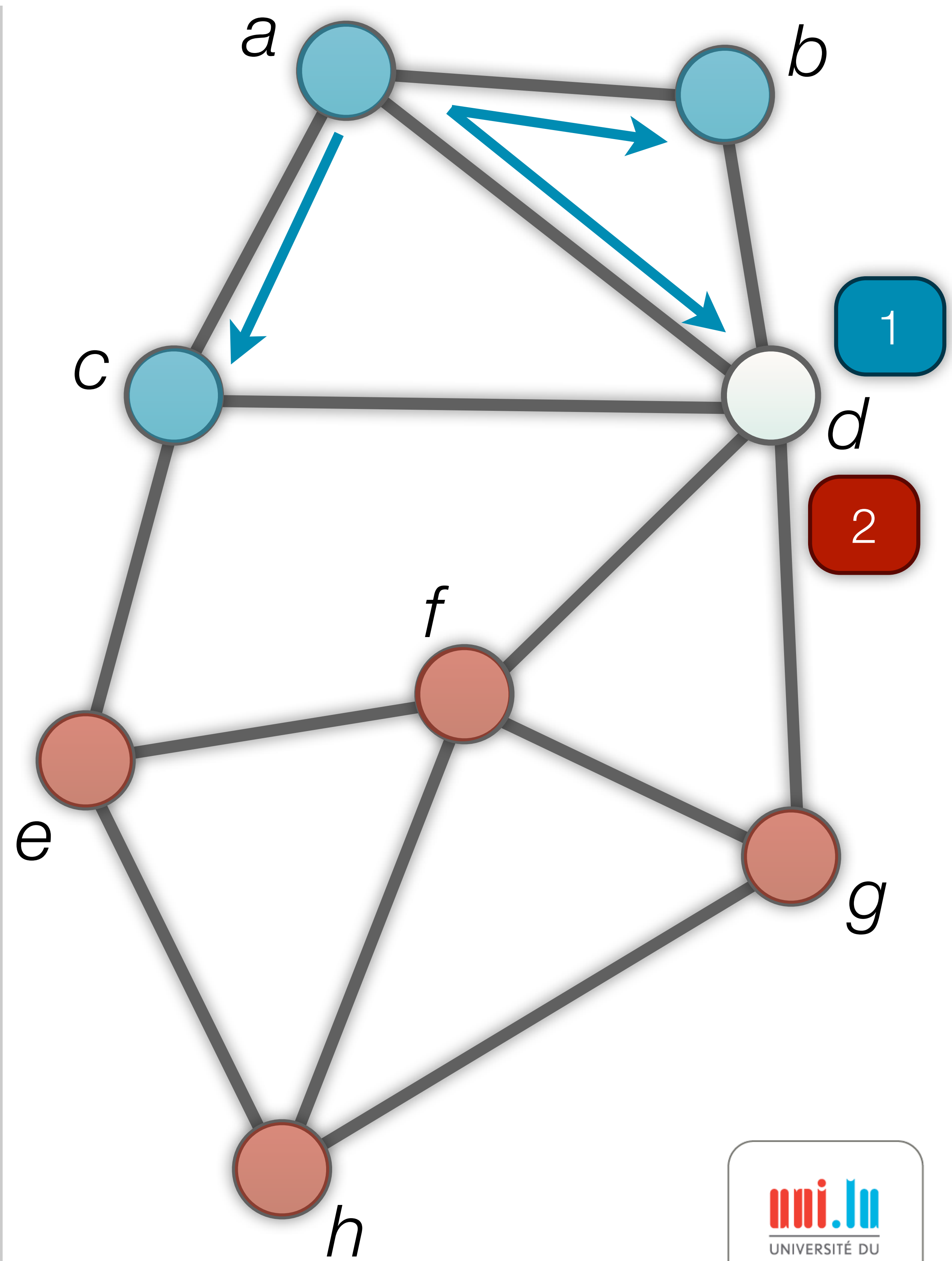

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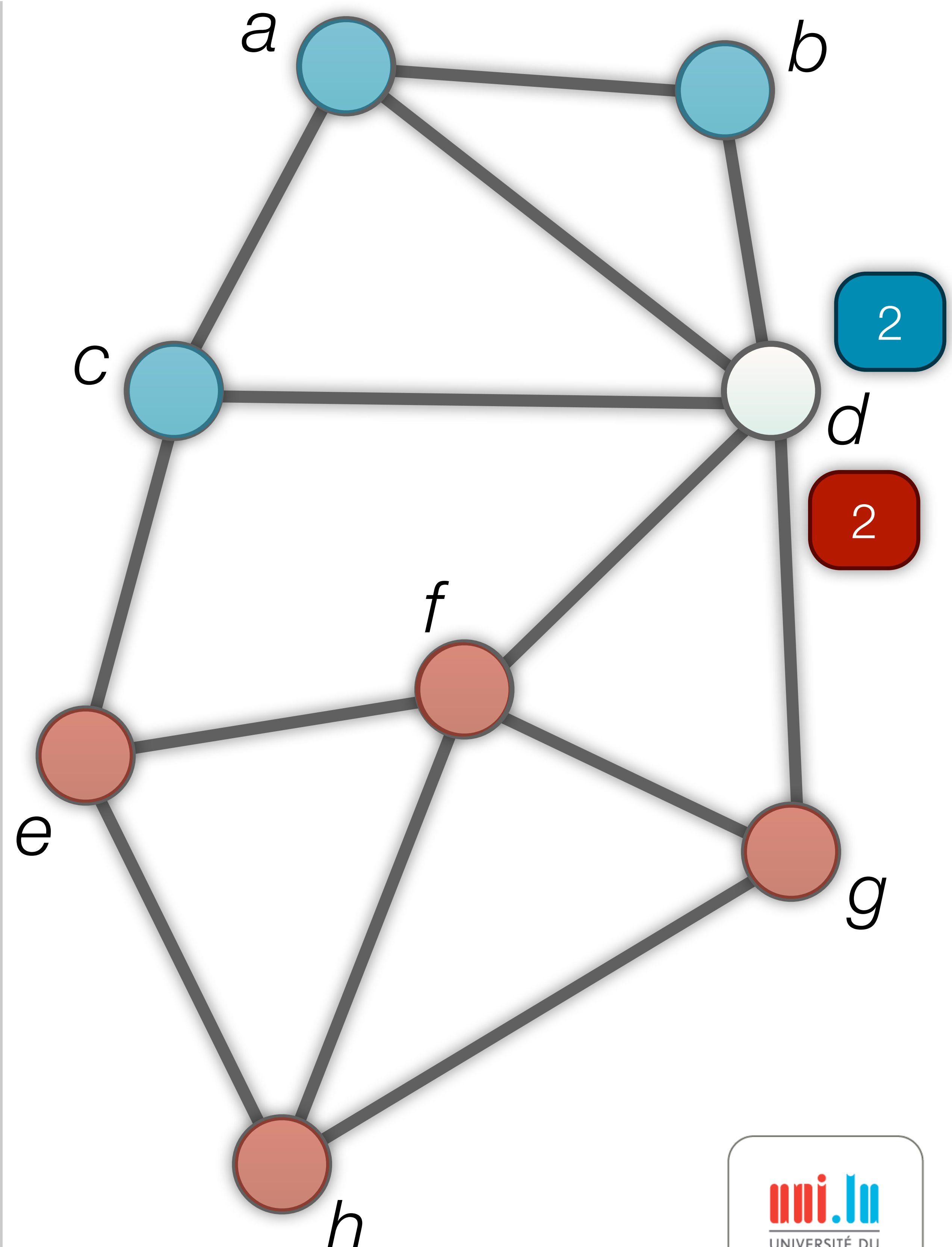

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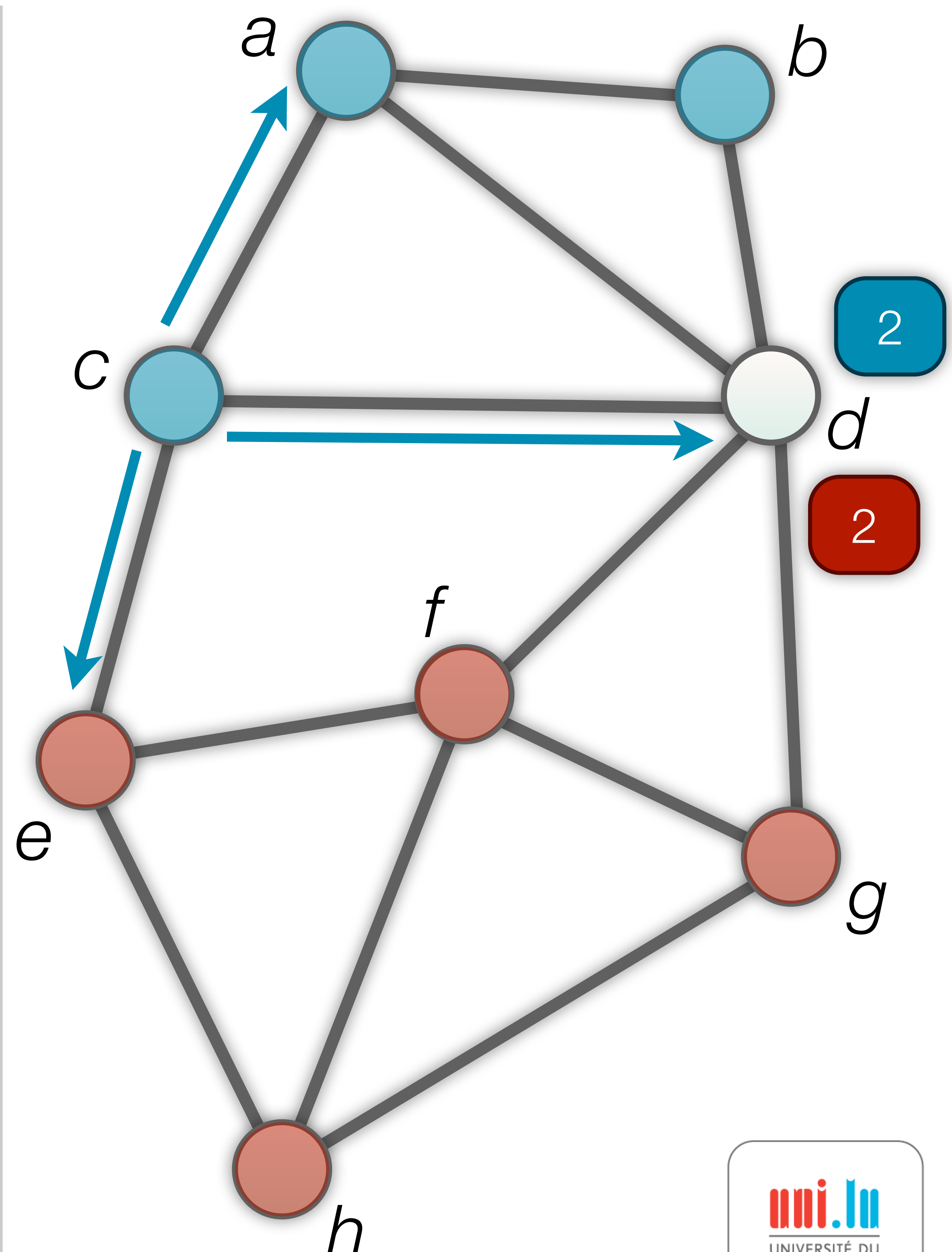

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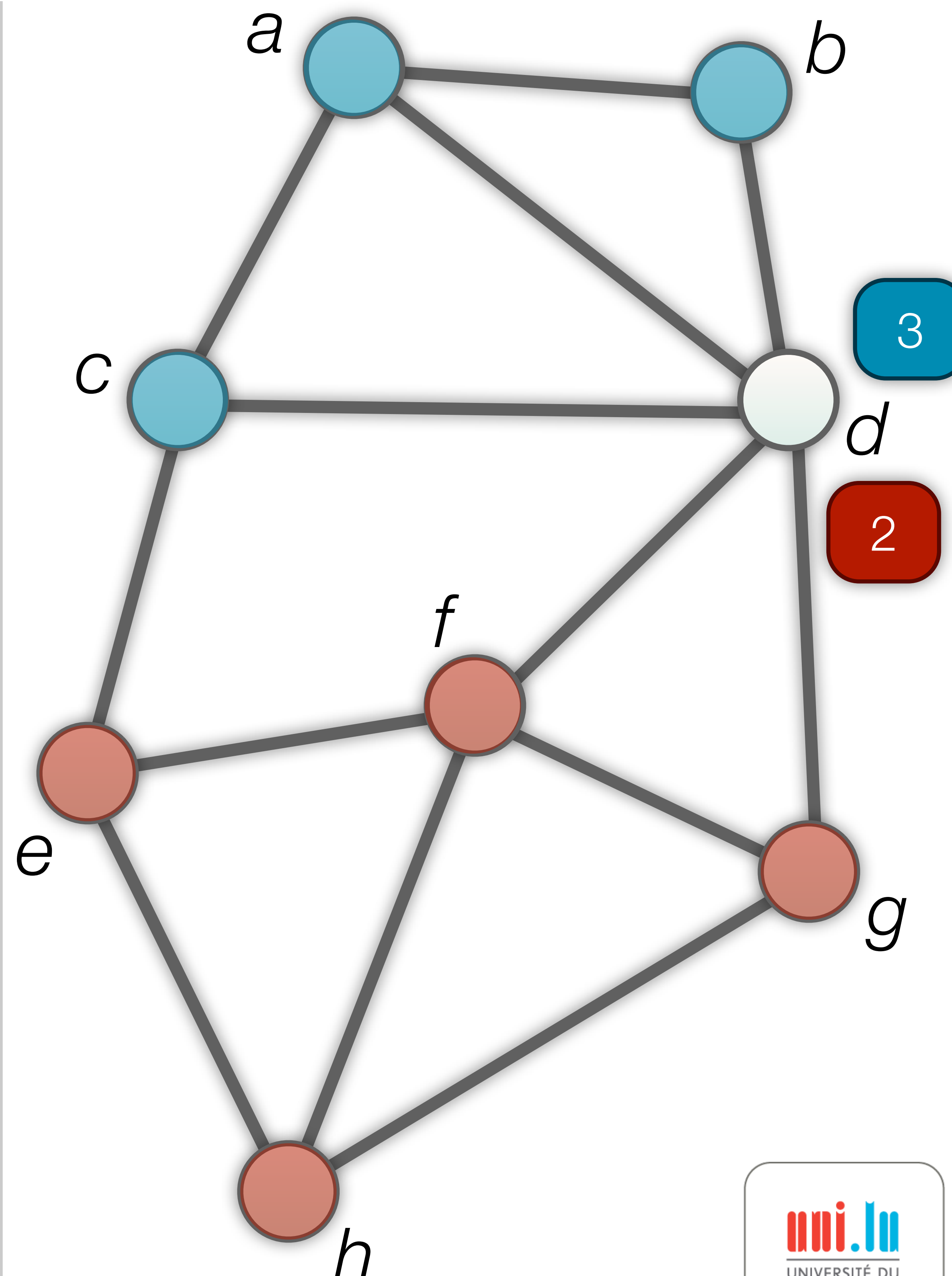

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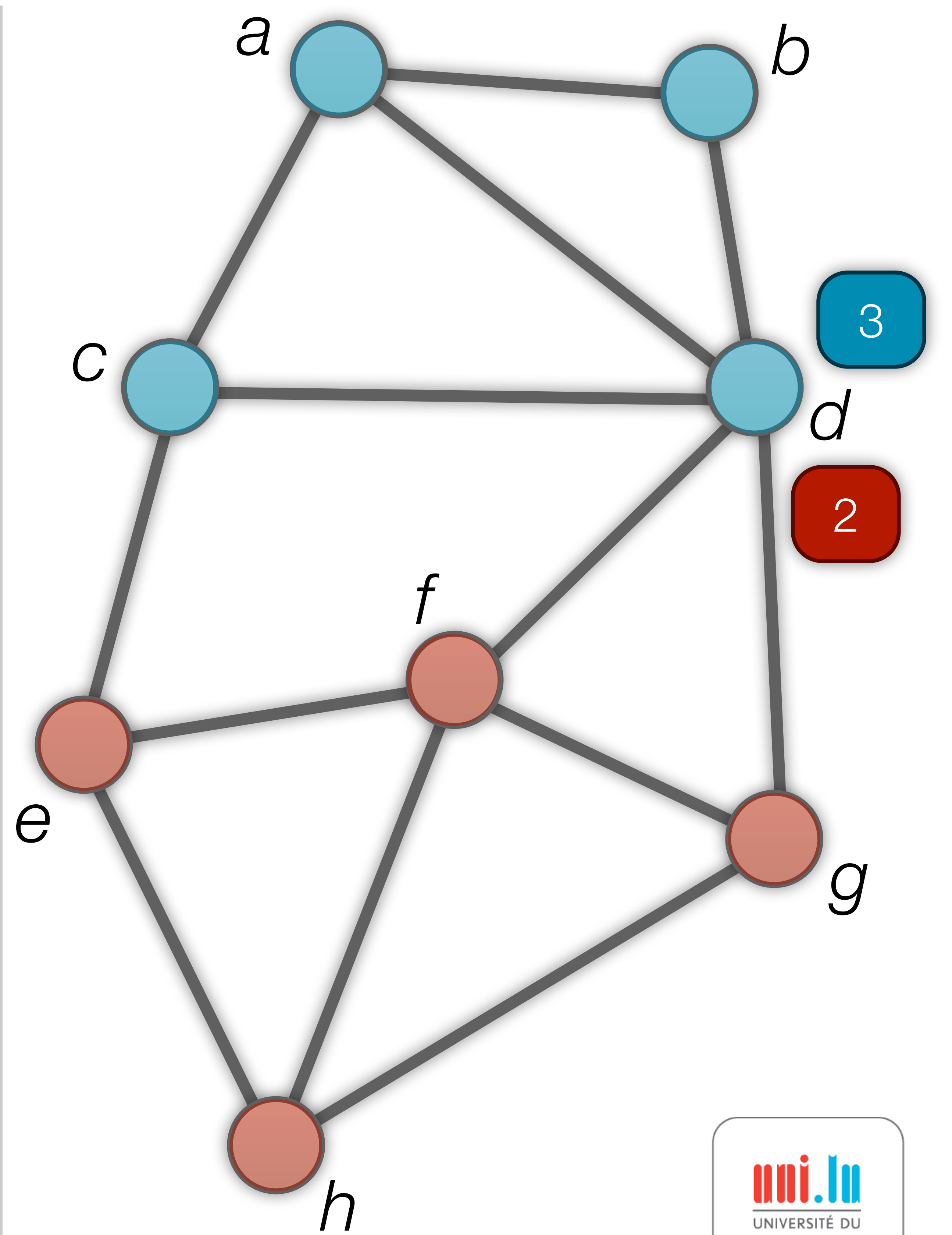

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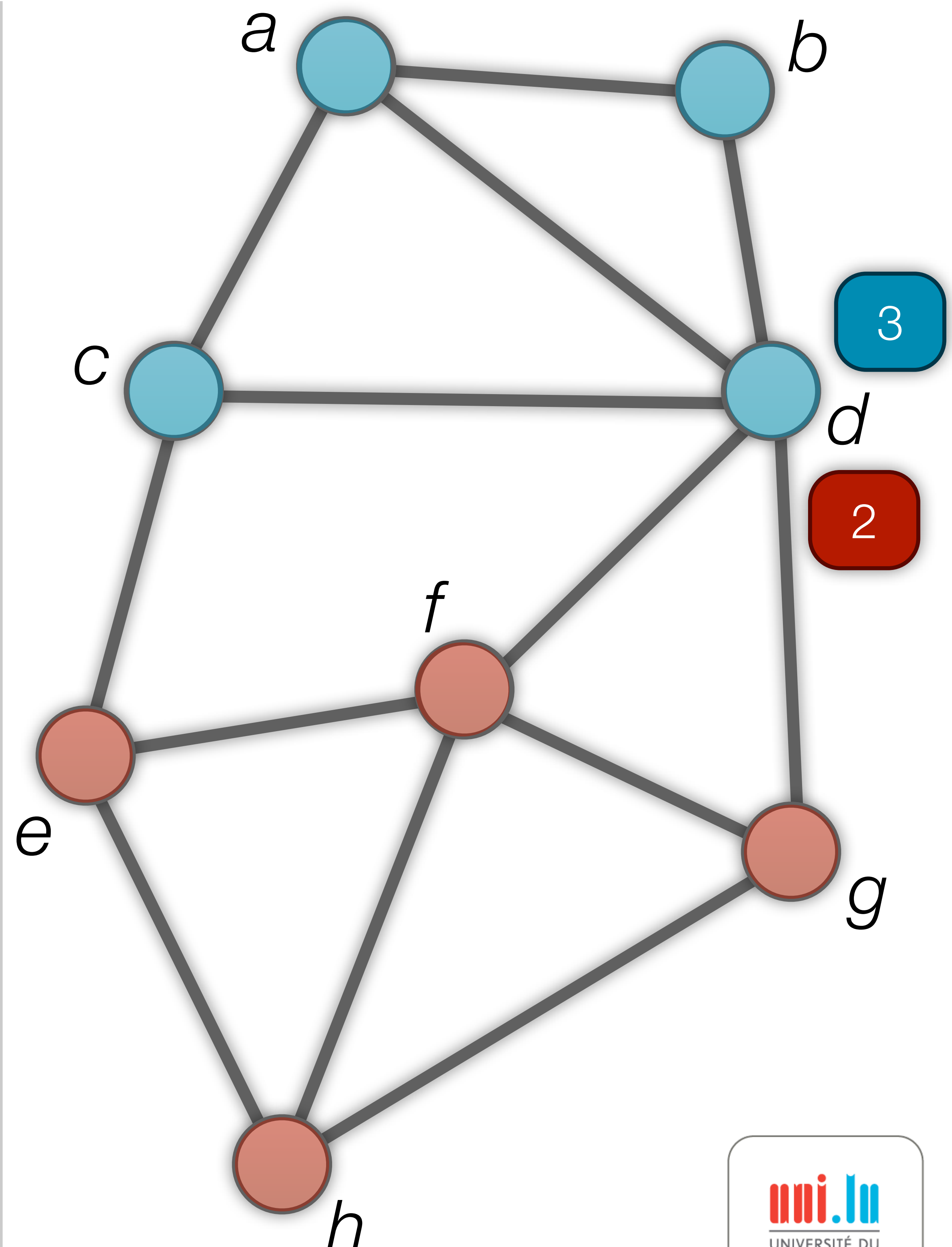

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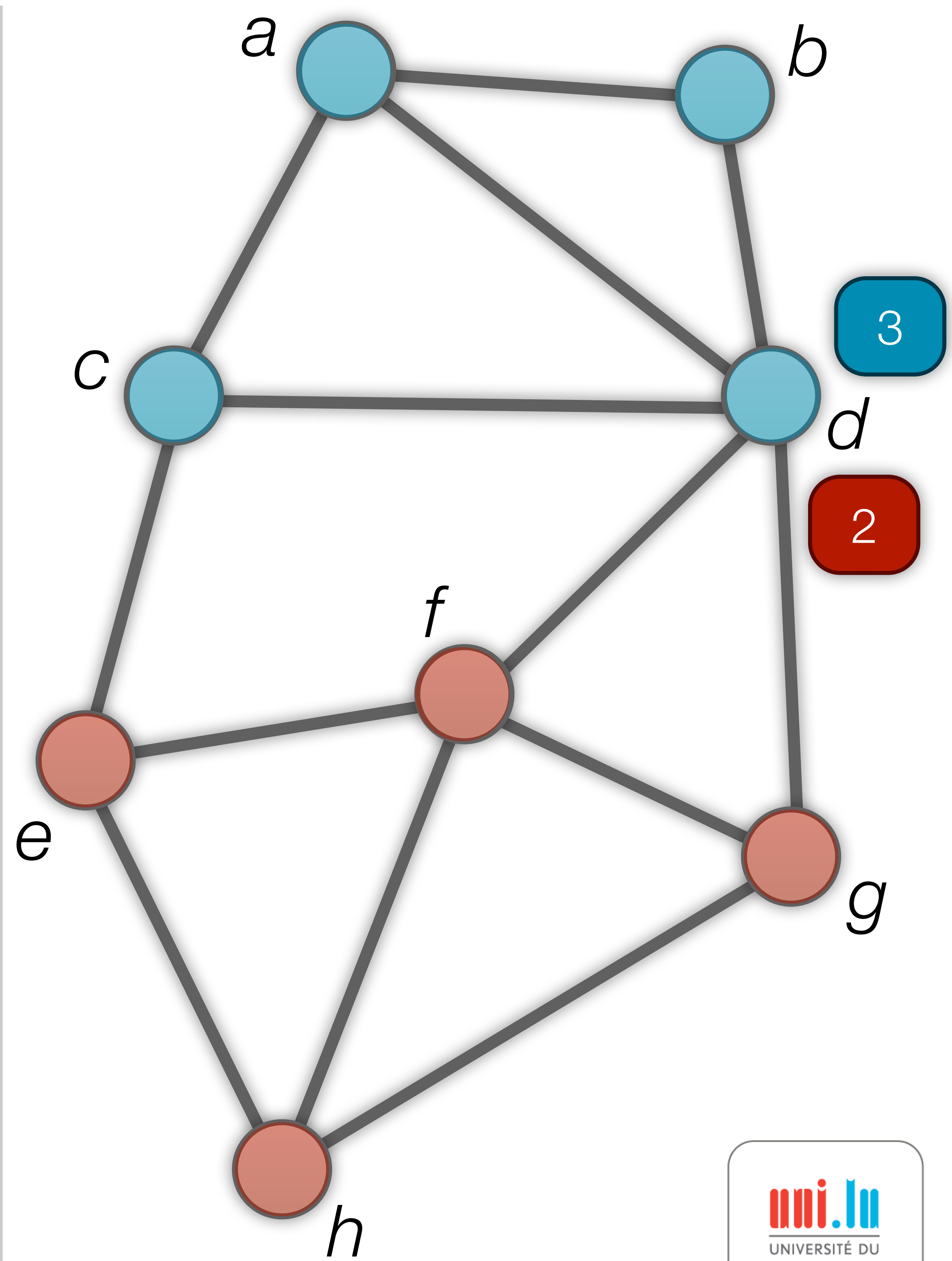

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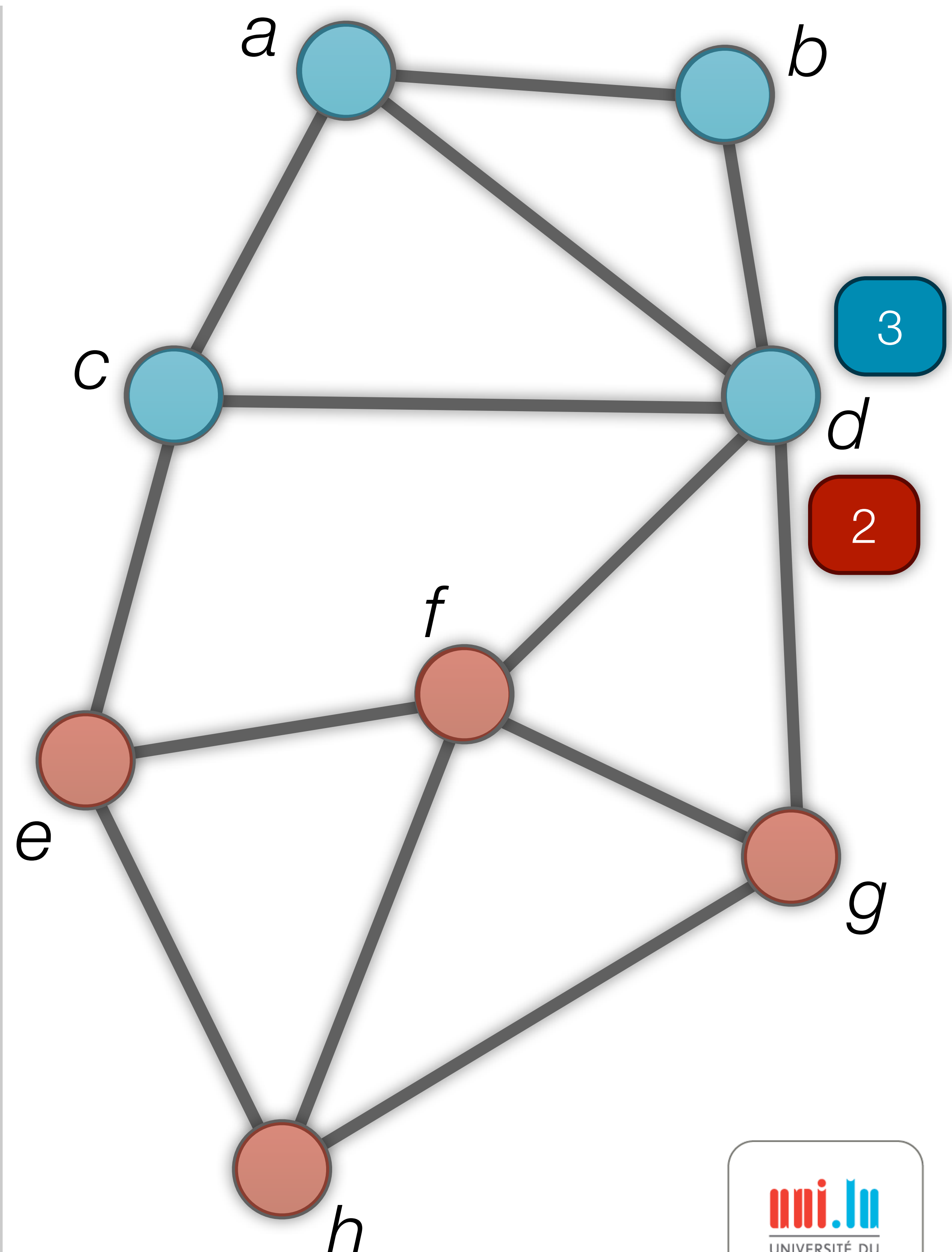

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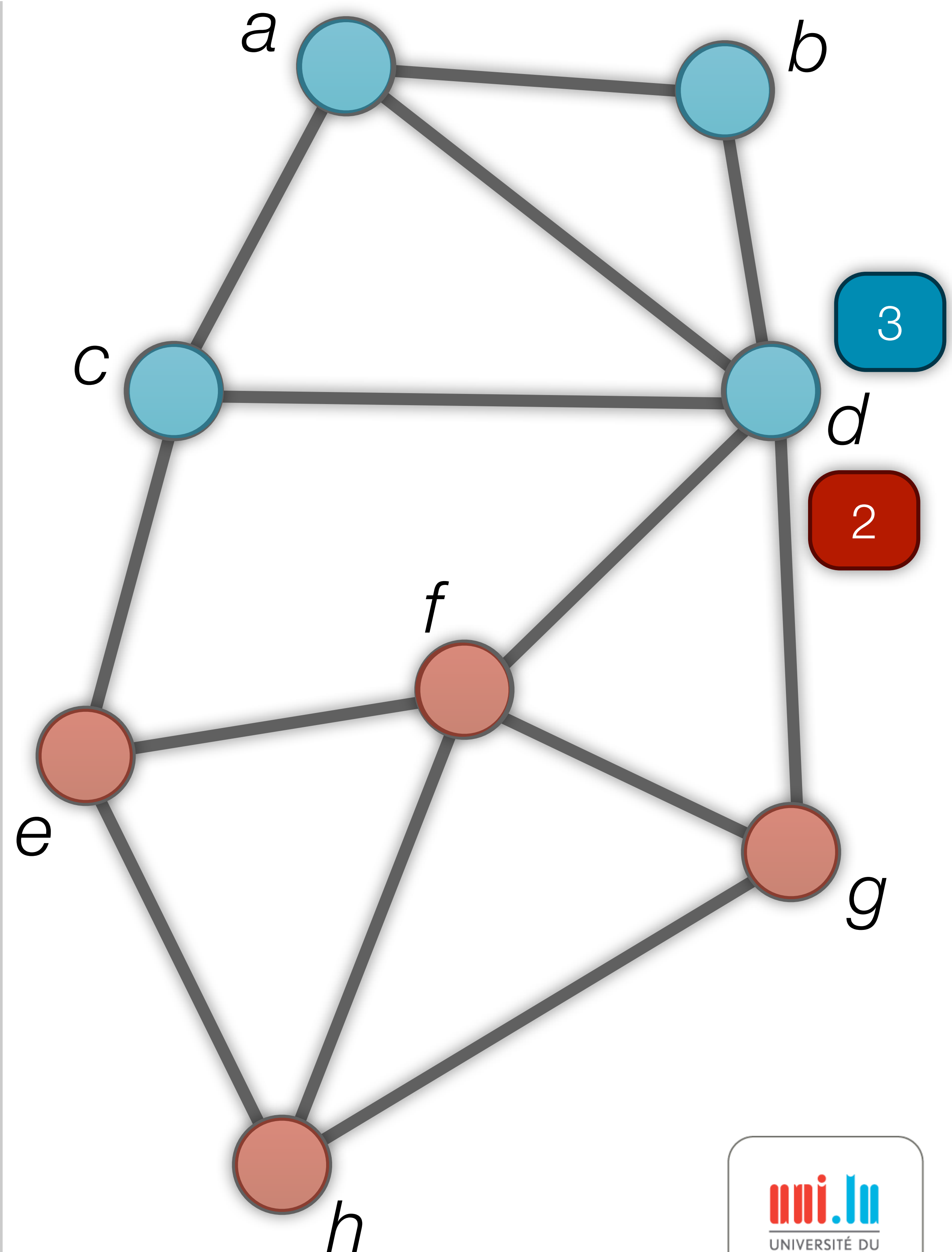

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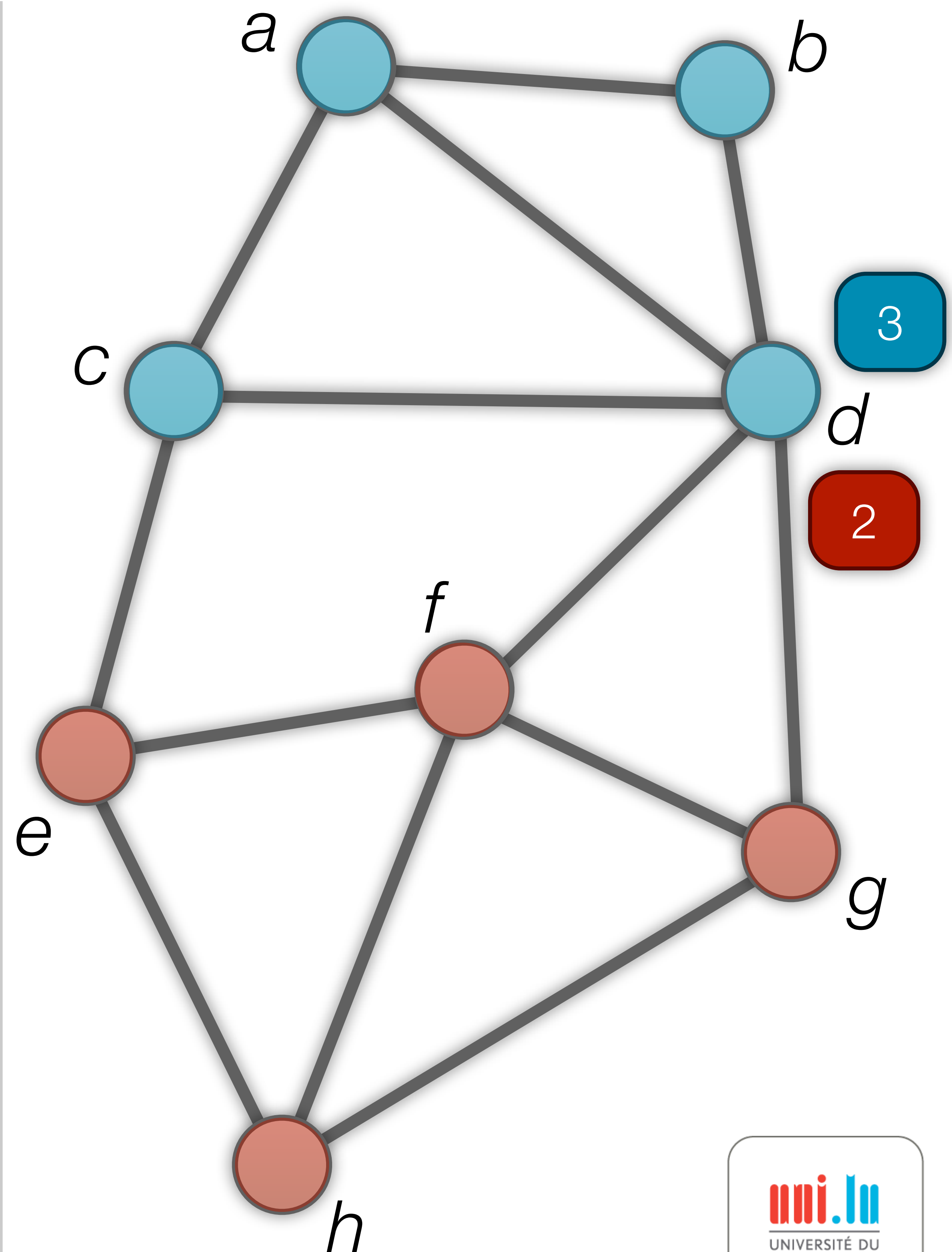

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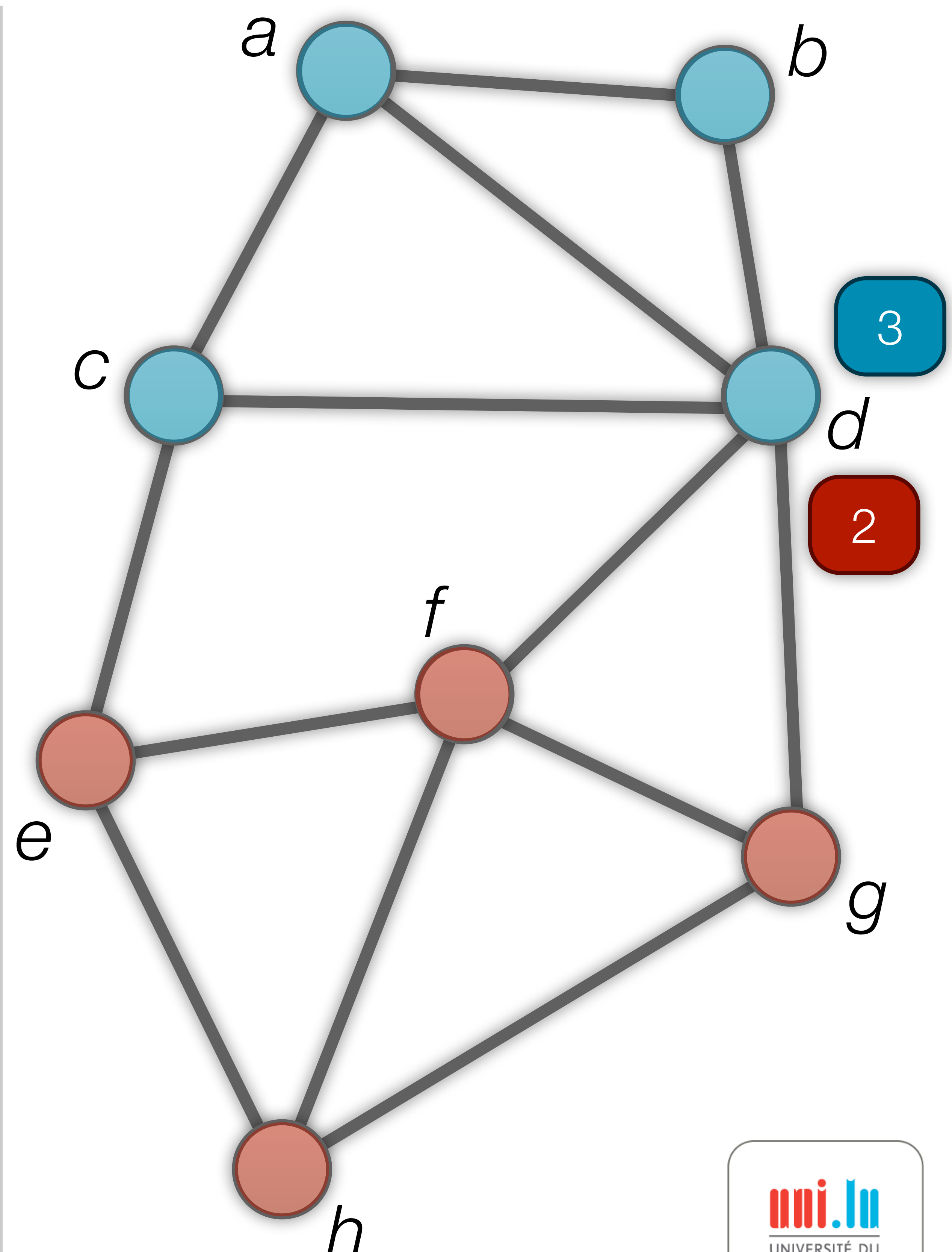
- Not really focusing on dynamic networks



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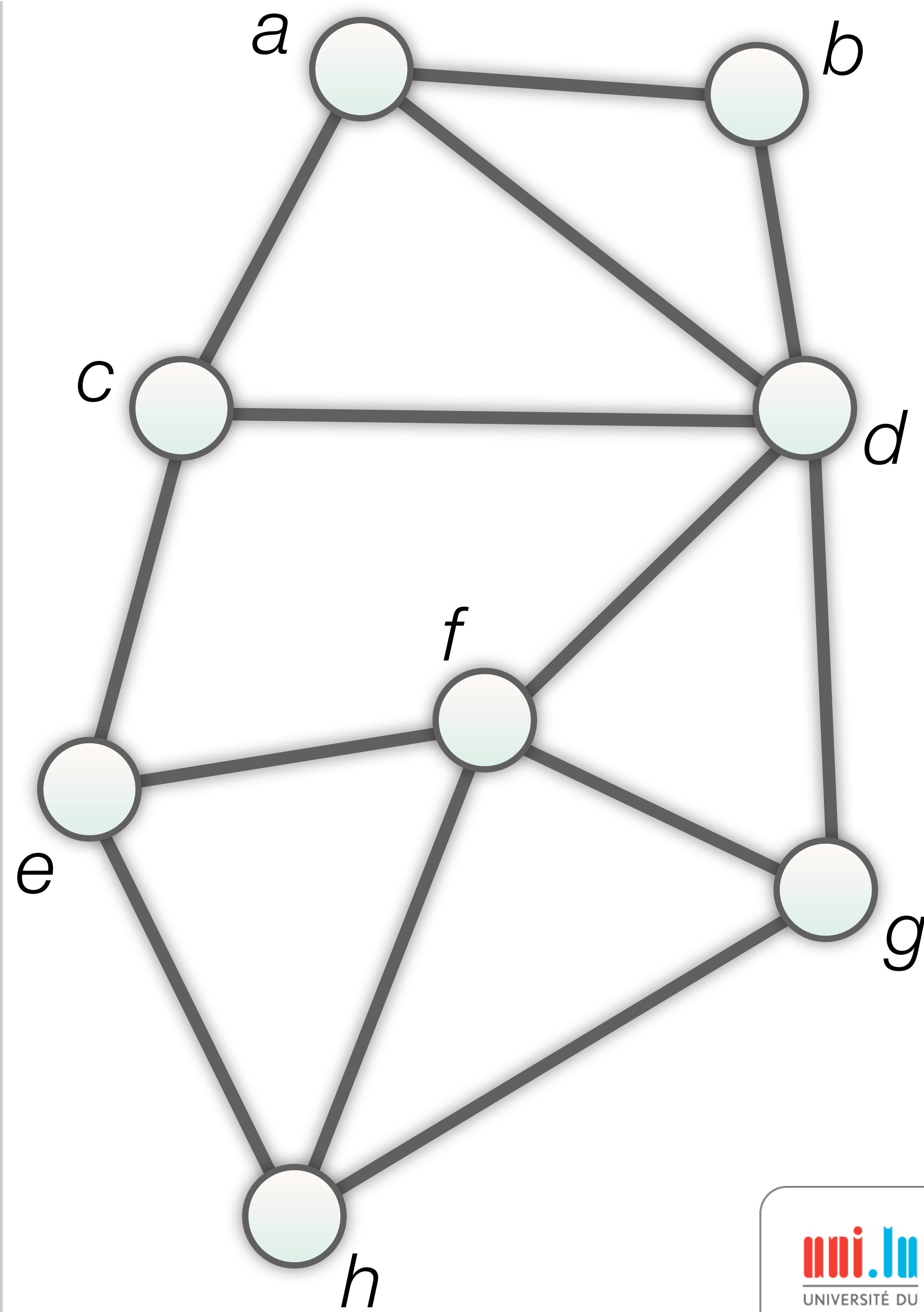

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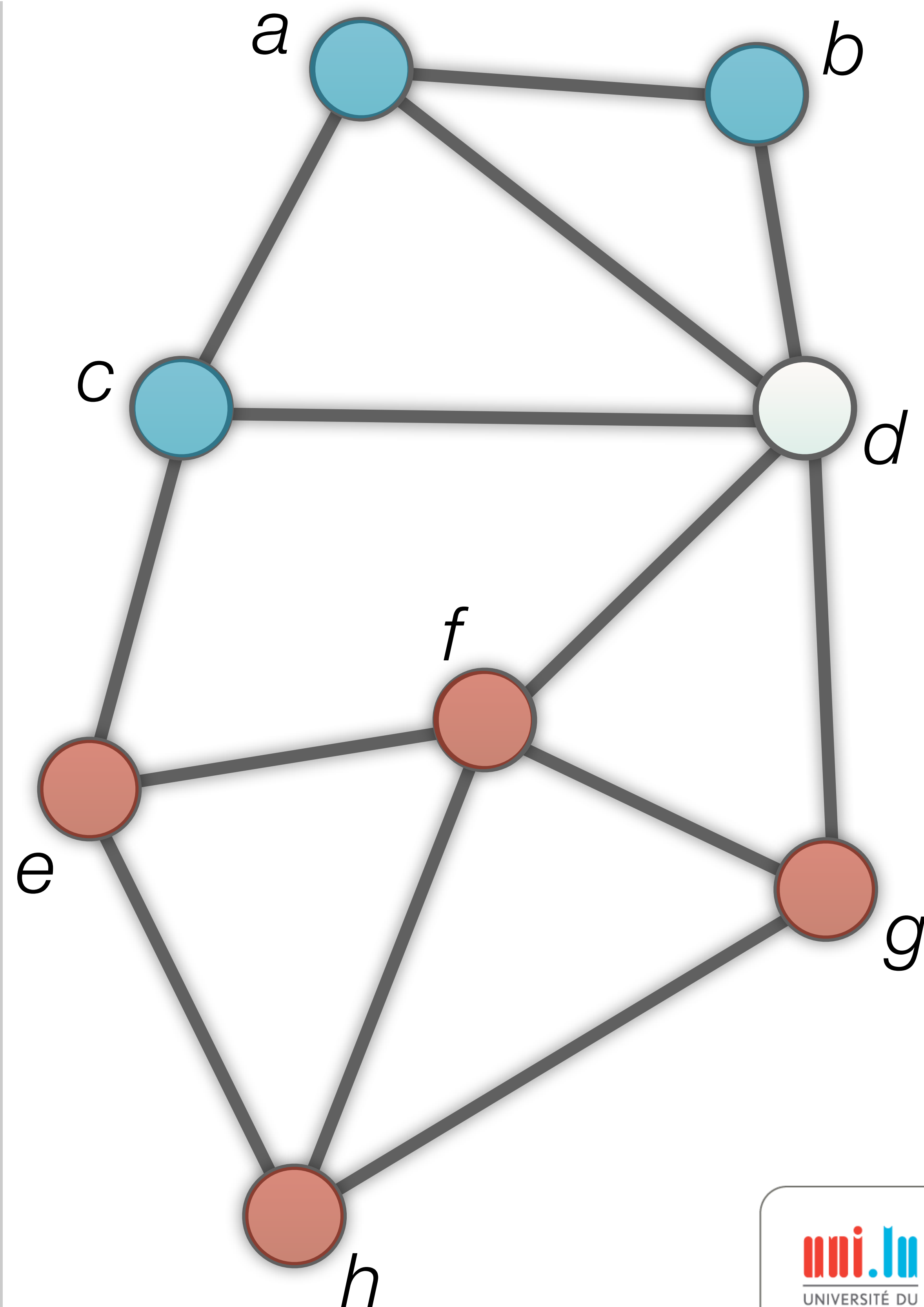

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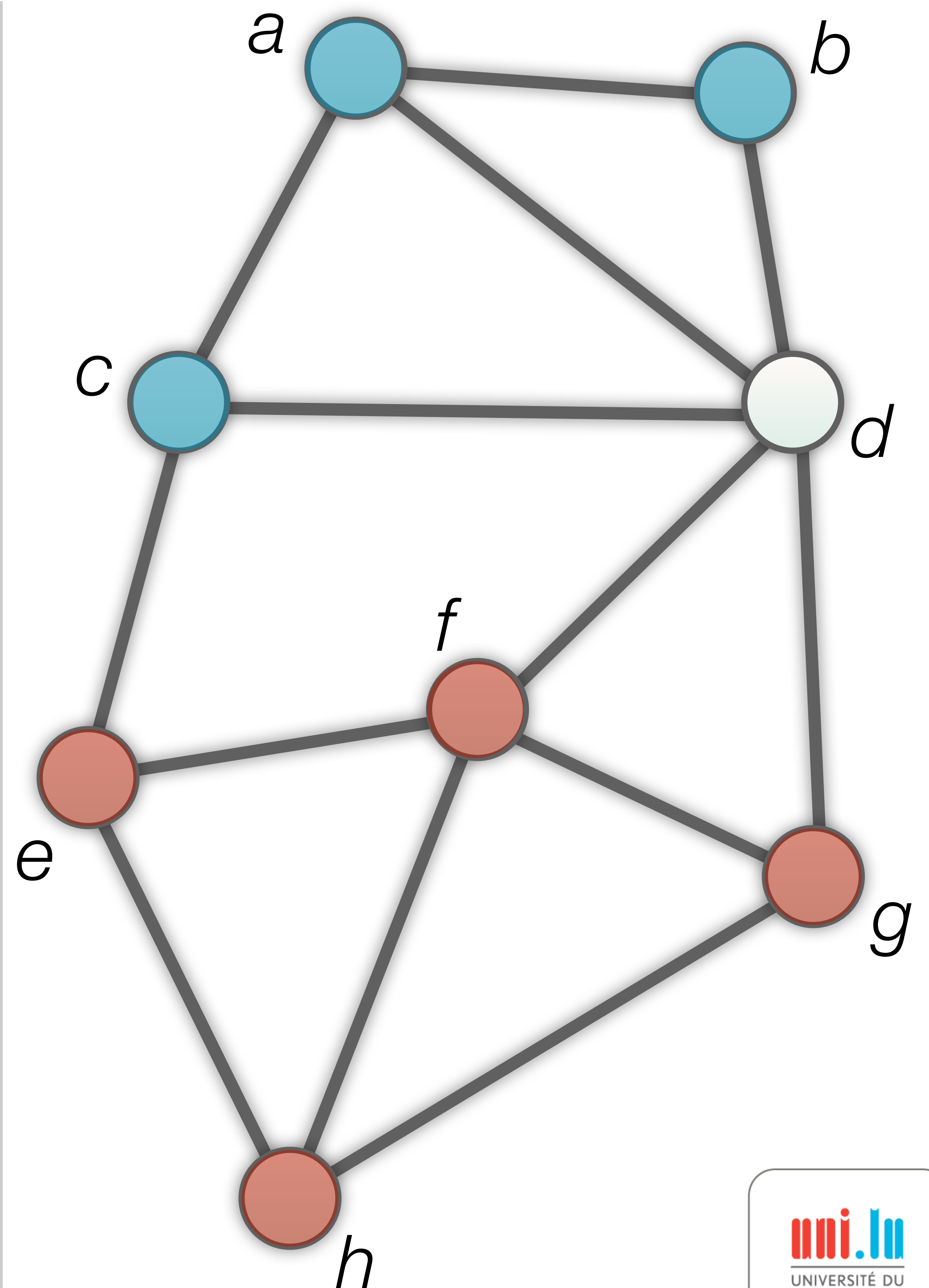

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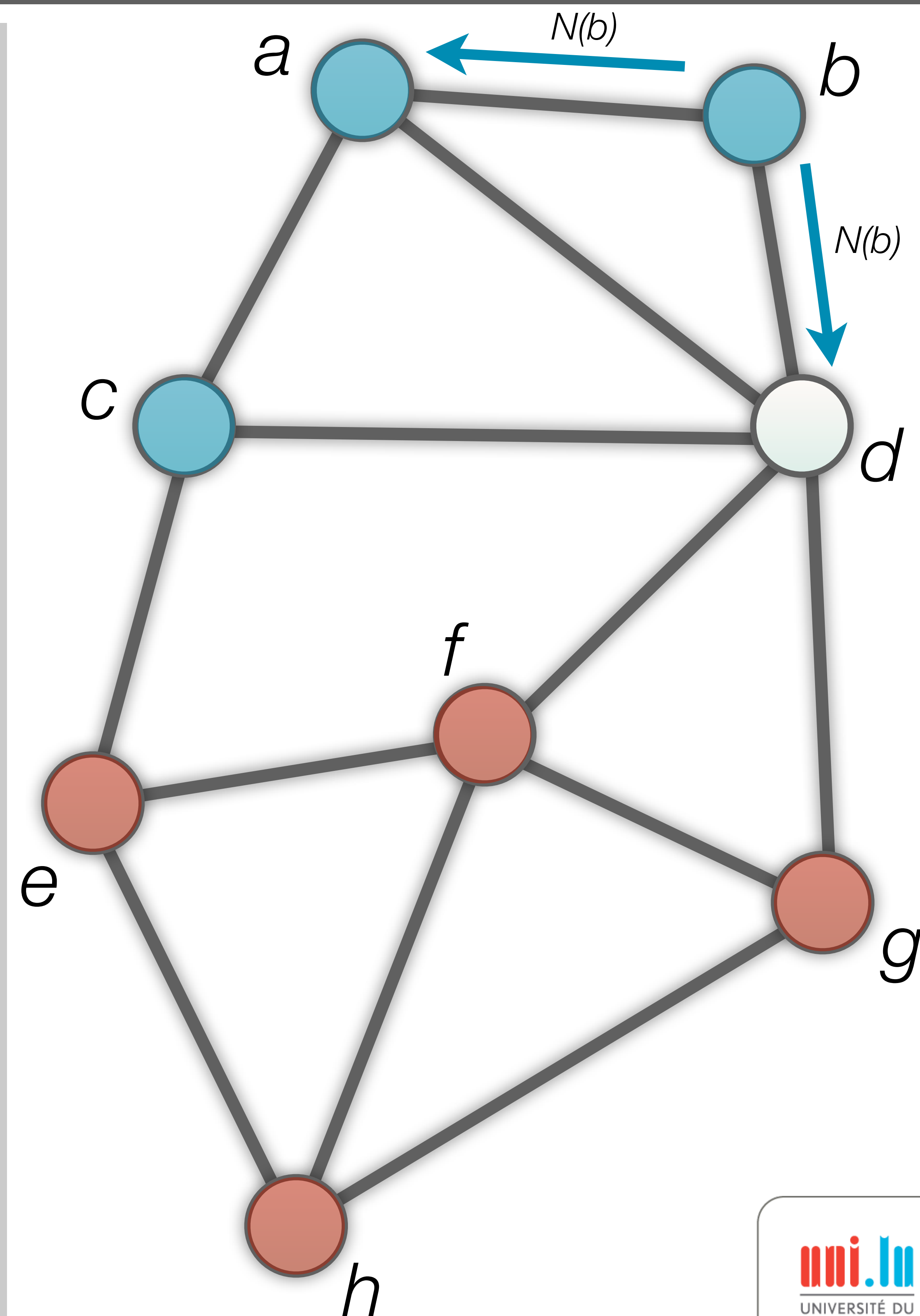

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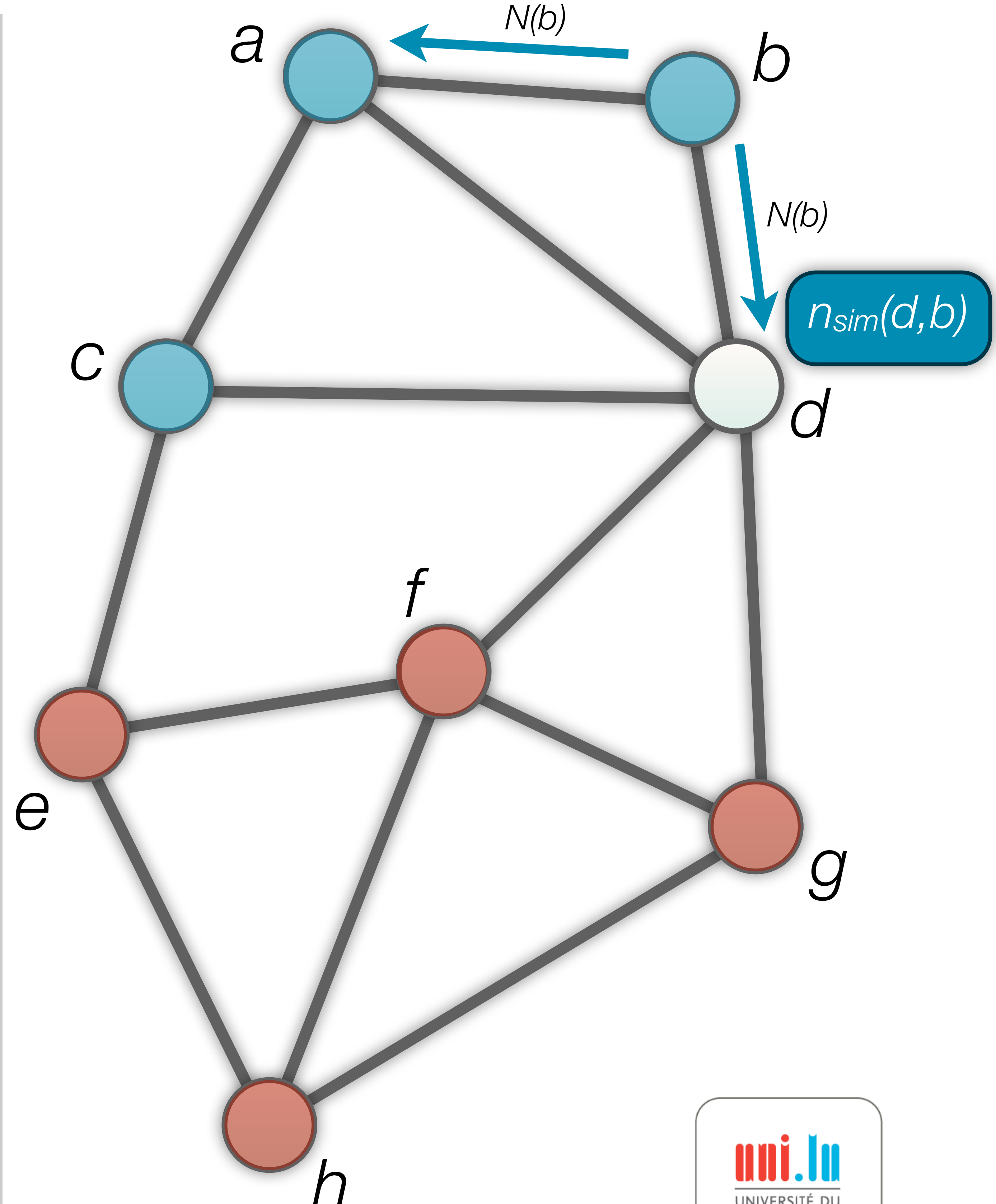

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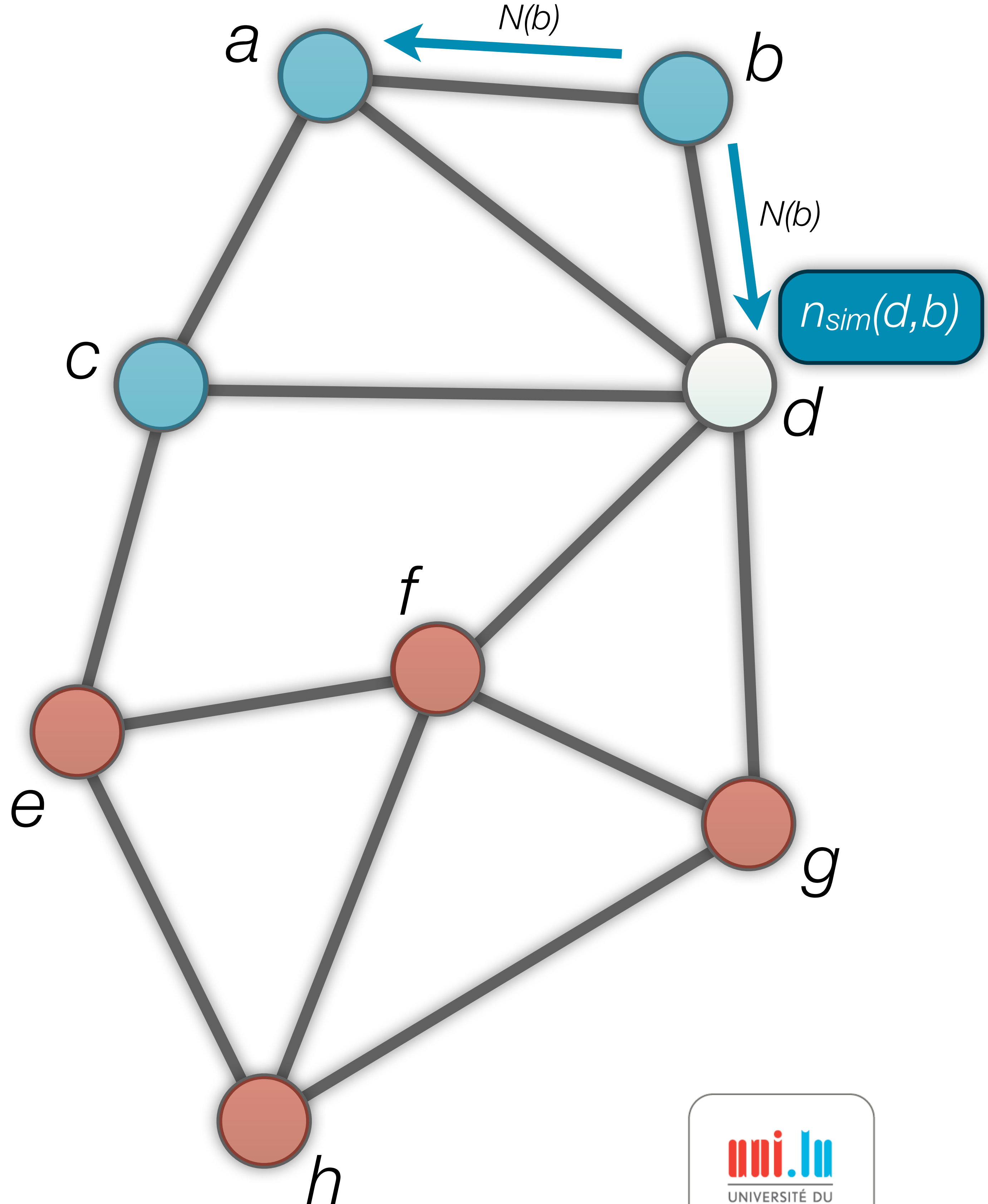

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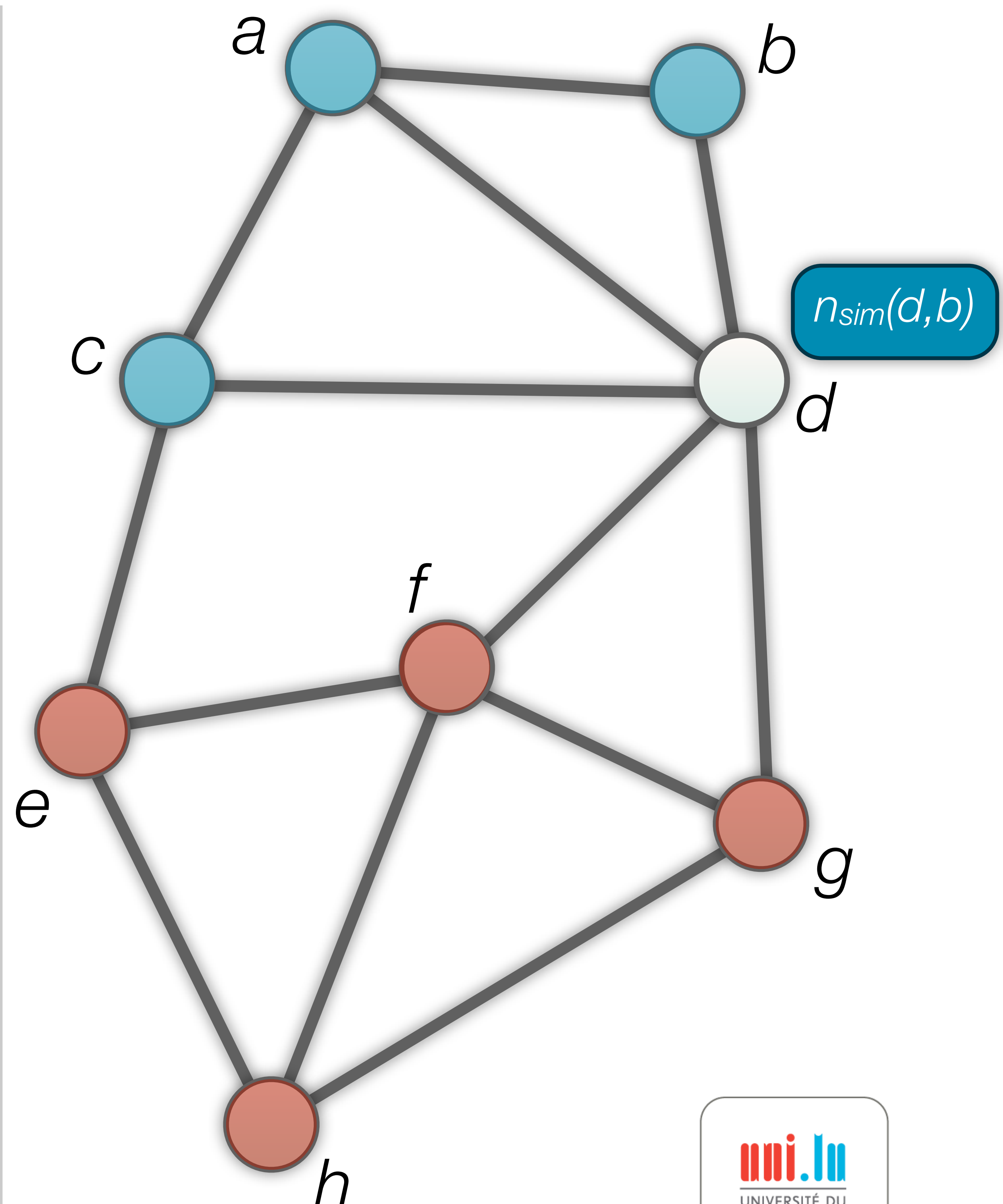

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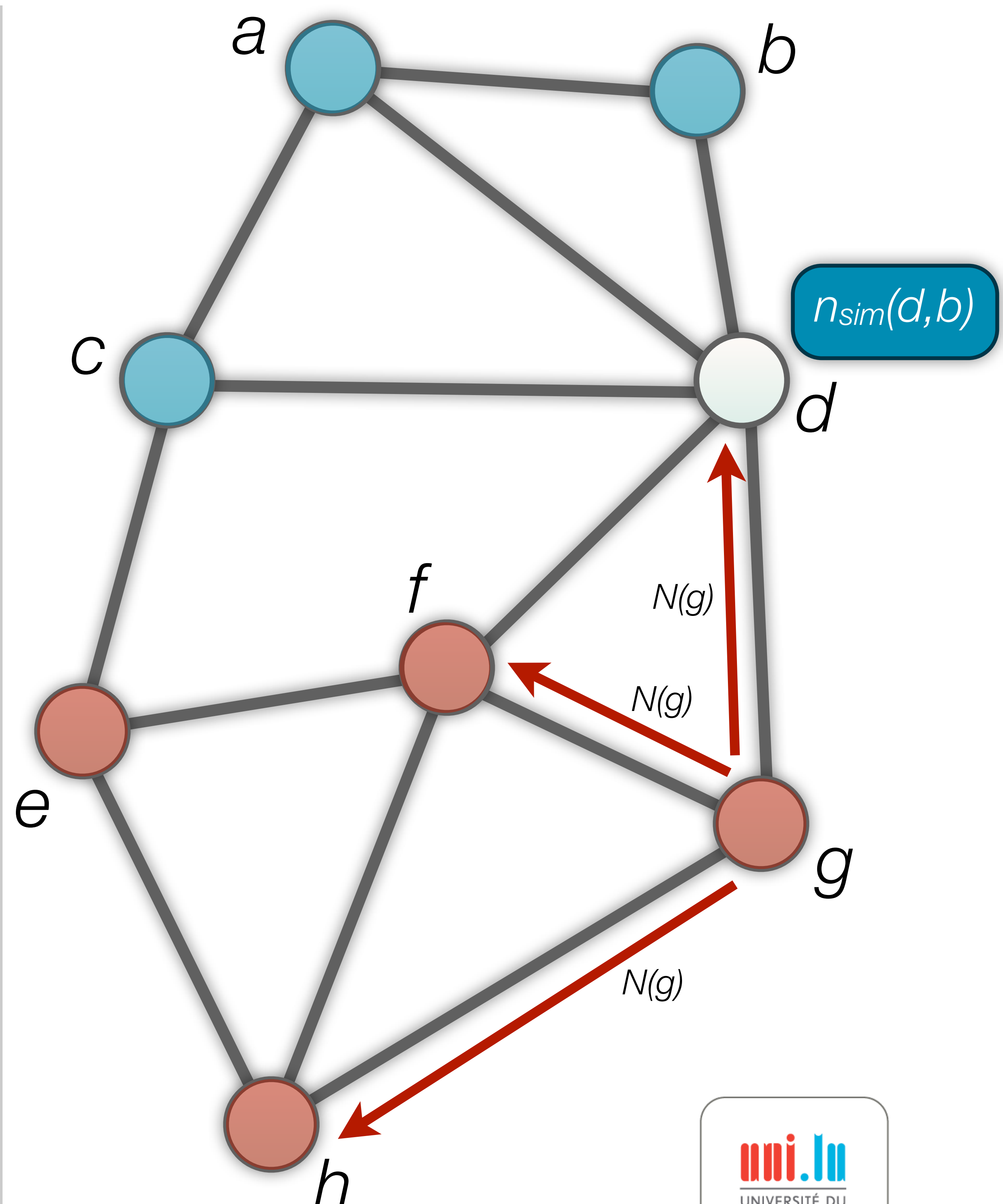

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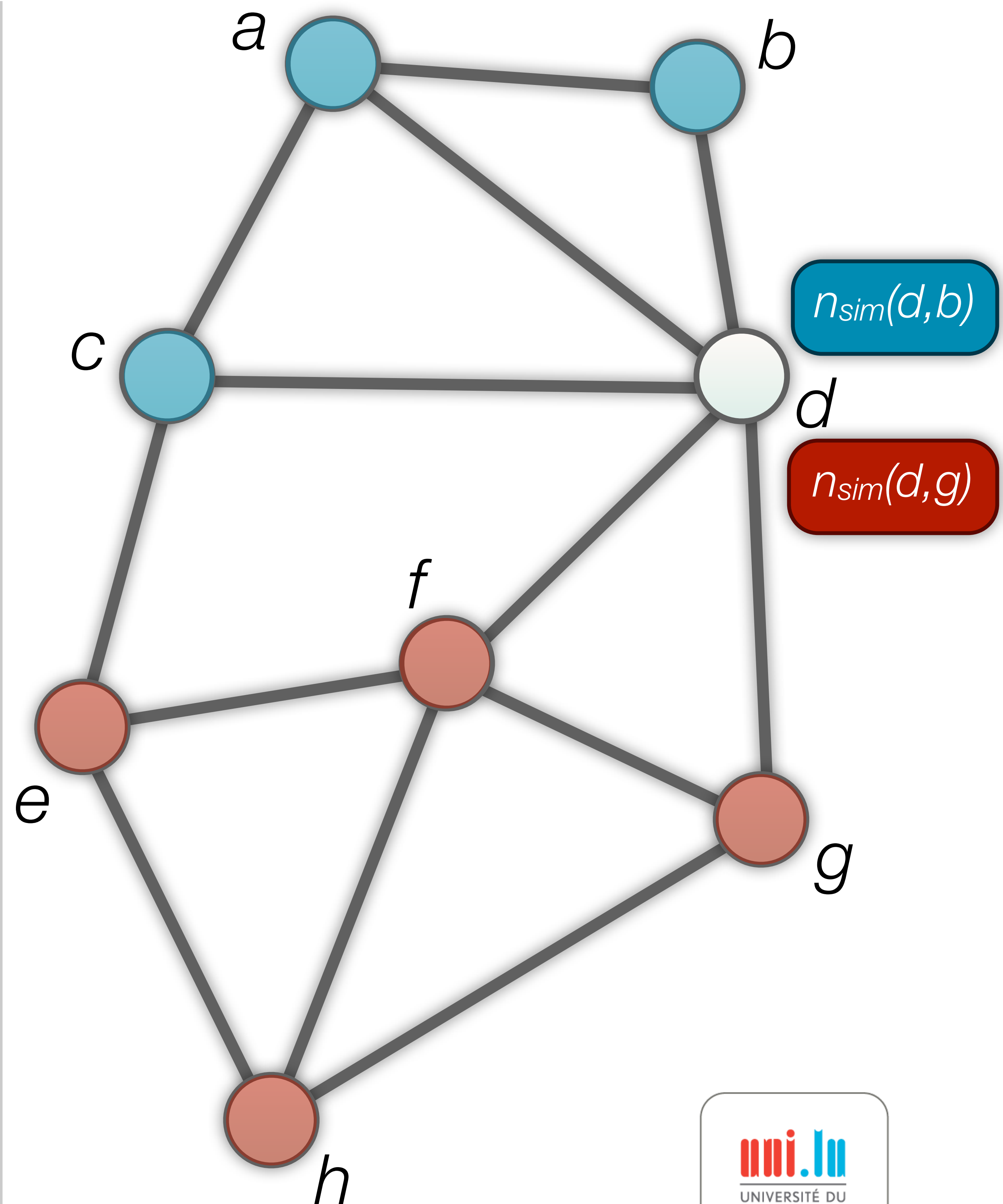

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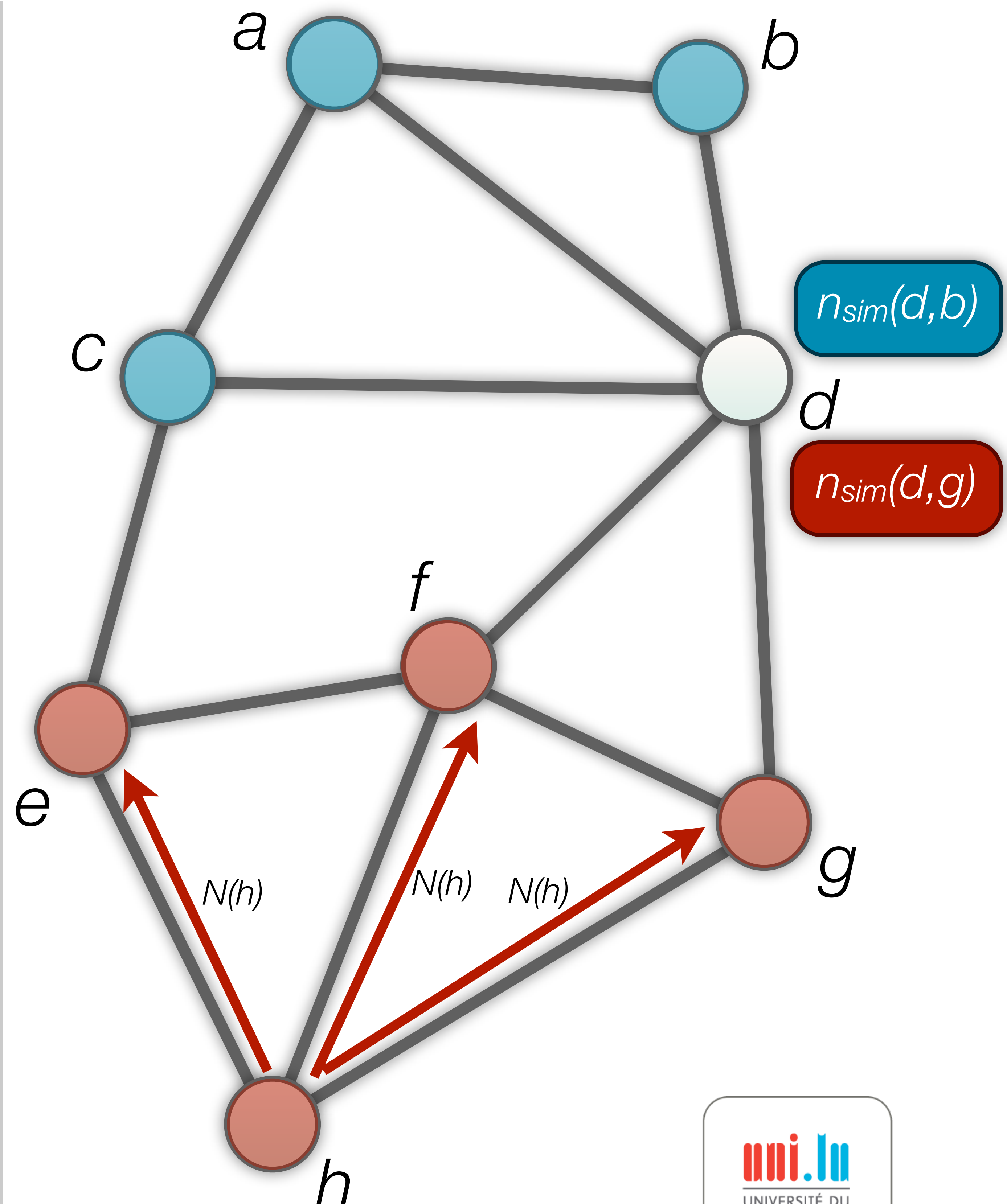

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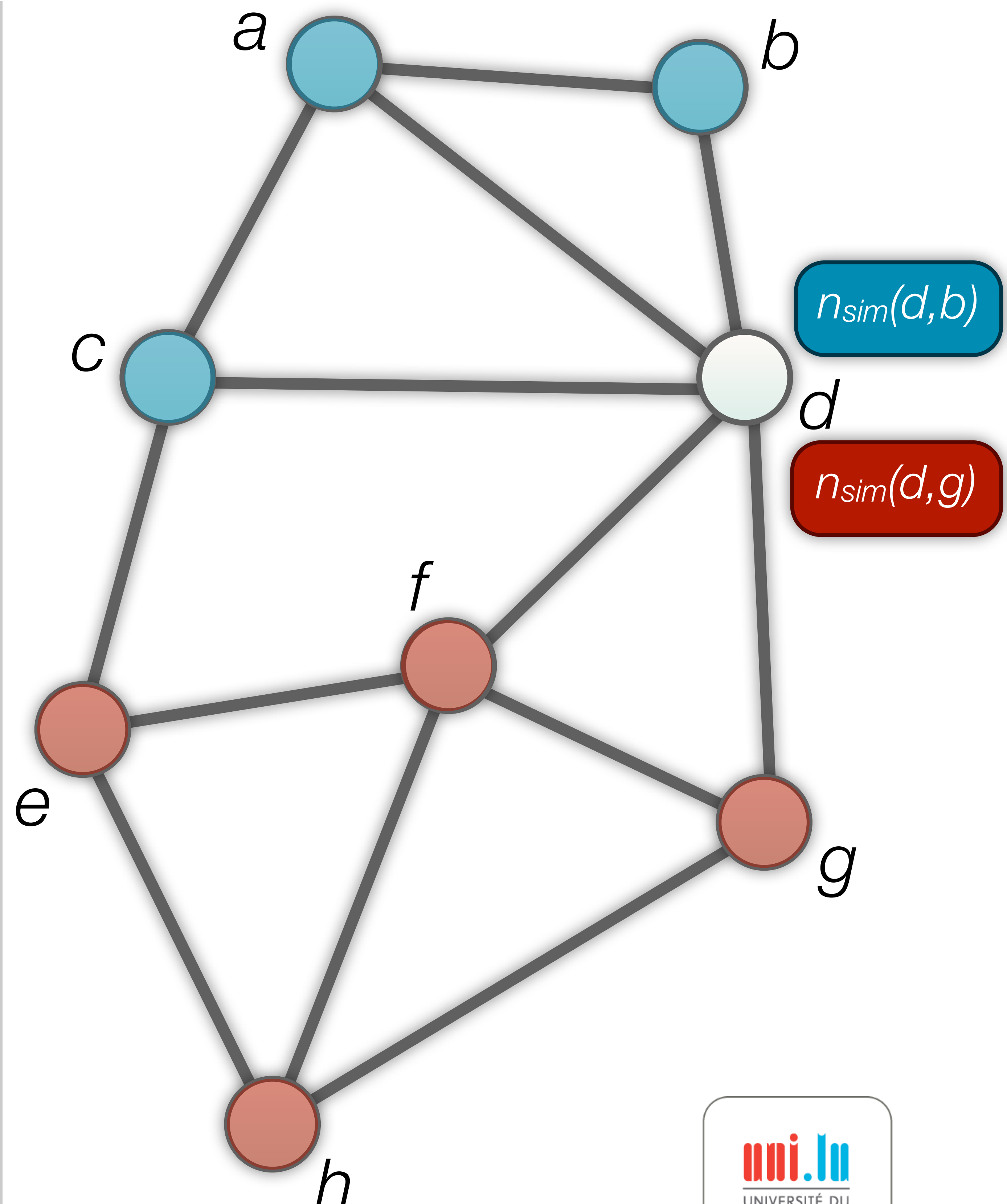

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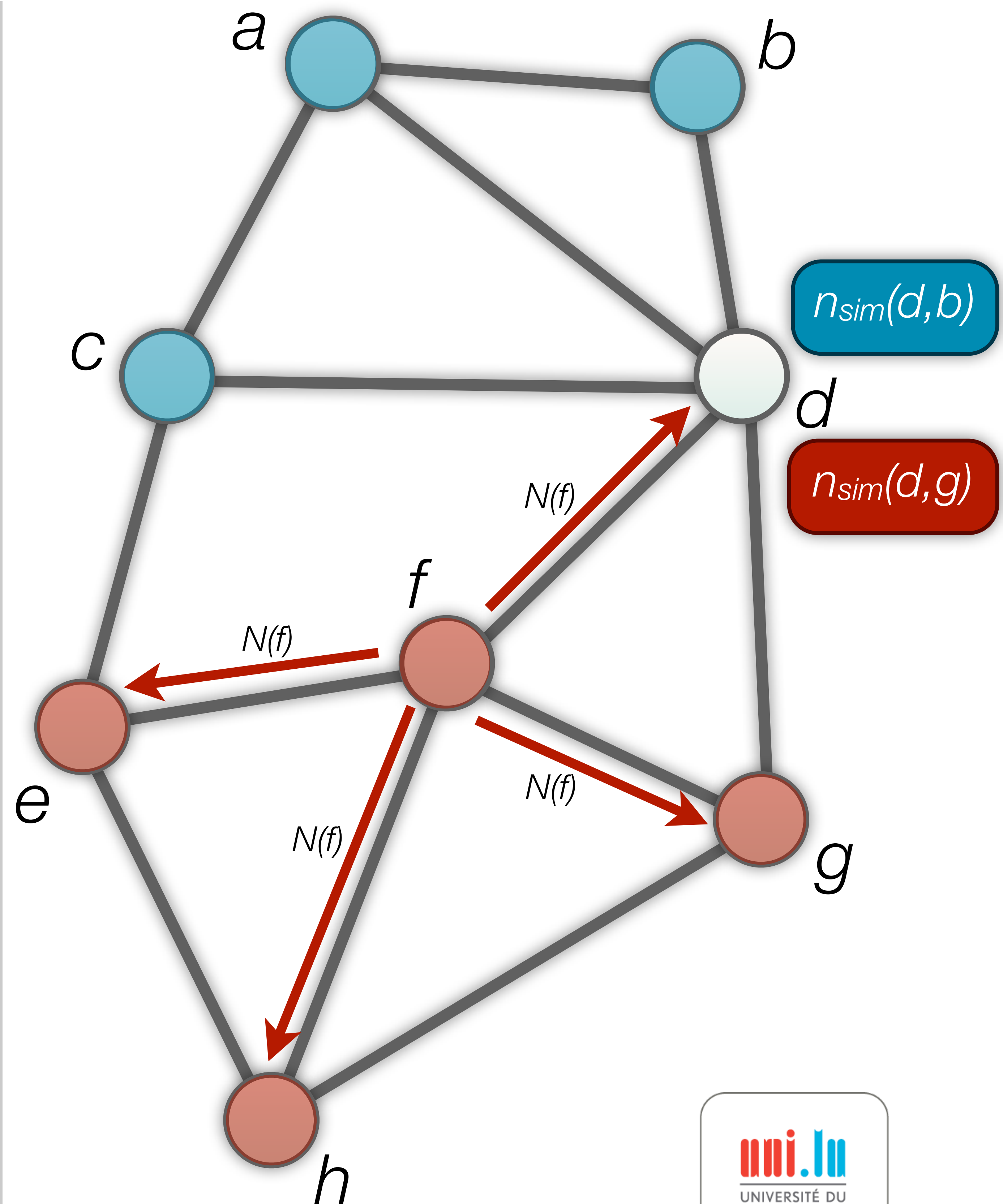

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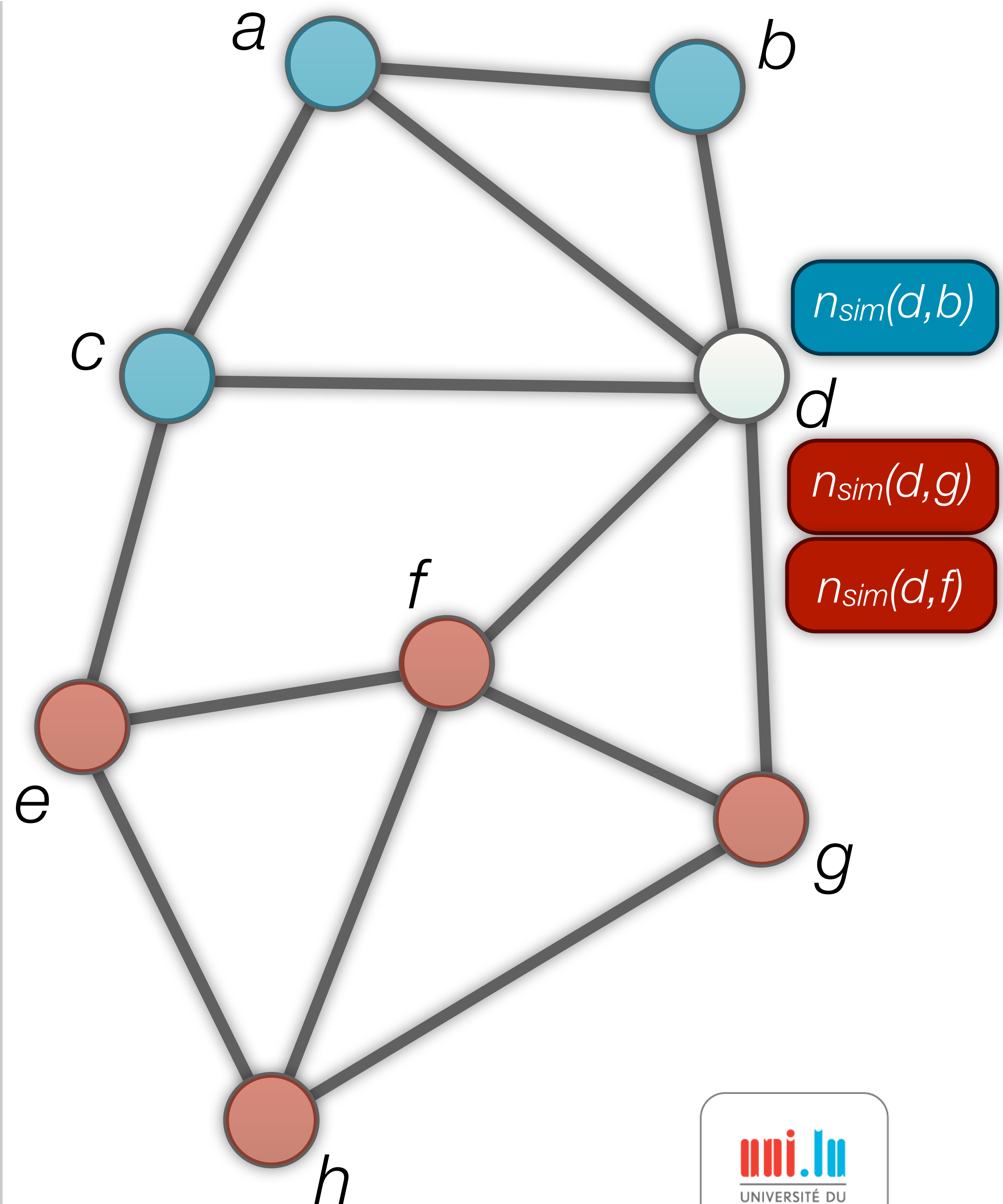

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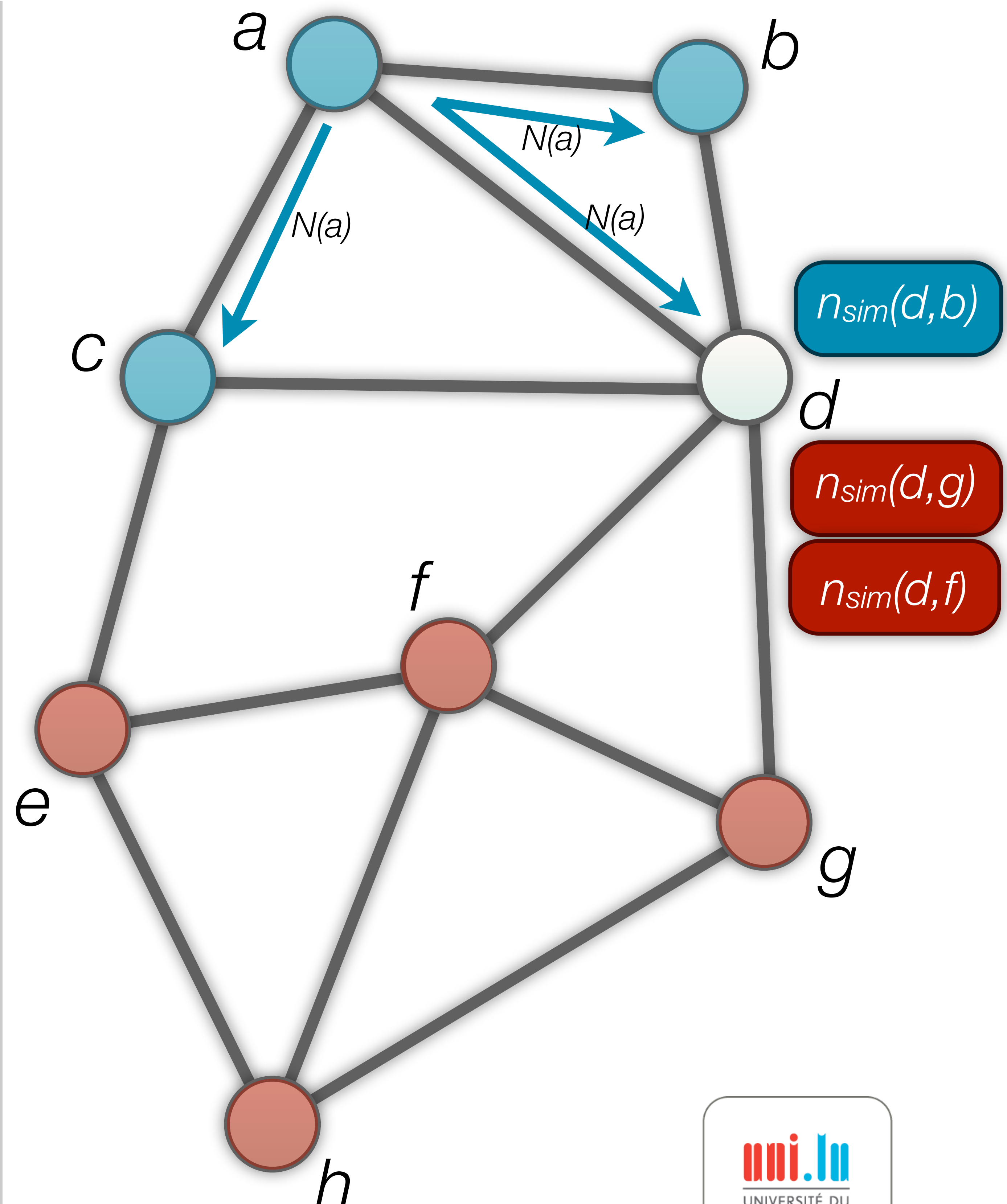

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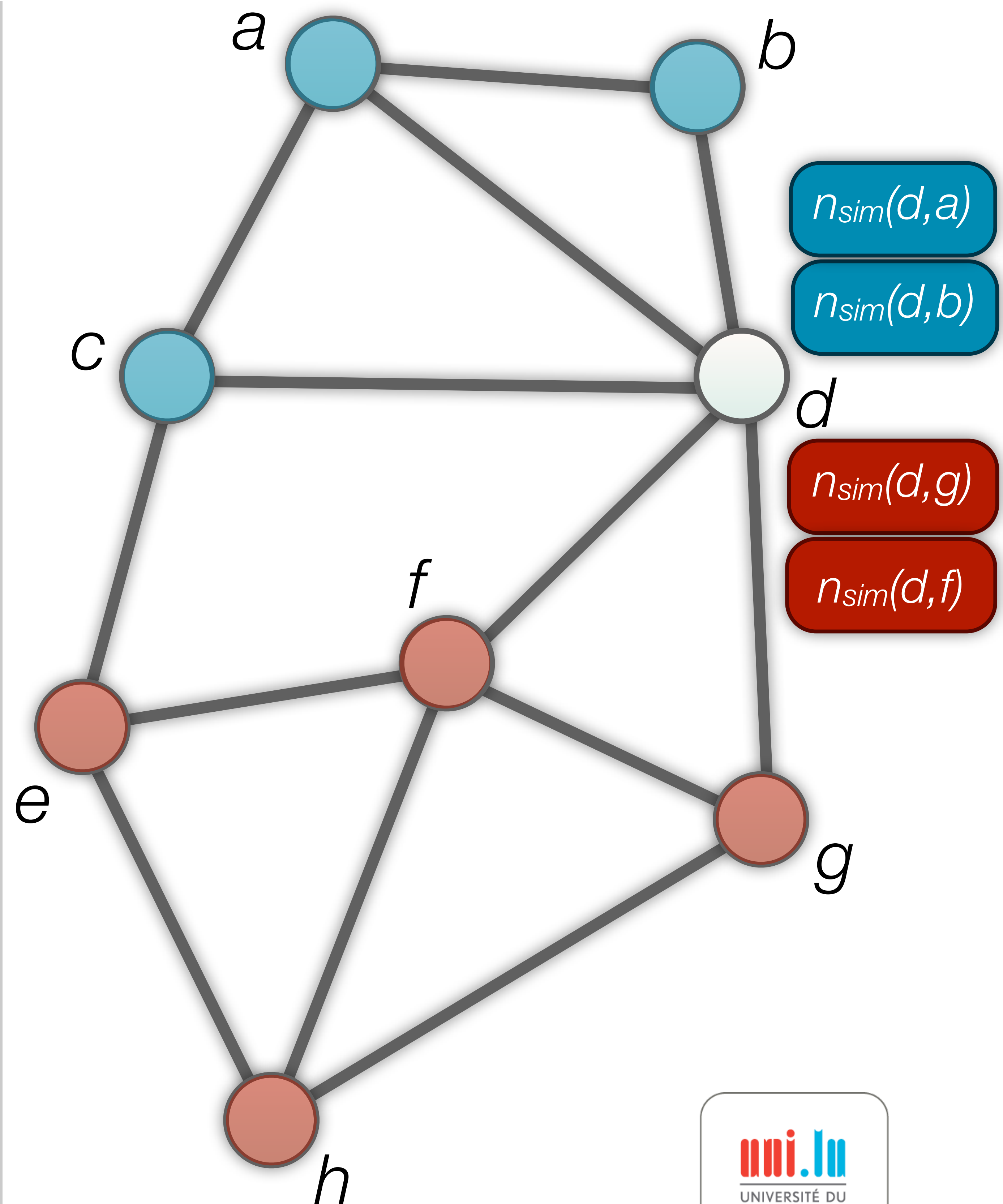

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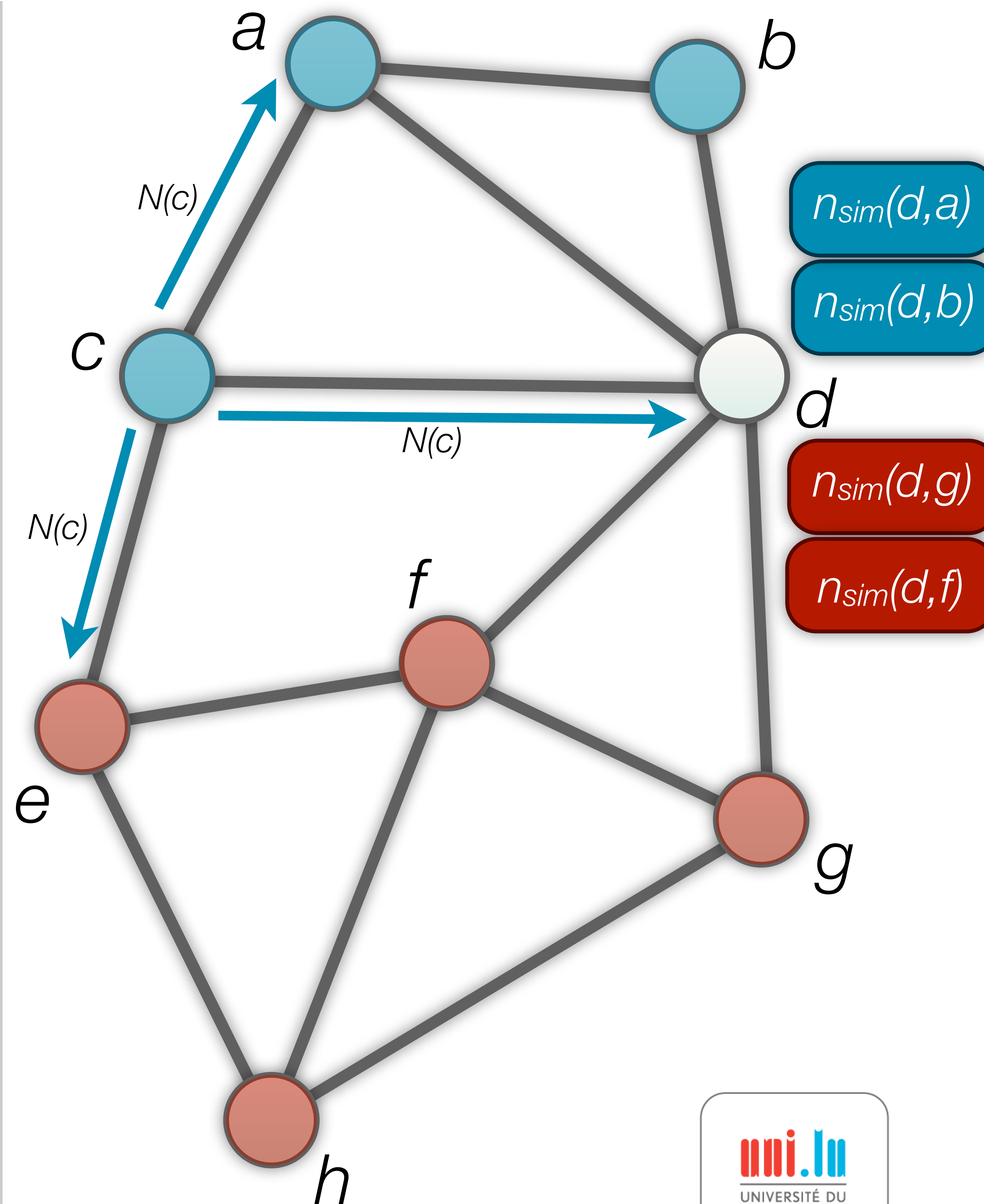

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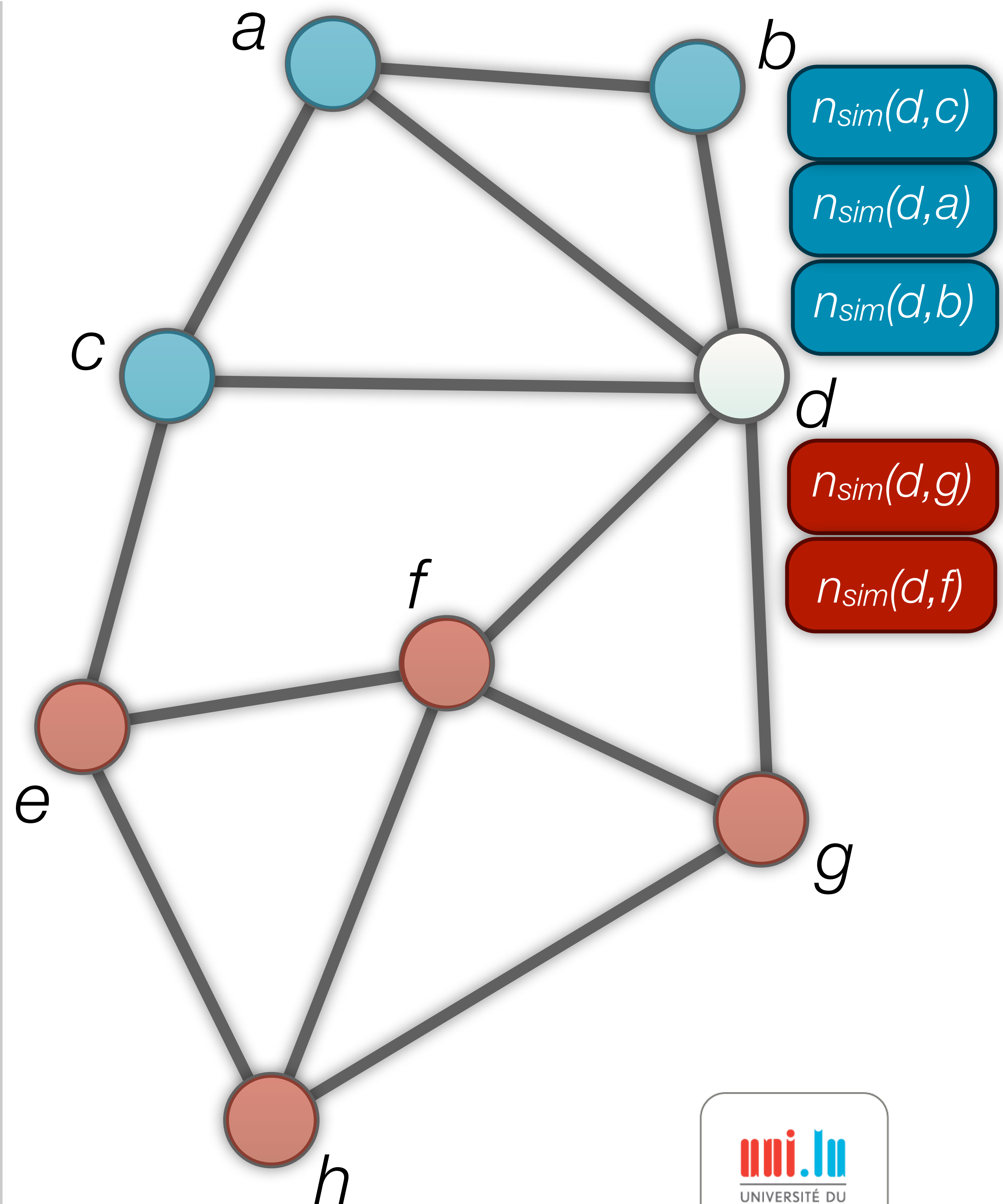

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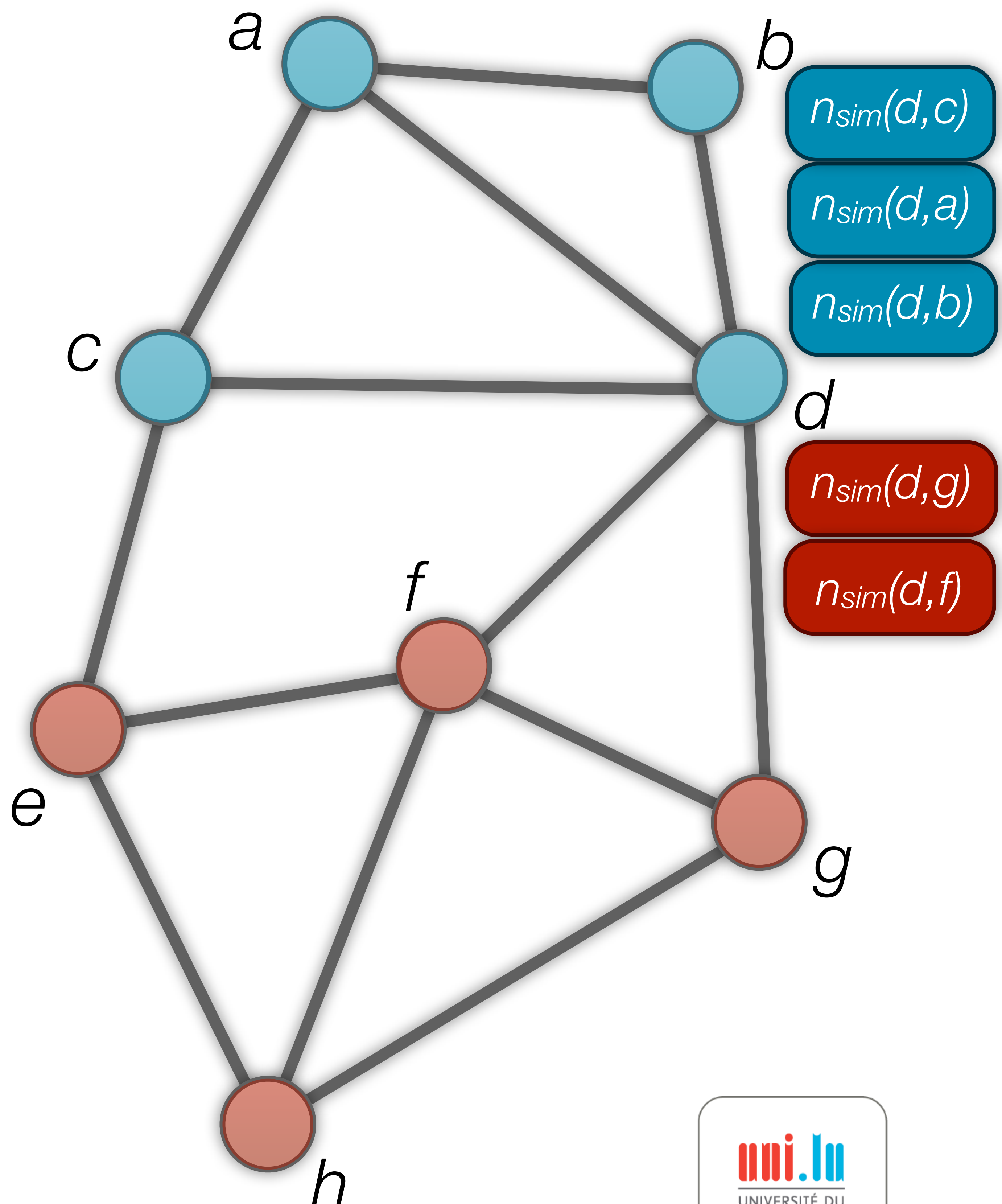

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- Objectives:
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  - Be more deterministic

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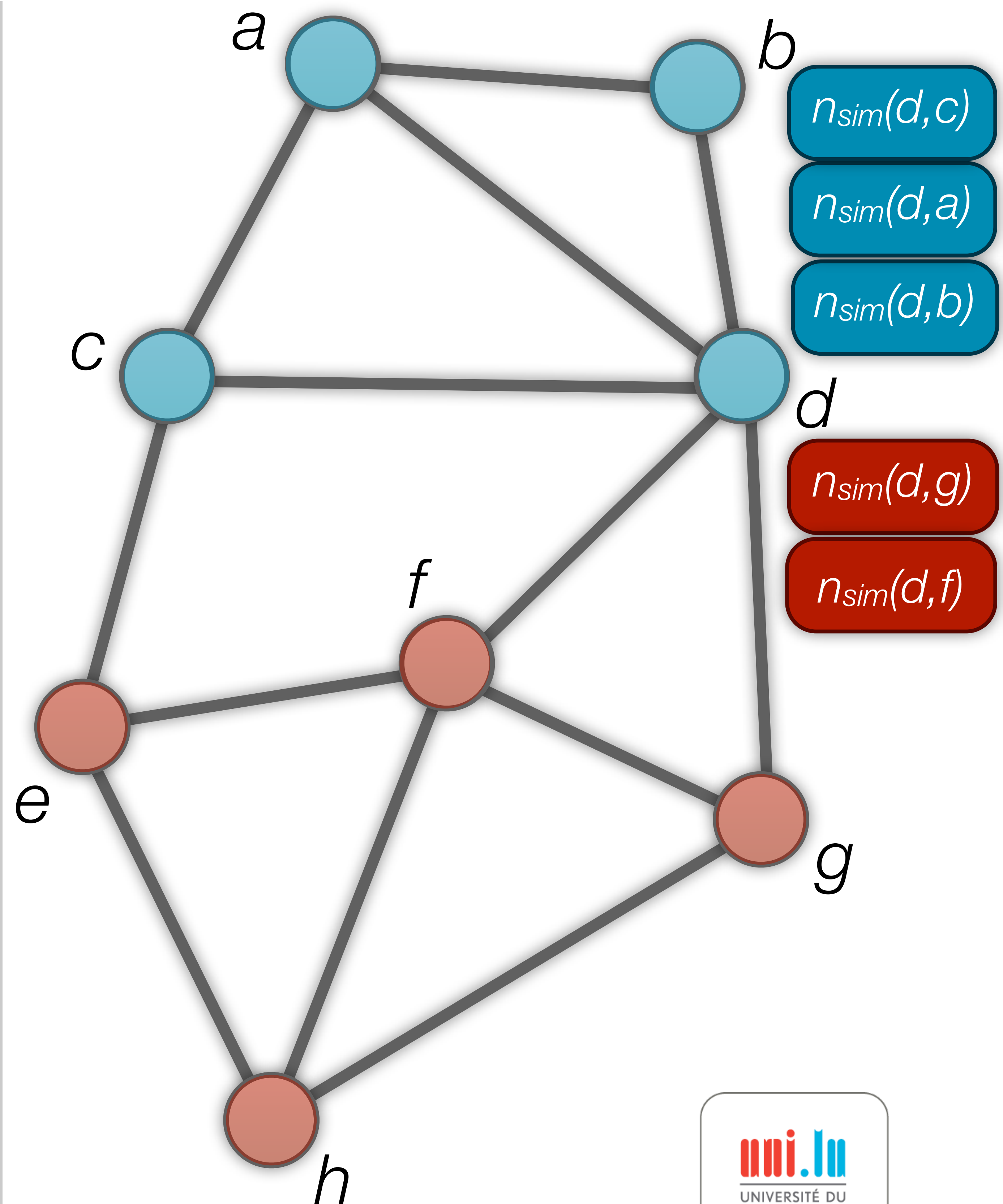

Additional SHARC improvements

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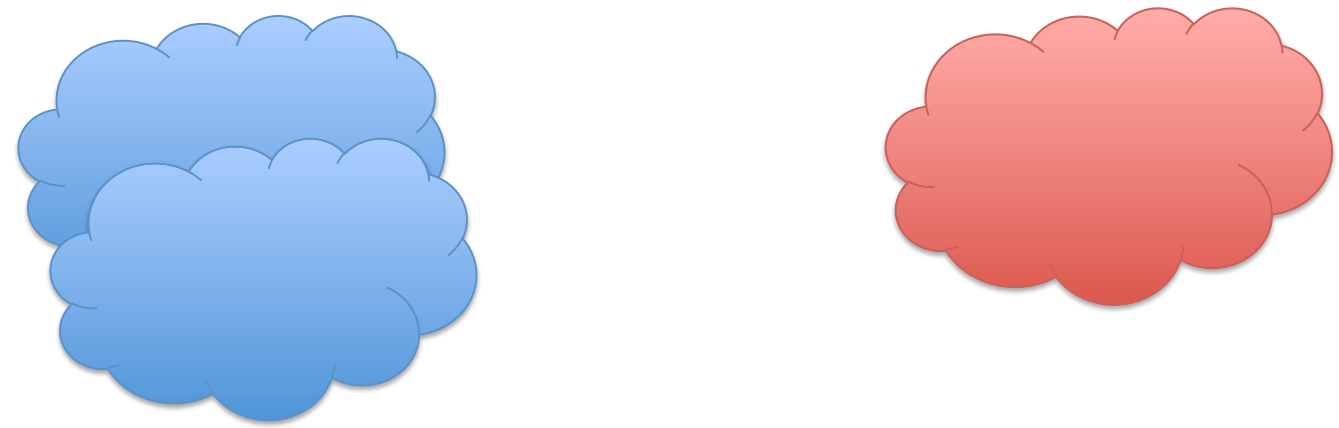
- Focus on dynamic networks:
  - **Break mode**: detects split of a community in two disconnected subset
    → prevent the *wandering community* effect

Wandering community effect



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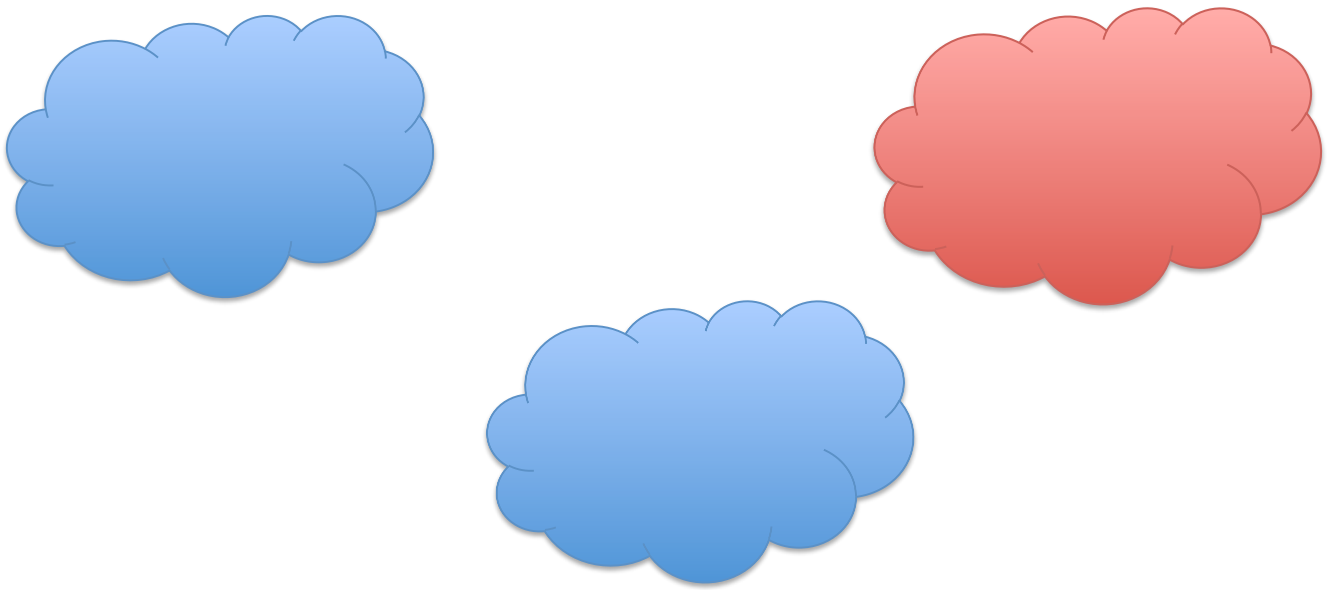

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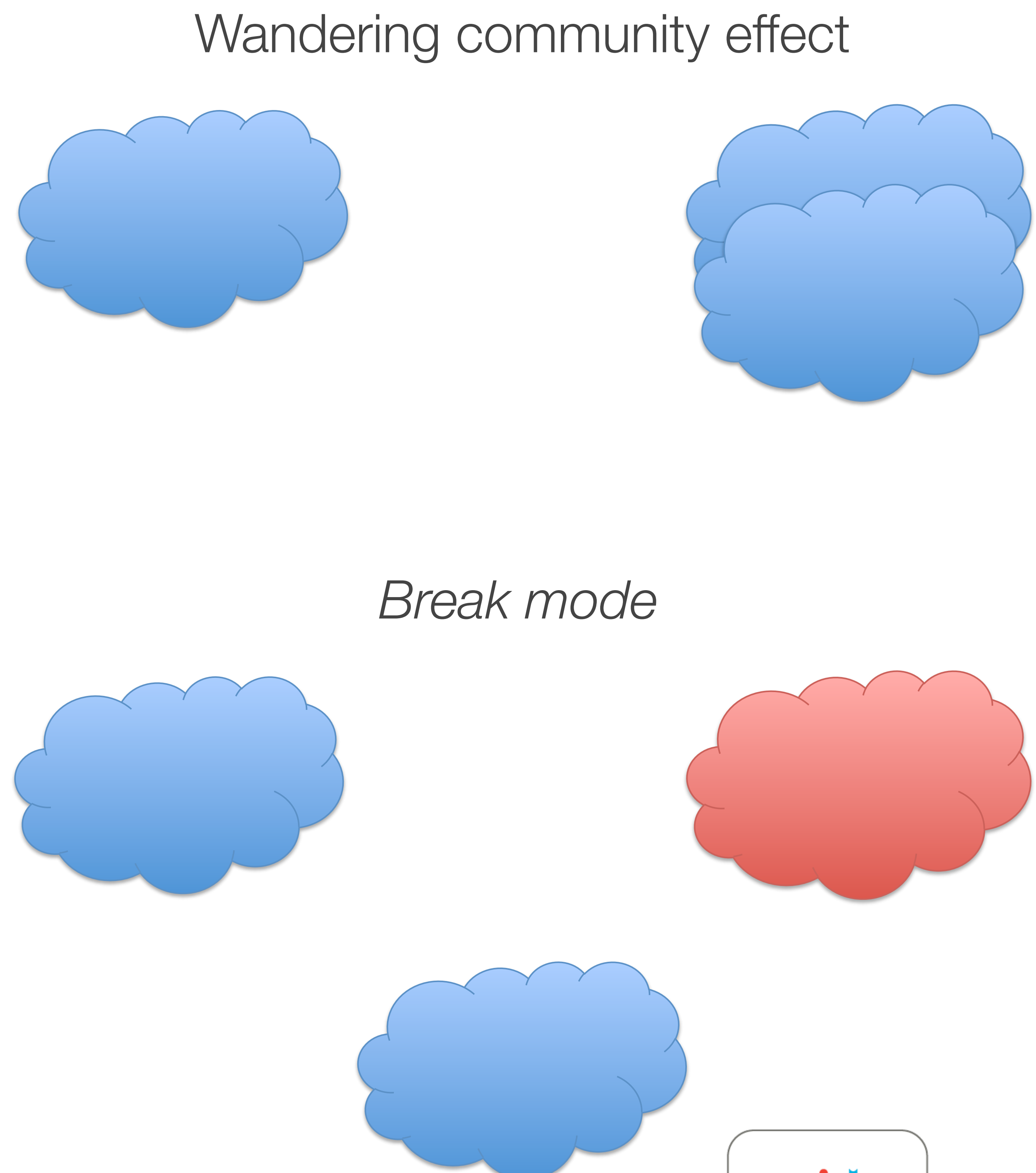

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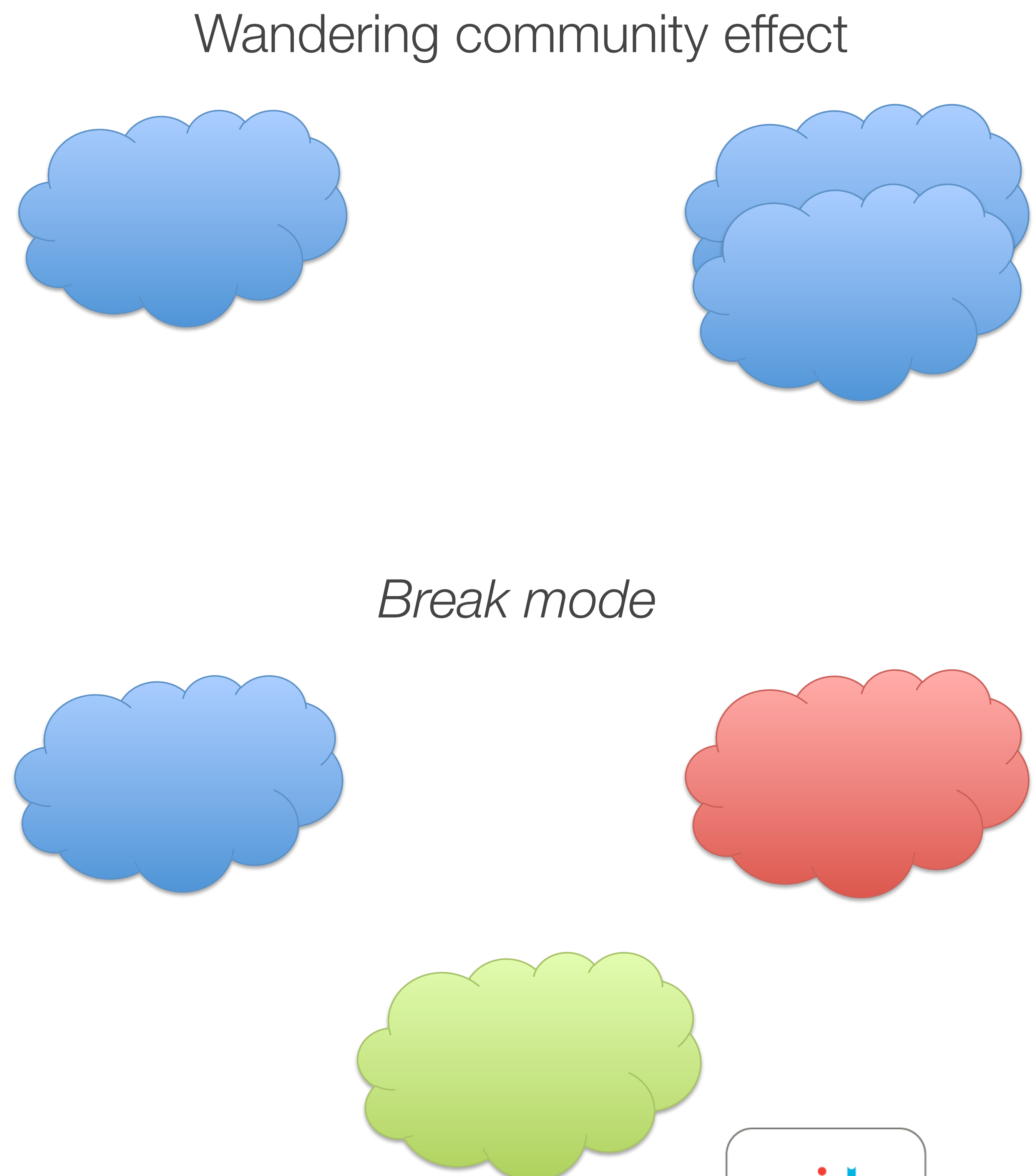

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  → can be helpful for delay-constrained applications
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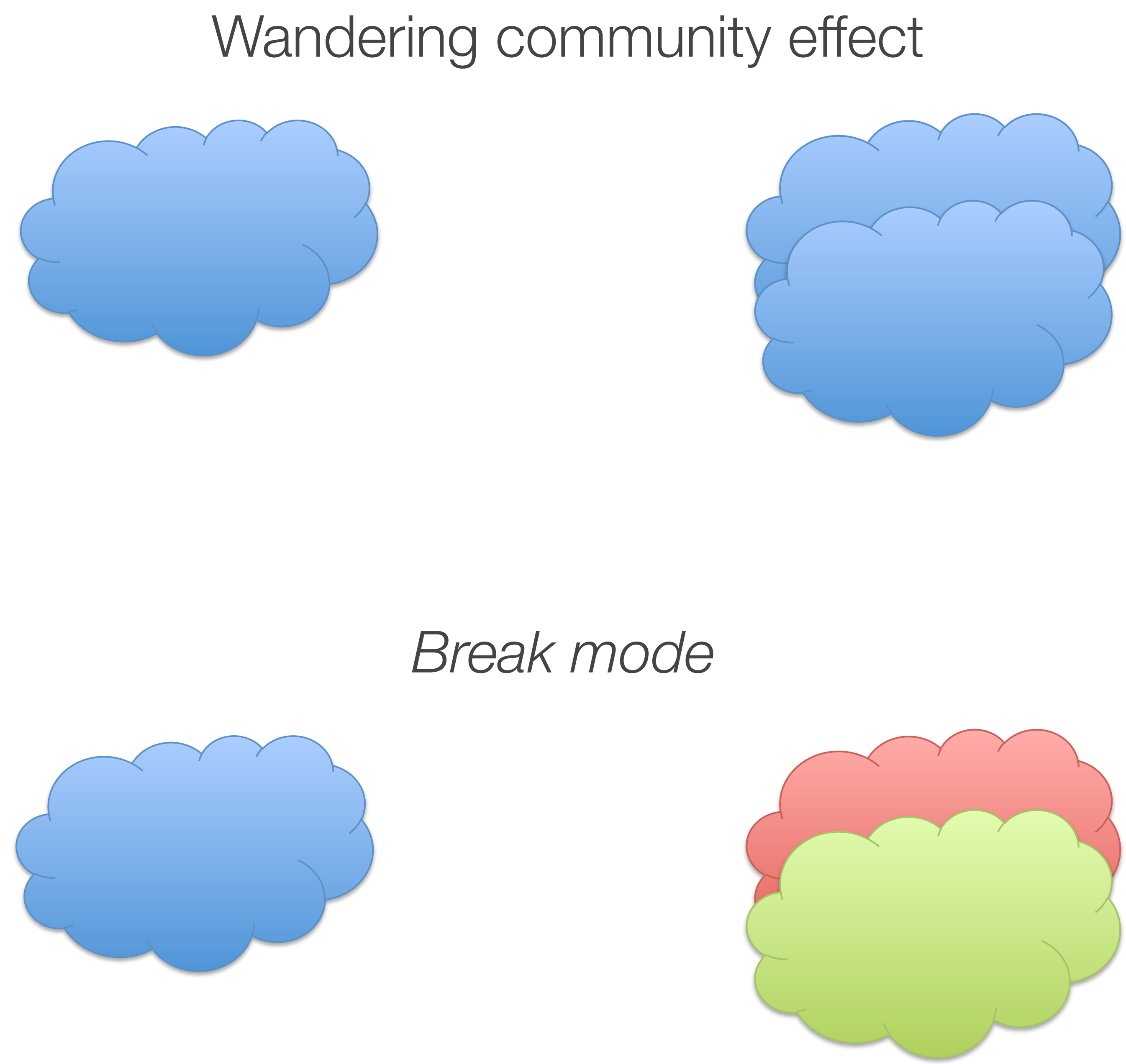

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- Shift from pure formal considerations to applicative constraints

Wandering community effect

Break mode

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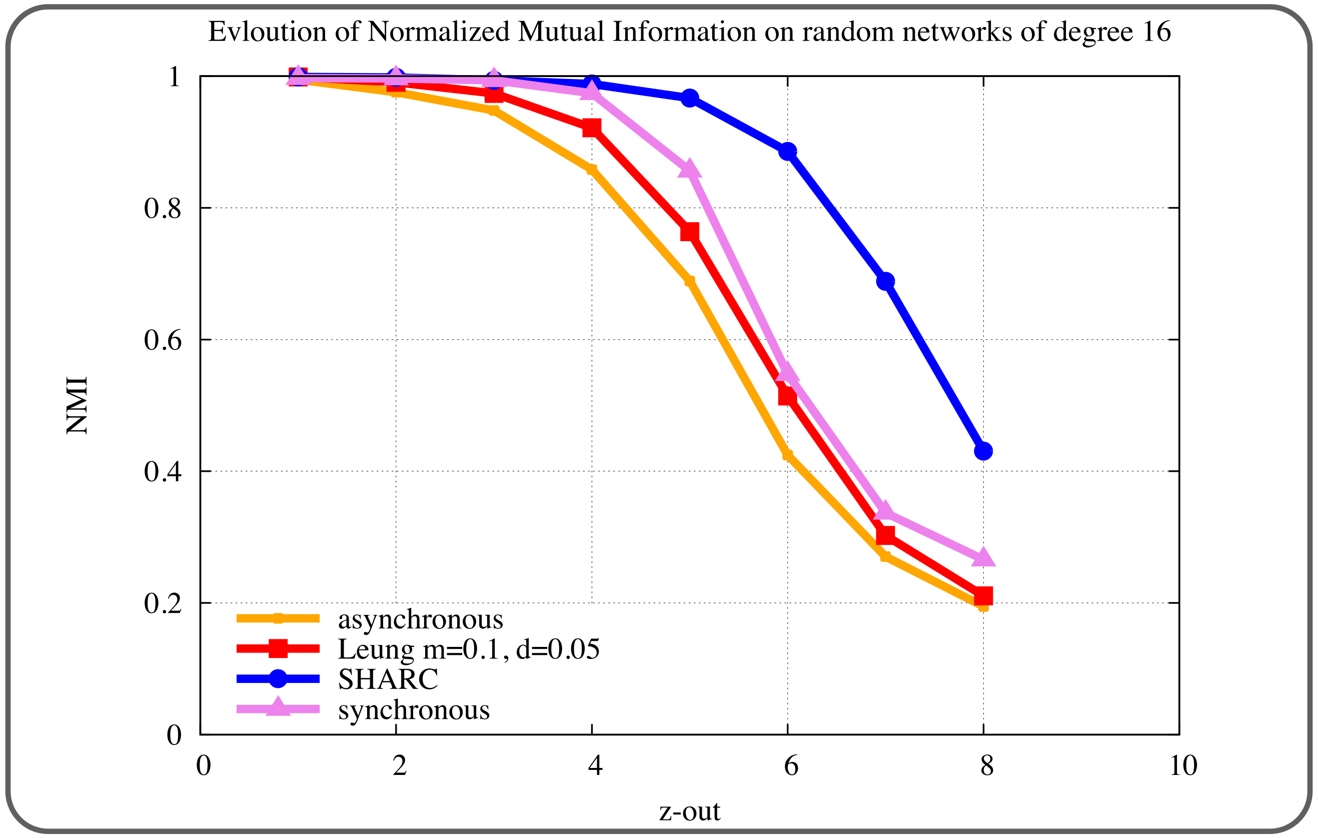
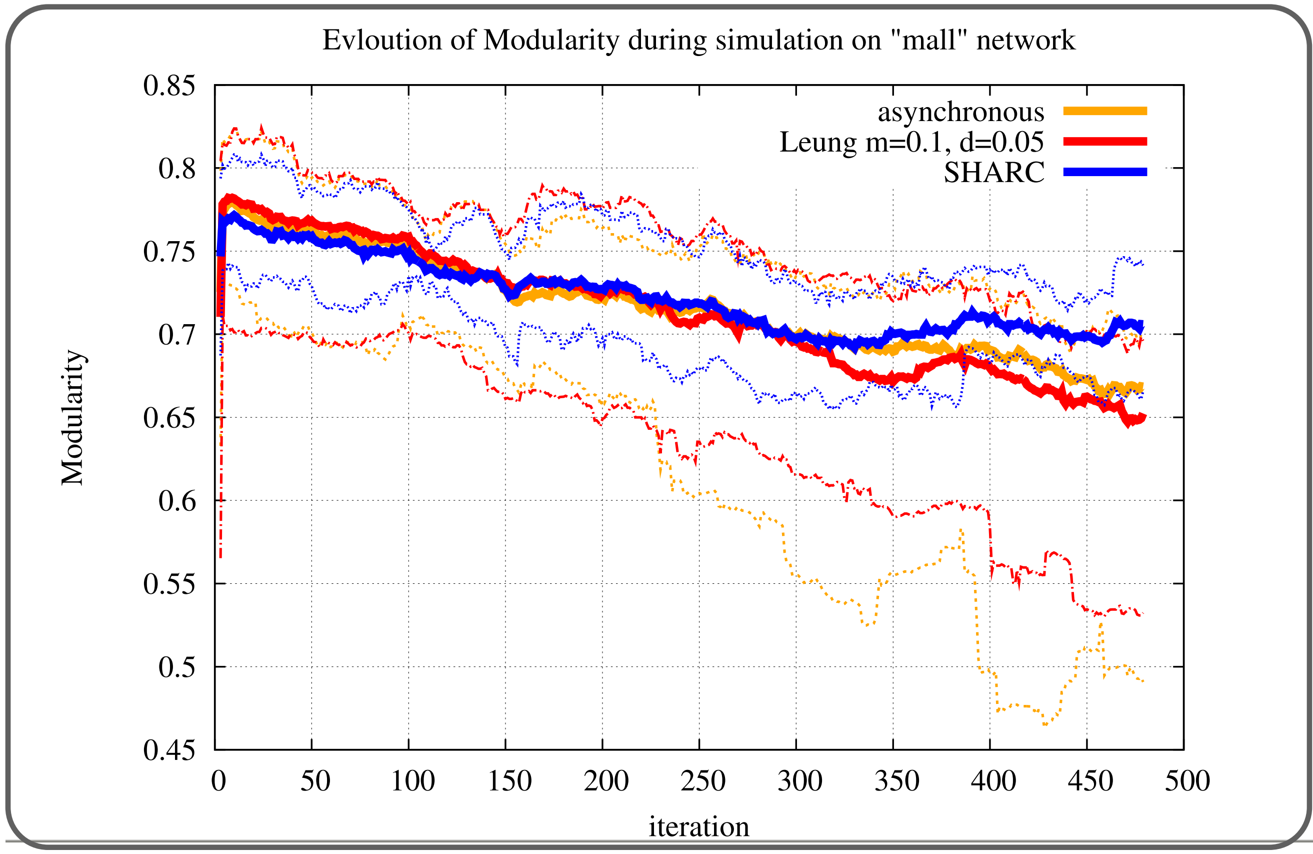
SHARC performances





- Sharper assignment :
  - Higher modularity Q and NMI
  - Limits *jumbo* community effect by bounding community size
  - Important for highly dynamic networks
- More robust assignment :
  - Less standard deviation in results (topology, protocol seed)
- Results submitted as conference paper in Dec. 2009 (WoWMoM)
  - Acceptance pending

SAw-SHARC: Stability Aware SHARC

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- Consider **link-stability as edge weight** in community assignment process
  - Normalized **stability estimator** (used to modulate the n_{sim} metric)
  - Auto-adaptive to current network conditions
  - Independent from underlying metric: age, average age, SNR (if X-layer), ...

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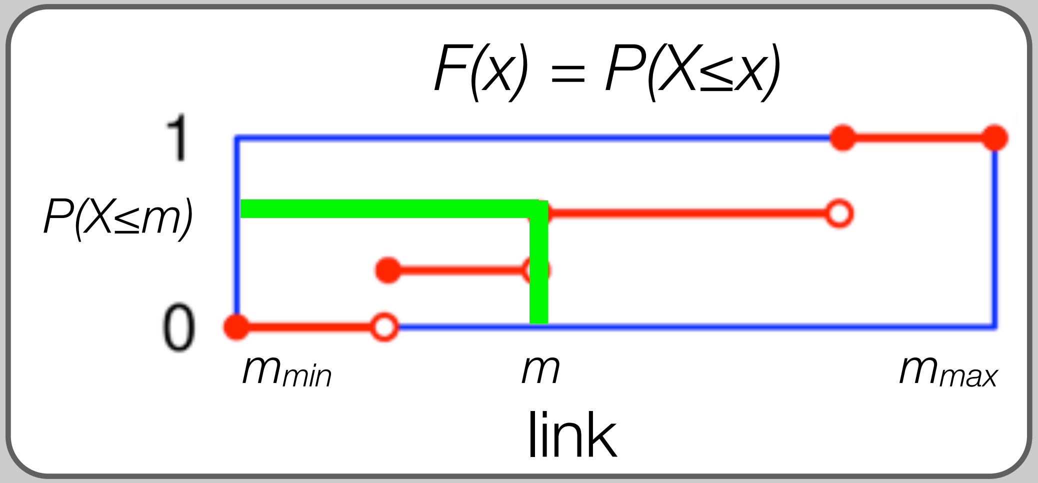
- Construct a CDF of link metrics amongst edges and use it as stability estimator
  - Gives the ratio of edges whose stability is equal or below the current edge value



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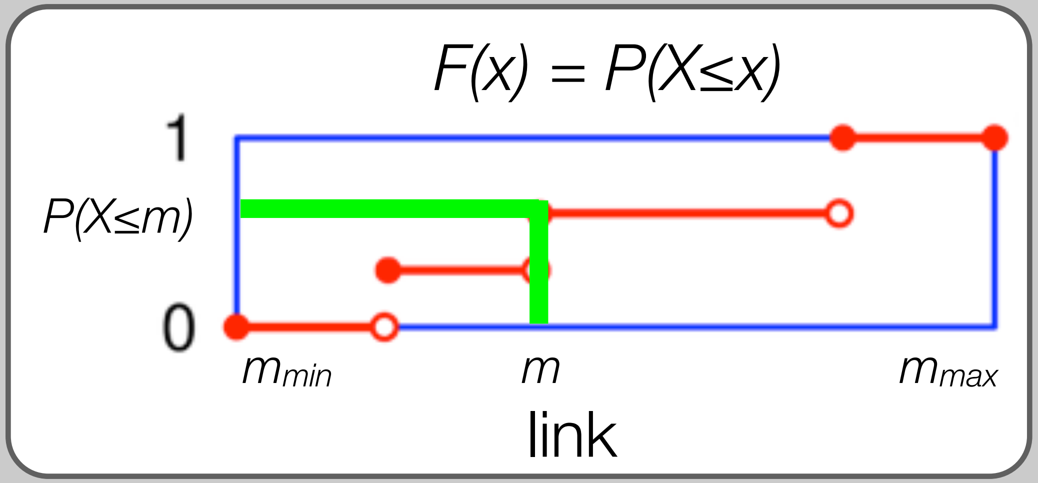
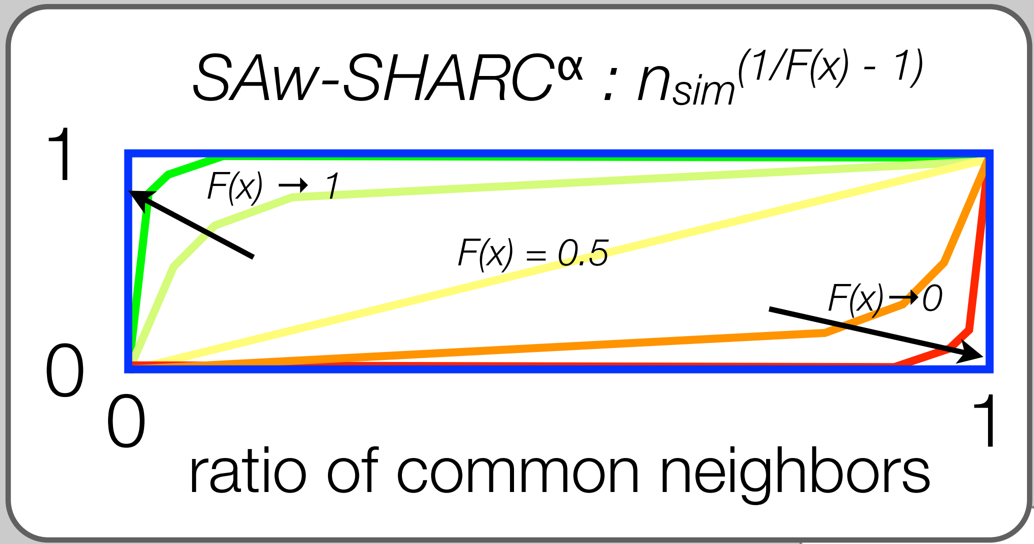
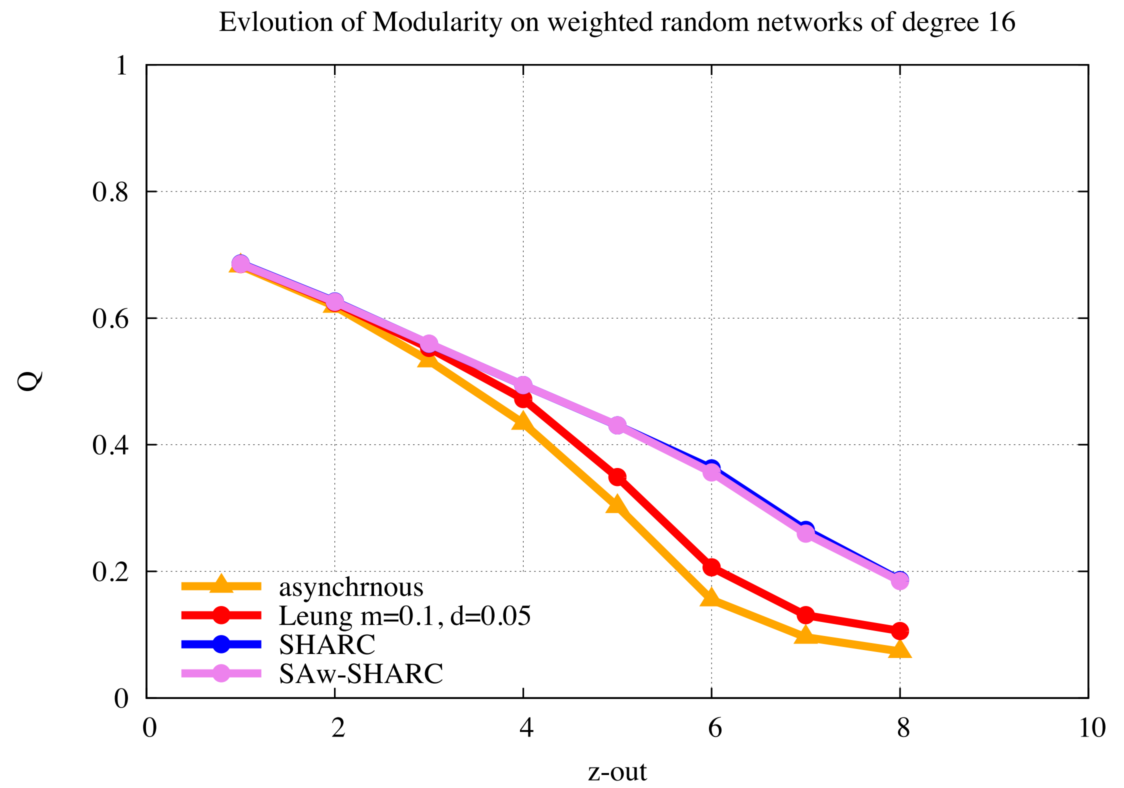
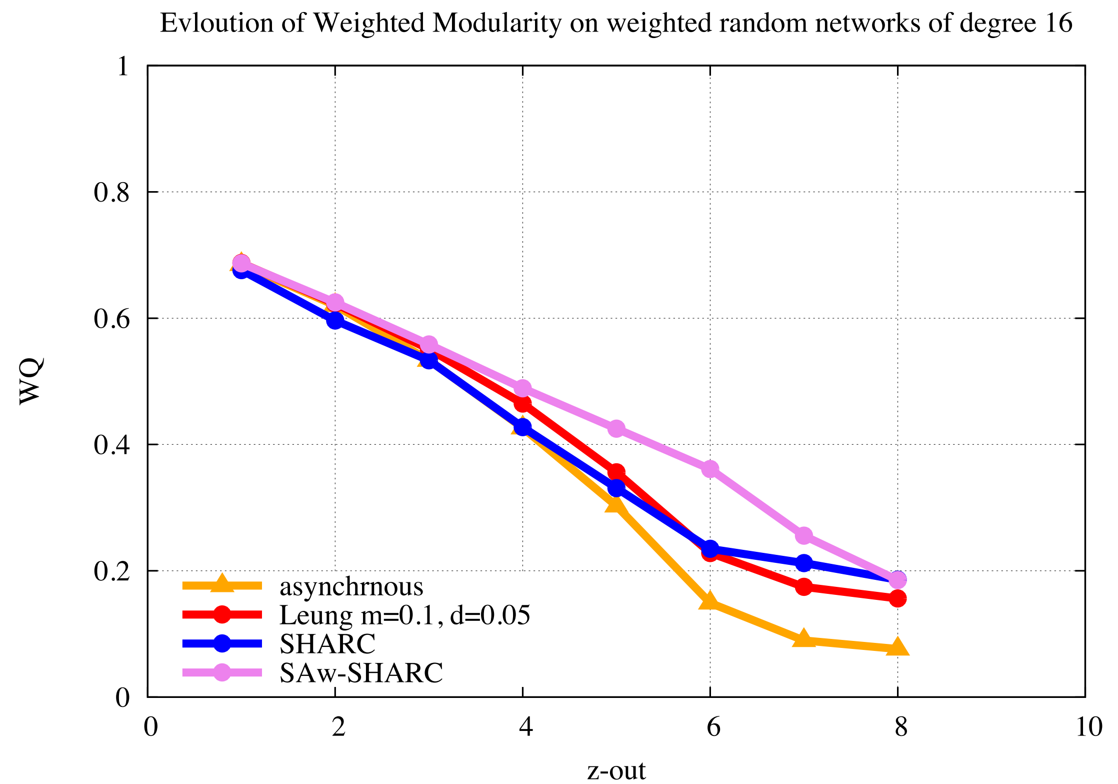


- CDF is used as modulation exponent of the neighborhood similarity measure
  - Neighbors with stable links contribute more to their community label score
  - Similar notions as in the α model of Watts and Strogatz for small-world



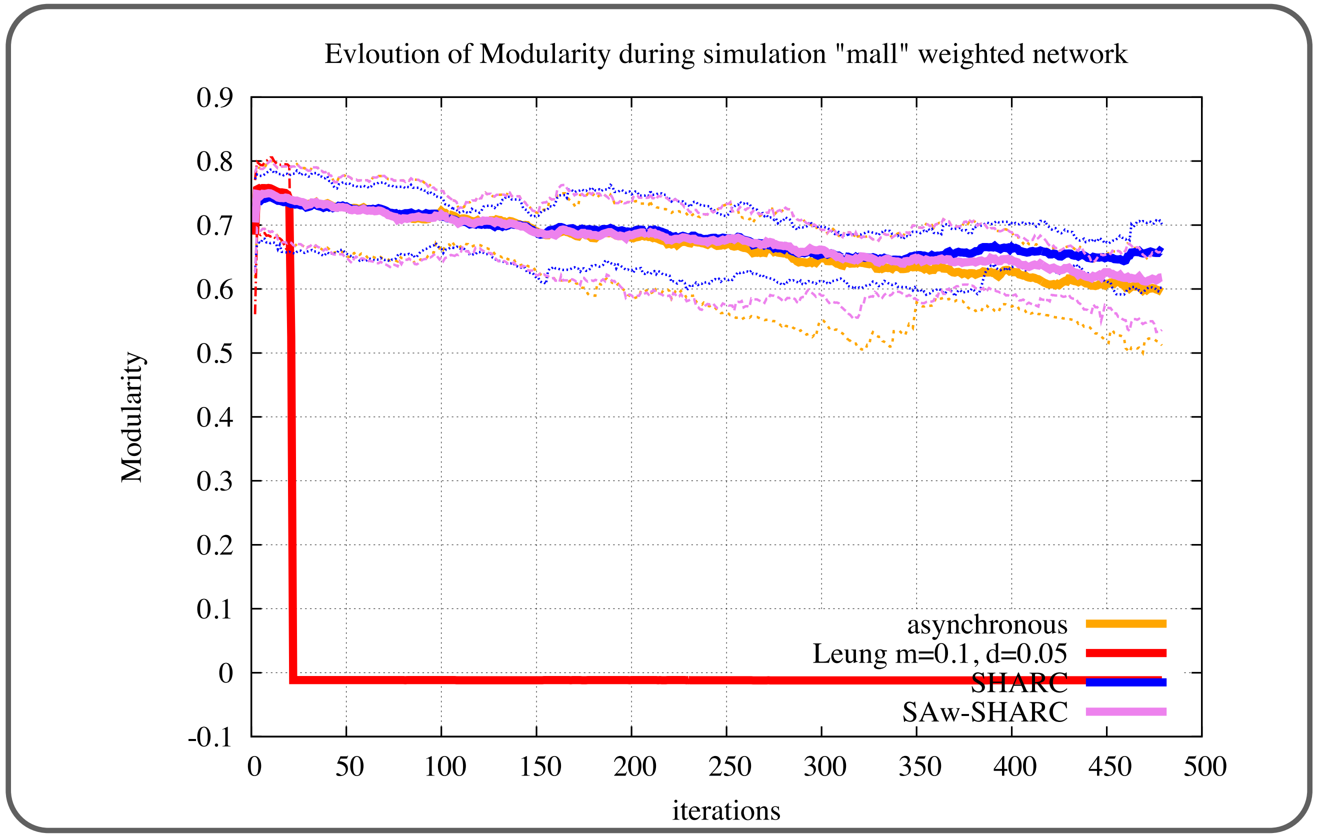
SAw-SHARC performances (static networks)

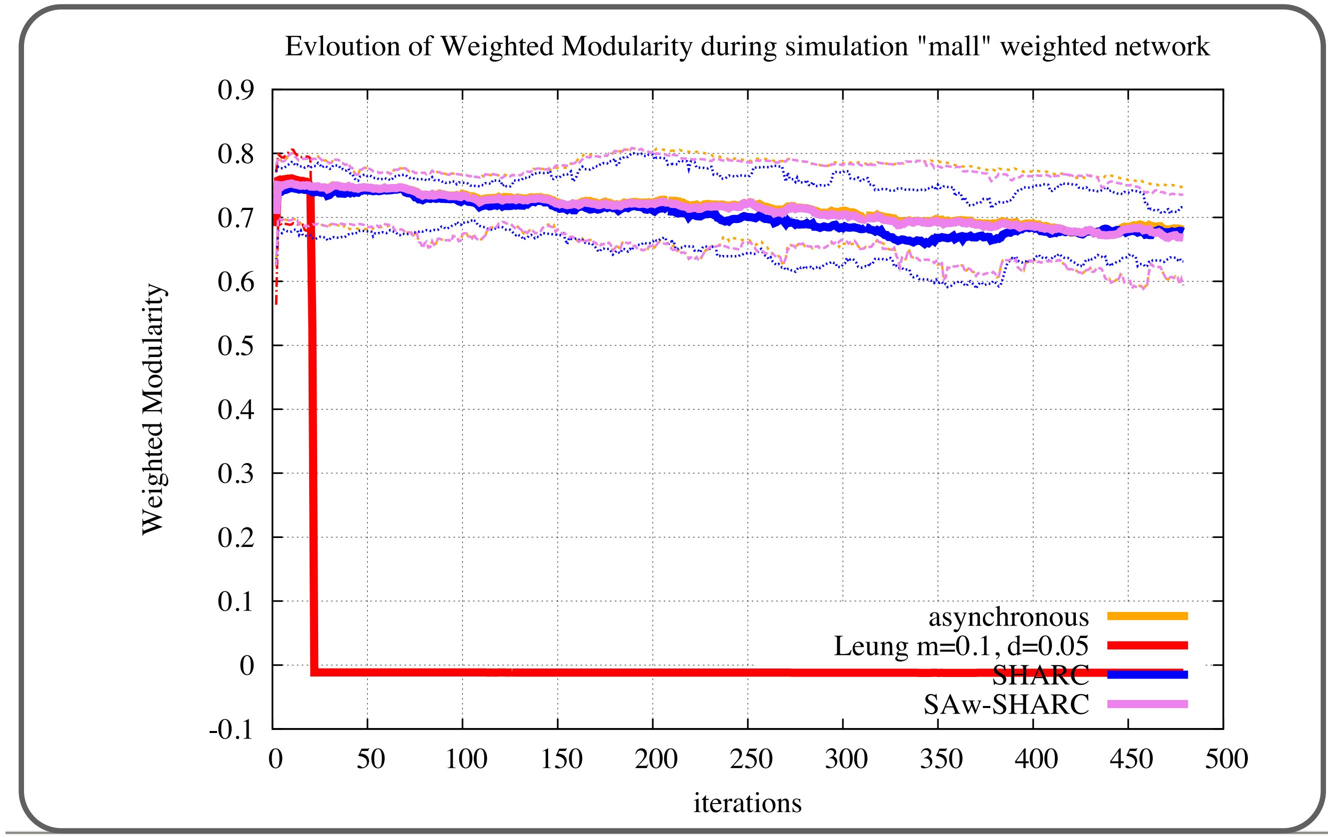




- Random networks with varying *z-out* and uniformly distributed edge weight
- SHARC and SAw-SHARC modularity Q are equivalent
- SAw-SHARC yields better results in terms of *weighted modularity WQ*
  - especially when compared with other *weight-aware* algorithms

SAw-SHARC performances (dynamic networks)





- "Mall" scenario with edge lifetime as quality metric
- SAw-SHARC performs good in terms of modularity *Q* and weighted modularity *WQ*
- Different trade-off between unweighted and weighted metrics
- Strange behavior for one of the algorithms on dynamic networks
- Need to investigate under more aggressive dynamic networks

Perspectives / Future work

- Use edge weight to represent **shared content/interest** between nodes
  - Application to MoSoNets (Mobile Social Networks)
  - Need a function to express the interest as a scalar (Locality Sensitive Hashing ?)
  - Maybe a mixed approach **stability+interest** in a **multi-objective** problem

- Introduce **long-term interaction** metrics to the assignment process
  - Favor people with regular interaction pattern to be grouped in the same community

- Use of community structures to **help algorithms with scalability**
  - Experiments on the tree/community structures matching
  - Scalability in k(connected)-m(dominant)-CDS creation

- Use of community structures for **reputation and trust**
  - Can we derive (partially ?) node reputation from its community reputation ?
  - Rough idea, further investigation needed

Contact information

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  L-1359 Luxembourg

- http://herbiet.gforge.uni.lu

Thanks for your attention

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$$s_{ik} = \sum_{j \in V} a_{ij} c_{jk} \left(1 - \frac{\sum_{p \in V} a_{ip}(1 - a_{jp}) + \sum_{q \in V} a_{jq}(1 - a_{iq})}{\sum_{n \in V} a_{in} + \sum_{m \in V} a_{jm}} \right)$$

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$$c_{ik} = \begin{cases} 1 & \text{if } s_{ik} = max_{c \in \mathcal{C}}(s_{ic}) \\ 0 & \text{otherwise} \end{cases}$$

SHARC Mathematical Model (2/2)

- Mathematically, the community assignment problem sums up to computing the **assignment matrix** $\mathbf{C}$ at each iteration step
- Problem is neither quadratic nor linear
- Proof of convergence is hard
- Need to investigate for mathematical programming model