Expert Finding using Markov Networks in Open Source Communities

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Outline

Expert Perspectives

Expert (Ericsson [2006])

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- Extended knowledge

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- Extended skills (1)
- Recognised expert status

2 perspectives:

1. **content-based** : One has special skills or knowledge, whether people assess them or not

Expert Perspectives

Expert (Ericsson [2006])

- Extended knowledge (1)
- Extended skills (1)
- Recognised expert status (2)

2 perspectives:

1. **content-based** : One has special skills or knowledge, whether people assess them or not
2. **social-based** : One shows special skills or knowledge, whether he actually has them or not

OSS and Hybrid Contexts

In OSS projects, both users and companies are involved:

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For huge OSS projects:

Perspectives need to be considered together.

General Idea

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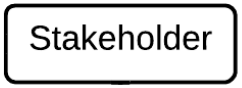
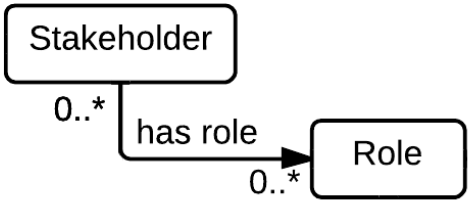
- Relations: evidences extracted from available sources of data
- Computation: Markov networks (expertise probability)
- Outcome: ranking of potential experts to recommend

Concepts and Relations



Concepts and Relations



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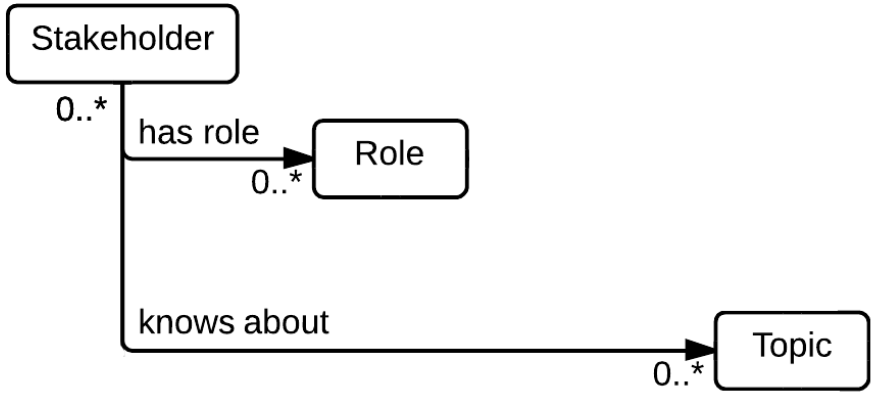

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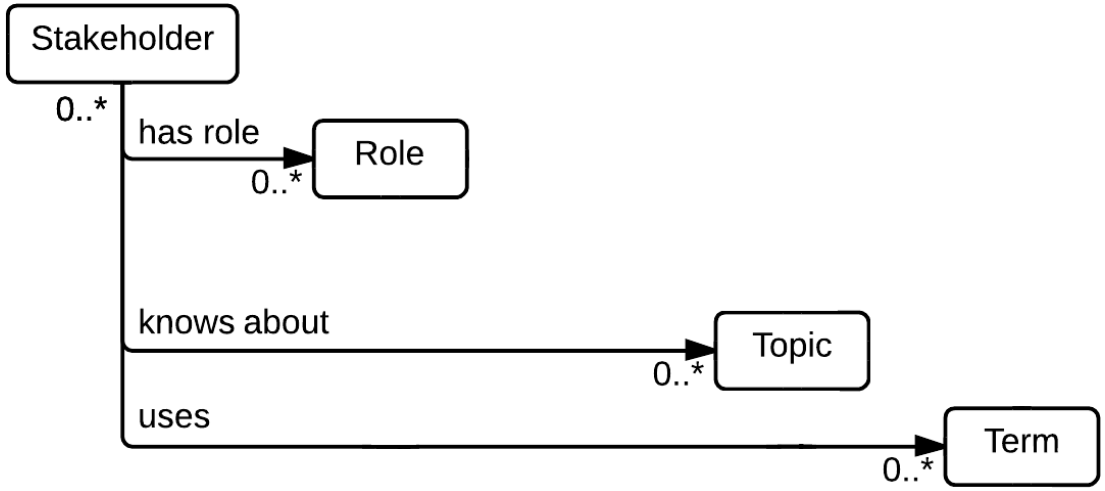

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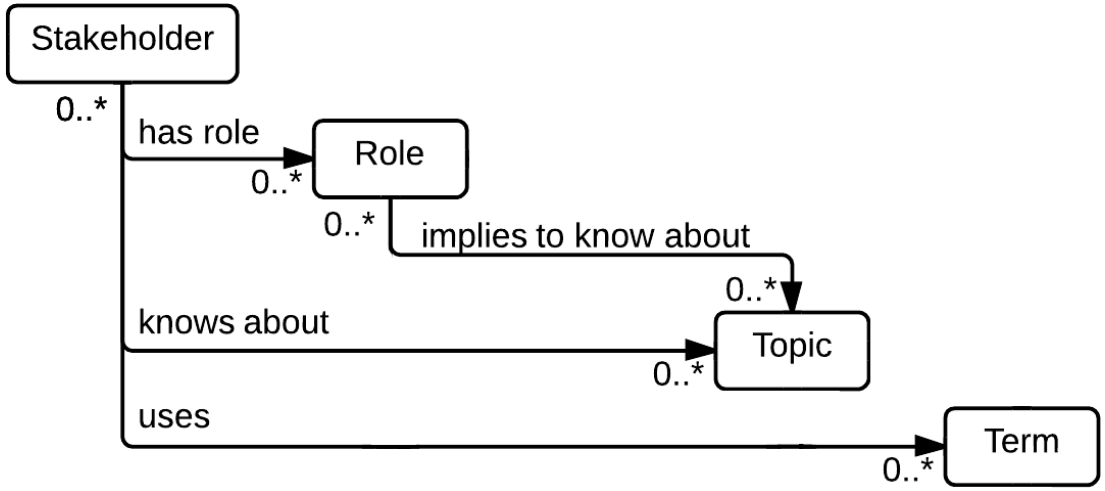

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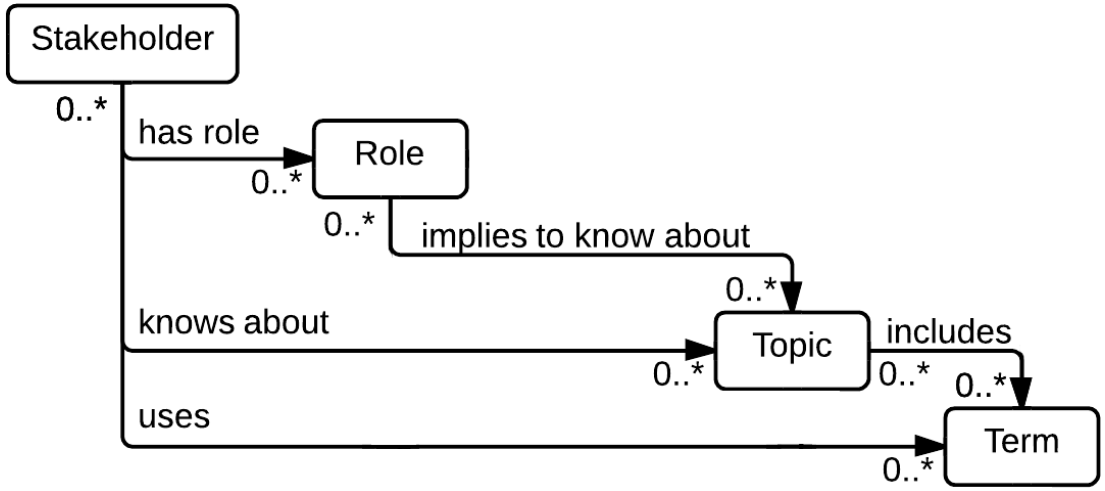

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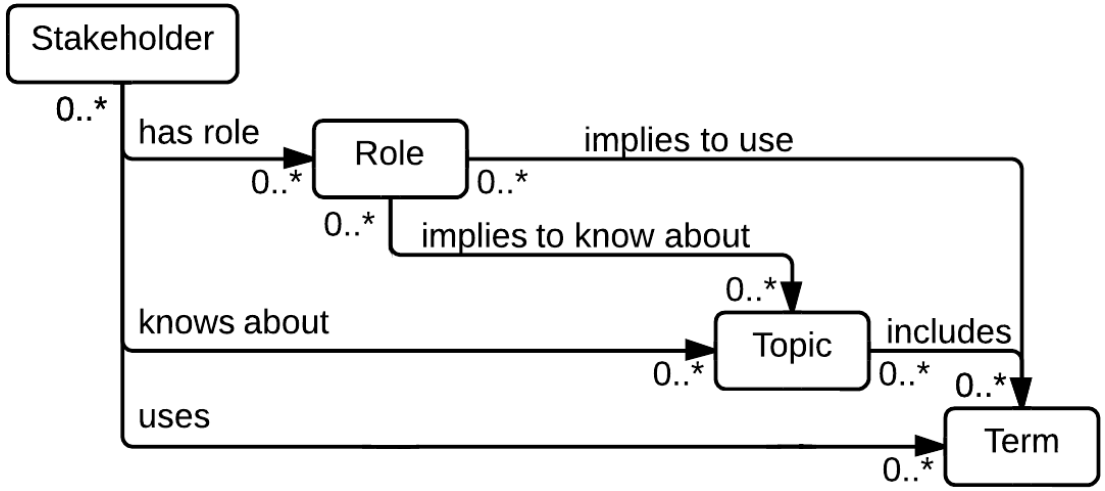

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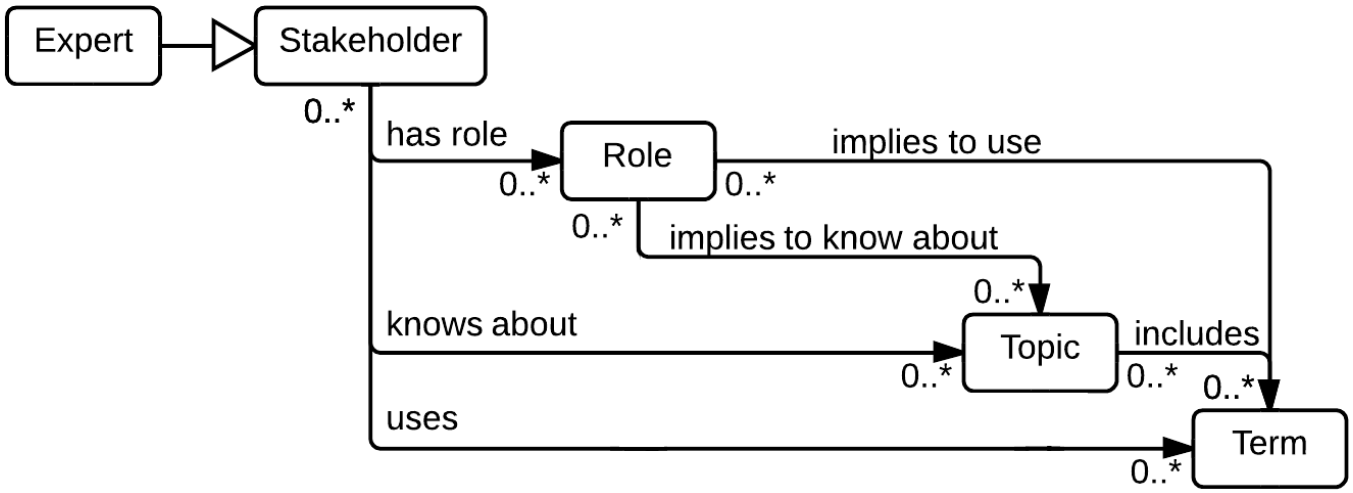

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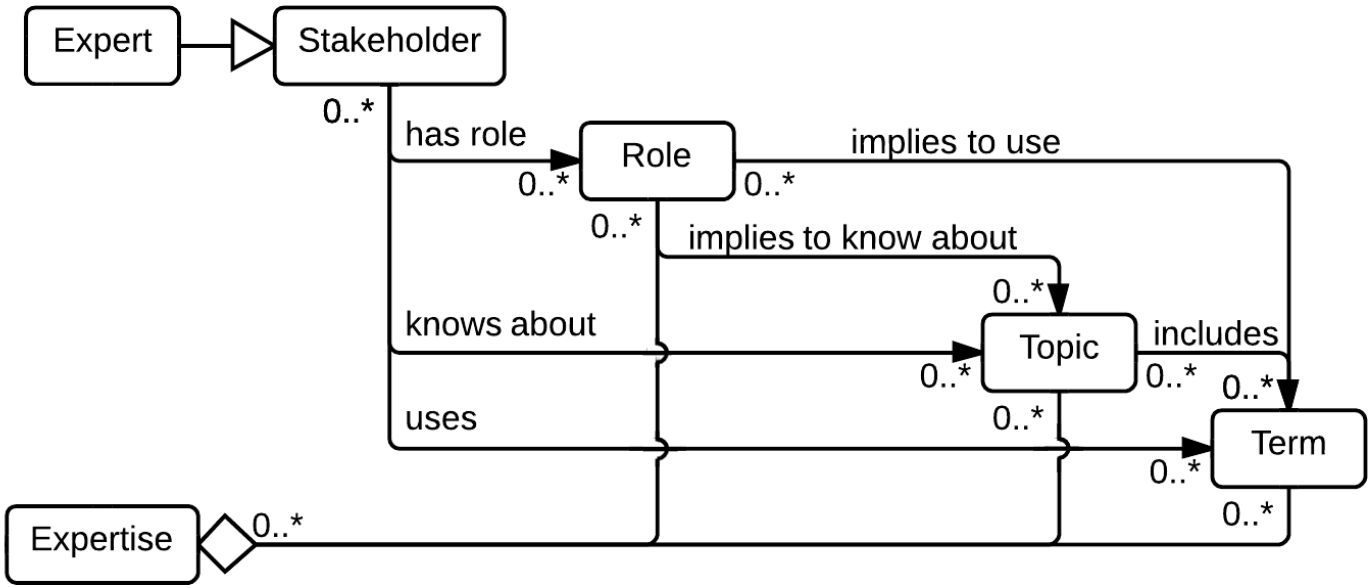

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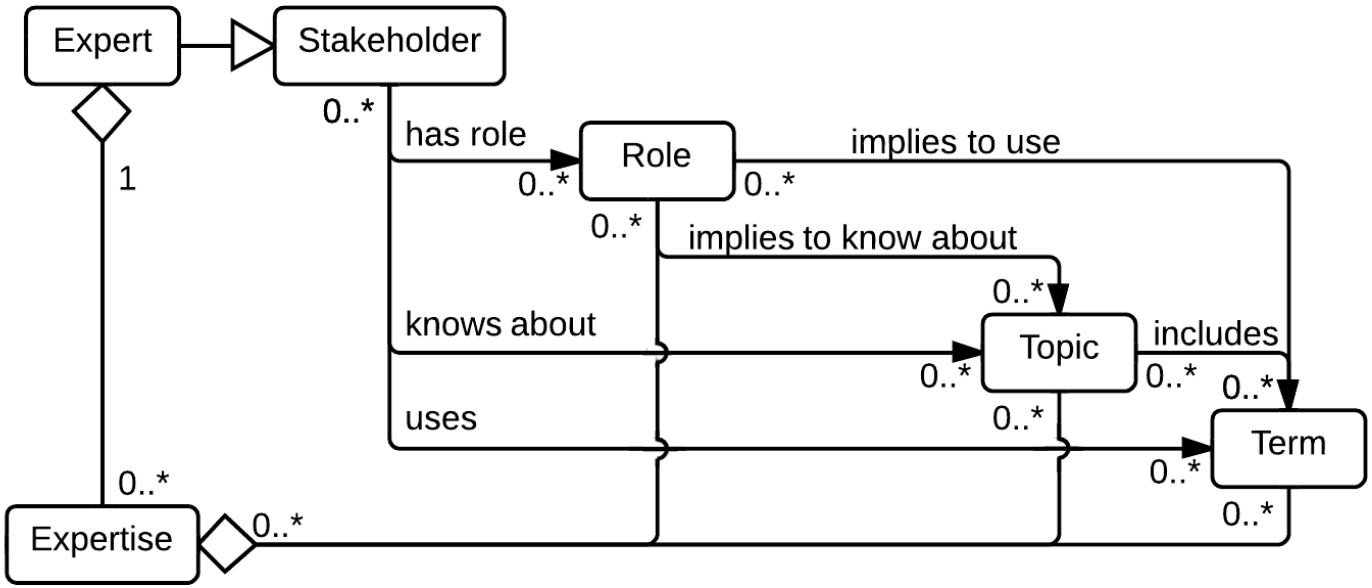

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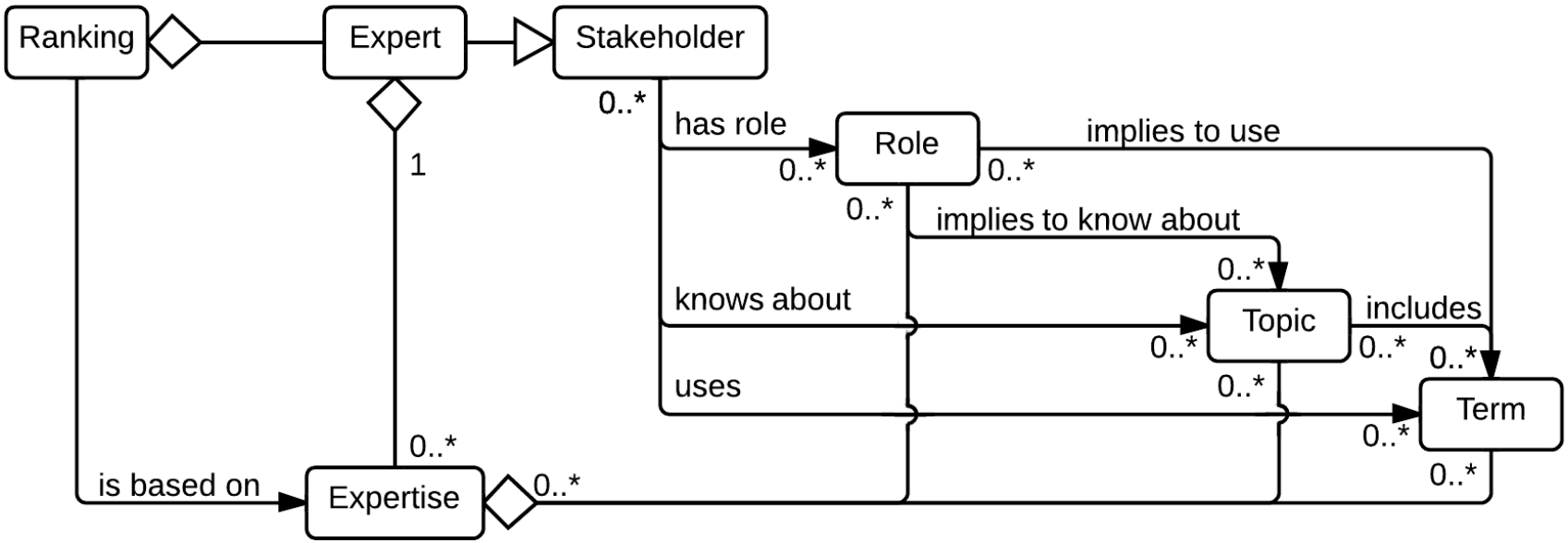

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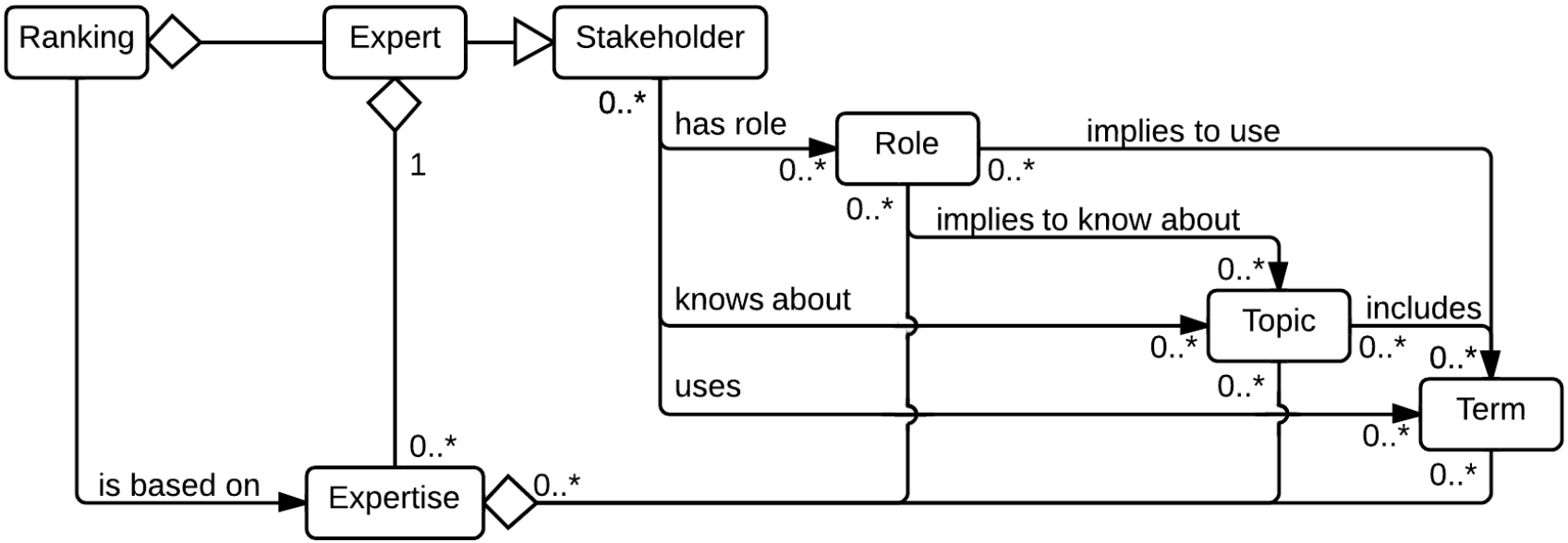
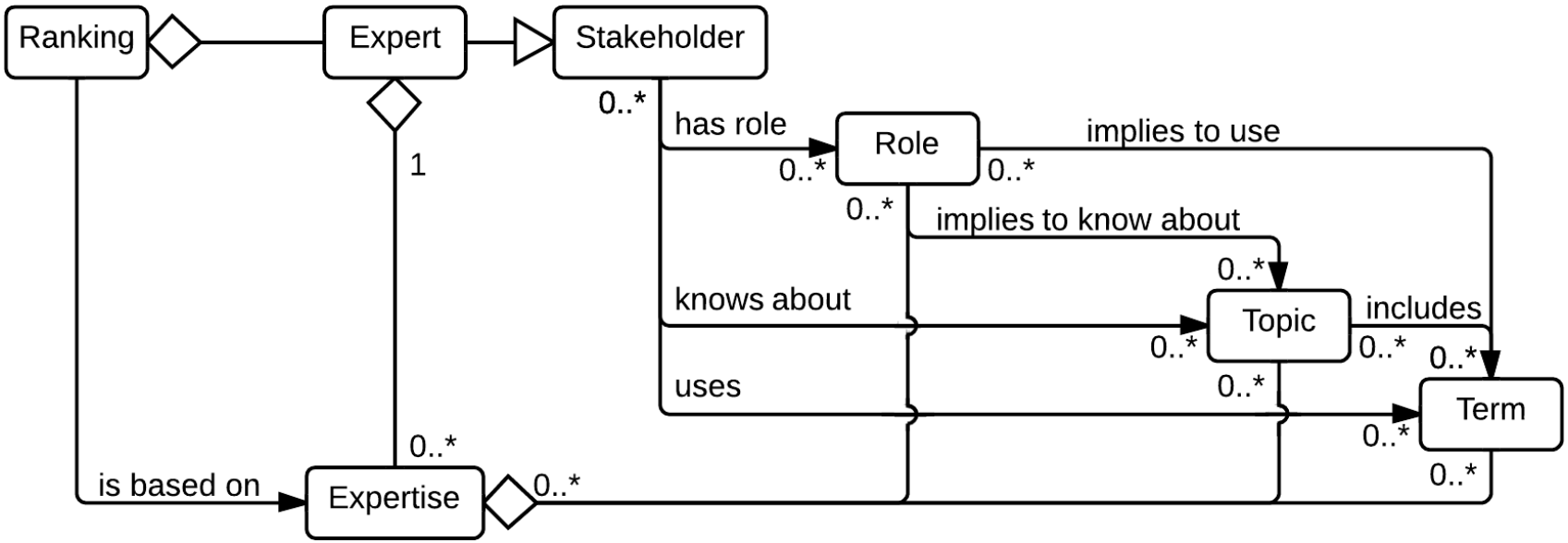


Remarks:

- Directed relations for clarity: undirected correlations.

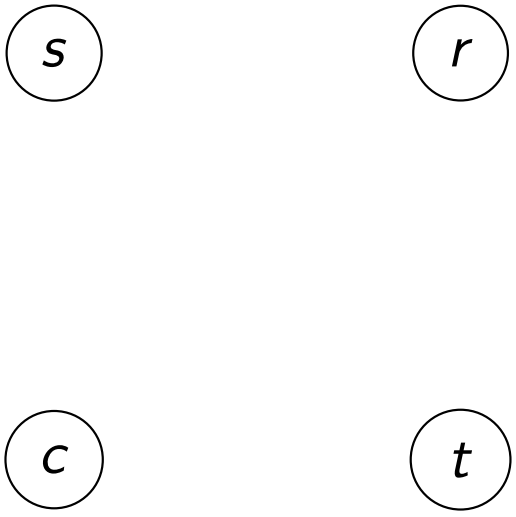
Concepts and Relations



Remarks:

- Directed relations for clarity: undirected correlations.
- Relative expertise: $A > B$, not $A = \mathit{level}$.

Model: Complete 4-Partite Weighted Graph



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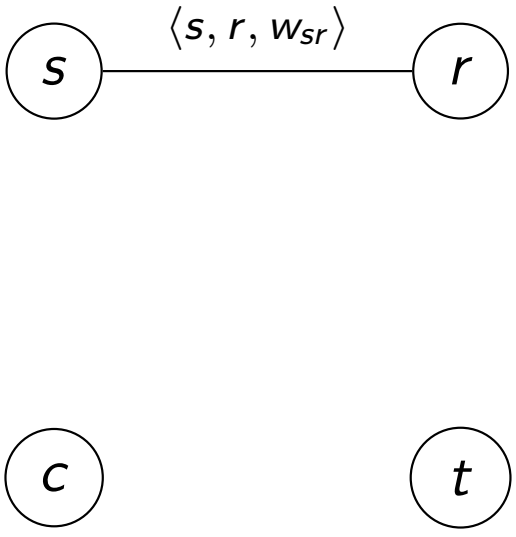

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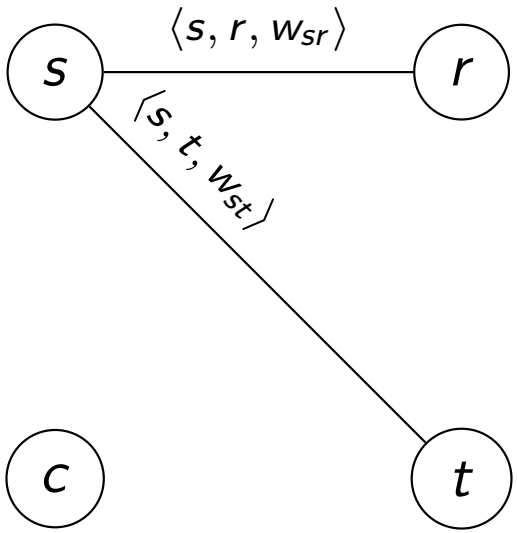

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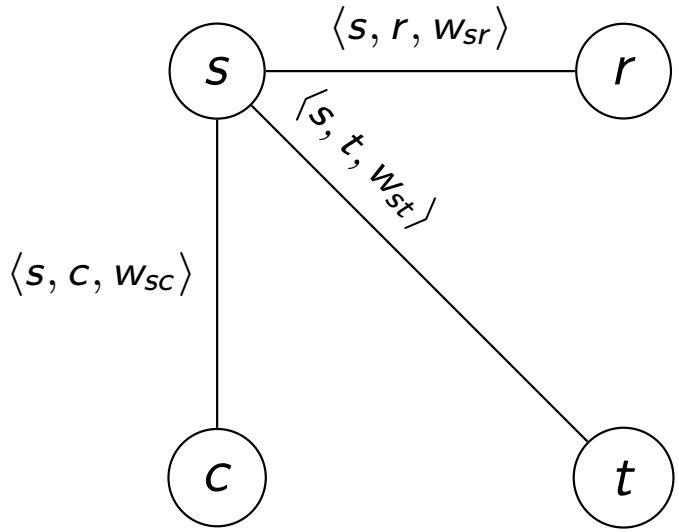

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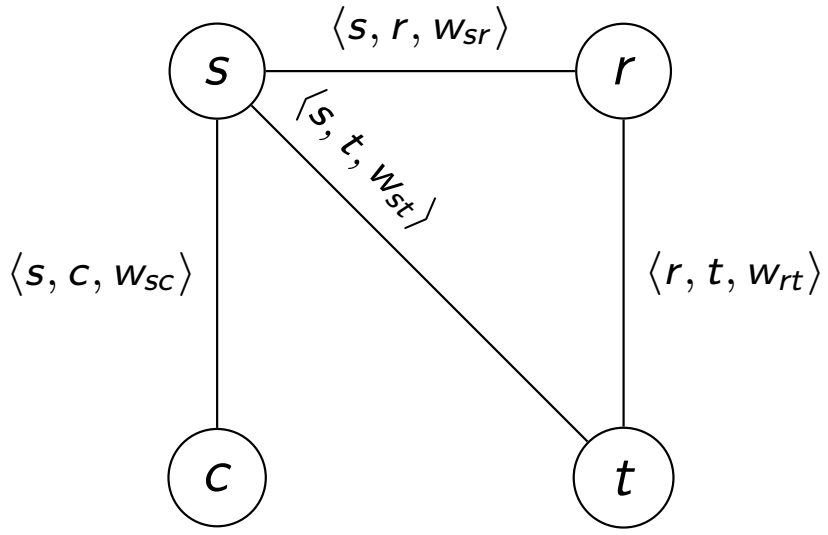

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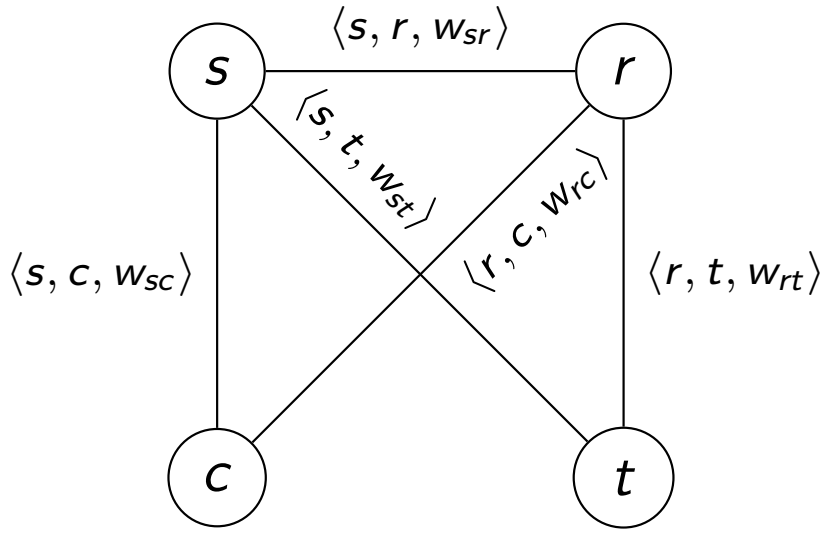

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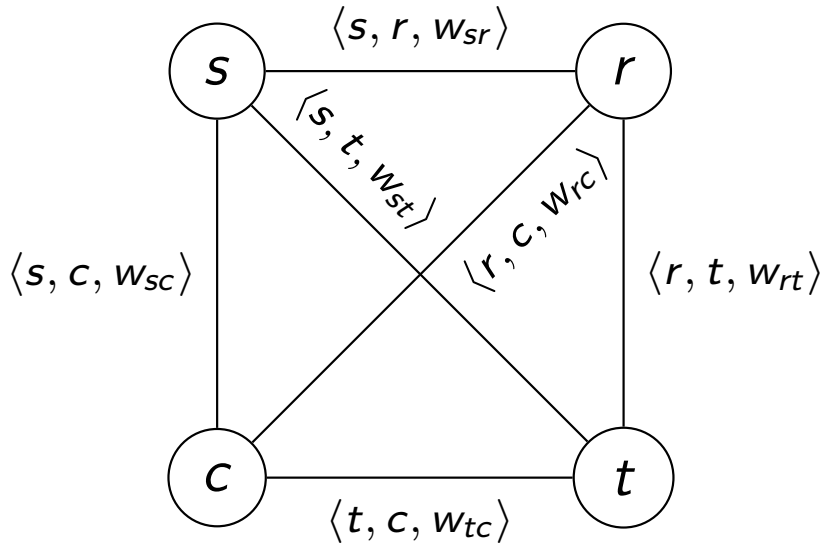

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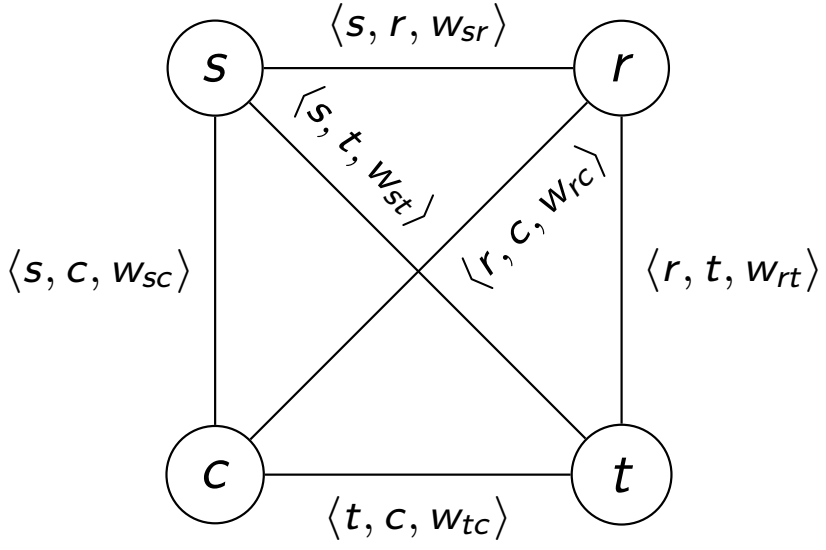

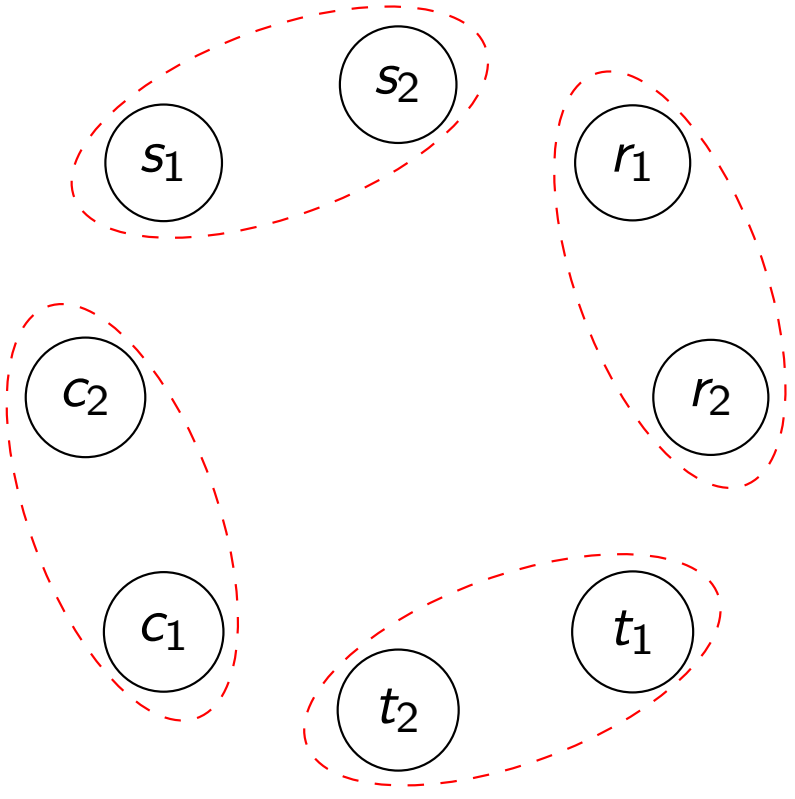

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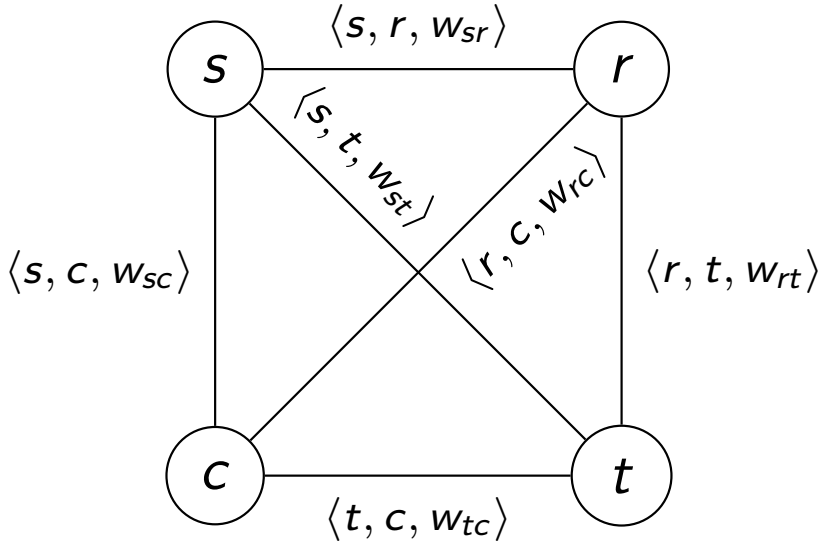

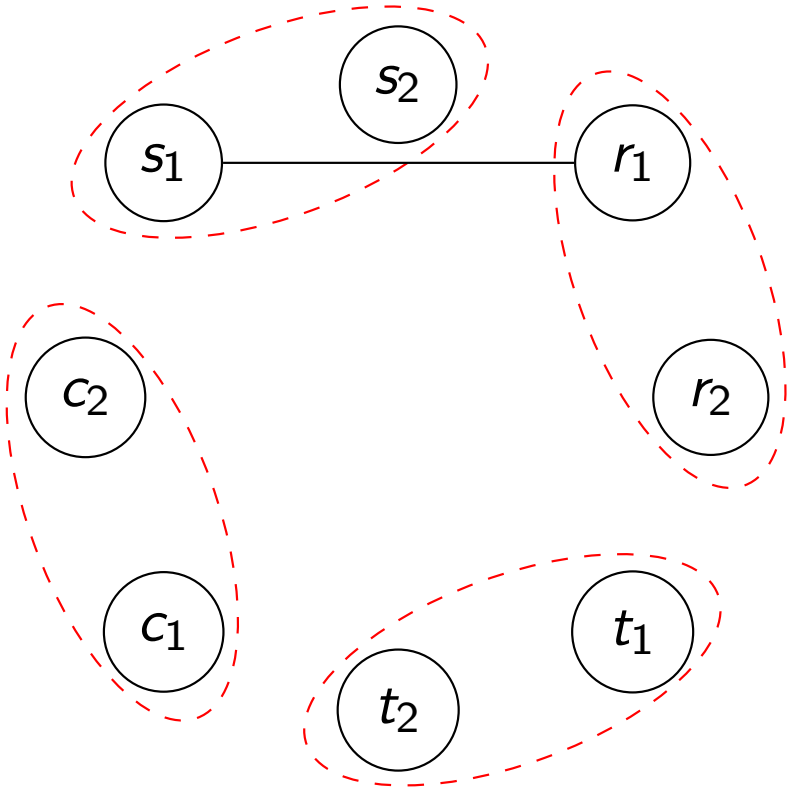

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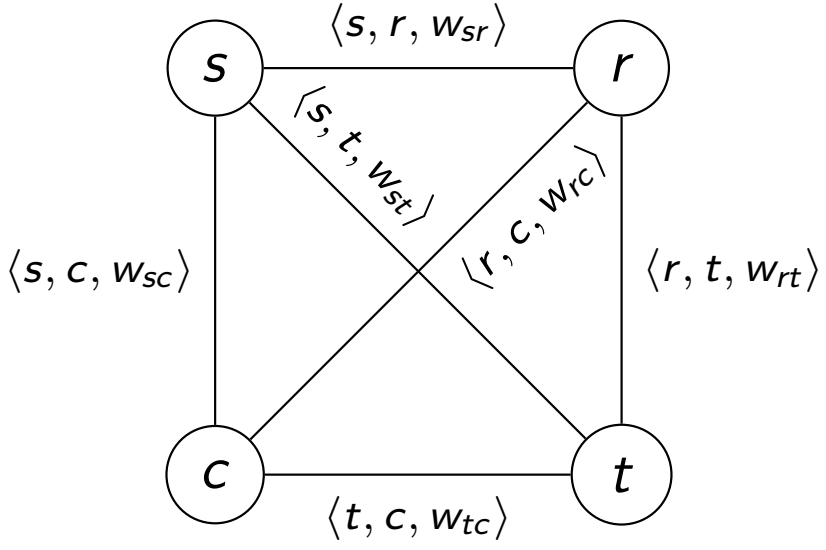

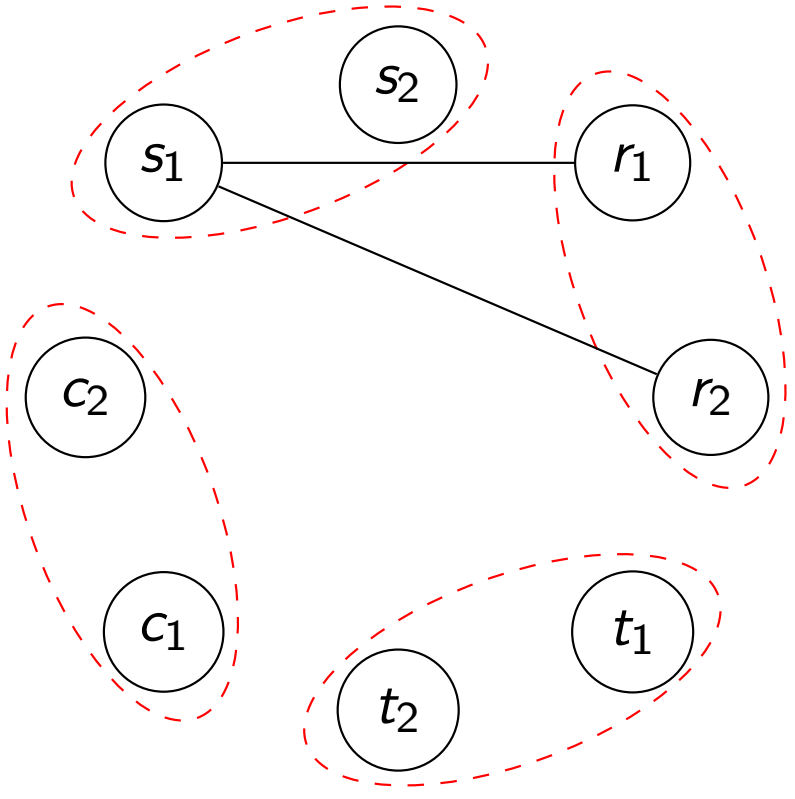

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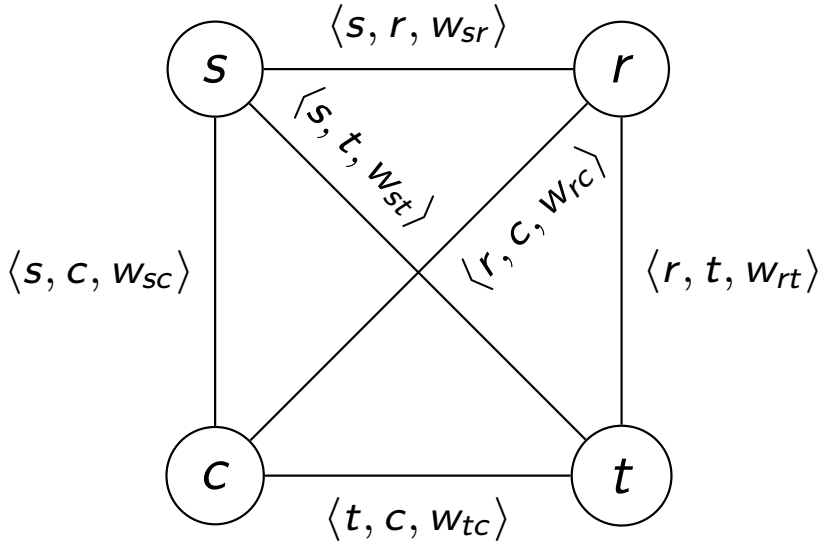

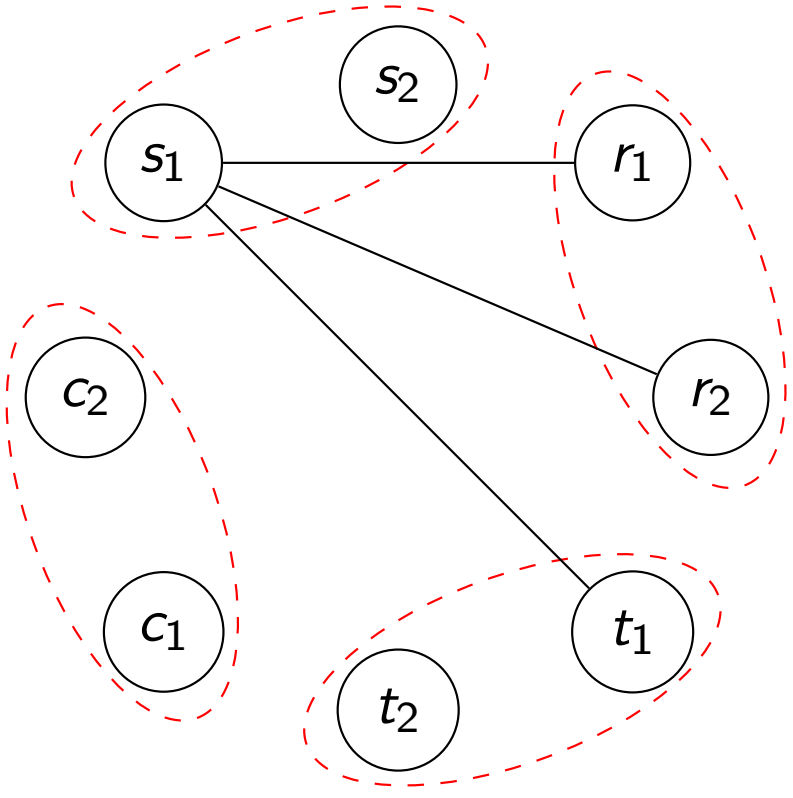

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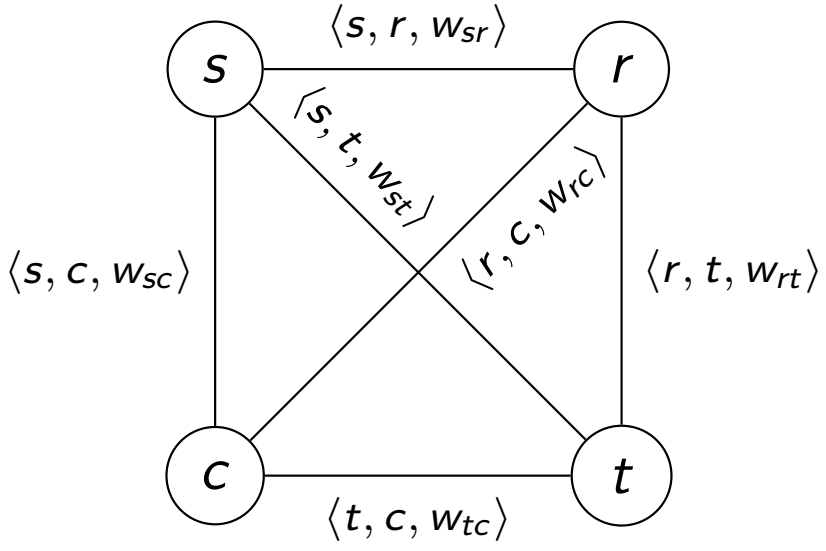

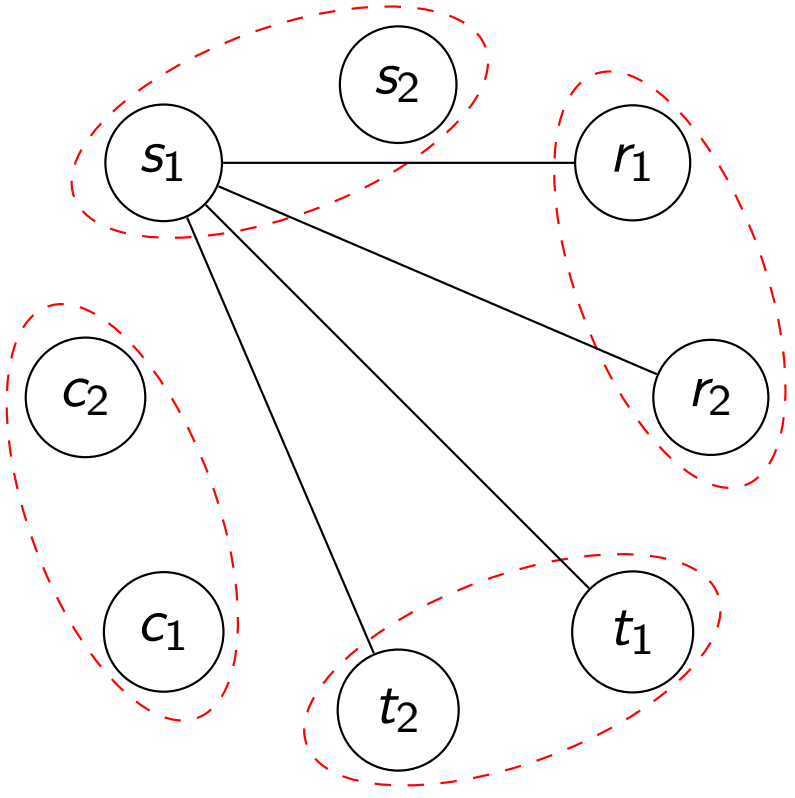

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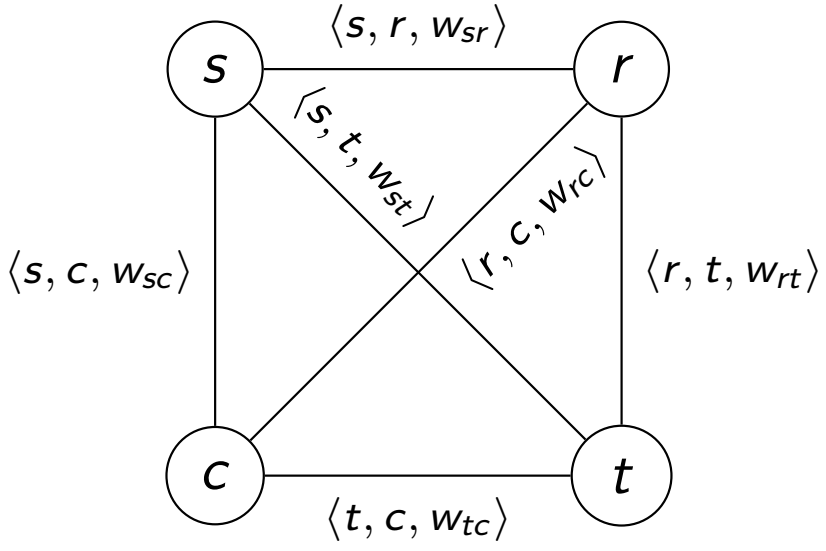

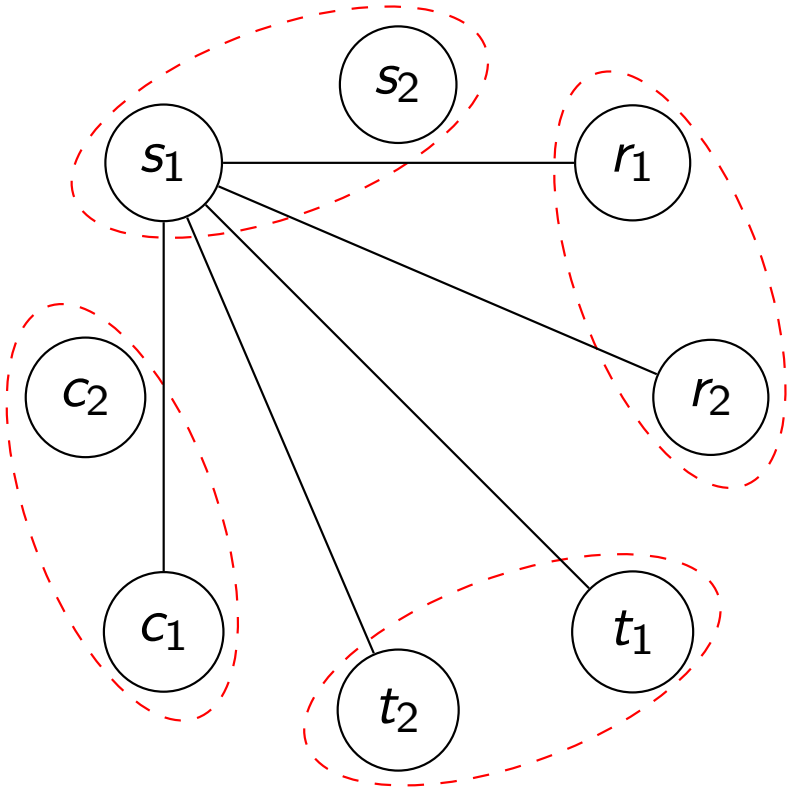

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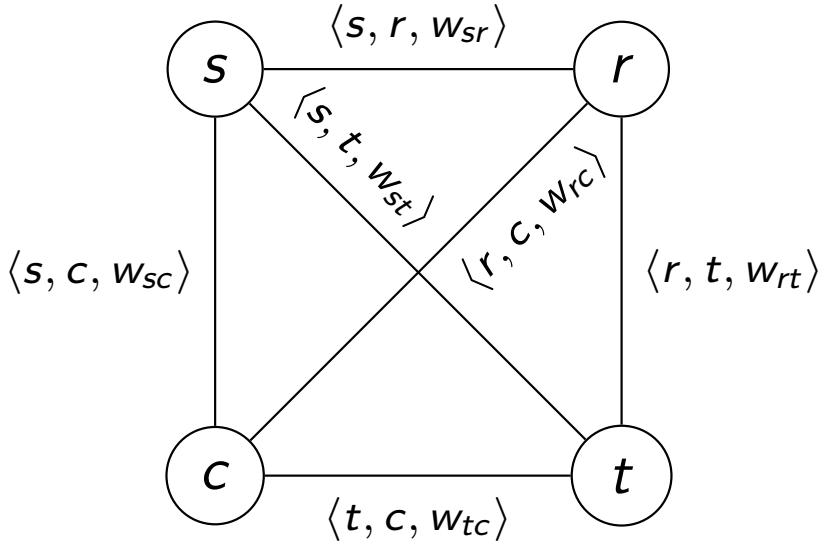

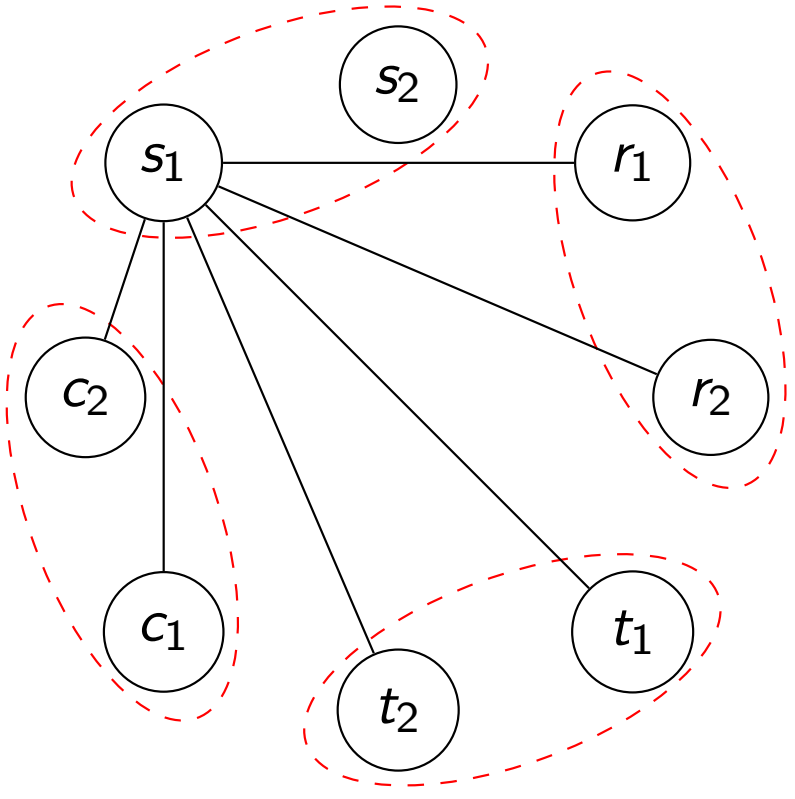

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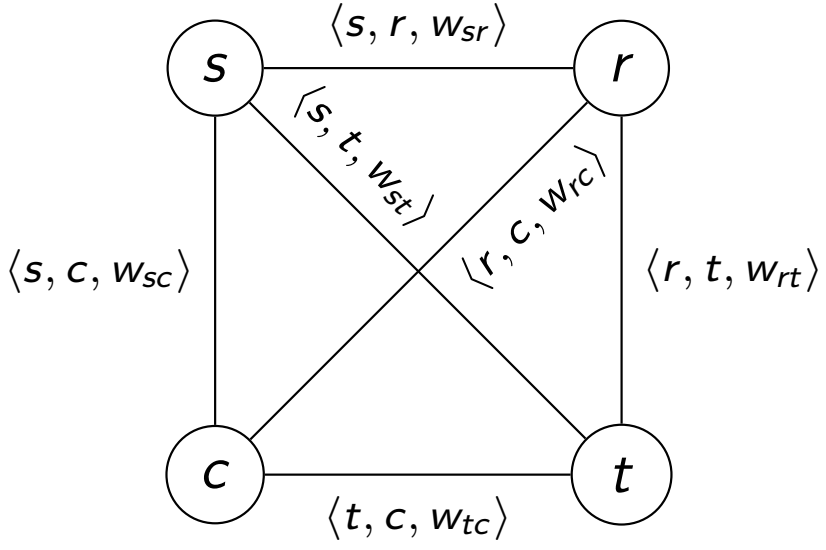

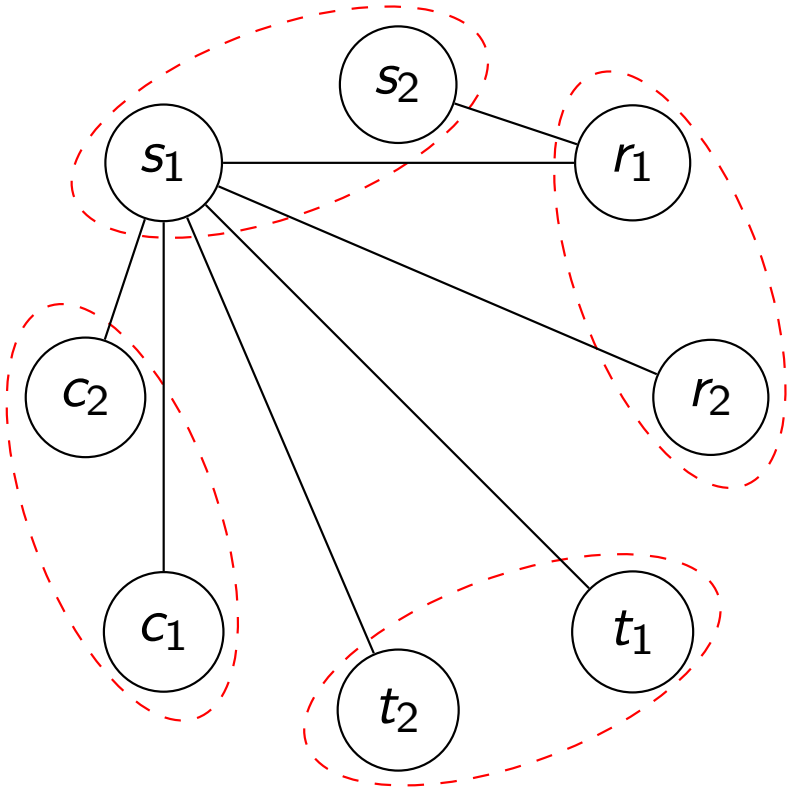

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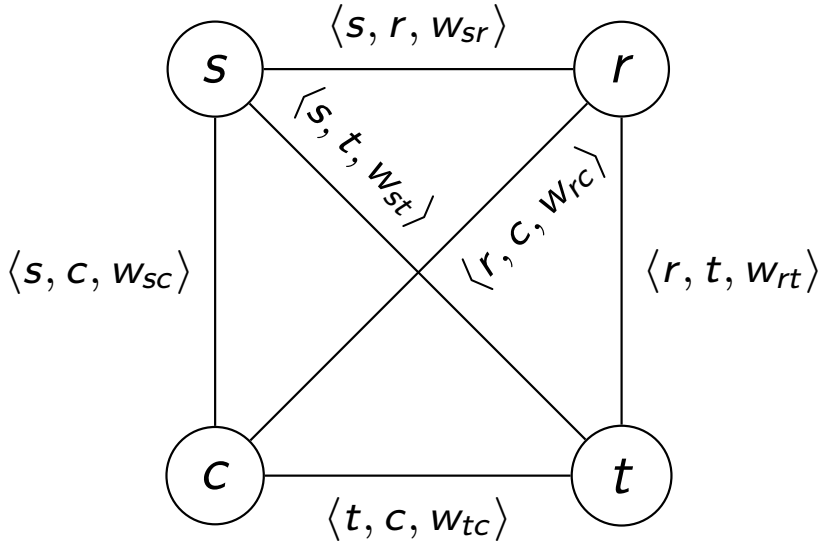

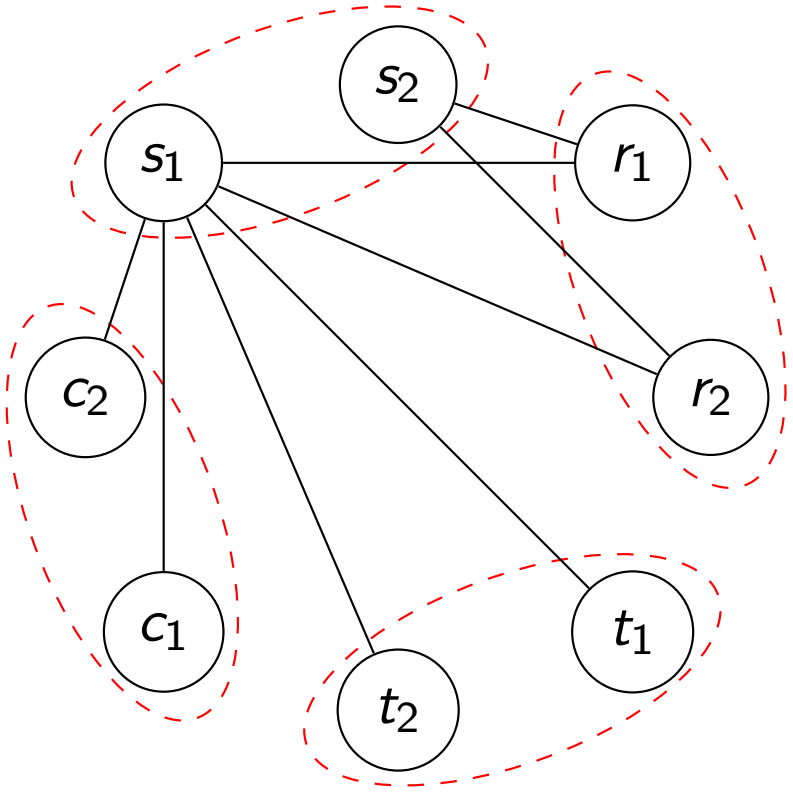

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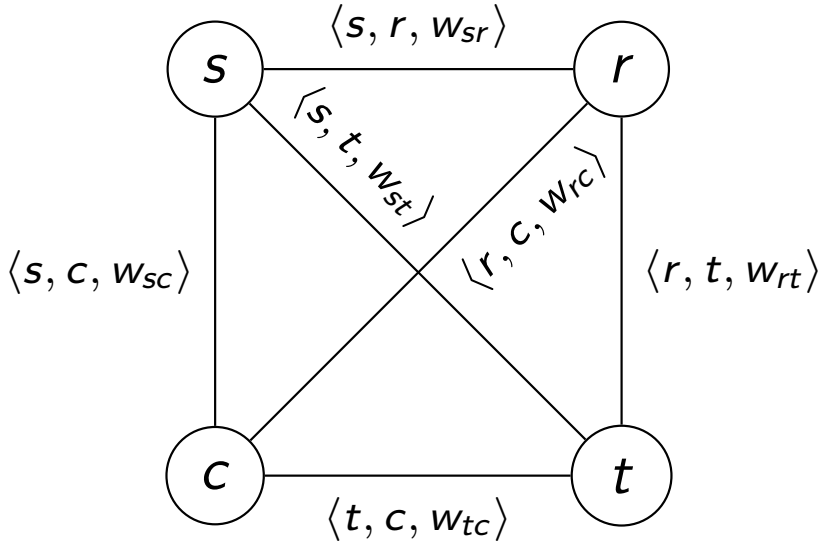

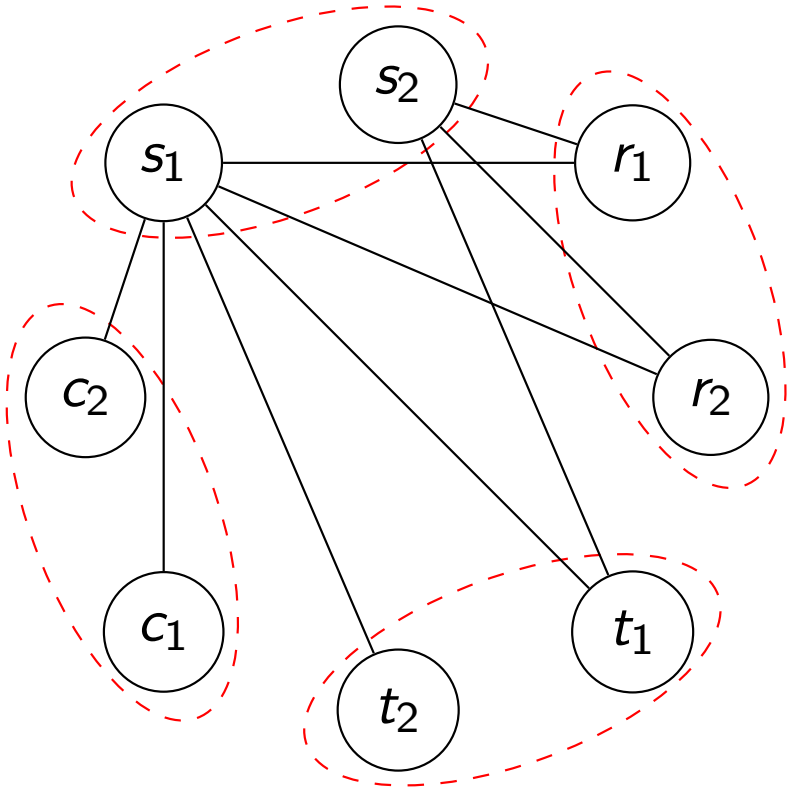

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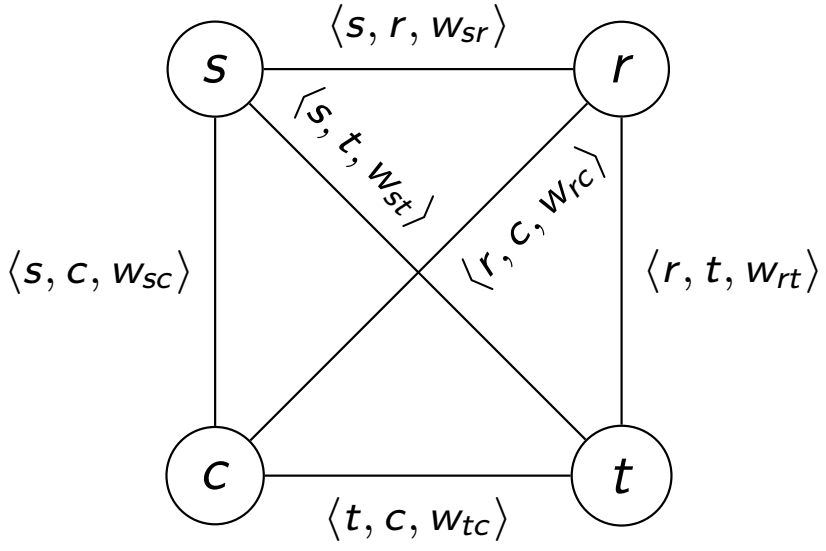

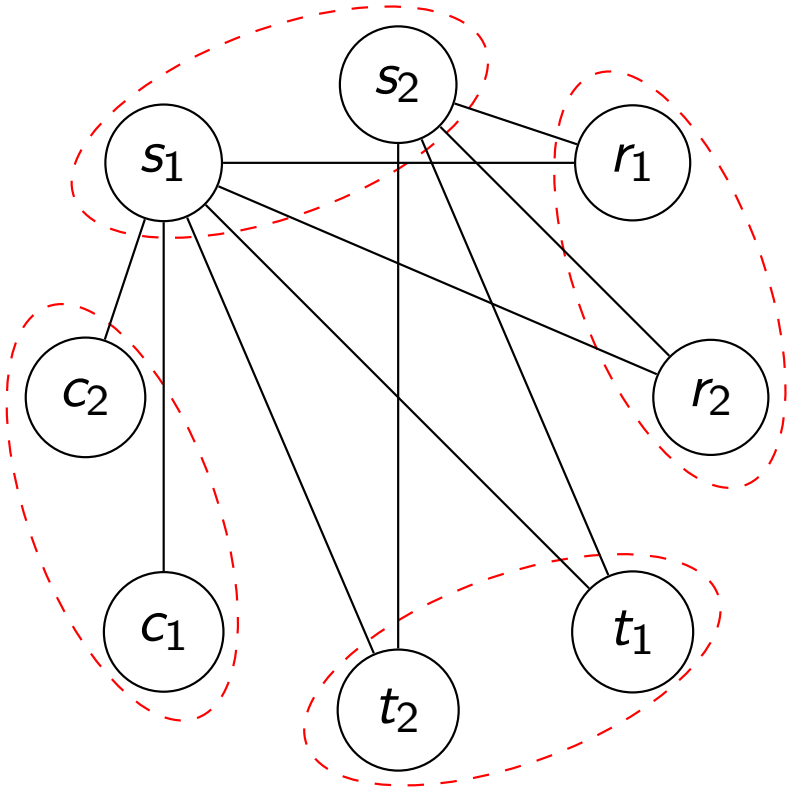

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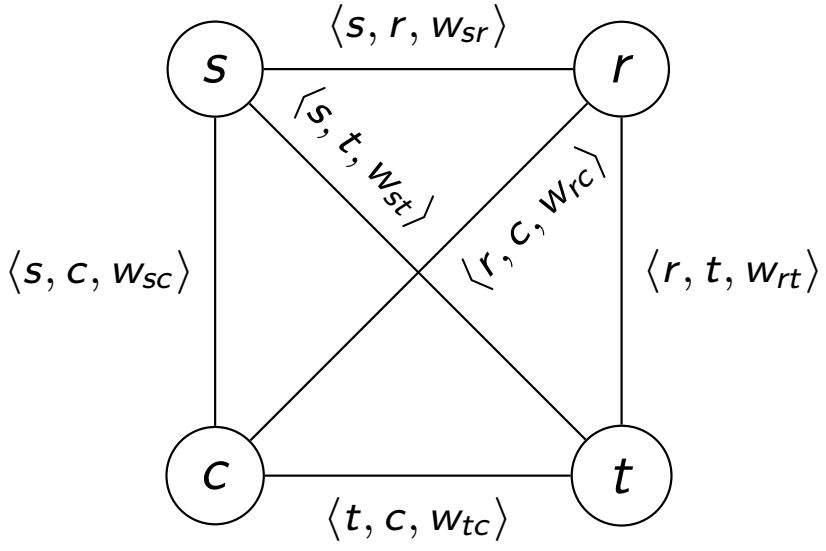

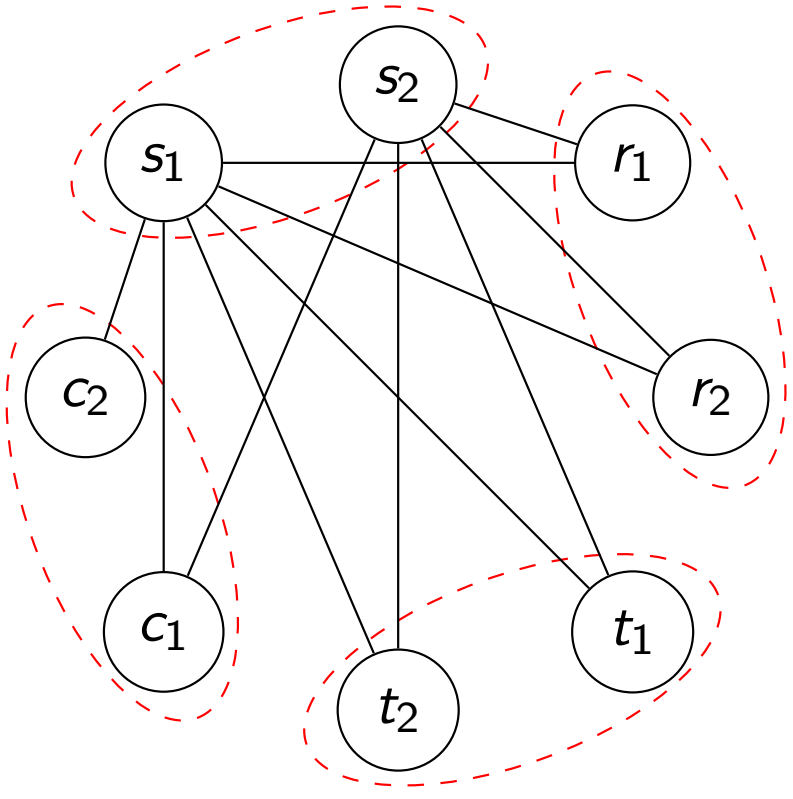

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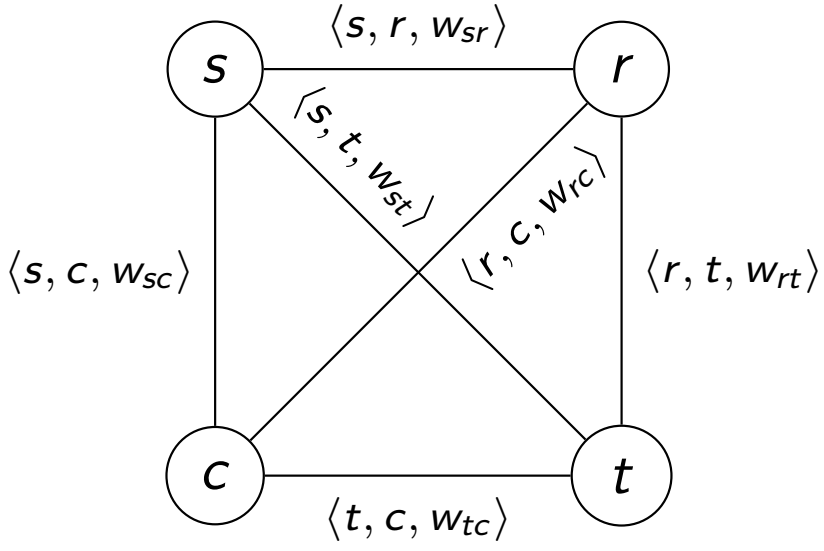

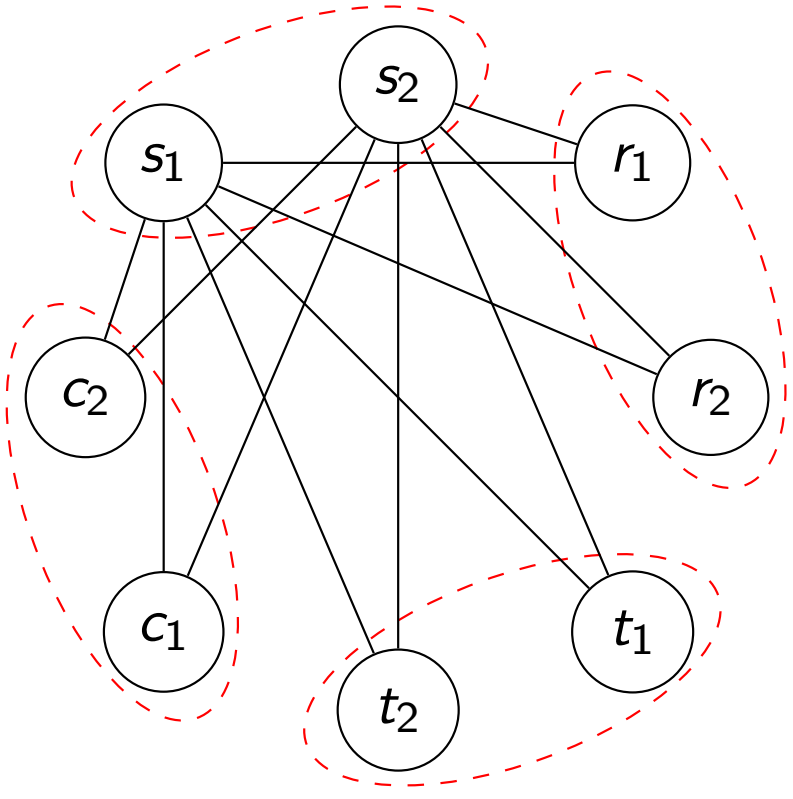

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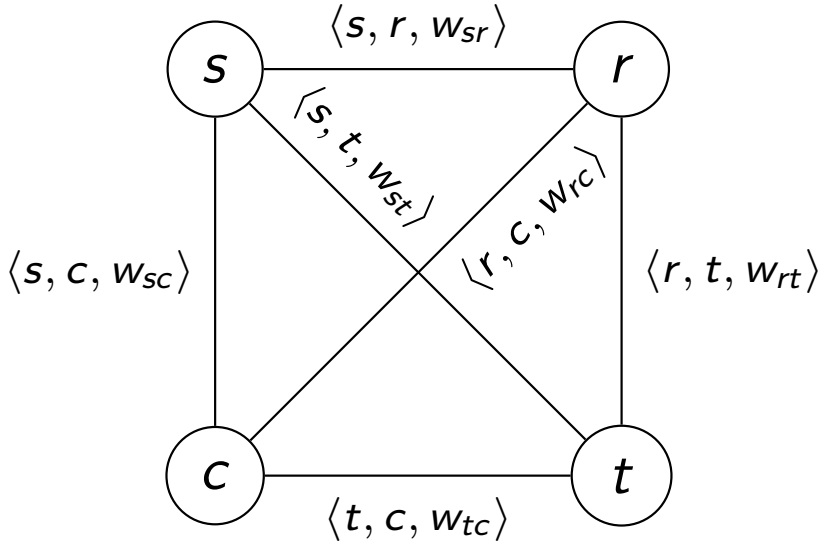

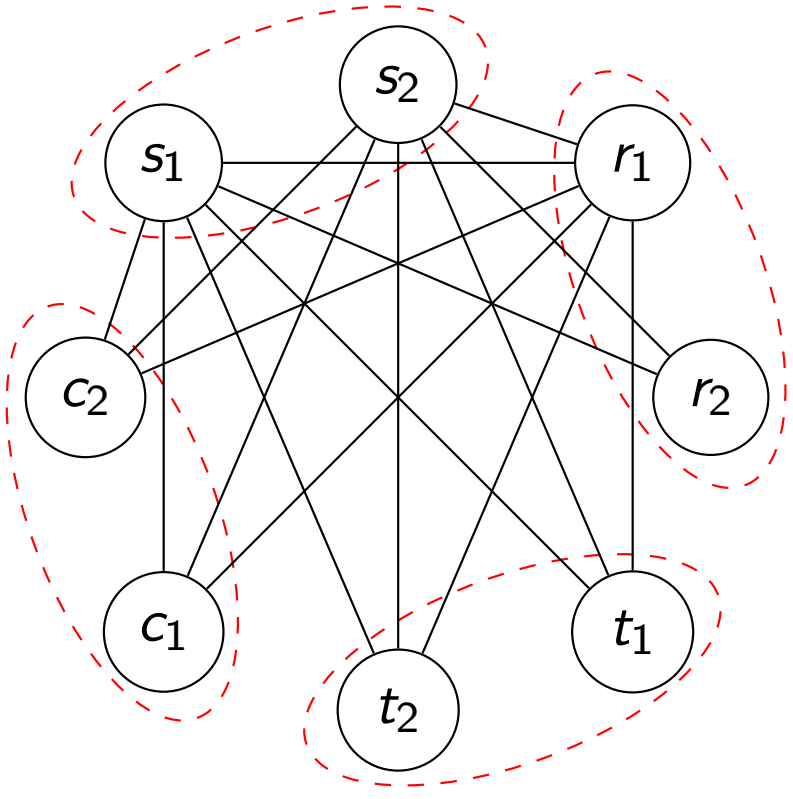

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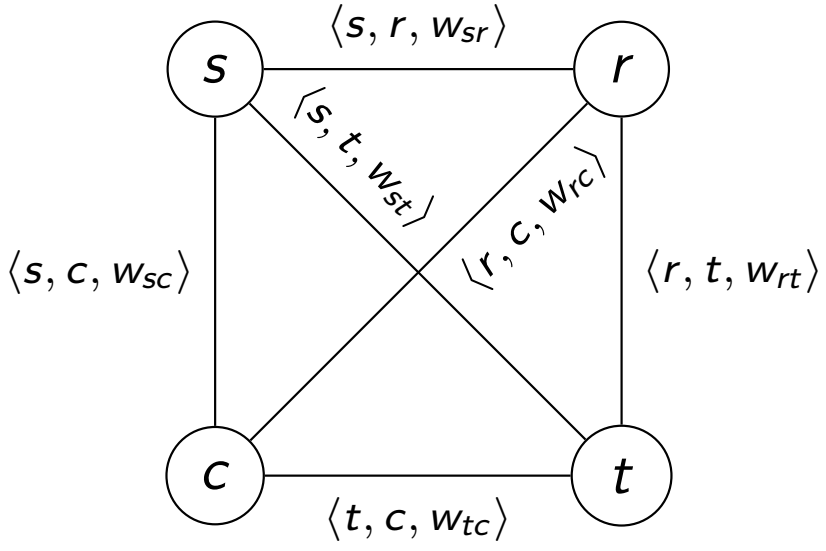

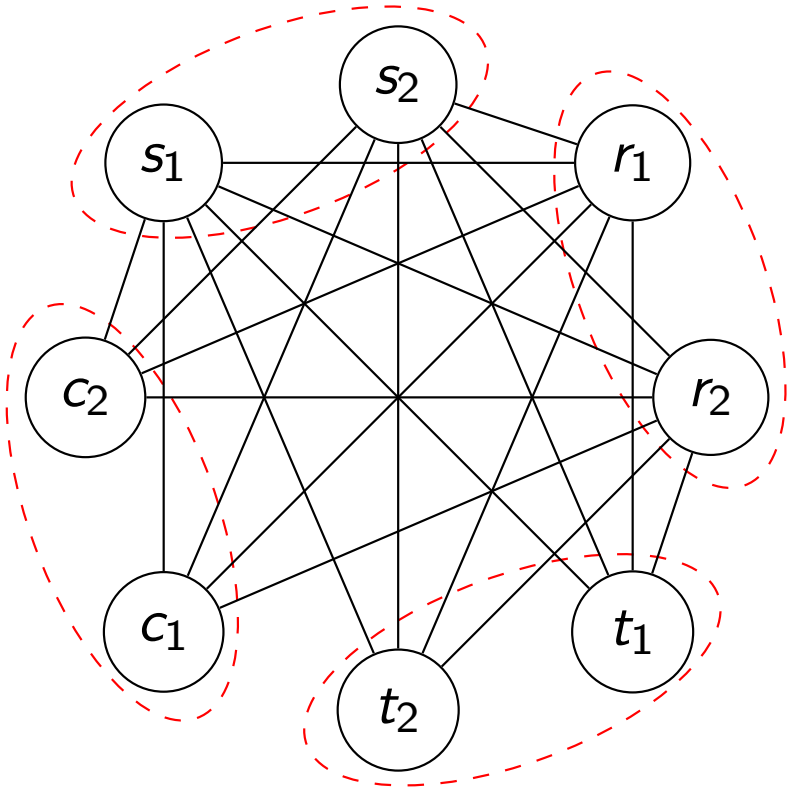

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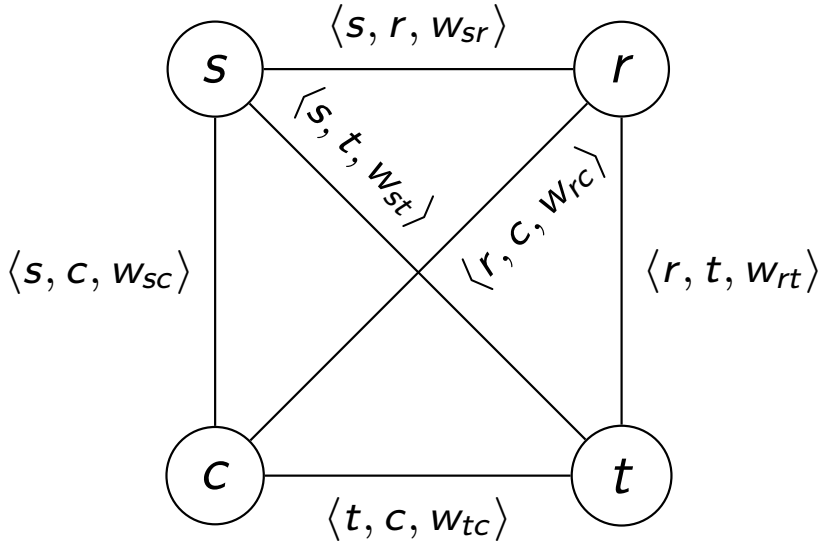

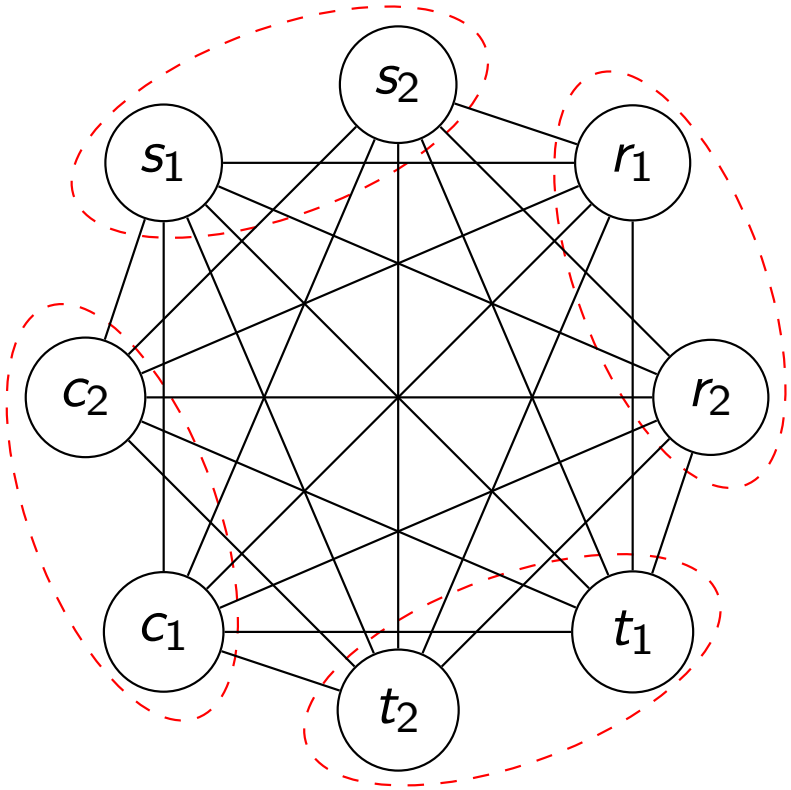

Weighting Policies

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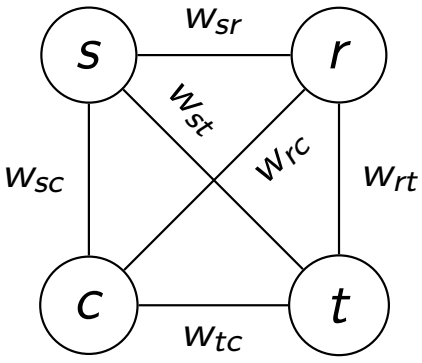
Markov Networks (Markov Random Field)



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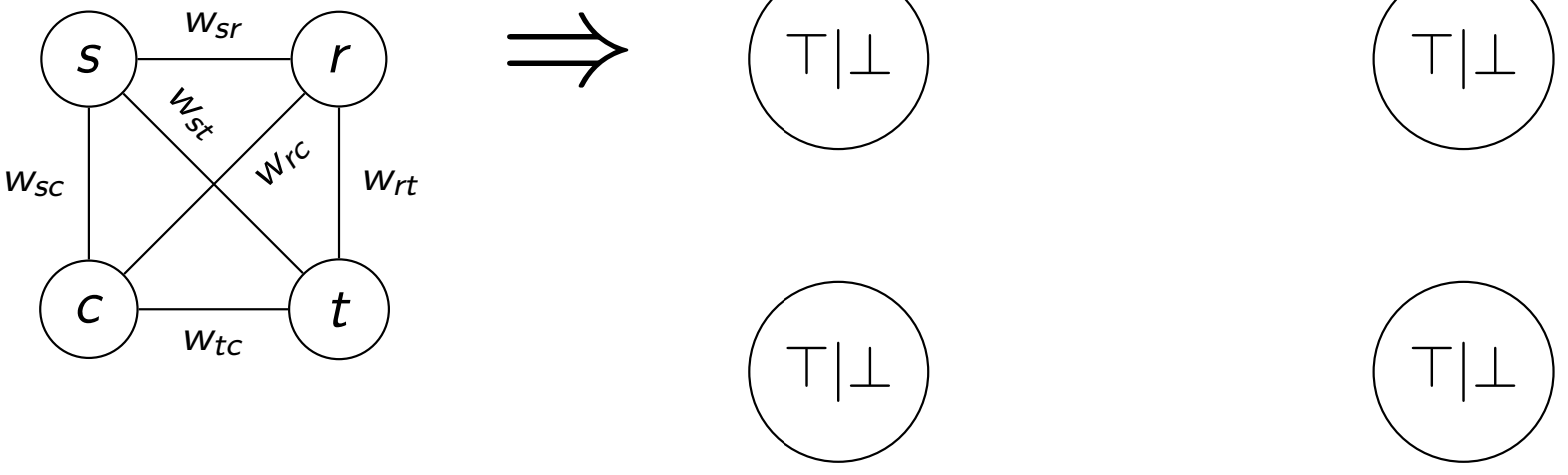

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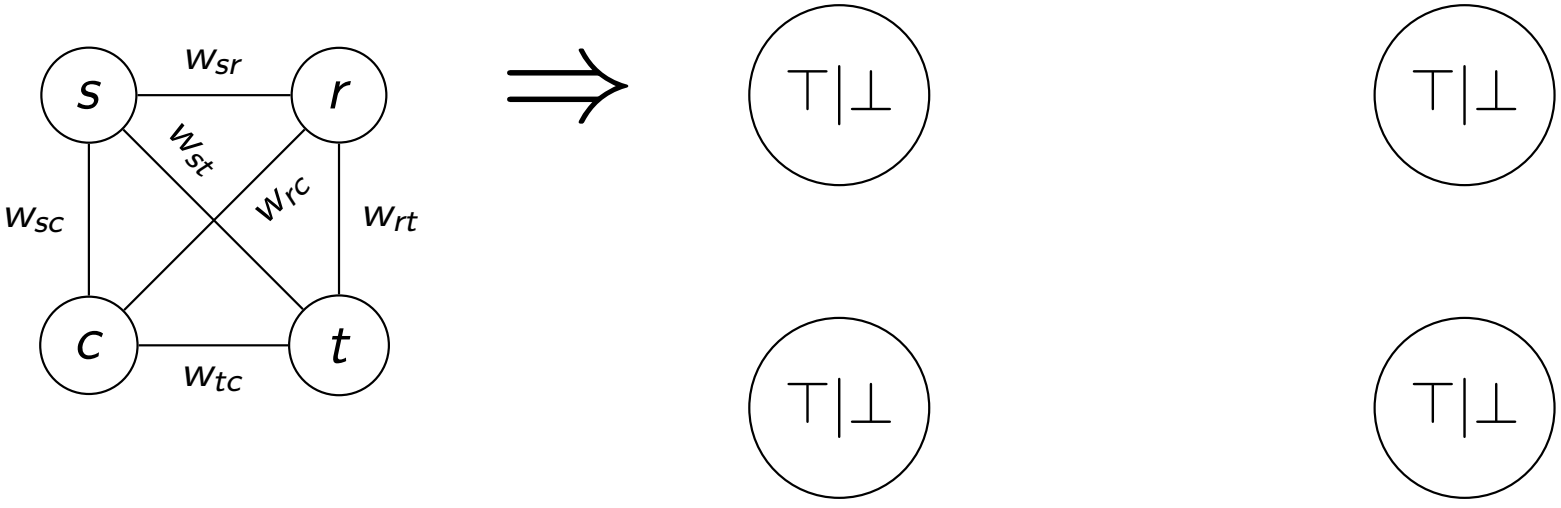

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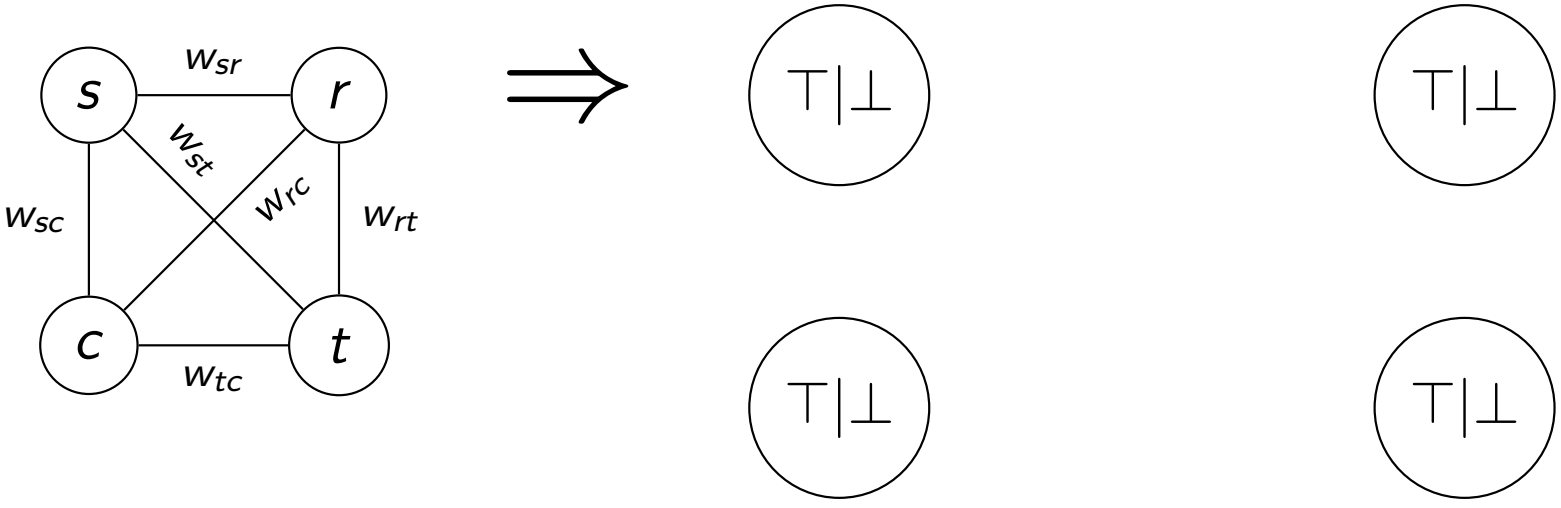

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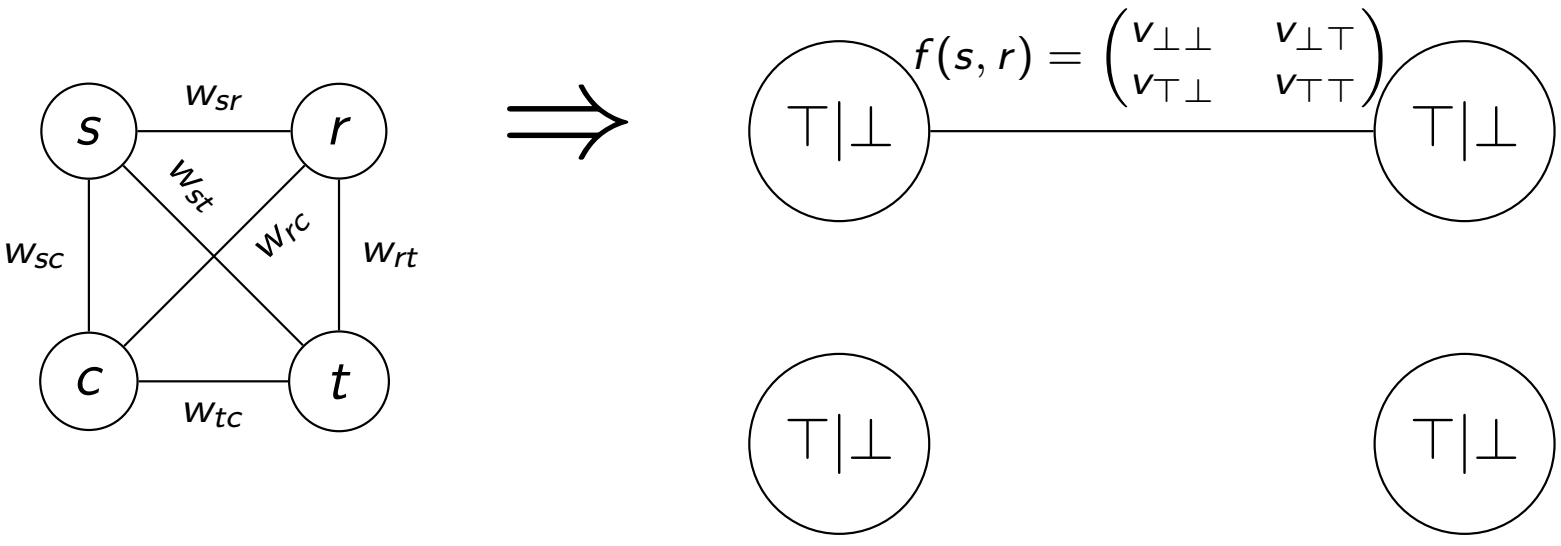

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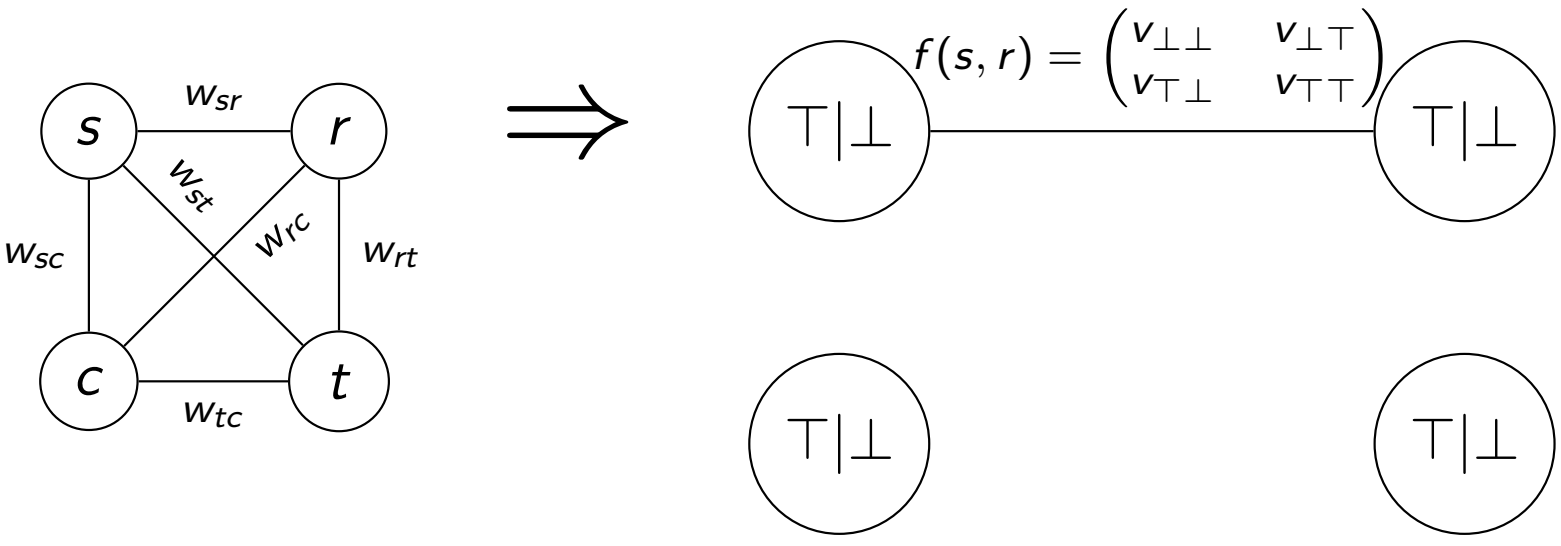

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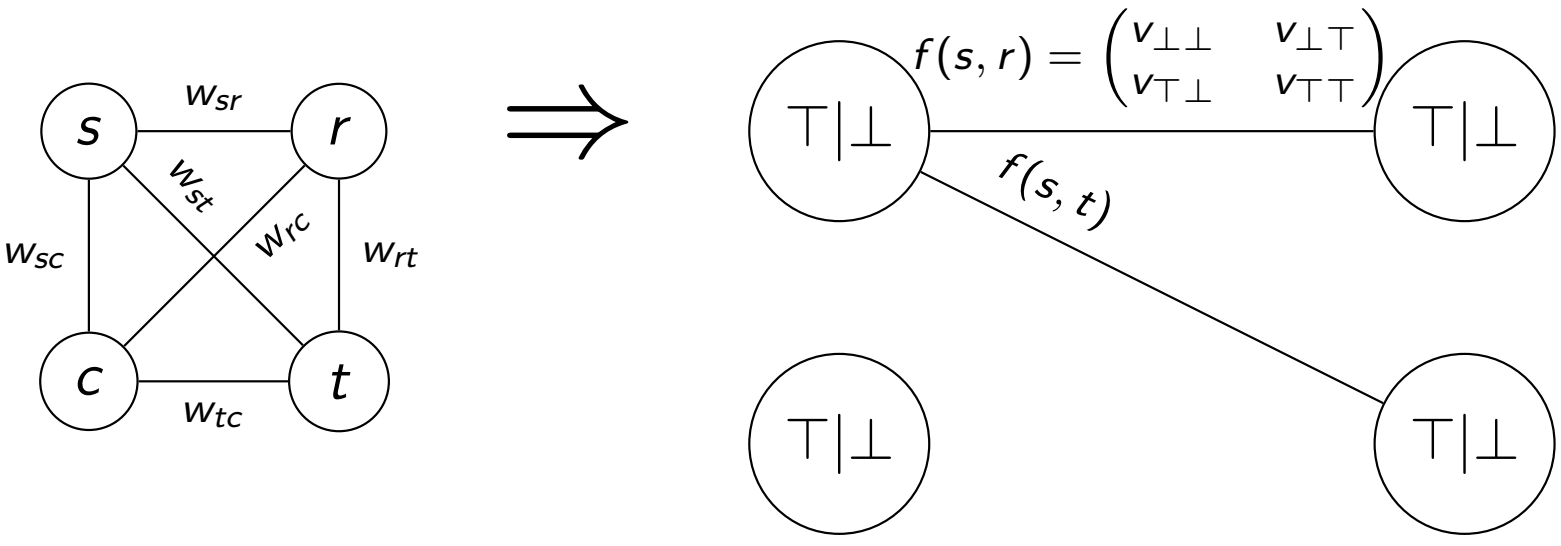

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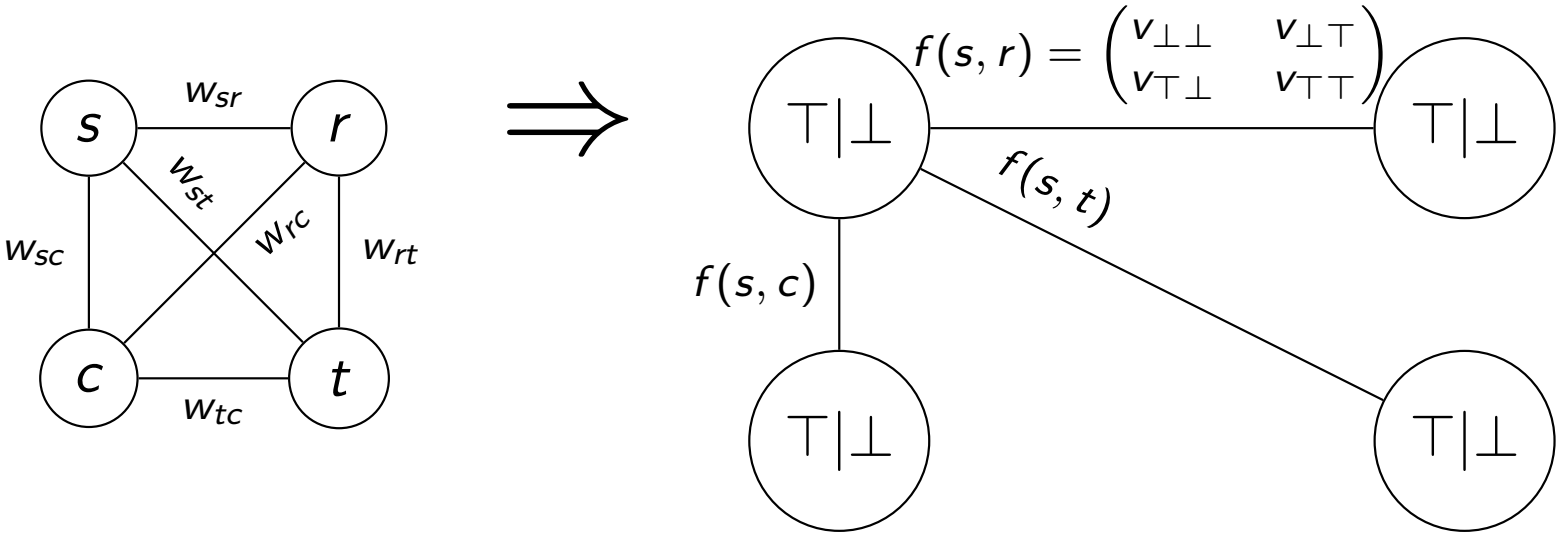

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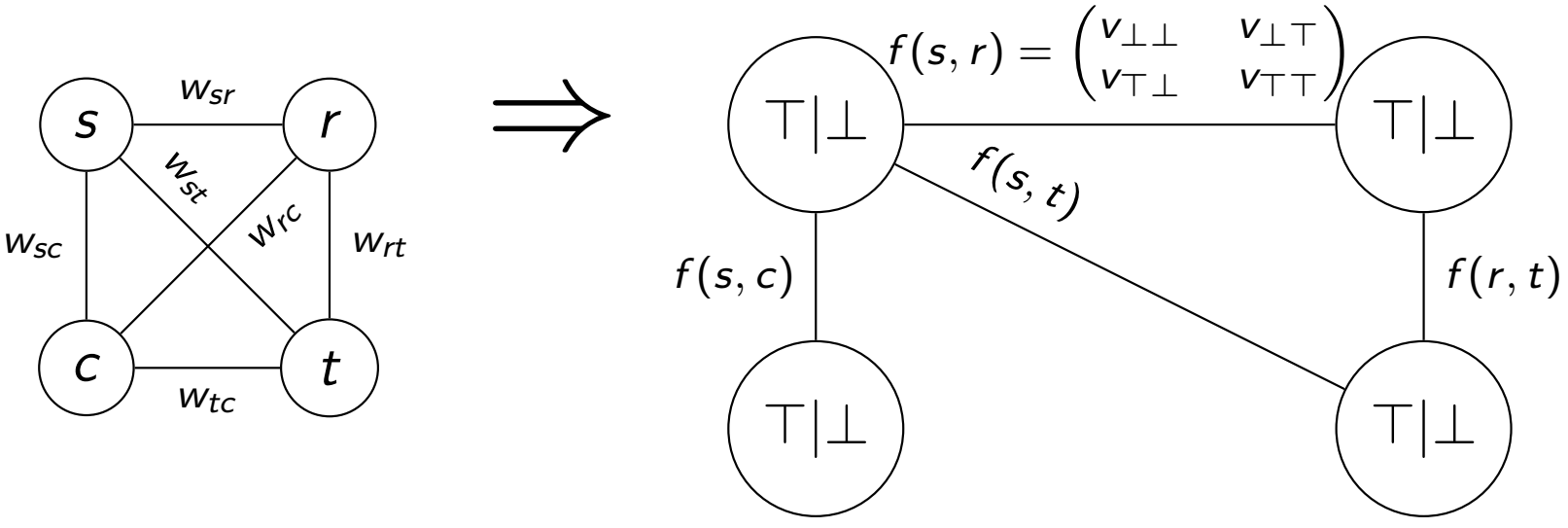

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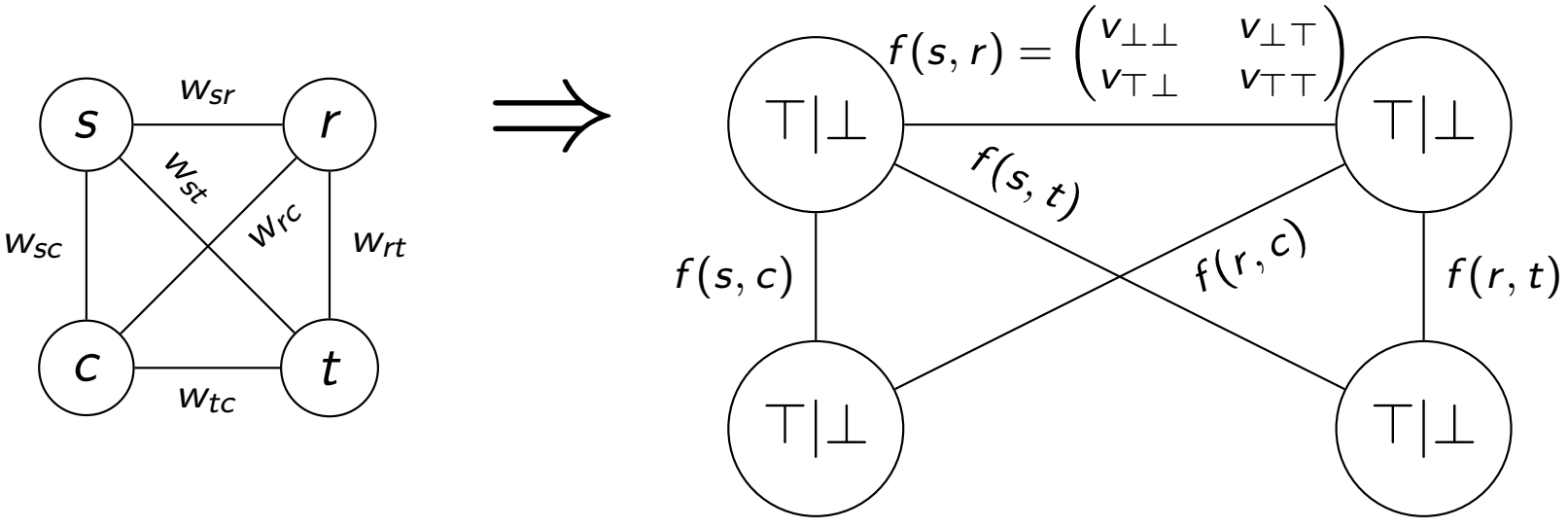

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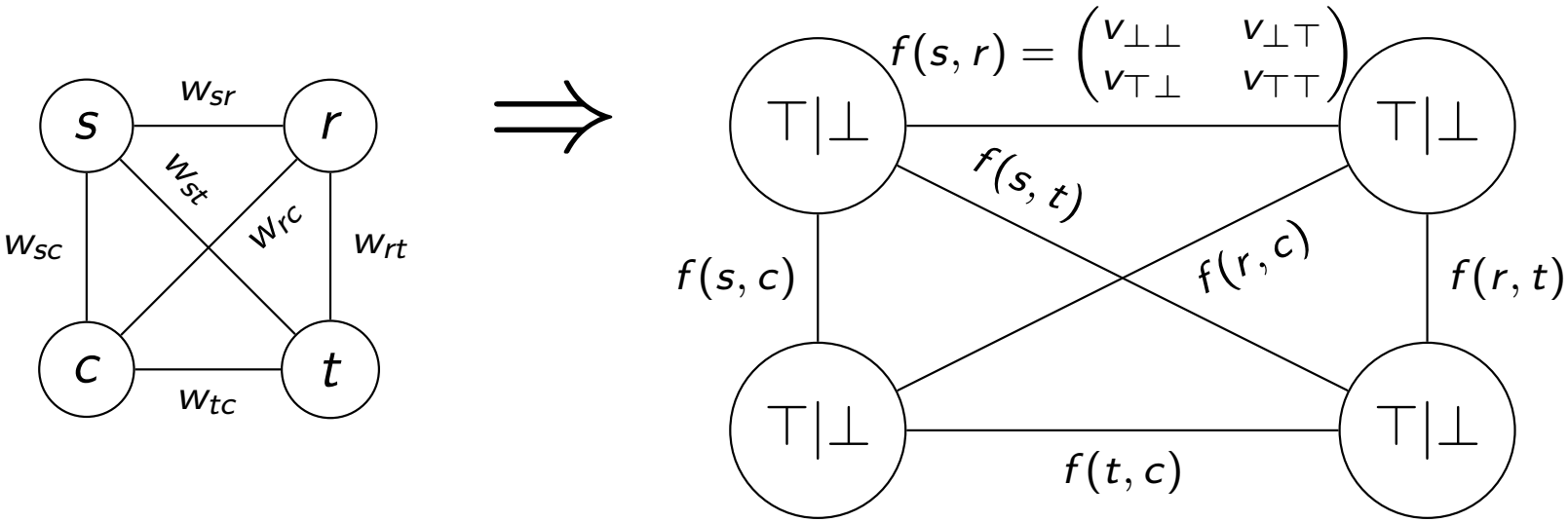

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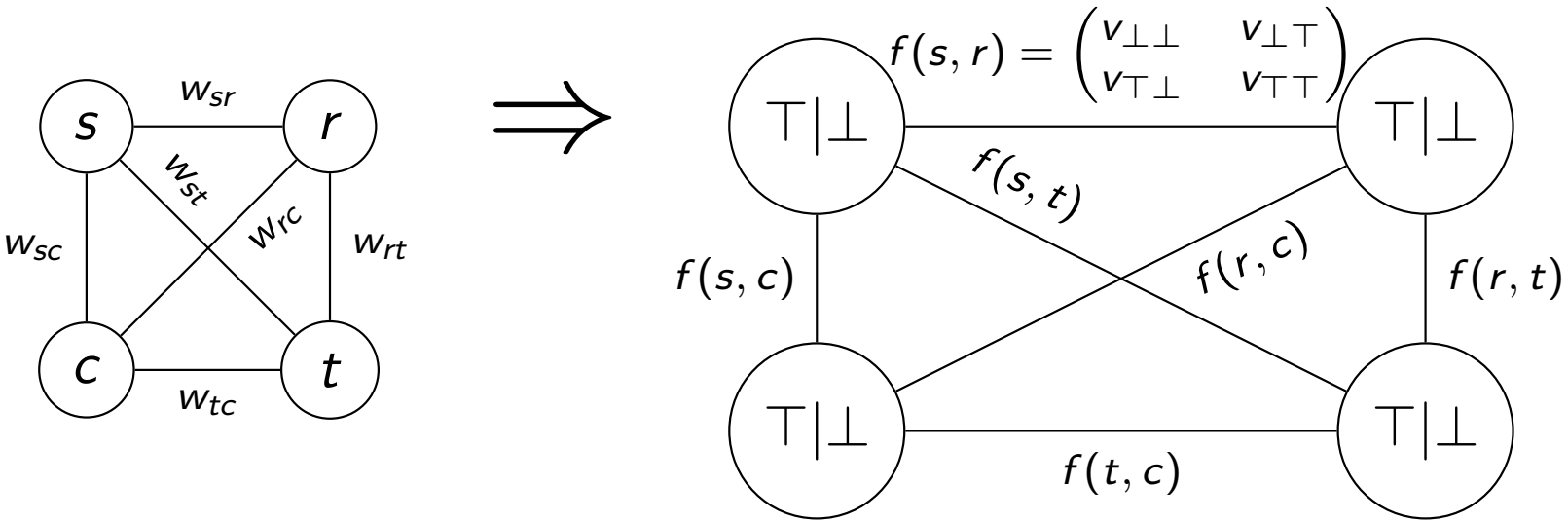

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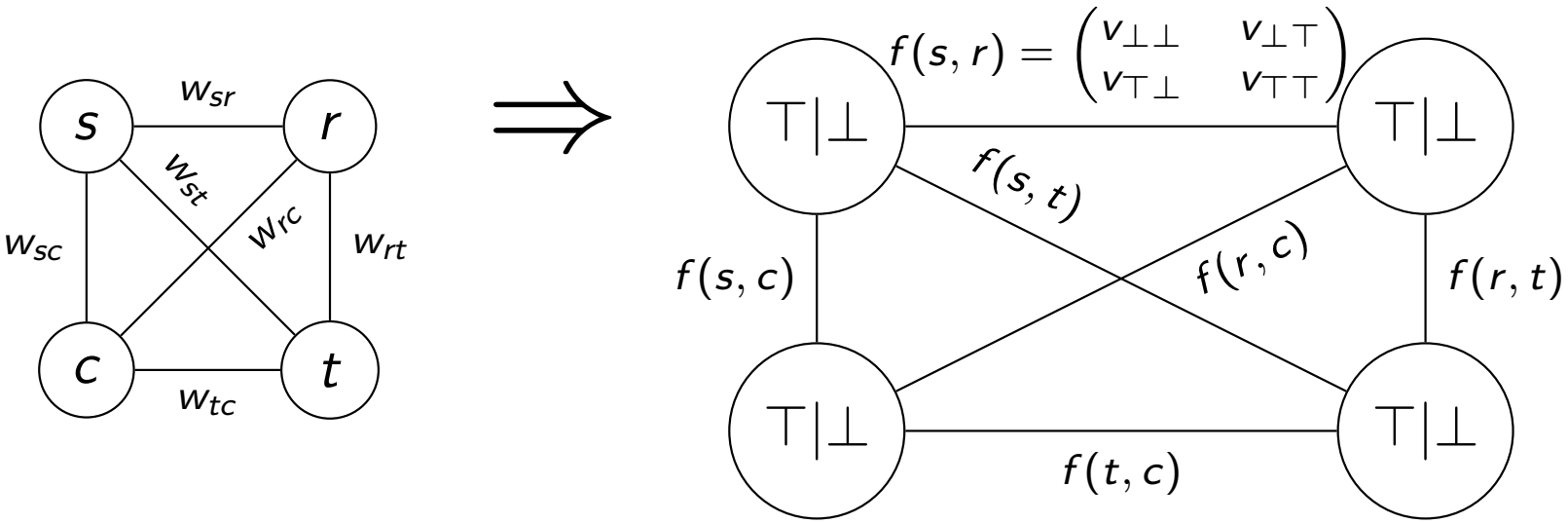

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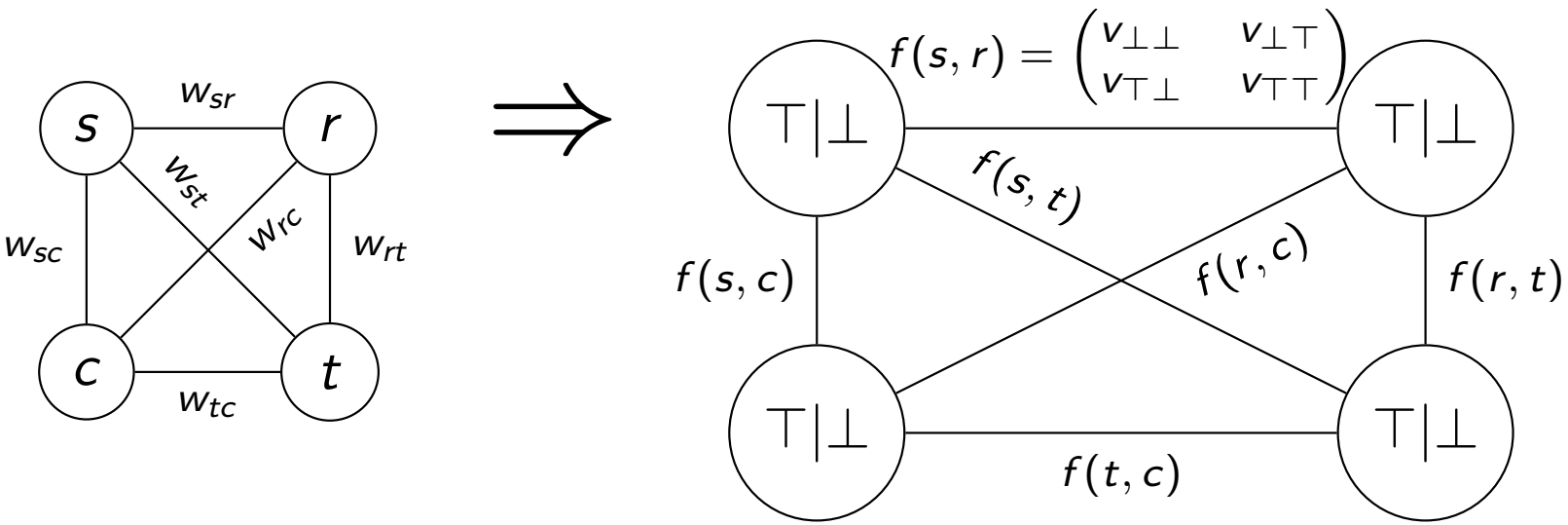

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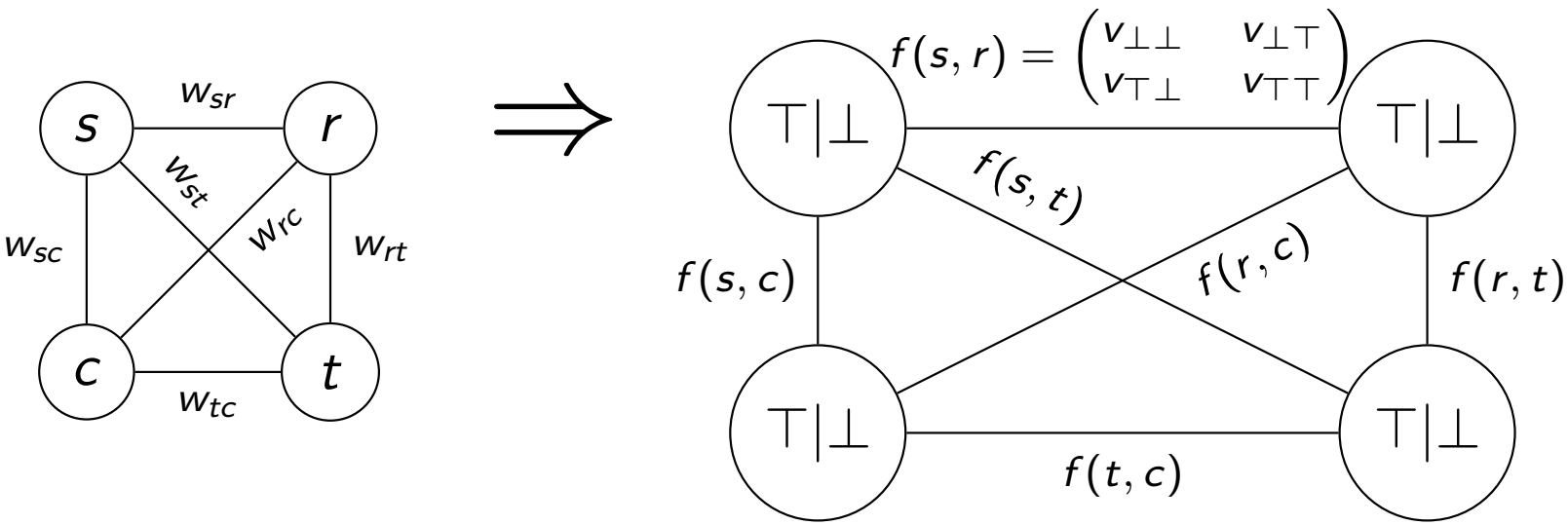

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Computation:

- Query: $P(s_i = \top | t_{cryptography} = \top)$

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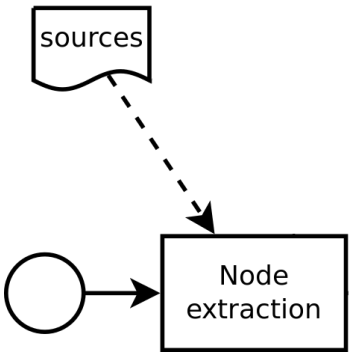

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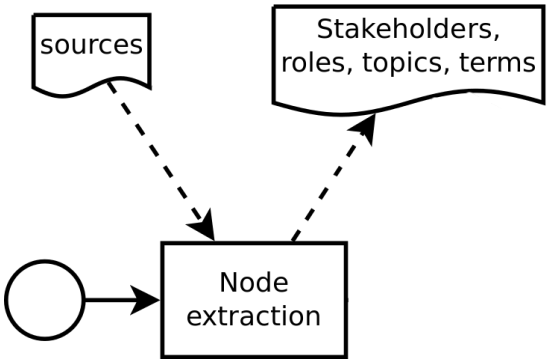

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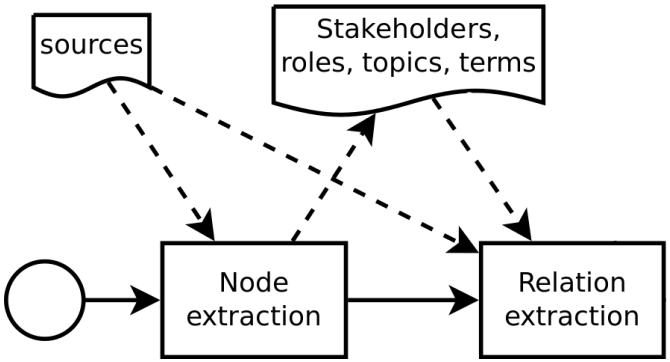

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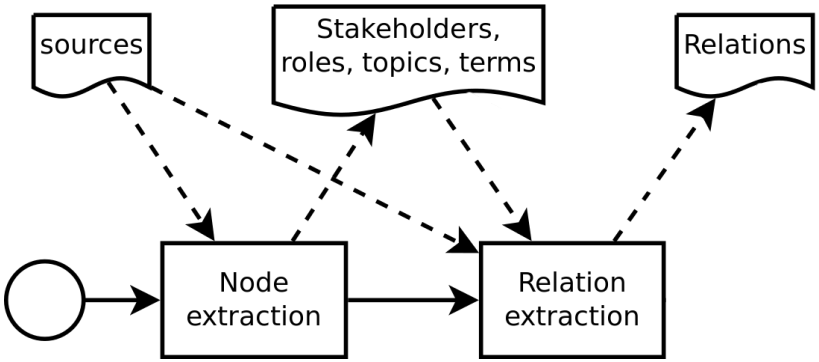

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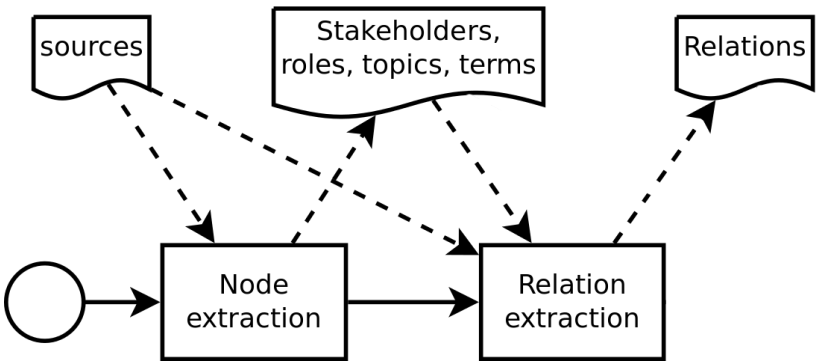

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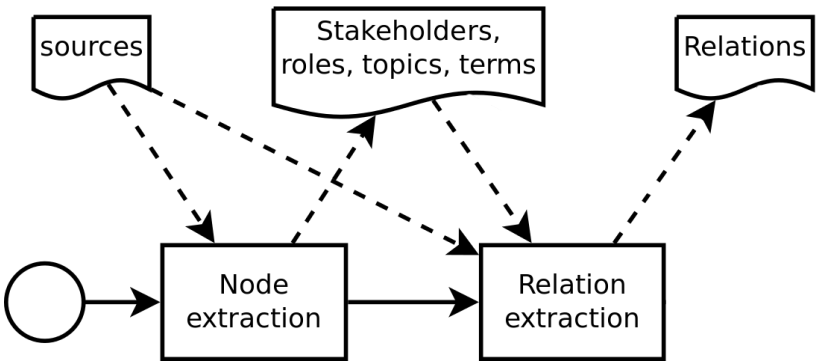

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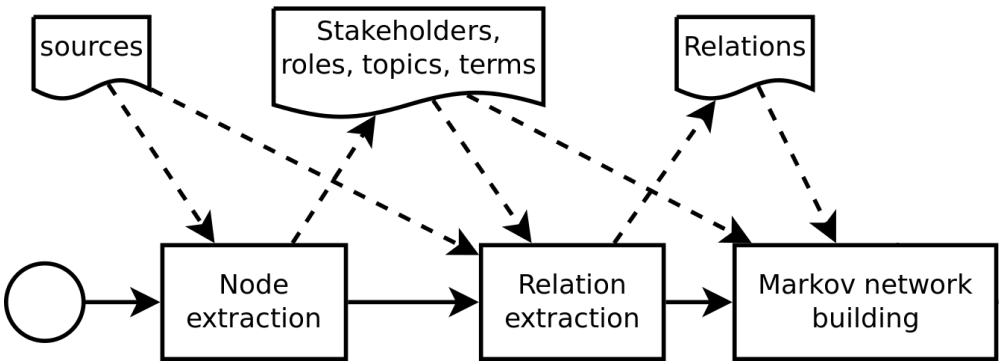

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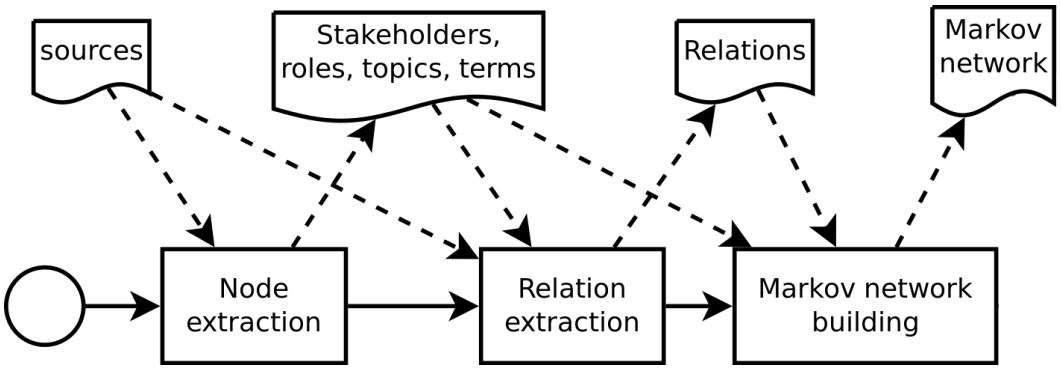

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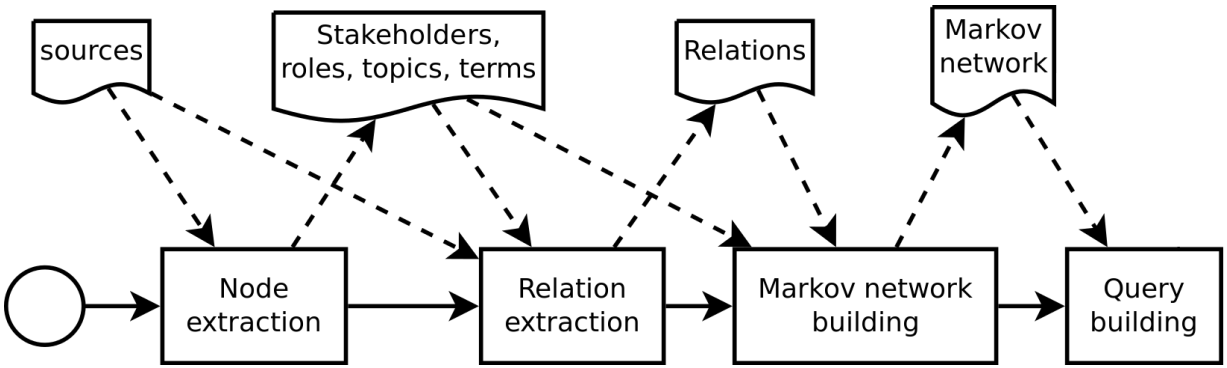

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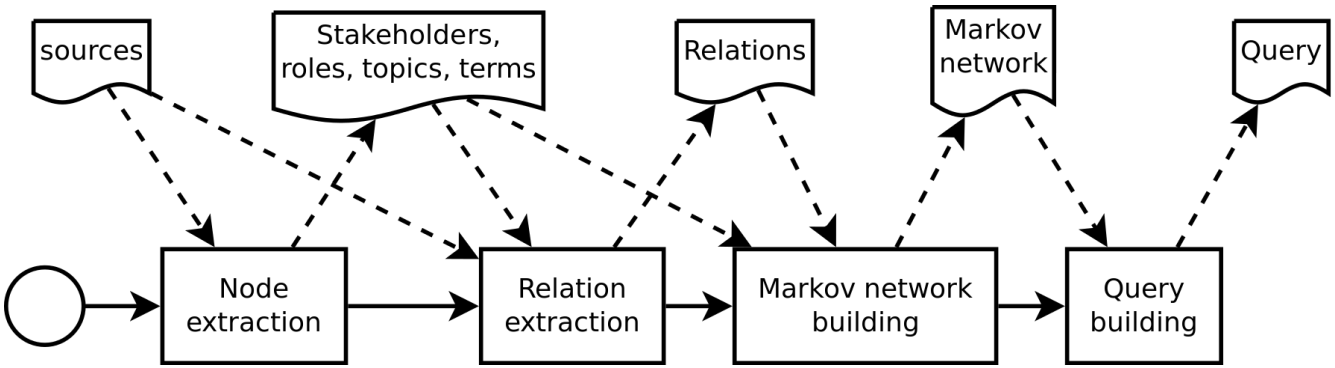

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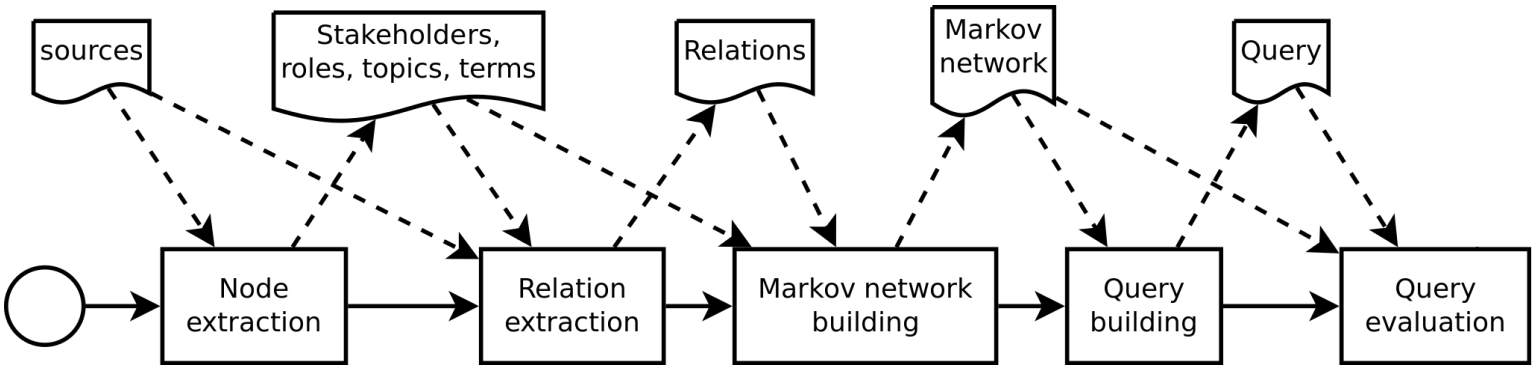

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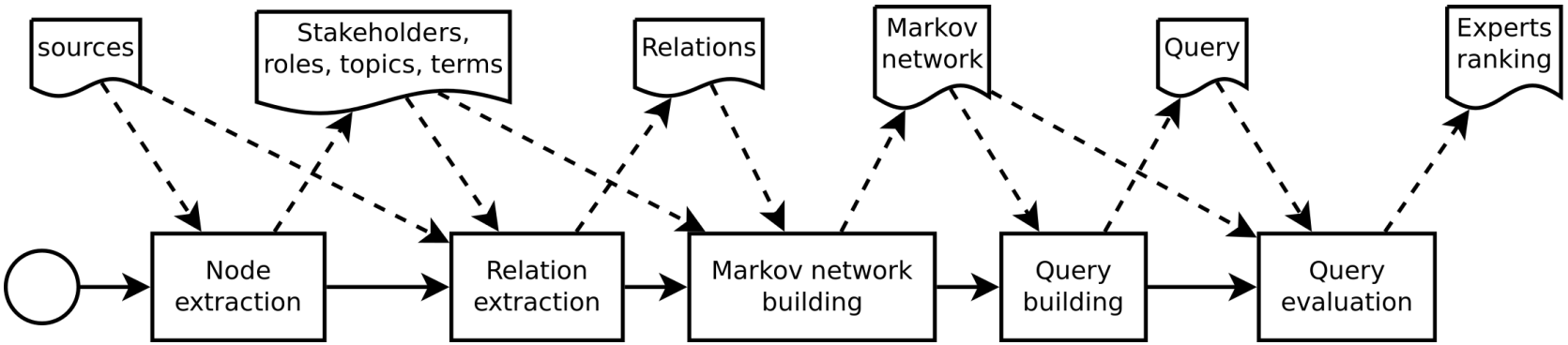

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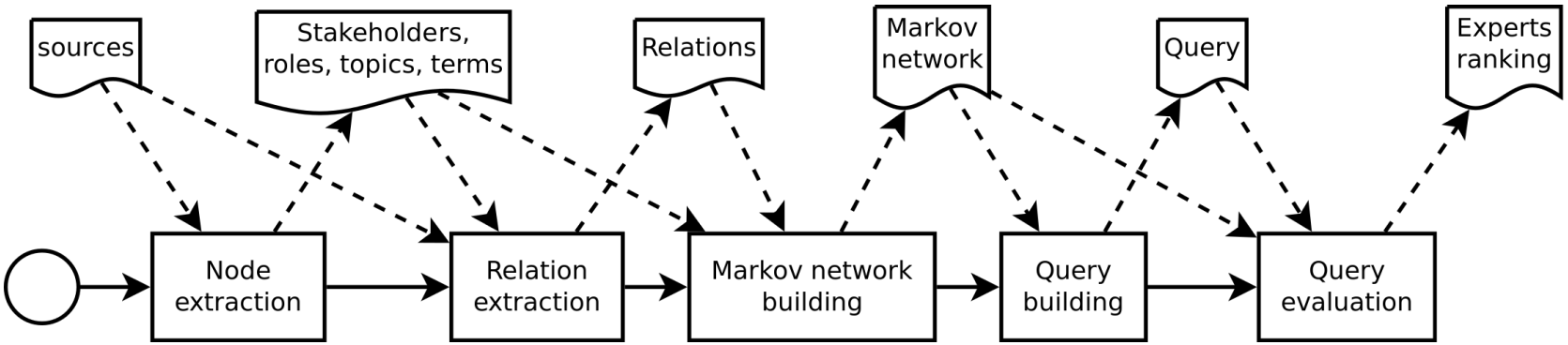

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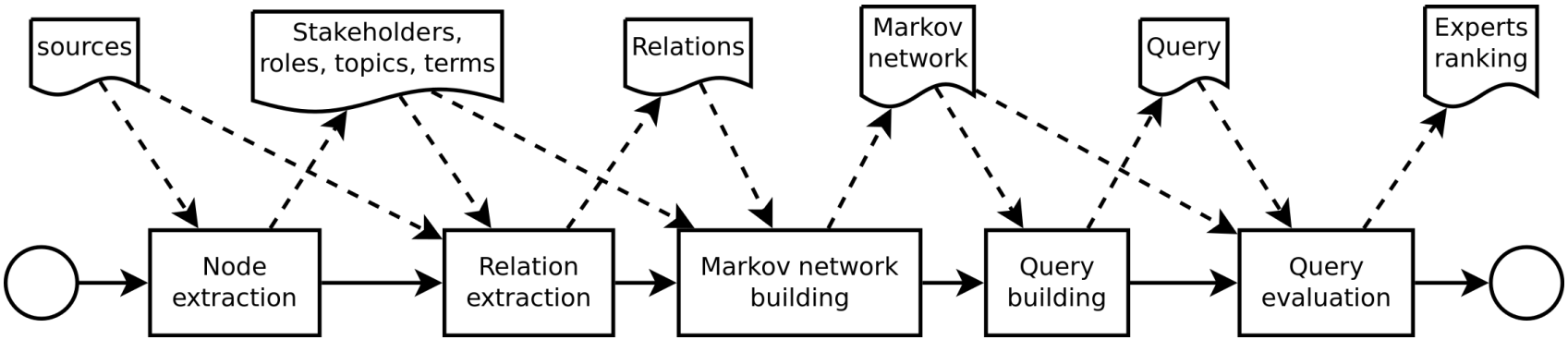

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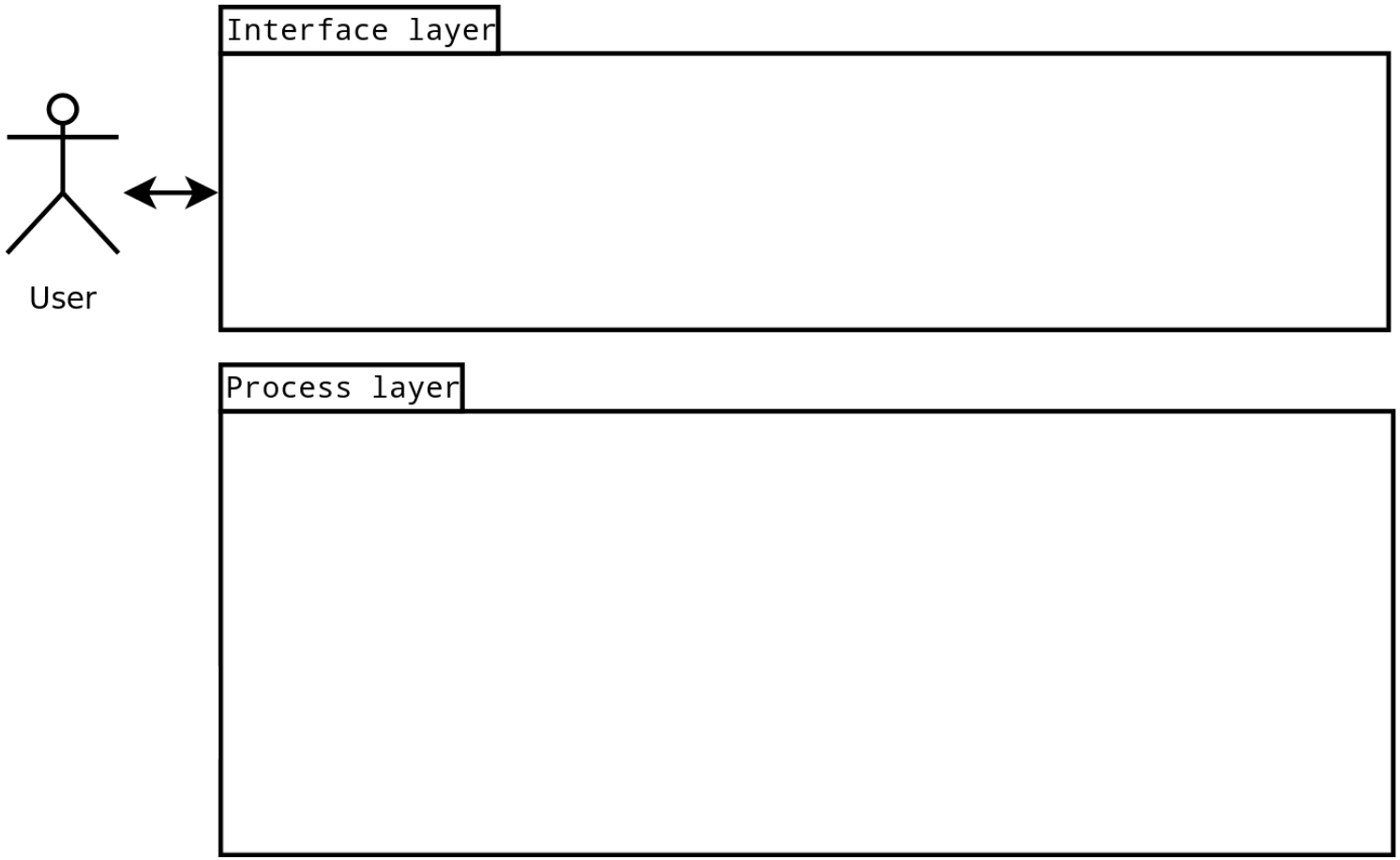

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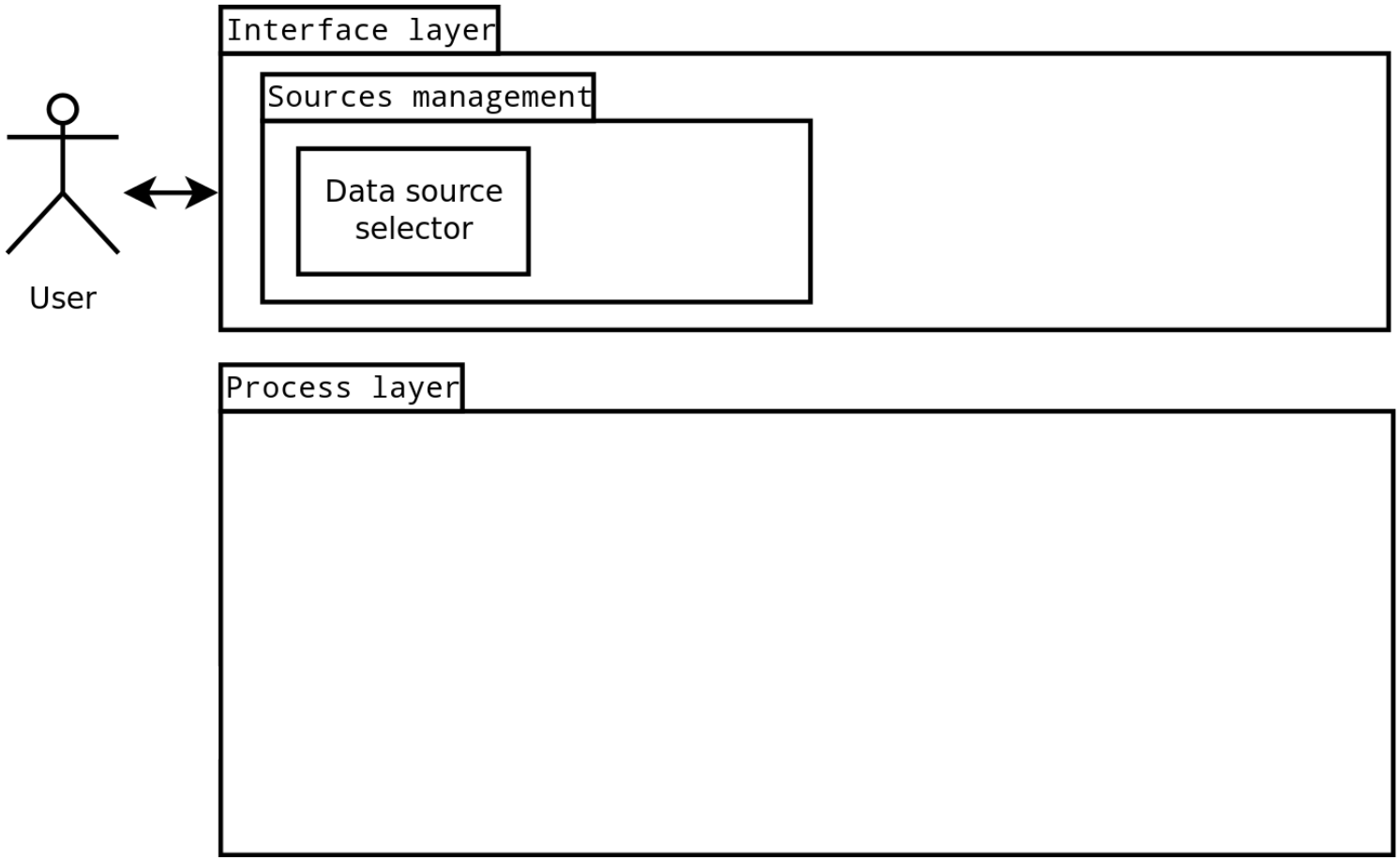

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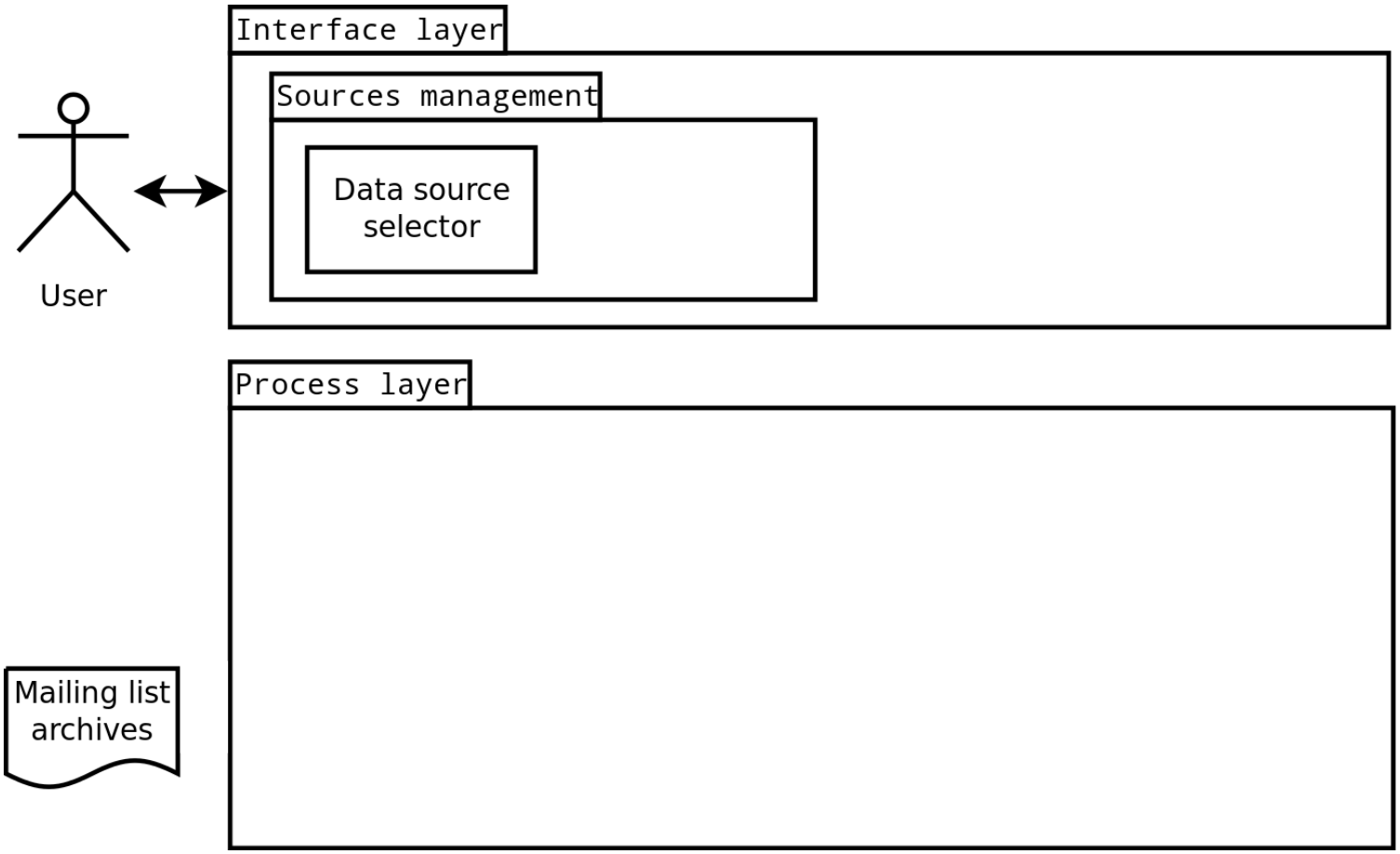

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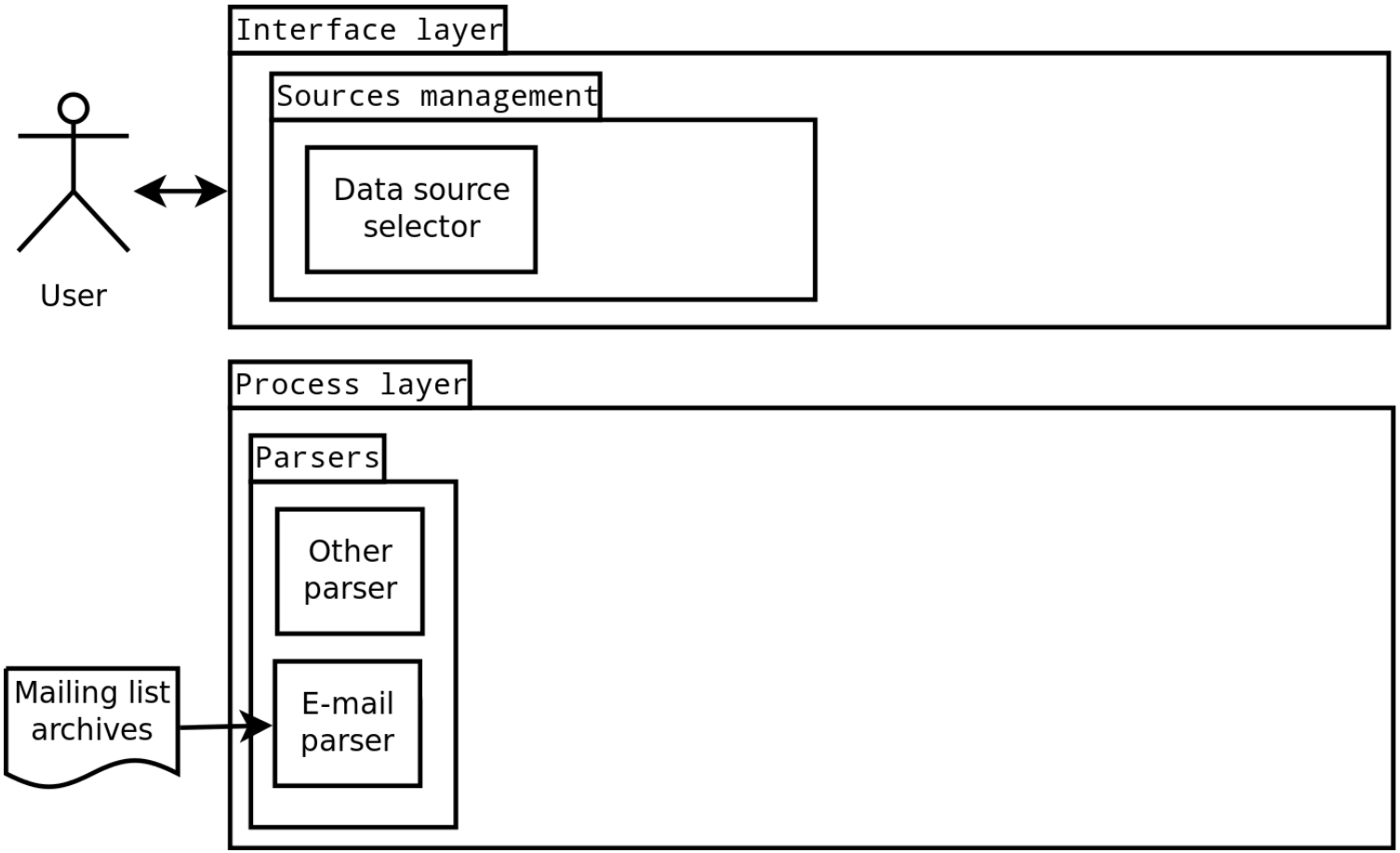

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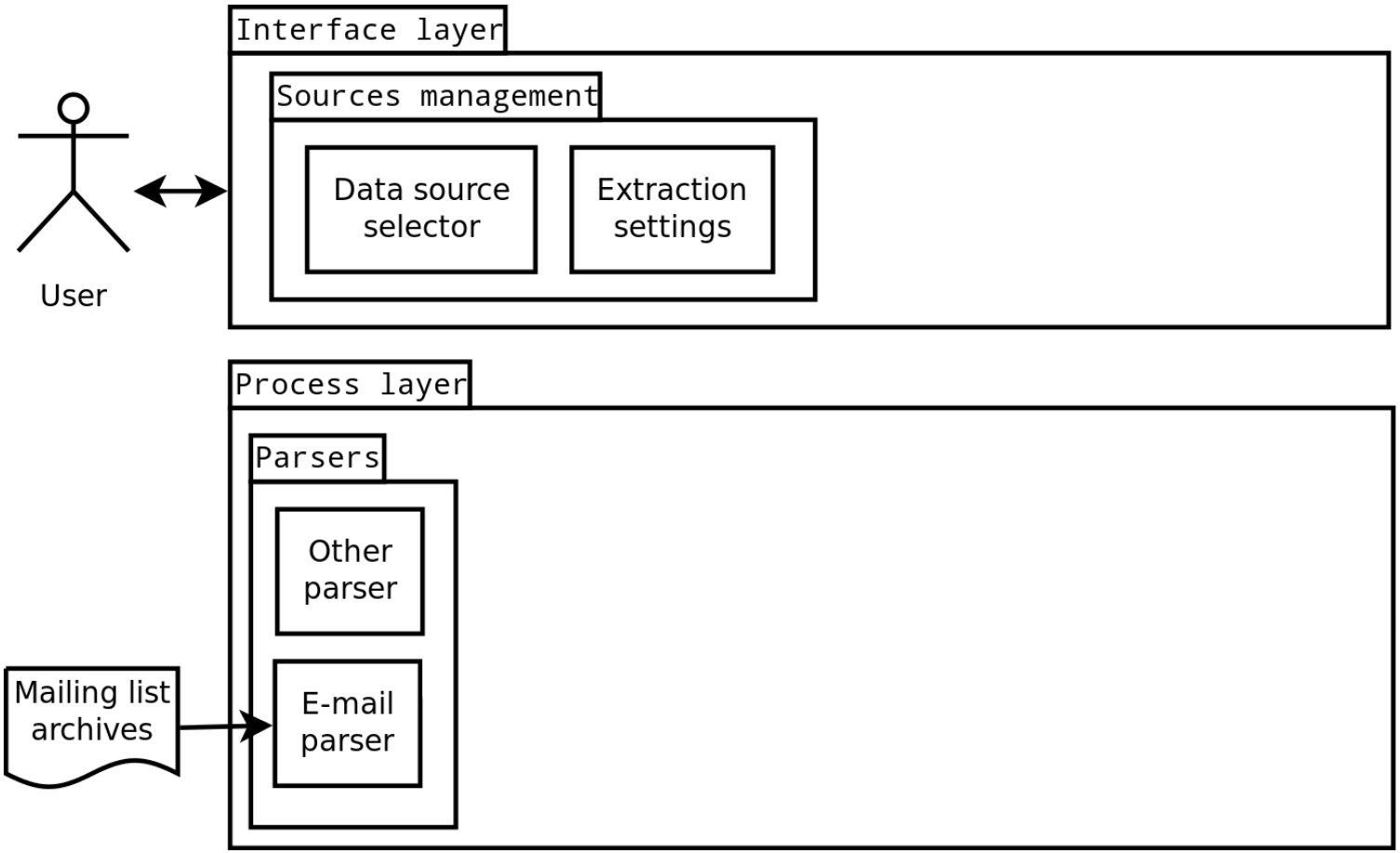

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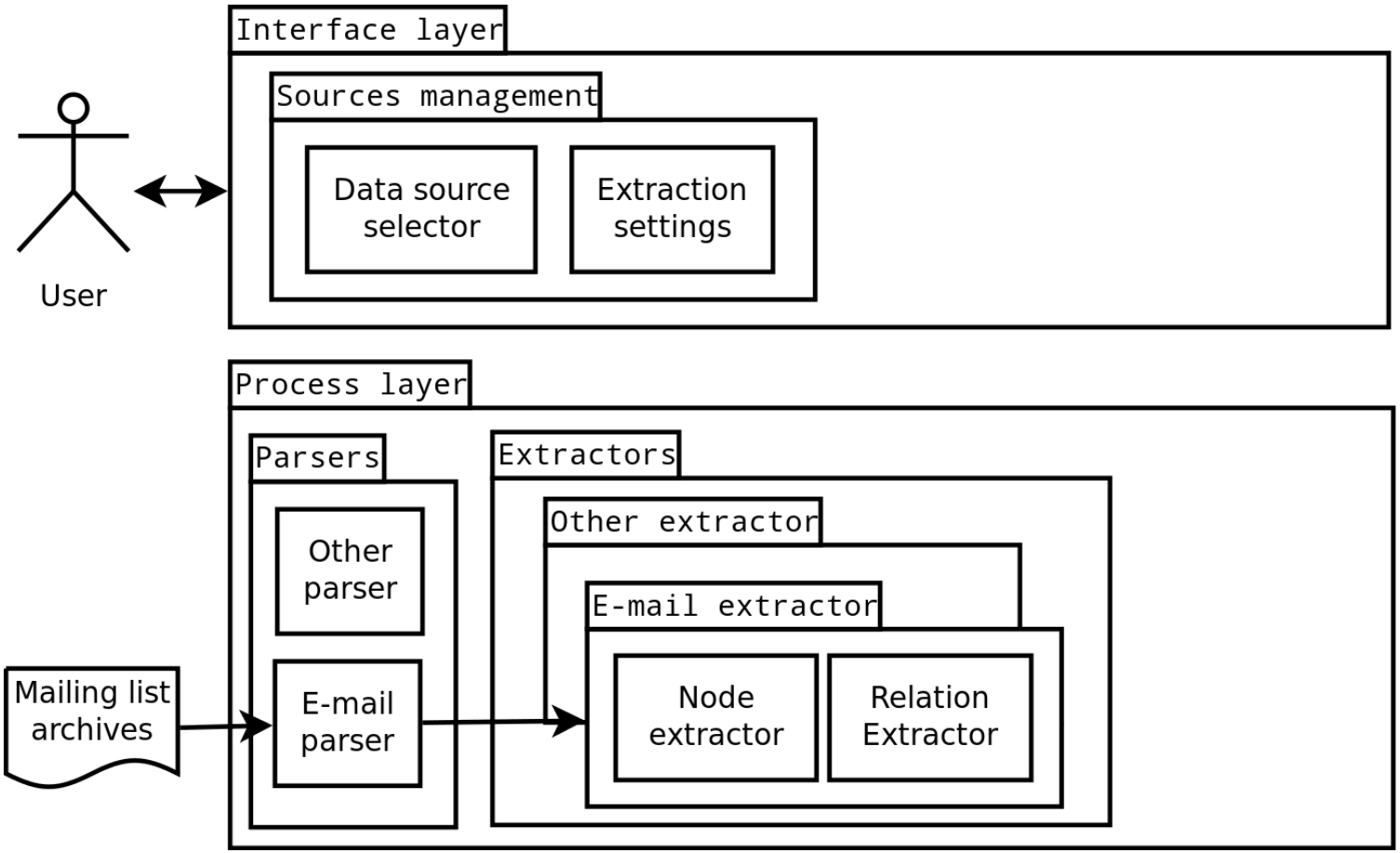

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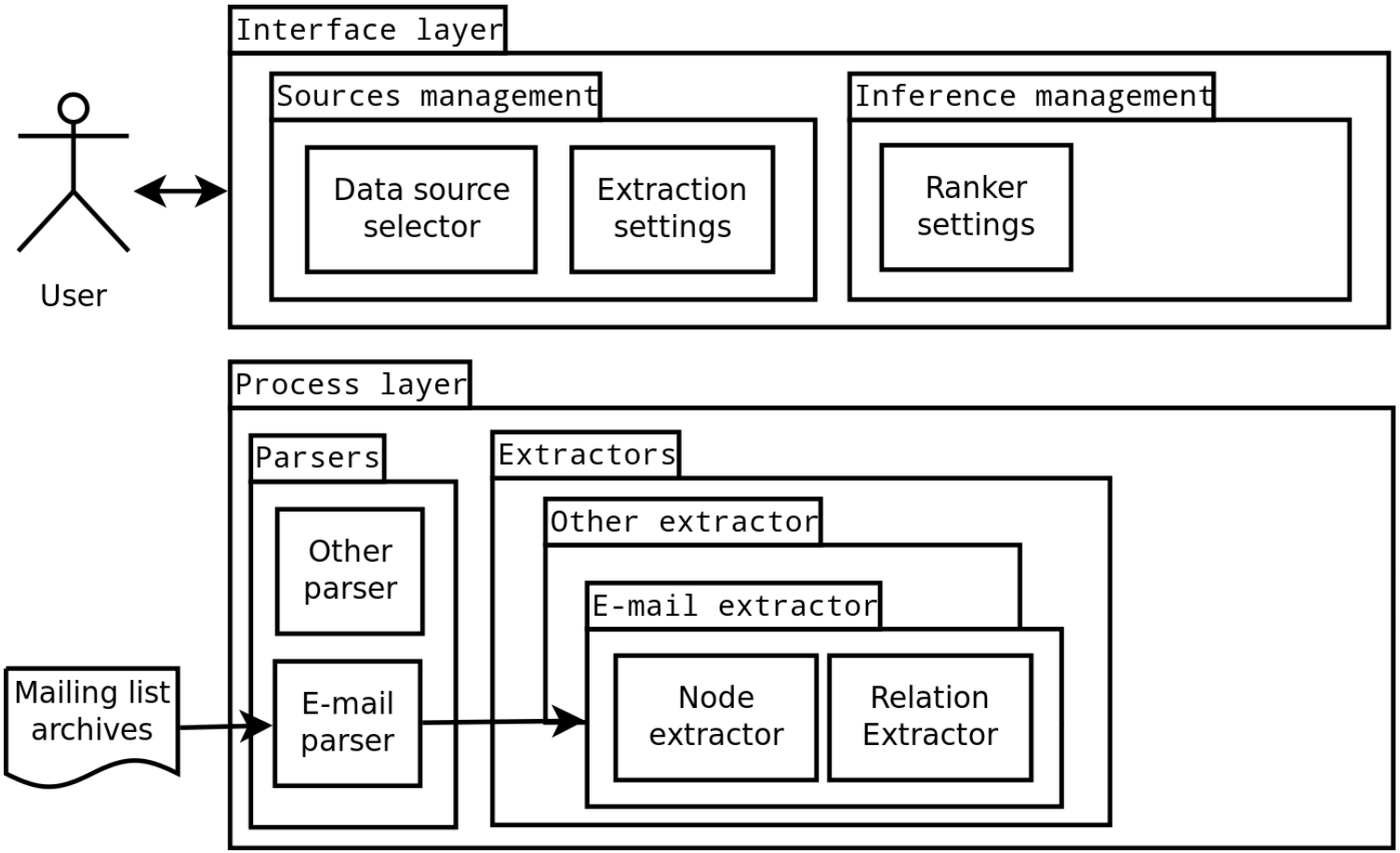

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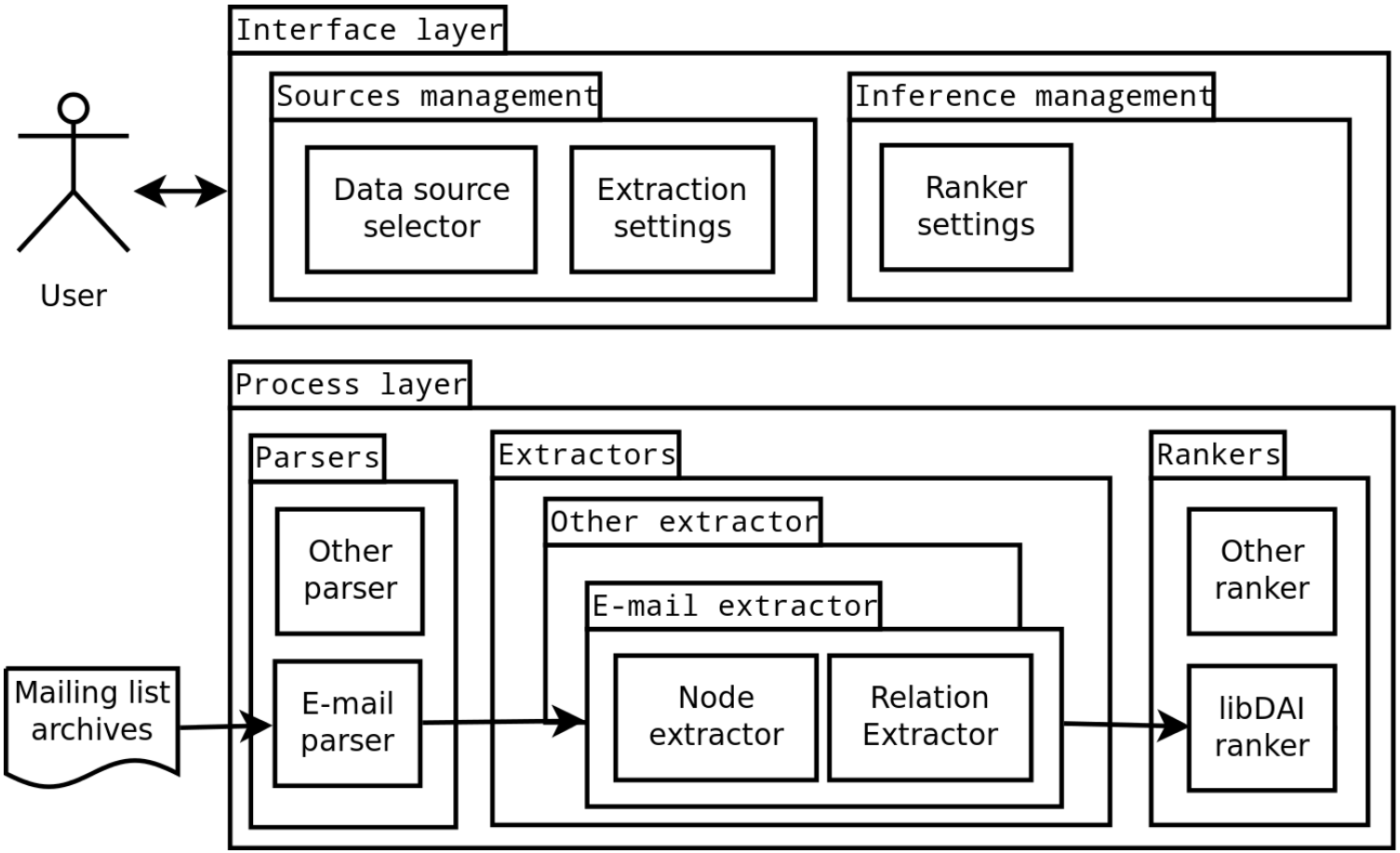

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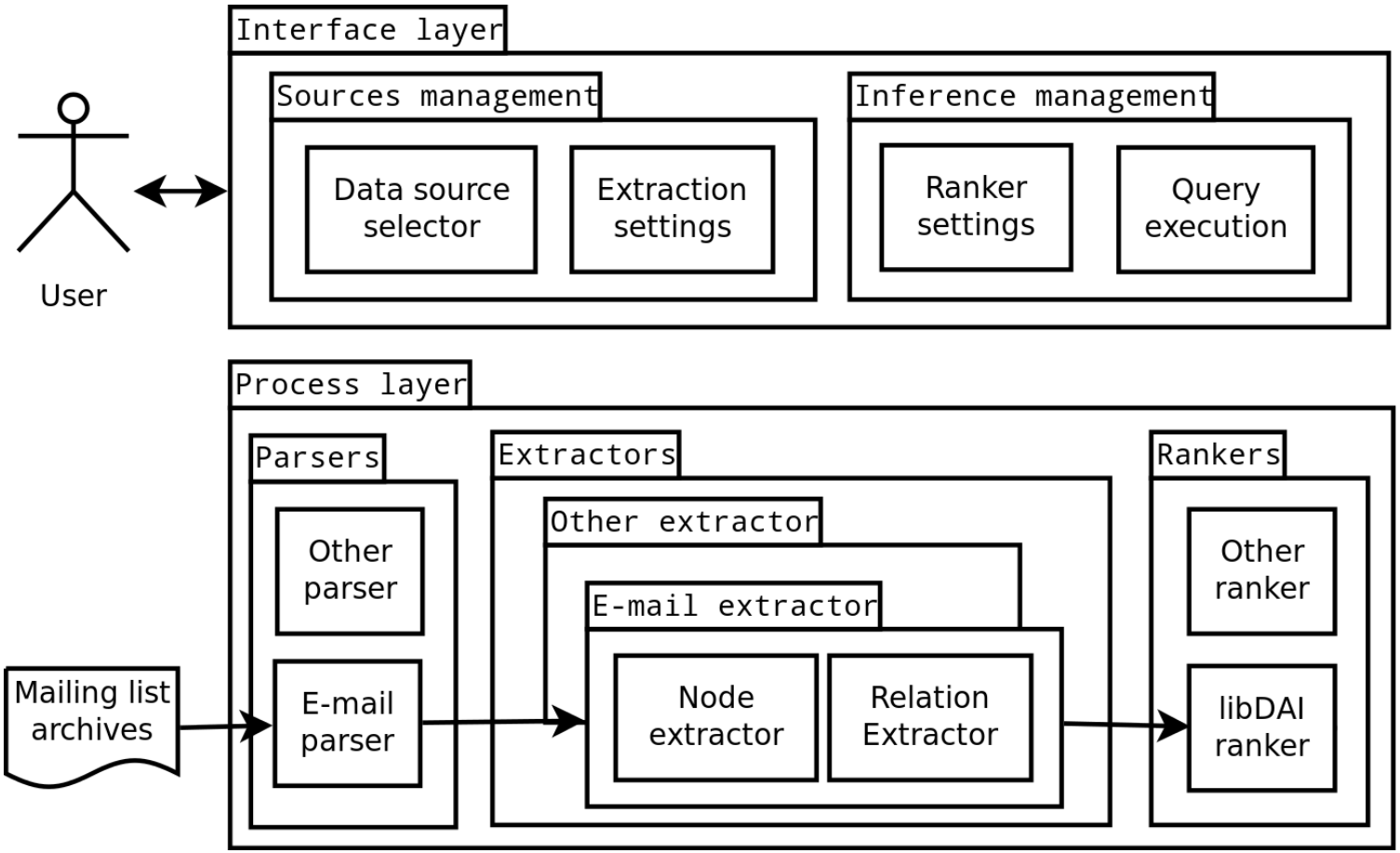

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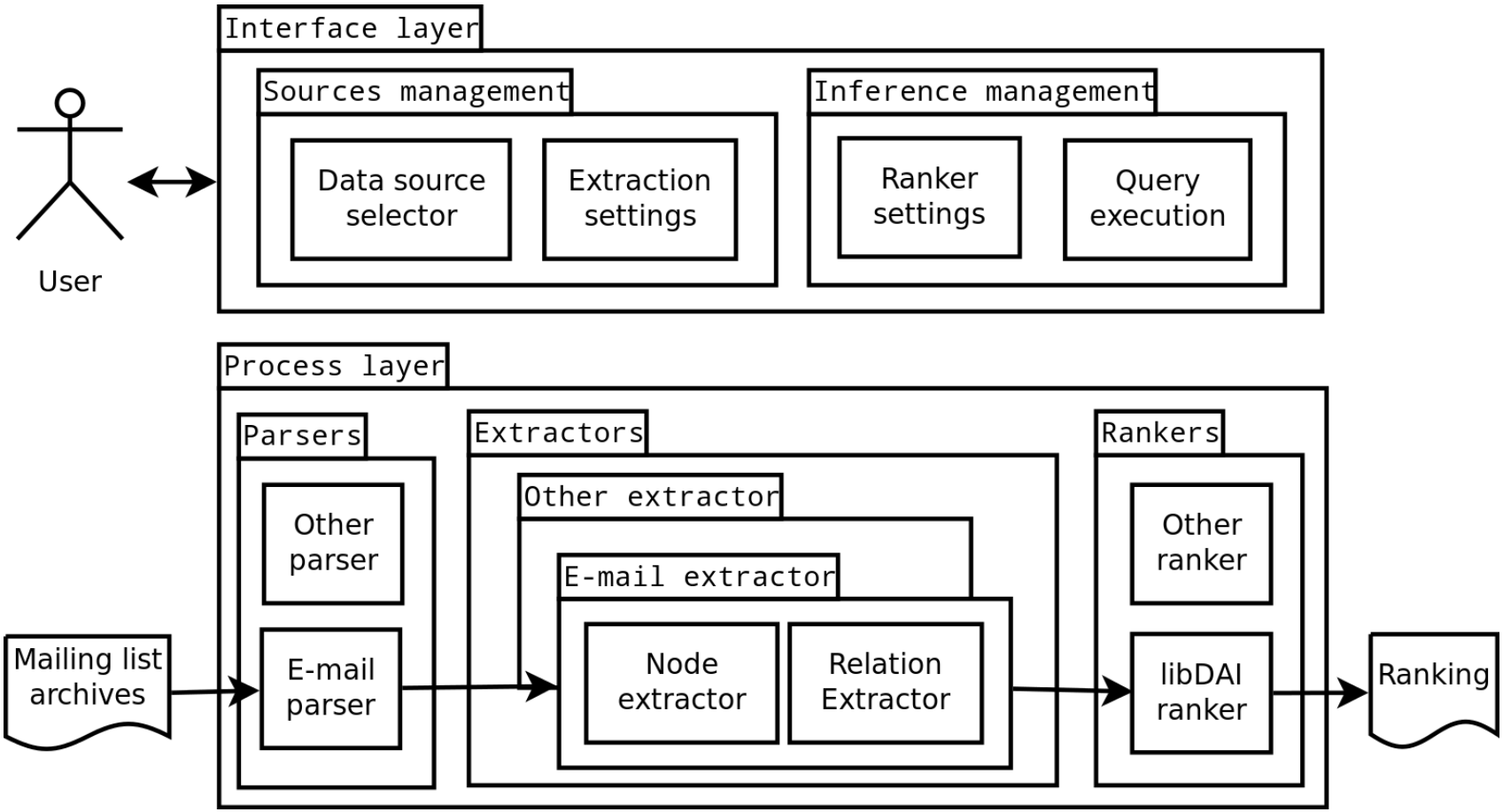

Simple Case: Cooking in Trento

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S	$Q = \emptyset$	Rank	GS	Q_1	Rank	GS	Q_2	Rank	GS
Carla	0.501	1	-	0.499	3	2	0.49978	1	1
Bob	0.500	2	-	0.500	2	1	0.49946	3	2
Alice	0.499	3	-	0.501	1	1	0.49975	2	2

Practical Case: XWiki OSS

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- Taxonomy and ontologies

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- Technique: use MN to compute expertise probability
- Results: good support from preliminary experiment

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Thanks for your attention.

Questions?

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Expert Finding Examples

content-based:

- Mockus and Herbsleb [2002]: written code evidence to evaluate expertise in software pieces.
- Serdyukov and Hiemstra [2008]: authors' contributions in documents to infer expertise in related topics.

social-based:

- Zhang et al. [2007]: compare algos on social network built from askers/repliers identification in online forums.

Both:

- Karimzadehgan et al. [2009] exploit relationships + e-mails content between employees of a company.

Stakeholders Recommendation in RE

Literature review Mohebzada et al. [2012]

- Castro-Herrera and Cleland-Huang [2010]
  - *evaluate stakeholders knowledge through participation in forum*
  - *build abstract topics (term vectors) depending on messages common terms*
  - *relate stakeholders to topics they participate in*
  - *recommend other stakeholders to participate in new, similar topics*
  - *content-based: exploit data provided directly by stakeholders*
- StakeNet Lim et al. [2010]
  - *prioritise requirements depending on stakeholders rating*
  - *core stakeholders suggests others influencing the project*
  - *role and salience describe influence*
  - *built social network + apply measures to evaluate global influence*
  - *social-based: evaluate influence based on other stakeholders suggestions*

Node extractor for e-mails

Require: *mail*: Natural language e-mail
Ensure: S, R, T, C: Extracted stakeholders, roles, topics and terms

1: $S \leftarrow \{stakeholder(authorOf(mail))\}$
2: $R \leftarrow \emptyset$
3: $T \leftarrow \{topic(x) | x \in nounsOf(subjectOf(mail))\}$
4: $C \leftarrow \{term(x) | x \in nounsOf(bodyOf(mail))\}$

Relation extractor for e-mails

Require: $mail, S, R, T, C$: E-mail, stakeholders, roles, topics, terms
Ensure: L: Weighted relations

$L \leftarrow \emptyset$
$a \leftarrow author(mail)$
if $stakeholder(a) \in S$ **then**
  for all $t \in termsOf(bodyOf(mail))$ **do**
    if $term(t) \in C$ **then**
      $L \leftarrow merge(L, \{\langle stakeholder(a), term(t), 1\rangle\})$
    end if
  end for
end if
for all $topic \in T$ **do**
  if $nounOf(topic) \in nounsOf(subjectOf(mail))$ **then**
    $L \leftarrow merge(L, \{\langle stakeholder(a), topic, 1\rangle\})$
    for all $t \in nounsOf(bodyOf(mail))$ **do**
      if $term(t) \in C$ **then**
        $L \leftarrow merge(L, \{\langle topic, term(t), 1\rangle\})$
      end if
    end for
  end if
end for

Main differences with Karimzadehgan et al. [2009]

- social relationships not only for post-processing
- inference technique manage multiple topics

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