# Goal Model-Based Expert Finding

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# Outline

# Expert Finding in RE

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- Need to find "people who know": expert finding.
  - *Actually "people who know **the best**".*

# Two Main Approaches (Mohebzada et al. [2012])

Lim et al. [2010, 2011], Lim and Finkelstein [2012]

- Based on stakeholders' recommendations.
- Relate stakeholders to *roles*.
- Weight regarding *salience* (i.e. "influence") and social network measures.
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Castro-Herrera and Cleland-Huang [2009, 2010]

- Based on stakeholders' contributions in a forum.
- Identify *topics* through their common *terms*.
- Relate stakeholders to the *topics*.
- Deep information, but restricted to contributors.

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**Principal inspiration:** consider *roles*, *topics* and *concepts* (prev. *terms*) as the basic blocks to describe the knowledge of the stakeholders.

**Actual focus:** identify the relevant blocks via the goal model and exploit other sources to relate stakeholders to these blocks.

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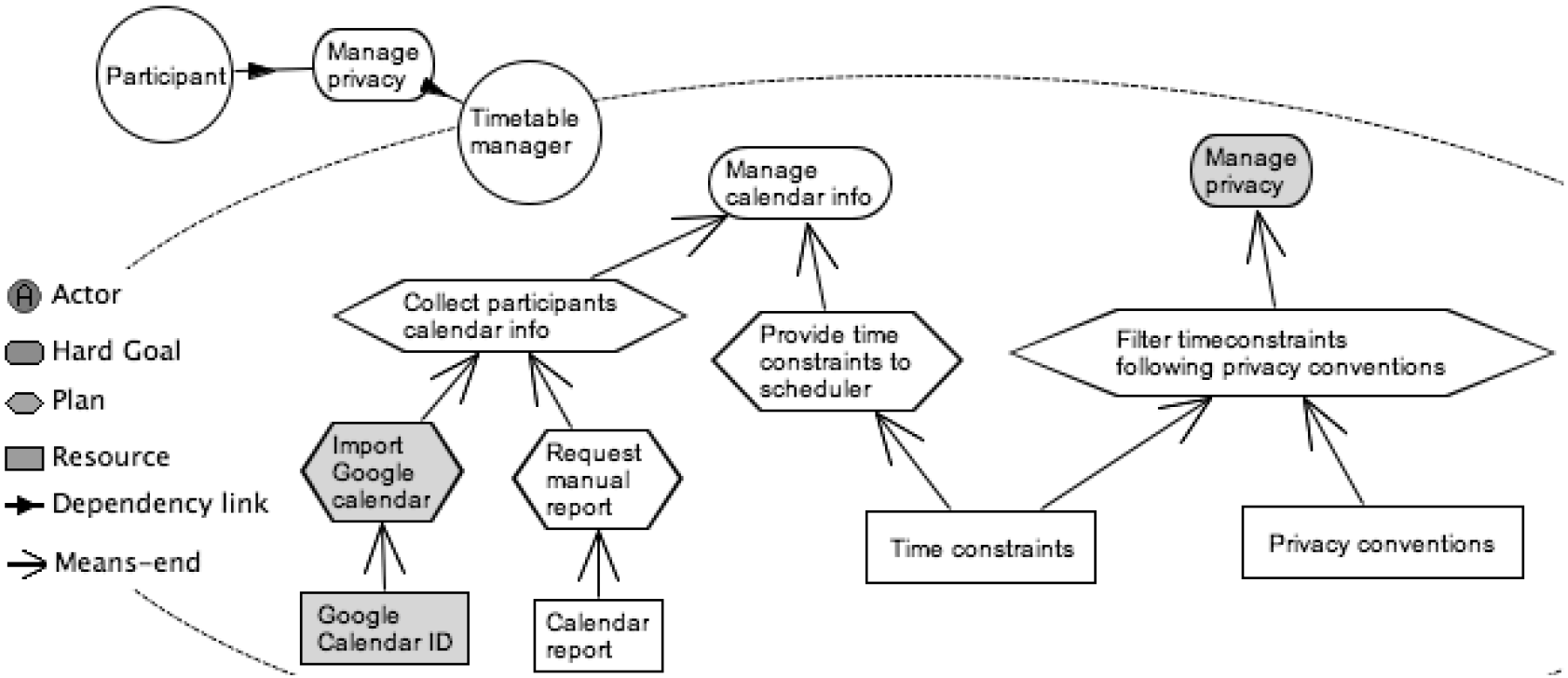
4. Rank the stakeholders depending on the portion of the GM that the analyst is focusing on.

# Goal Model Analysis: Roles, Topics, Concepts

From the goal model...



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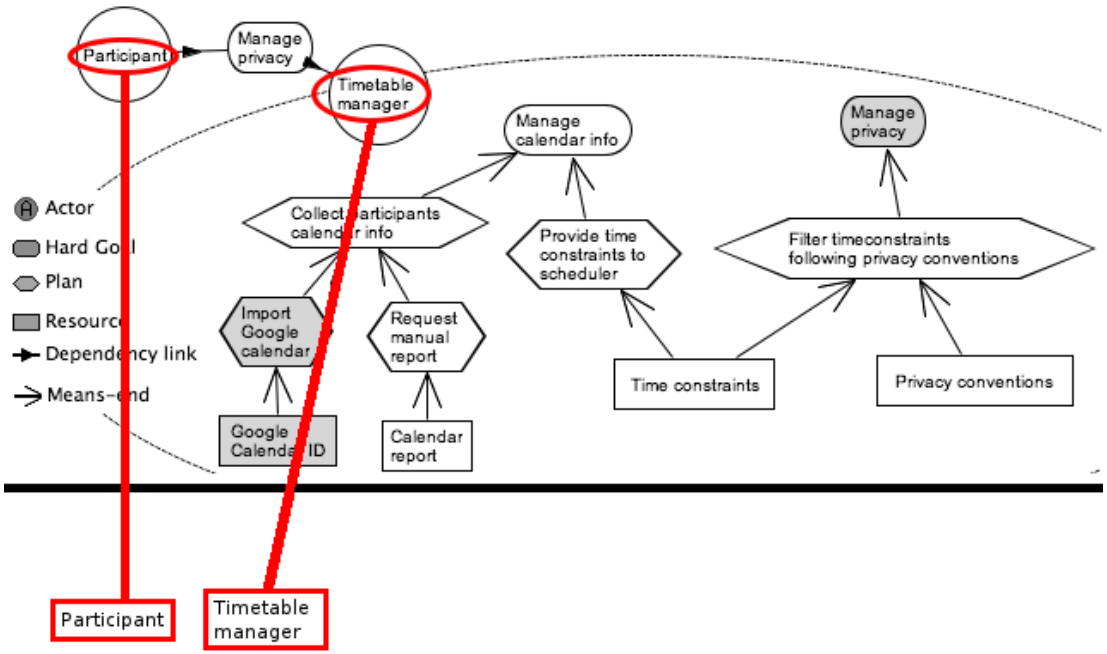

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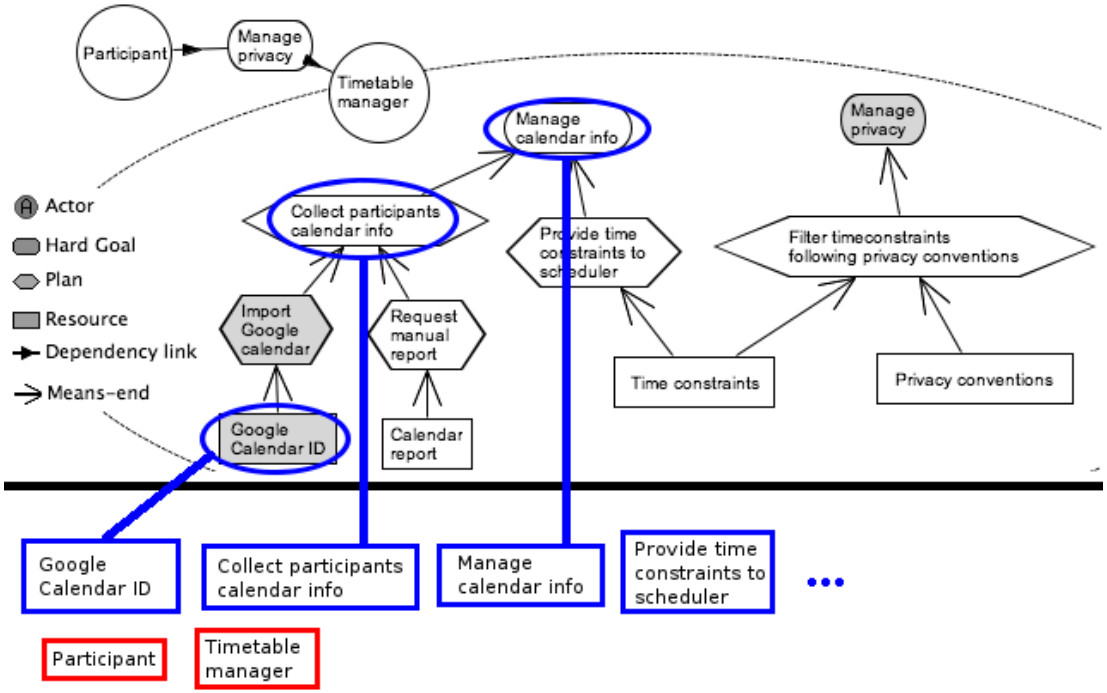

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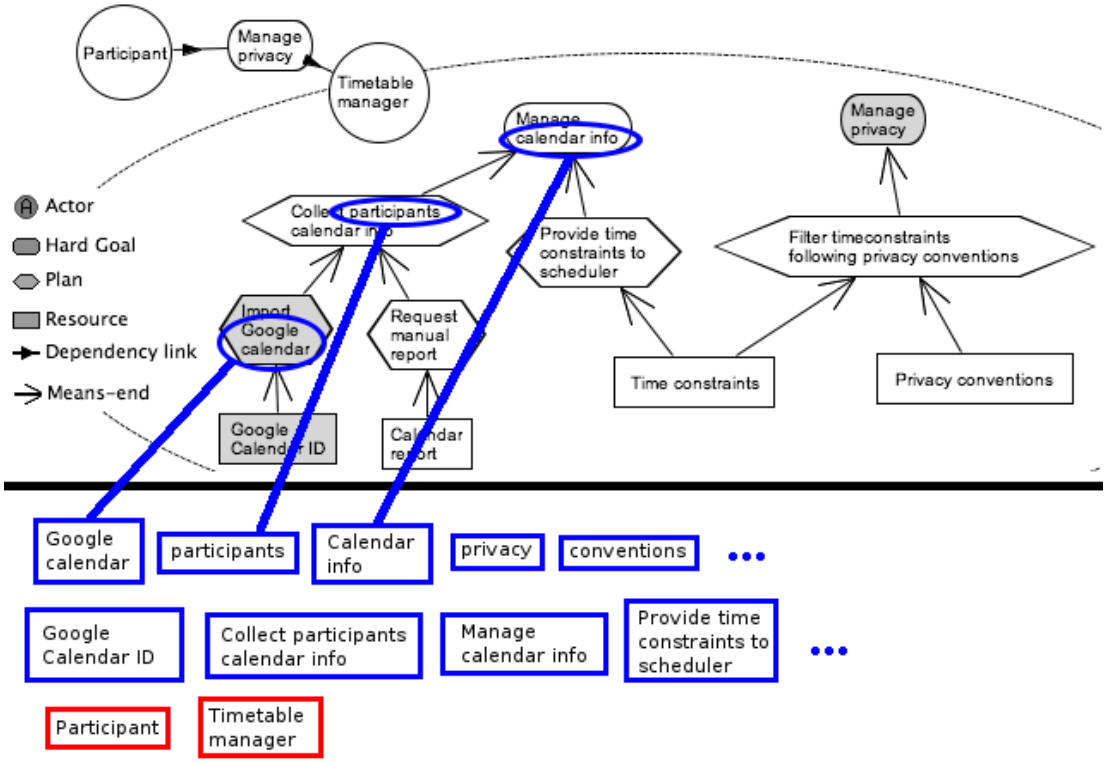

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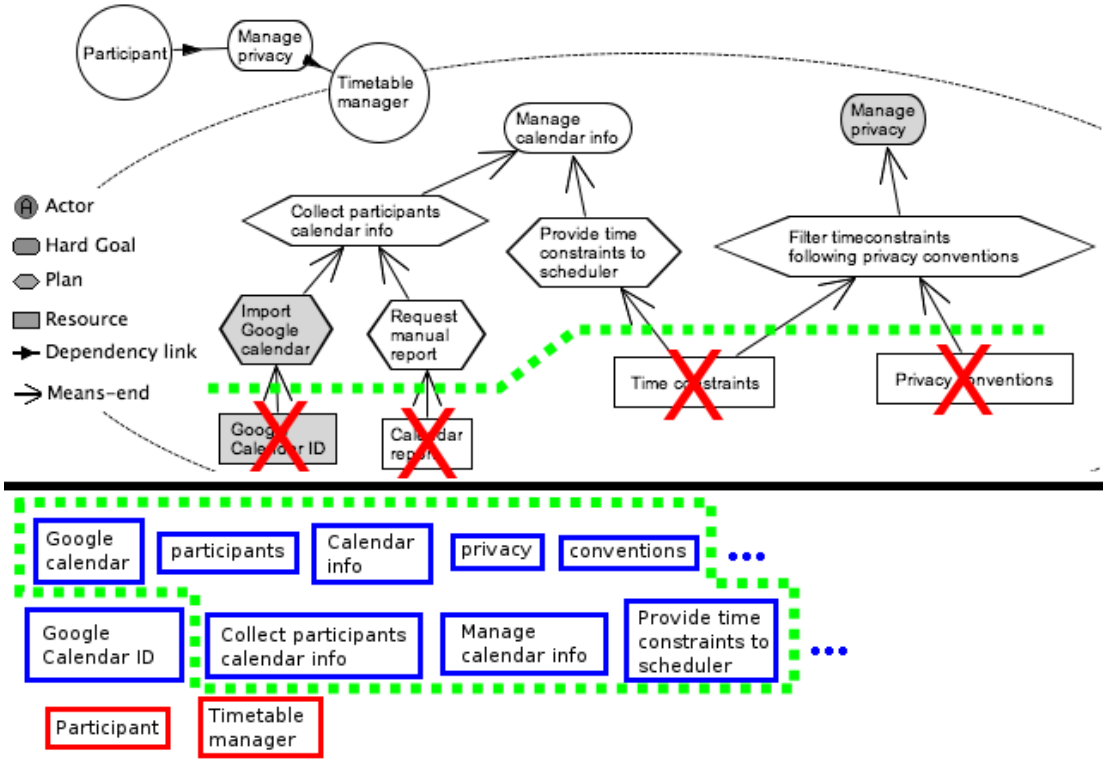

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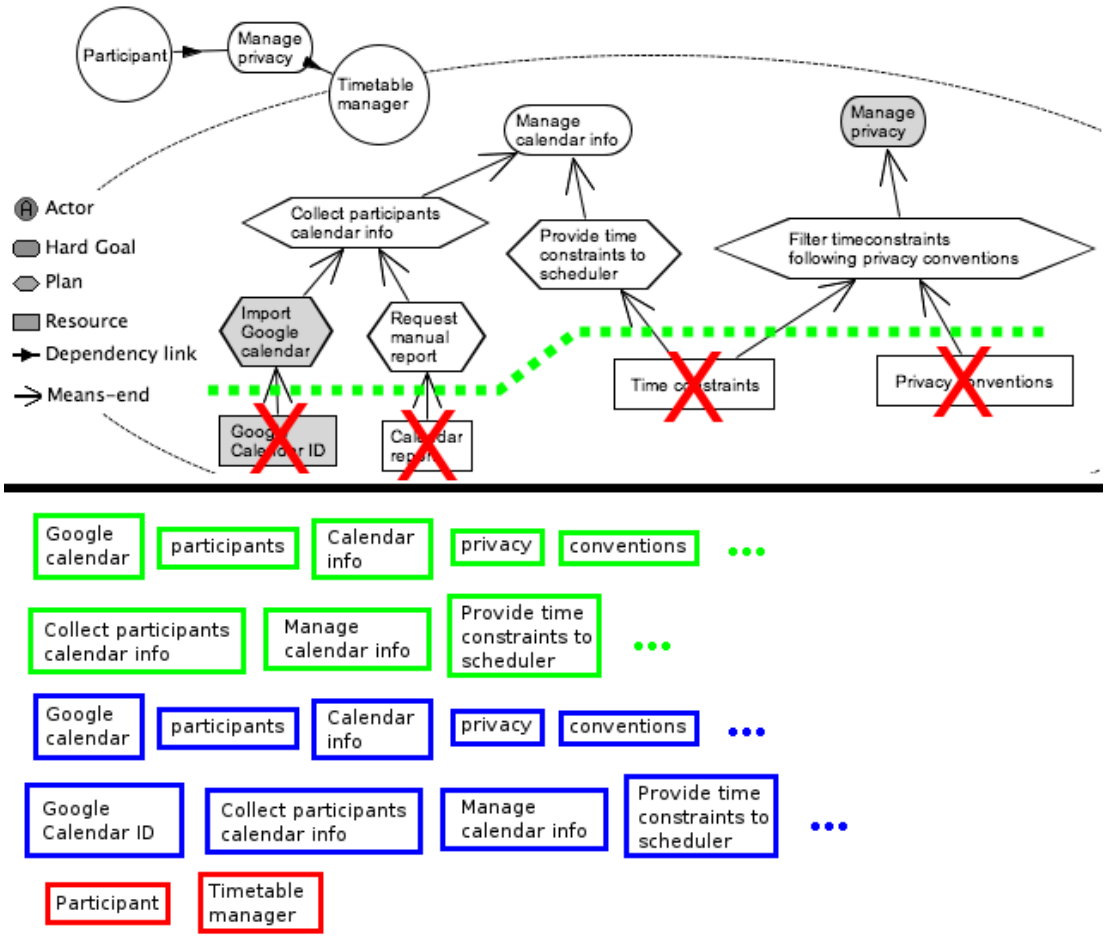

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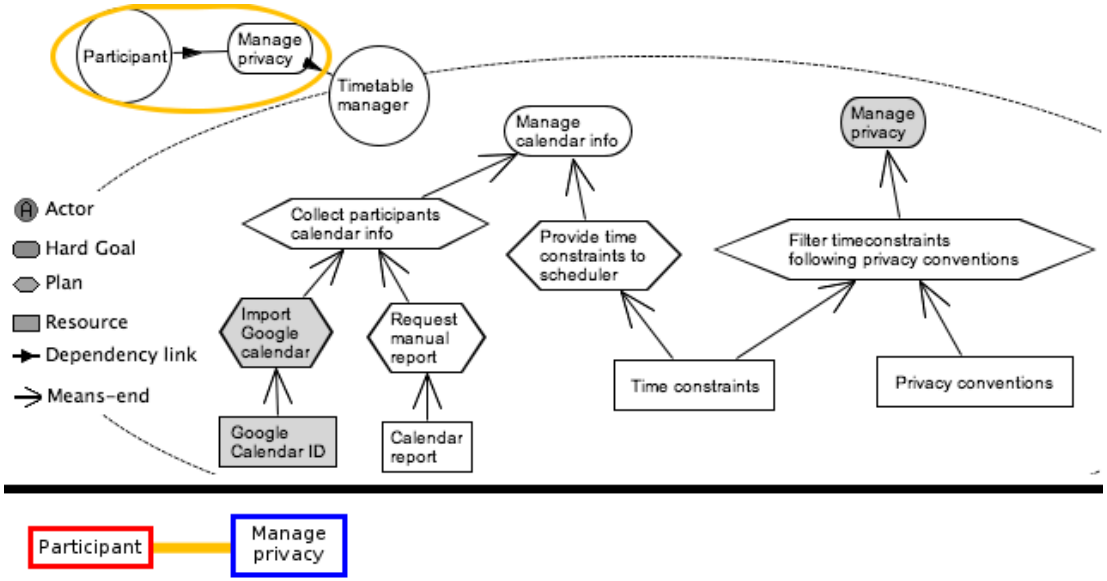

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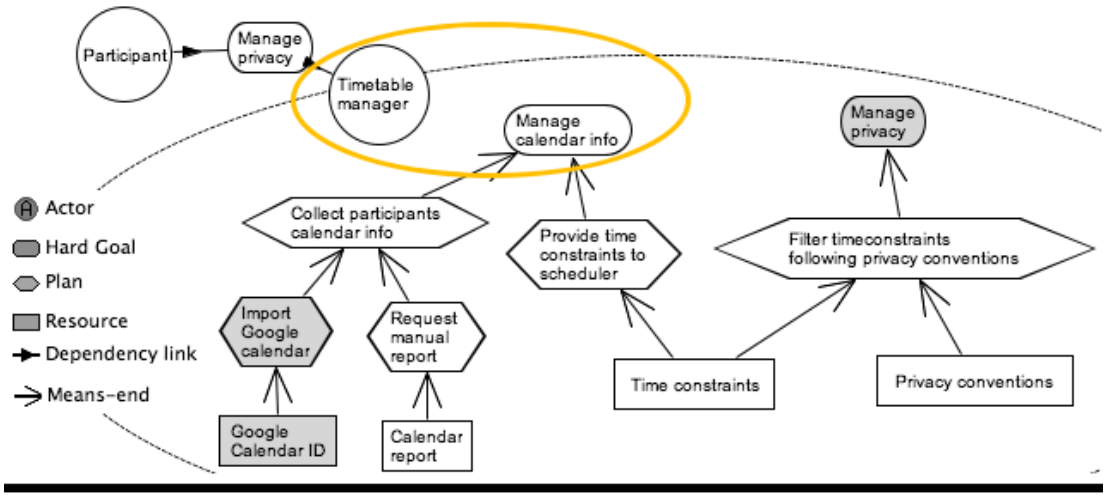


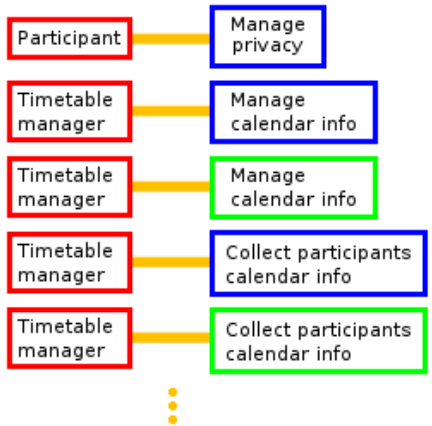

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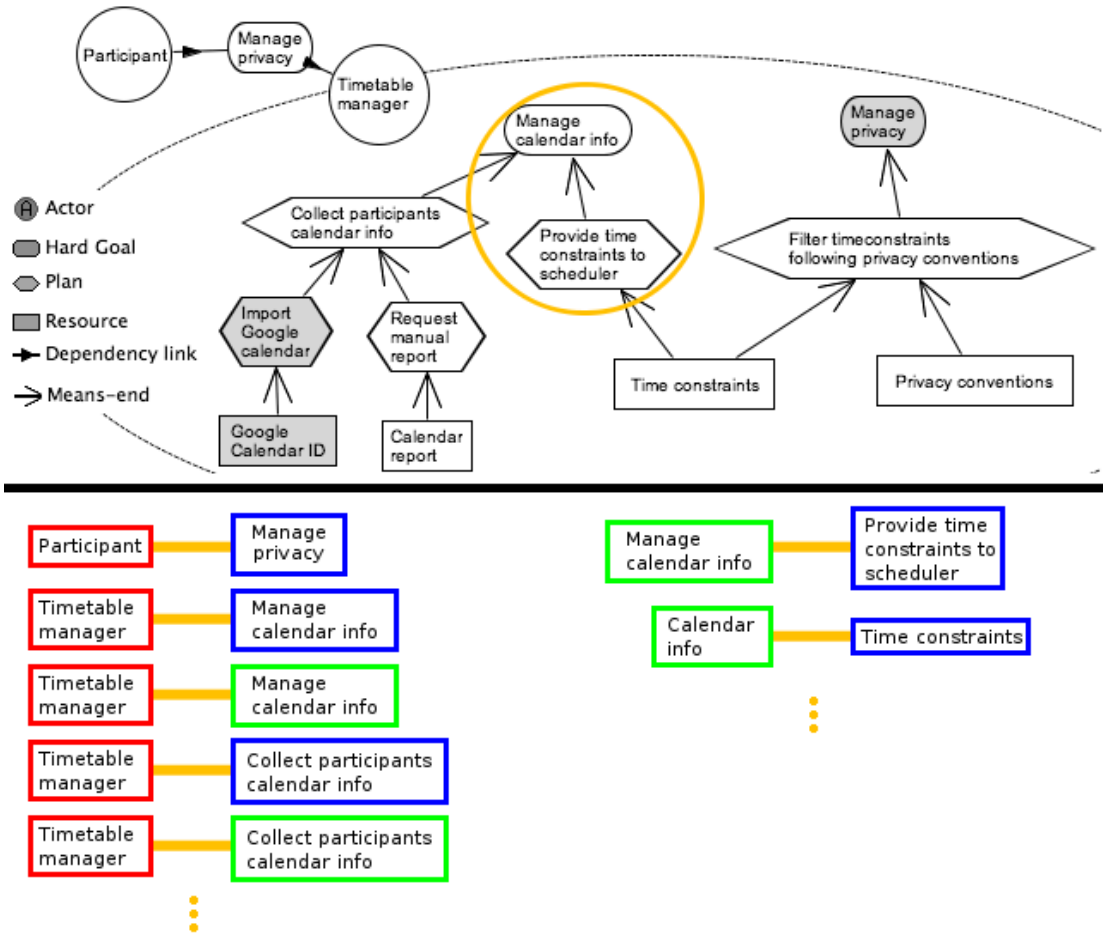

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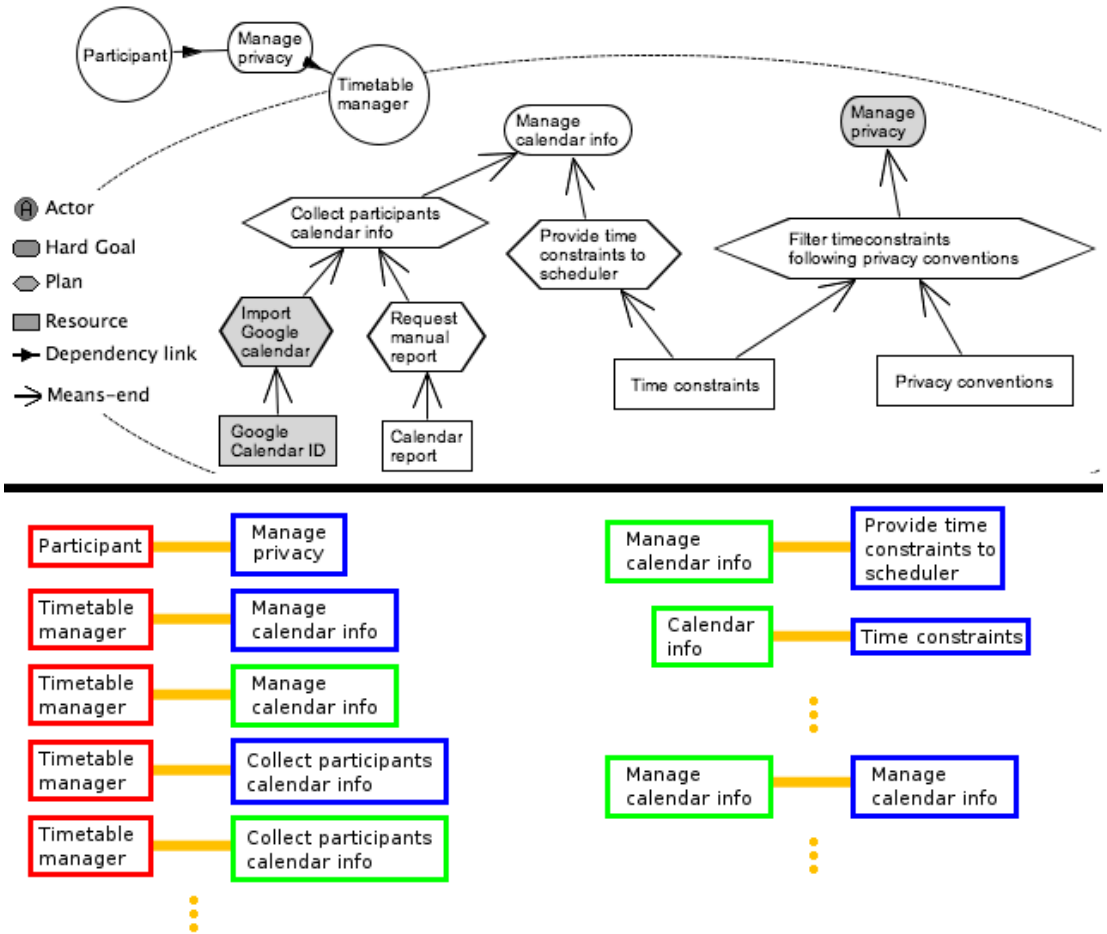
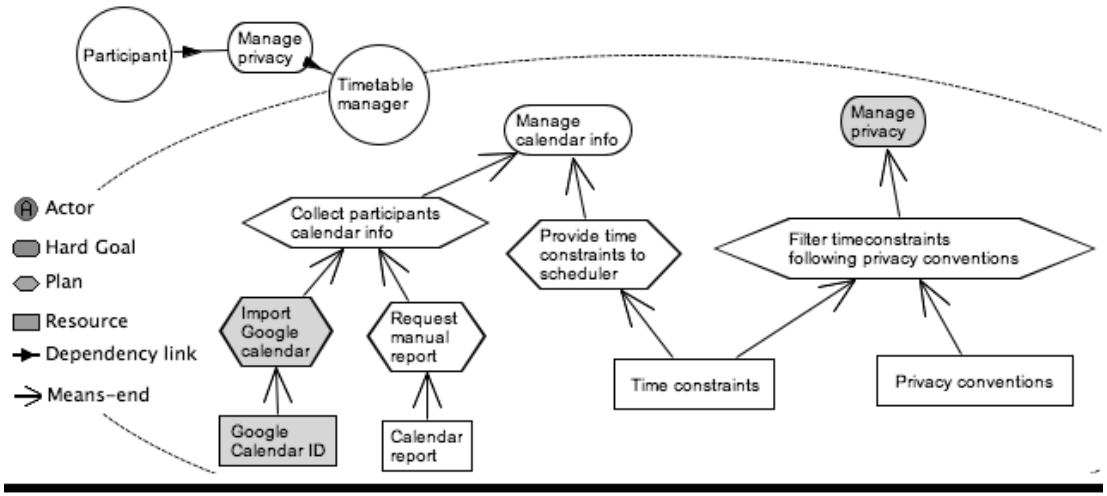
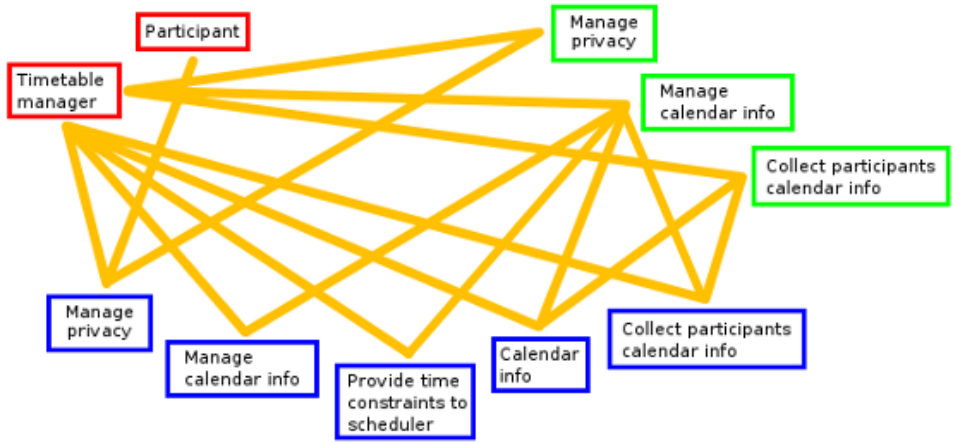


# Goal Model Analysis: Roles, Topics, Concepts

5) Build the graph:



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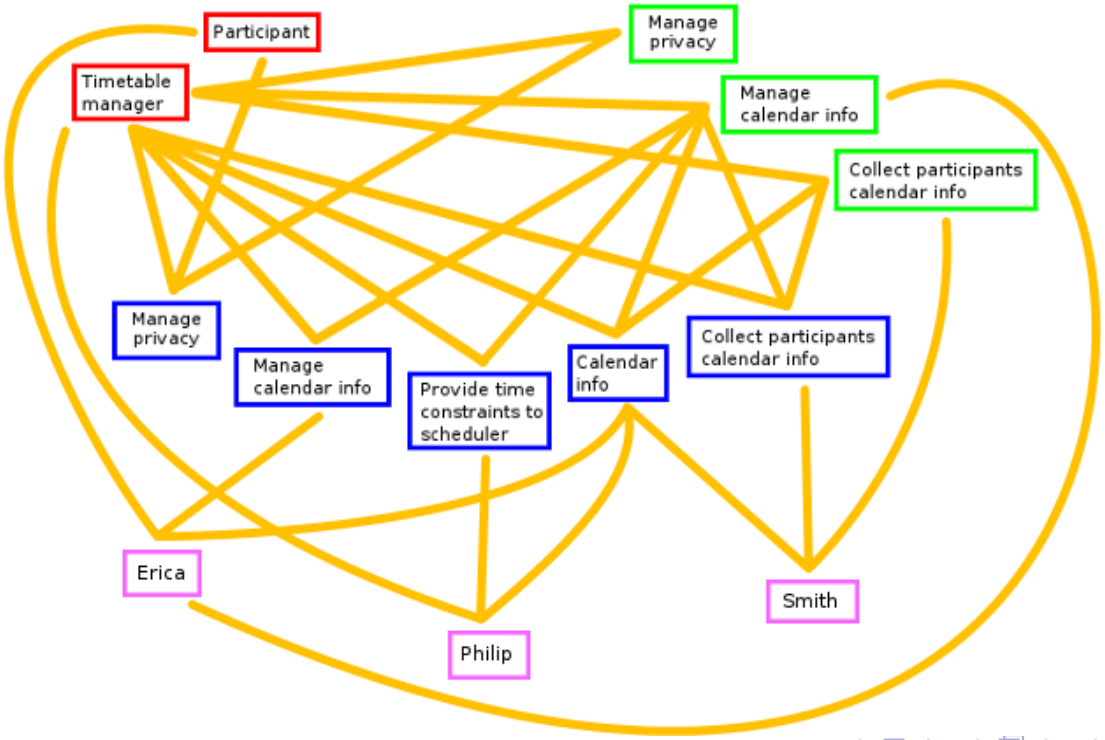

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Open question: How to quantify one source regarding the others?
Let assume that we have a reliable weighted graph for now...

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**Stakeholders ranking**

$P(S_1|Q) > P(S_2|Q) \Rightarrow S_1 > S_2$ for query $Q$.

# Markov Network Engine: libDai

- free and open source[1] C++ library.

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- **Main interest: compute loops!**

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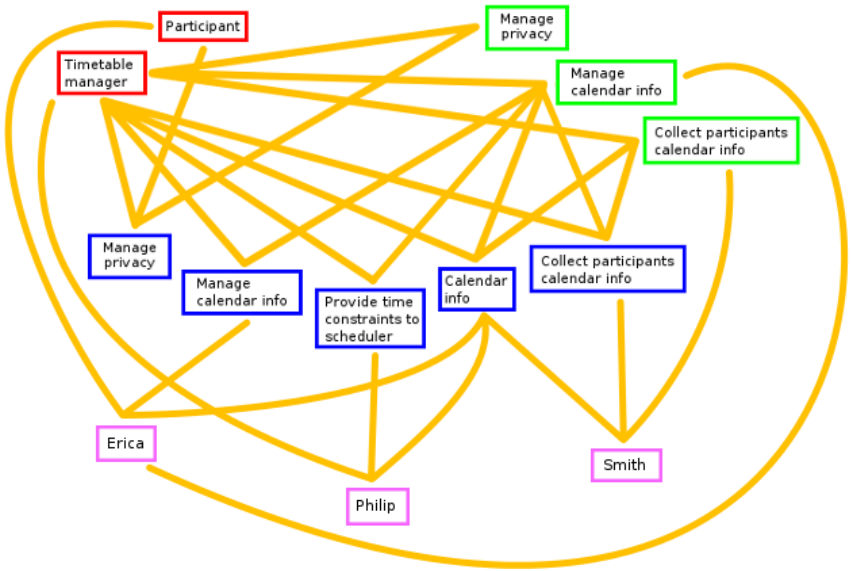
# Queries




Queries tested in $\wp(R \cup T \cup C)$:

- $\|Q\| = 0$ $(Q = \emptyset)$.
- $\|Q\| = 1, 2, 3$.
- Exhaustive test (all combinations) $= 176$ queries.

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- Different weights for different relations (e.g. S-T > R-T).
- High weight for trivial topic-concept relations.
  - *Ex: Manage privacy*$_T \rightarrow$ *Manage privacy*$_C$*.*

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- $Q_1 = \{B_1\}, ..., Q_n = \{B_n\}$ have common partial rankings
  $\Rightarrow Q = \{B_1, ..., B_n\}$ have the same partial rankings.

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- × But the assumption on empty query is generally NOT satisfied. (close world representation?)
- × With data, only 1 case satisfies all the applicable assumptions (*symmetric WoE* instead of classical *identity* + *prior*)

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Future work:

- Analyse experiments' results.
- Fix and improve.
- Look at other techniques able to exploit the graph.
- Develop process to integrate specific techniques for concept extraction.

Thanks for your attention.

Questions?

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