Expert Finding for Requirements Engineering

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Center for ICT, Fondazione Bruno Kessler

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Scenario

In 2015, new canteen rules: immediate feedback from unsatisfied users.

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You have to design the specifications of the system!
→ You need the right experts!

Outline

Requirements Engineering Field

Requirements engineering is the branch of software engineering concerned with the real-world goals for functions of and constraints on software systems. It is also concerned with the relationship of these factors to precise specifications of software behavior, and to their evolution over time and across software families.

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Need of Experts

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- Validation: subjective evaluation of informal/undocumented requirements.
- Verification & management: more about automation, experts can help to adapt to workflow.

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Recommender Systems (Felfernig and Burke [2008], Ricci et al. [2011])

- Recommend experts based on users needs (Expert Recommendation).

Expert Finding: Techniques

Recommend experts on software (Mockus and Herbsleb [2002])

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Improve EF with sparse data (Karimzadehgan et al. [2009])

- Exploit employees e-mails (knowledge) + hierarchy (social).

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Not EF systems, but recommend stakeholders based on similar indicators (knowledge, reputation) $\rightarrow$ can be exploited.

Problem

Poor support for Expert Finding in RE

Few works available, and each considers only a single aspect of expertise: knowledge and social recognition.

Research Objectives & Contributions

Goal: improve support for Expert Finding in RE.

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- *Recall-like metrics based on pairs agreement.*

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- *Exploit in evaluation process.*

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Meta-model Overview

Goal: identify relevant concepts for expertise evaluation.

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- PERFORMANCE EVALUATION (ranking)

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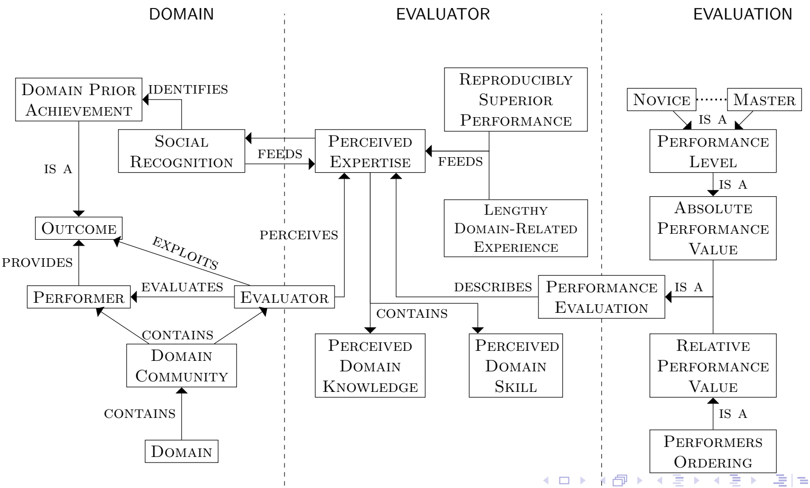
Meta-Model Excerpt



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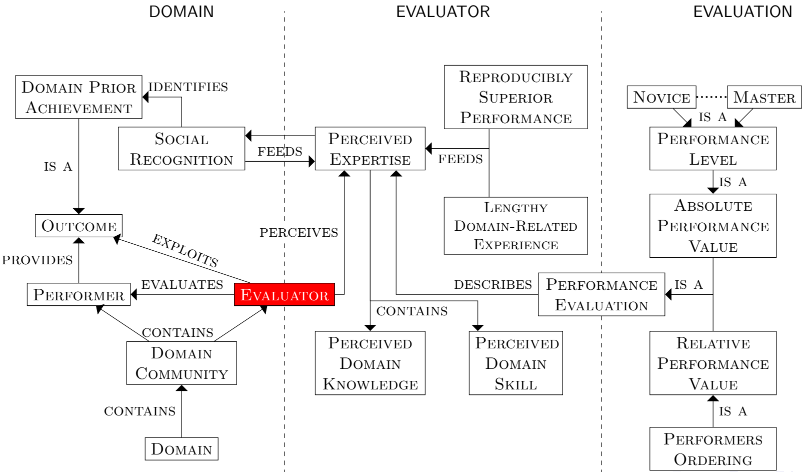

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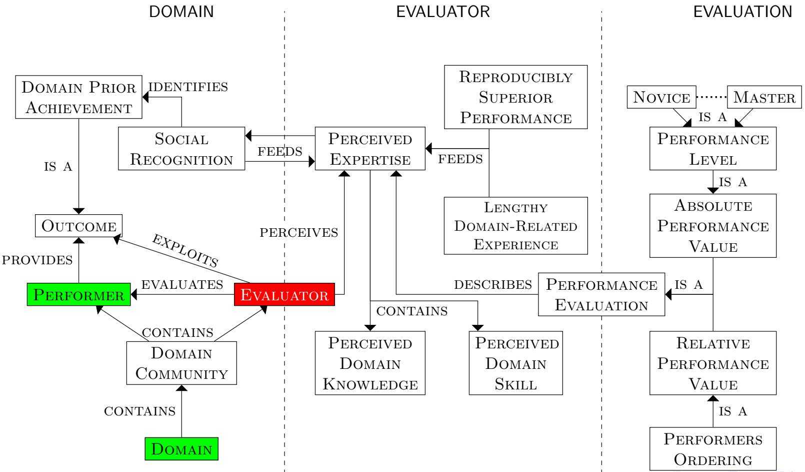

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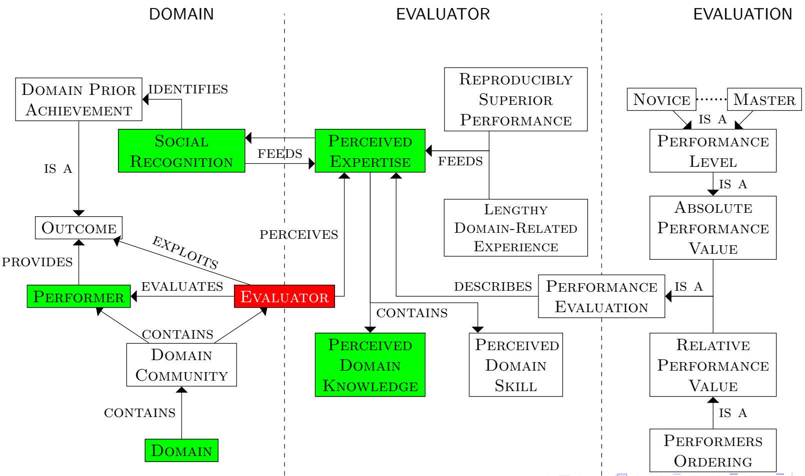

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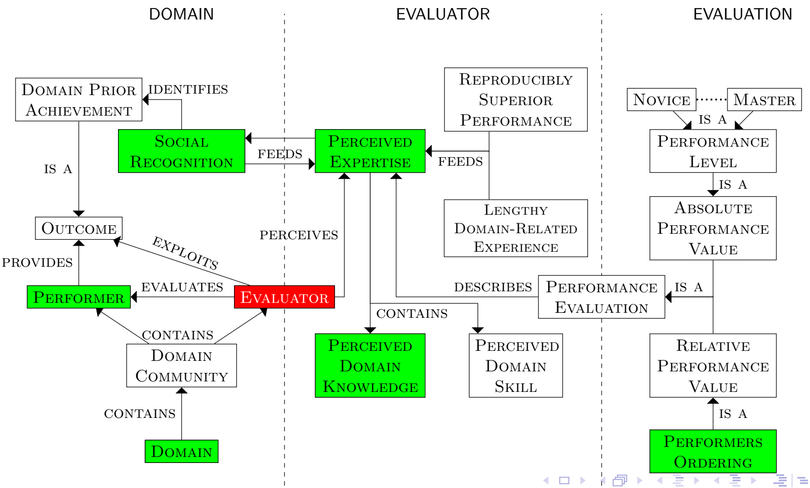
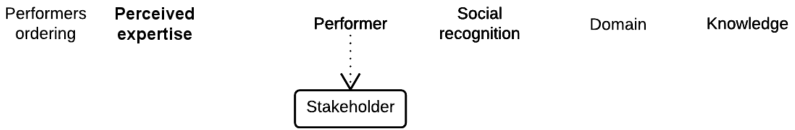


Expert Finding Process

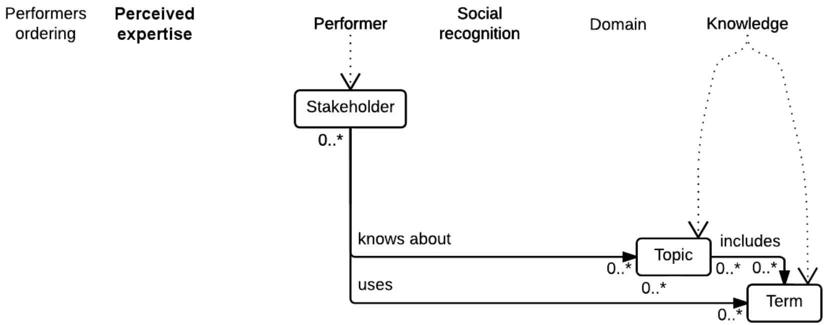
Performers ordering	**Perceived expertise**	**Performer**	**Social recognition**	Domain	**Knowledge**

Expert Finding Process



1. Extraction: stakeholders

Expert Finding Process



1. Extraction: stakeholders, topics, terms

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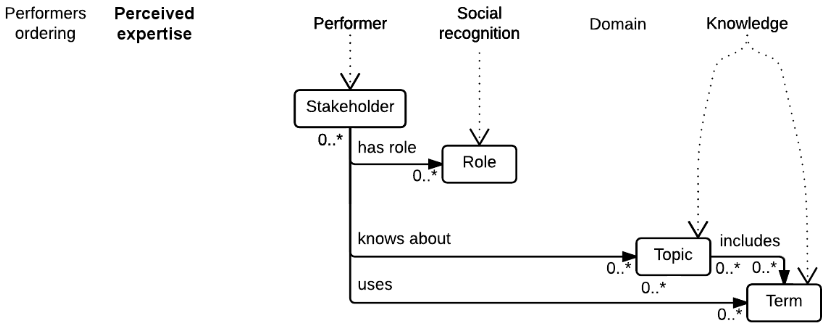

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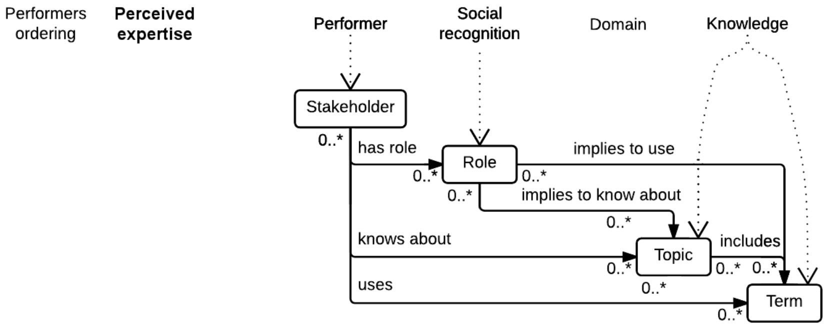

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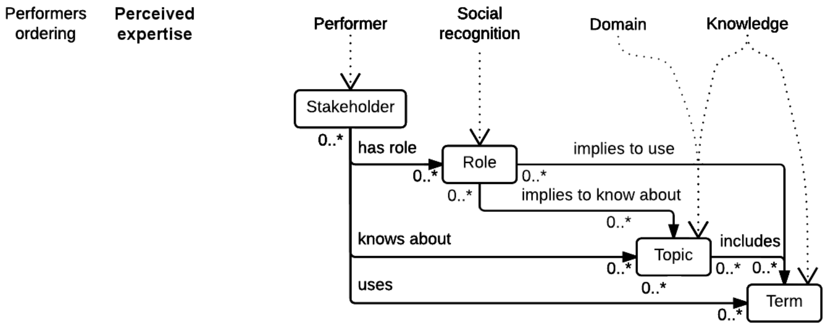

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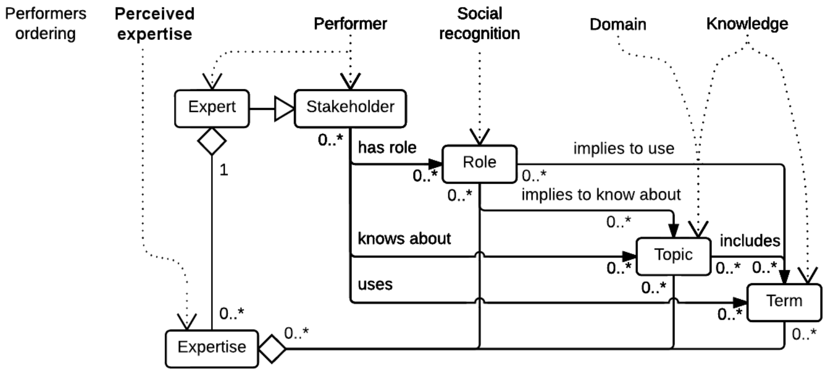

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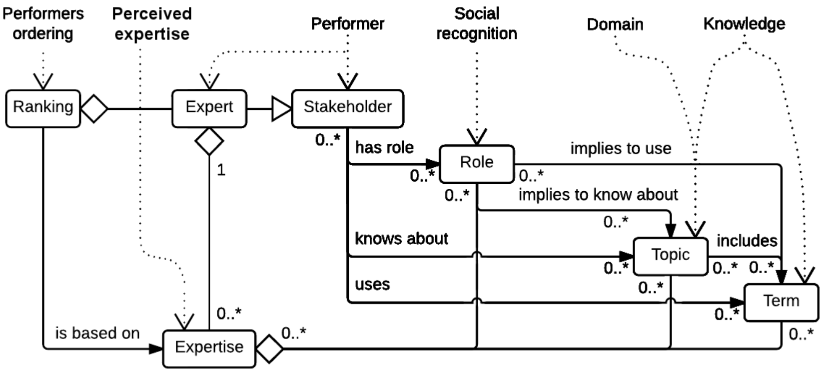

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2. Query: selection of domain-relevant topics.
3. Inference: evaluate expertise to build rankings.

Extraction

$$\underbrace{\text{Reports, diagrams, hierarchy, etc.}}$$
$$\Downarrow$$

Graph building:

1. Extract nodes

Extraction

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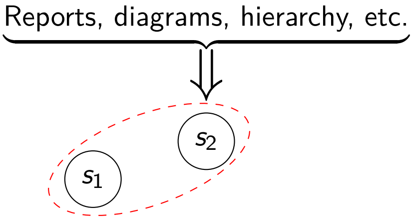
   - *Stakeholders S*



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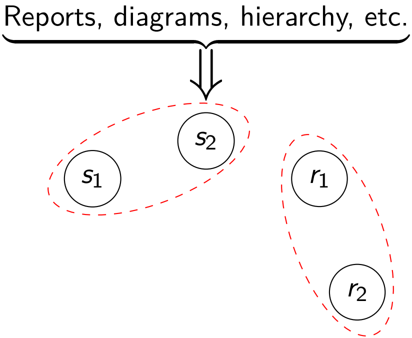

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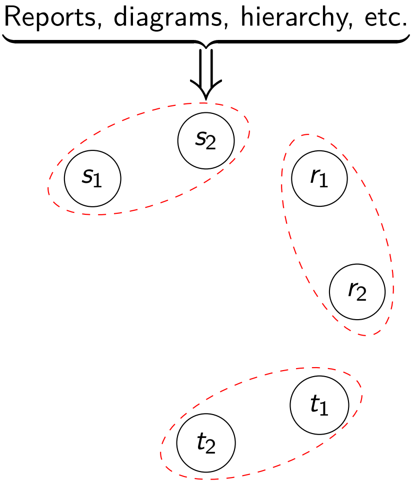

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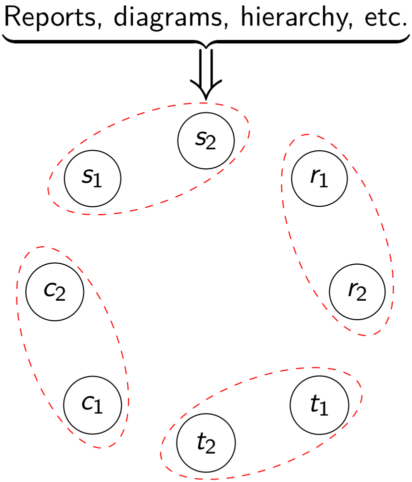

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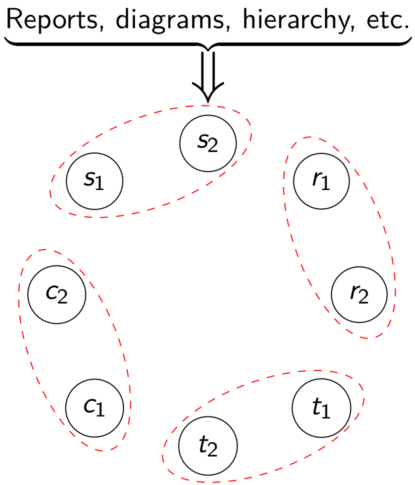

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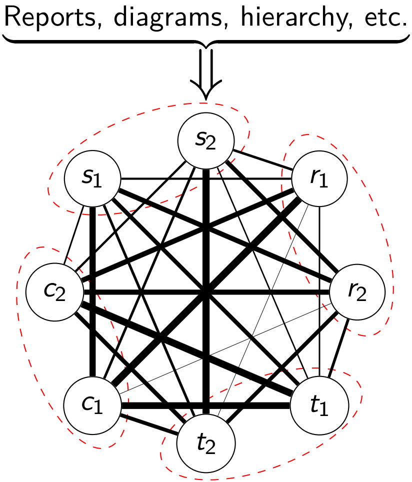
2. Extract relations
   - *Weighted edges*



Query Building

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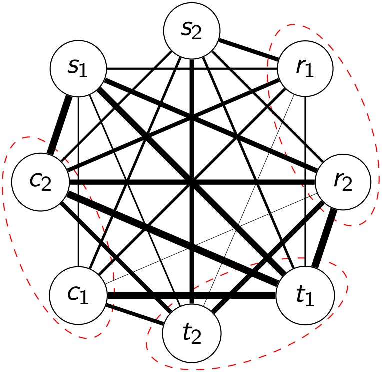

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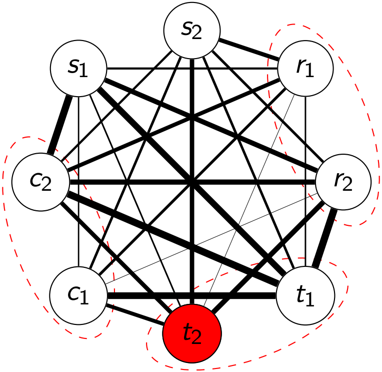
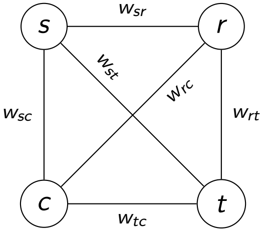


Query: $\{t_{\text{Cooking}}\}$

MN Inference: Transformation



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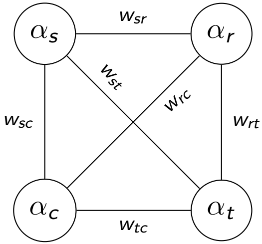

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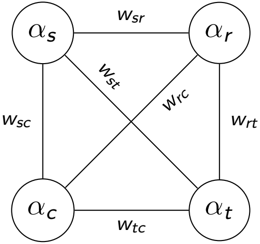

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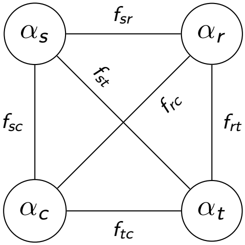
Interpretation:

- $s = \top \Rightarrow s$ is an expert
- $r/t/c = \top \Rightarrow$ looking for experts in $r/t/c$

MN Inference: Transformation



- Binary state for each node $\alpha_x \in \{\top, \bot\}$
- Function for each edge $f(\alpha_x, \alpha_y) \in \mathbb{R}^+$

Interpretation:

- $s = \top \Rightarrow s$ is an expert
- $r/t/c = \top \Rightarrow$ looking for experts in $r/t/c$

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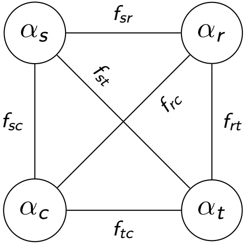

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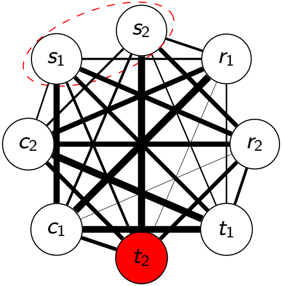
Interpretation:

- $s = \top \Rightarrow s$ is an expert
- $r/t/c = \top \Rightarrow$ looking for experts in $r/t/c$

Compute partial + conditional probability: $P(s = \top | t = \top)$

MN Inference: Exploitation

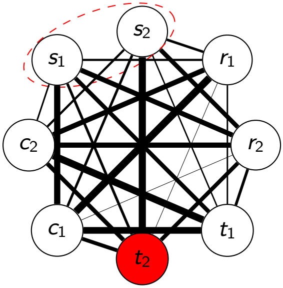
Expert Finding for Cooking:



MN Inference: Exploitation

Expert Finding for Cooking:

- Compute $P(s_i = \top | t_{\text{Cooking}} = \top)$ for each stakeholder s_i.



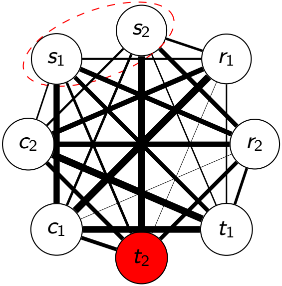
Probabilities:

- $P(s_1 | t_2) = 0.365$
- $P(s_2 | t_2) = 0.834$

MN Inference: Exploitation

Expert Finding for Cooking:

- Compute $P(s_i = \top | t_{\text{Cooking}} = \top)$ for each stakeholder s_i.
- Ranking: sort from most to least probable experts.



Probabilities:

- $P(s_1|t_2) = 0.365$
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Ranking:

1. s_2
2. s_1

MN Limitations

Exact computation:

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Exact computation:

- Not scalable.

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- Global scale independence only.

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Approximative computation (Gibbs sampling):

- Not precise (enforce orders).

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Idea:

- Precision: compute exactly.

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- Precision: compute exactly.
- Scalability: compute on relevant sub-graph.

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- Global scale independence only.

Idea:

- Precision: compute exactly.
- Scalability: compute on relevant sub-graph.
- Scale independence: compute relationship-specific relevance.

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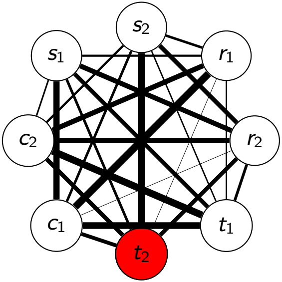
GA Inference: Relevance on Partial Graph

Goal: find most relevant sub-graph to compute based on Q



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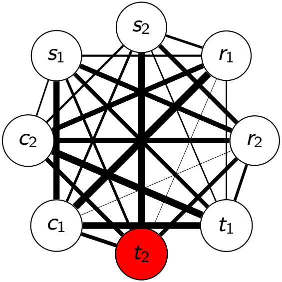

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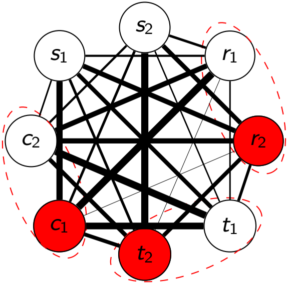
Sub-graph building:

- $\hat{Q}$ Roles/topics/terms related to Q



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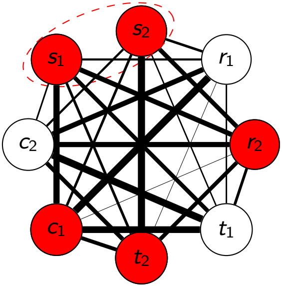

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Sub-graph building:

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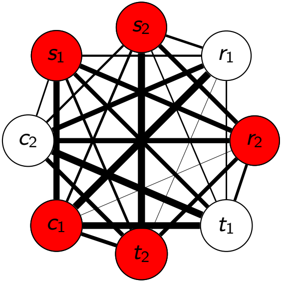
Objective: max relevance of $(\hat{Q}, \hat{S})$.



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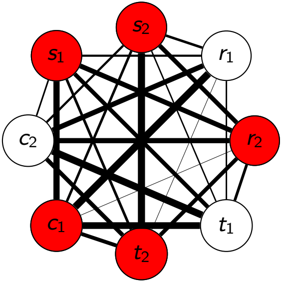

Relevance computation:

1. Type specific: $rel(x, R), rel(x, T), rel(x, C) \in [0; 1]$.

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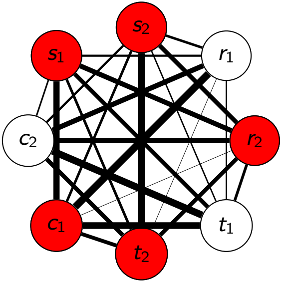

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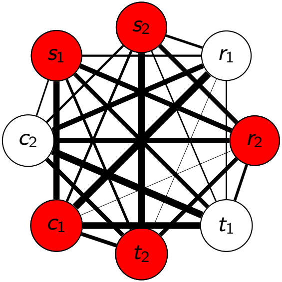

Relevance computation:

1. Type specific: $rel(x, R), rel(x, T), rel(x, C) \in [0; 1]$.
2. Overall: $rel(x)$ = average on type specific

Ex: $rel(s) = \frac{rel(s,R)+rel(s,T)+rel(s,C)}{3} = \frac{0.5+0.1+0.3}{3} = 0.3$

GA Inference: Relevance Maximisation

Genetic Algorithm:

GA Inference: Relevance Maximisation

Genetic Algorithm:

1. Generate random population: $\{(\hat{Q}_1, \hat{S}_1), \ldots, (\hat{Q}_n, \hat{S}_n)\}$

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GA Inference: Relevance Maximisation

Genetic Algorithm:

1. Generate random population: $\{(\hat{Q}_1, \hat{S}_1), ..., (\hat{Q}_n, \hat{S}_n)\}$
2. Loop: crossover

$$
\begin{array}{ccccc}
 & & (\hat{Q}_\alpha, \hat{S}_\alpha) & & \\
(\hat{Q}_1, \hat{S}_1) & \nearrow & & \searrow & \\
\dots & & & & (\hat{Q}_\gamma, \hat{S}_\gamma) \\
(\hat{Q}_n, \hat{S}_n) & \searrow & & \nearrow & \\
 & & (\hat{Q}_\beta, \hat{S}_\beta) & &
\end{array}
$$

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GA Inference: Relevance Maximisation

Genetic Algorithm:

1. Generate random population: $\{(\hat{Q}_1, \hat{S}_1), ..., (\hat{Q}_n, \hat{S}_n)\}$
2. Loop: crossover + mutation

$$
\begin{tikzcd}
 & (\hat{Q}_\alpha, \hat{S}_\alpha) \arrow[ddr] & & n' \arrow[dd] \\
(\hat{Q}_1, \hat{S}_1) \arrow[ur] & & & \\
\dots & & (\hat{Q}_\gamma, \hat{S}_\gamma) \arrow[r] & (\hat{Q}'_\gamma, \hat{S}'_\gamma) \arrow[dd] \\
(\hat{Q}_n, \hat{S}_n) \arrow[dr] & & & \\
 & (\hat{Q}_\beta, \hat{S}_\beta) \arrow[uur] & & n
\end{tikzcd}
$$

GA Inference: Relevance Maximisation

Genetic Algorithm:

1. Generate random population: $\{(\hat{Q}_1, \hat{S}_1), \dots, (\hat{Q}_n, \hat{S}_n)\}$
2. Loop: crossover + mutation + selection

$$
\begin{tikzcd}
 & (\hat{Q}_\alpha, \hat{S}_\alpha) \arrow[dr] & & n' \arrow[d] & & \\
\begin{matrix} (\hat{Q}_1, \hat{S}_1) \\ \dots \\ (\hat{Q}_n, \hat{S}_n) \end{matrix} \arrow[ur] \arrow[dr] & & (\hat{Q}_\gamma, \hat{S}_\gamma) \arrow[r] & (\hat{Q}'_\gamma, \hat{S}'_\gamma) \arrow[r] \arrow[d] & \begin{matrix} rel(\hat{Q}_1/\hat{S}_1) \\ \dots \\ rel(\hat{Q}_n/\hat{S}_n) \\ rel(\hat{Q}^1_\gamma/\hat{S}^1_\gamma) \\ \dots \\ rel(\hat{Q}^m_\gamma/\hat{S}^m_\gamma) \end{matrix} \arrow[r, Rightarrow] & \begin{matrix} (\hat{Q}'_1, \hat{S}'_1) \\ \dots \\ (\hat{Q}'_n, \hat{S}'_n) \end{matrix} \\
 & (\hat{Q}_\beta, \hat{S}_\beta) \arrow[ur] & & n & &
\end{tikzcd}
$$

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1. Generate random population: $\{(\hat{Q}_1, \hat{S}_1), \ldots, (\hat{Q}_n, \hat{S}_n)\}$
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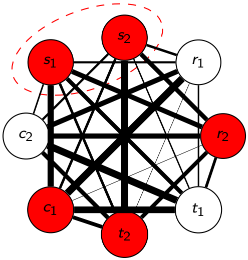
3. Return best individual $(\hat{Q}, \hat{S})$



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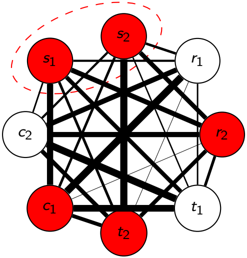
Ranking: sort from most to least relevant stakeholder in $\hat{S}$.



Relevance:

$$\hat{S} \begin{cases} rel(s_1) = 0.365 \\ rel(s_2) = 0.834 \end{cases}$$

$$\hat{Q} \begin{cases} rel(r_2) = 0.251 \\ rel(t_2) = 1.000 \\ rel(c_1) = 0.123 \end{cases}$$

Ranking:

1. s_2
2. s_1

Evaluation Scenarios

Three scenarios:

1. Fully controlled: synthetic data

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   - *Free question-answers between 3 participants*

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3. Realistic: Wiki manager project

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Evaluation Design

Three phases:

Evaluation Design

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1. Generate rankings for different settings

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Evaluation Design

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2. Identify stable settings

Evaluation Design

Three phases:

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Evaluation Design

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Evaluation Design

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Four validation criteria:

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Evaluation Design

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Four validation criteria:

- No network bias (no query)

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Three phases:

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Metric: ratio of compliant pairs.

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Some Results

	MN (exact)	MN (approx.)	GA
Synthetic			
Cuisine			
Wiki			

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Some Results

	MN (exact)	MN (approx.)	GA
Synthetic	29.8%		
Cuisine			
Wiki			

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Some Results

	MN (exact)	MN (approx.)	GA
Synthetic	29.8%	63.1%	
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Some Results

	MN (exact)	MN (approx.)	GA
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Wiki			

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Some Results

	MN (exact)	MN (approx.)	GA
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Cuisine	1 query 100%, 1 query 0%		
Wiki			

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- MN can be more interesting if run approximatively.

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- MN can be more interesting if run approximatively.
- Generally GA provides the best results.
- More investigation needed for realistic data.

Objectives Satisfaction

RO1 Support the design of EF systems

RO2 Design an EF system on RE indicators

RO3 Design metrics for incomplete/partial rankings

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Objectives Satisfaction

RO1 Support the design of EF systems

- Meta-model provides relevant concepts to consider.

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Objectives Satisfaction

RO1 Support the design of EF systems
- Meta-model provides relevant concepts to consider.
- Need more investigation to confirm ability to help.

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- Good with synthetic data, but more investigation needed with realistic cases.

RO3 Design metrics for incomplete/partial rankings

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RO3 Design metrics for incomplete/partial rankings

- Expressive and helpful metrics.

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RO2 Design an EF system on RE indicators
- Approximative MN + GA interesting.
- Good with synthetic data, but more investigation needed with realistic cases.

RO3 Design metrics for incomplete/partial rankings
- Expressive and helpful metrics.
- Some fixes still needed for extreme cases.

Further Research

Meta-model:

Expert Finding approaches:

Metrics:

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Further Research

Meta-model:

- Could be exploited as ontology.

Expert Finding approaches:

Metrics:

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Further Research

Meta-model:

- Could be exploited as ontology.

Expert Finding approaches:

- Formal reasoning based on meta-model (ontology).

Metrics:

Further Research

Meta-model:

- Could be exploited as ontology.

Expert Finding approaches:

- Formal reasoning based on meta-model (ontology).

Metrics:

- Consider measures giving priority to top items.

Publications

Conferences:

ICSE'14 Morales-Ramirez, M. Vergne, M. Morandini, A. Siena, A. Perini, and A. Susi. Who is the Expert? Combining Intention and Knowledge of Online Discussants in Collaborative RE Tasks. In ICSE Companion 2014, pages 452–455, New York, NY, USA, May 2014. ACM. ISBN 978-1-4503-2768-8. doi: 10.1145/2591062.2591103.

CAISE'14 M. Vergne and A. Susi. Expert Finding Using Markov Networks in Open Source Communities. In CAISE, number 8484 in LNCS, pages 196–210. Springer International Publishing, June 2014. ISBN 978-3-319-07880-9 978-3-319-07881-6.

ER'15 M. Vergne and A. Susi. Breaking the Recursivity: Towards a Model to Analyse Expert Finders. In Conceptual Modeling, vol. 9381, pages 539–547. Springer International Publishing, Cham, Oct. 2015. ISBN 978-3-319-25263-6 978-3-319-25264-3.

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Workshops:

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RIGiM'12 Morales-Ramirez, M. Vergne, M. Morandini, L. Sabatucci, A. Perini, and A. Susi. Where Did the Requirements Come from? A Retrospective Case Study. In ACM vol. 7518 in LNCS, pages 185–194. Springer Berlin Heidelberg, Jan. 2012b. ISBN 978-3-642-33998-1 978-3-642-33999-8.

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- M. Vergne. Gold Standard for Expert Ranking: A Survey on the XWiki Dataset. Technical Report arXiv:1603.03809 [cs.SE], Mar. 2016a.
- M. Vergne. Mitigation Procedures to Rank Experts through Information Retrieval Measures. Technical Report arXiv:1603.04953 [cs.IR], Mar. 2016b.

Thanks for your attention.

Questions?

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Expertise In Psychology: Definitions

Expert:

- having or showing special skill or knowledge because of what you have been taught or what you have experienced[2]
- Ericsson [2006]:
  - *lengthy, domain-related experience*
  - *reproducibly superior performance*
  - *social criteria*

Expertise:

- What is required to achieve an expert level (domain-centric) Vs. actual skills/knowledge of someone (performer-centric).
- Sonnentag et al. [2006]
  - *years of experience*
  - *high performance*

[2] Merriam-Webster Dictionary: `http://www.merriam-webster.com/`

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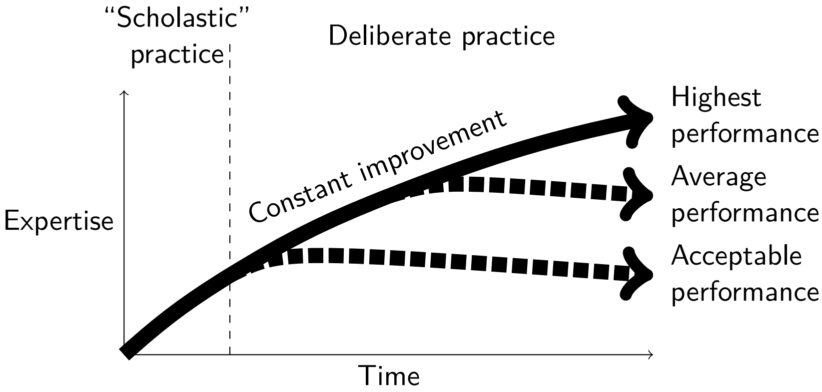
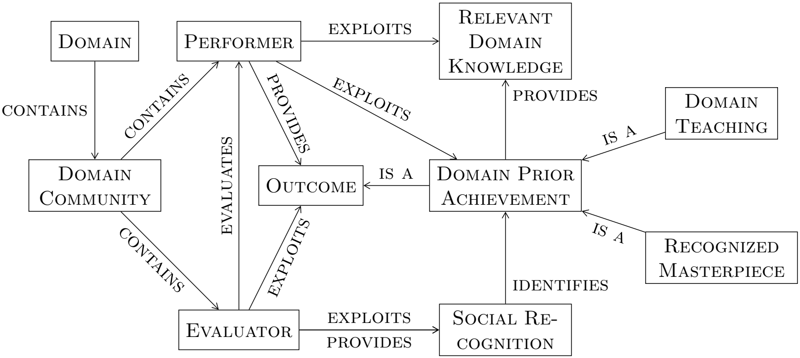
Expertise In Psychology: Building

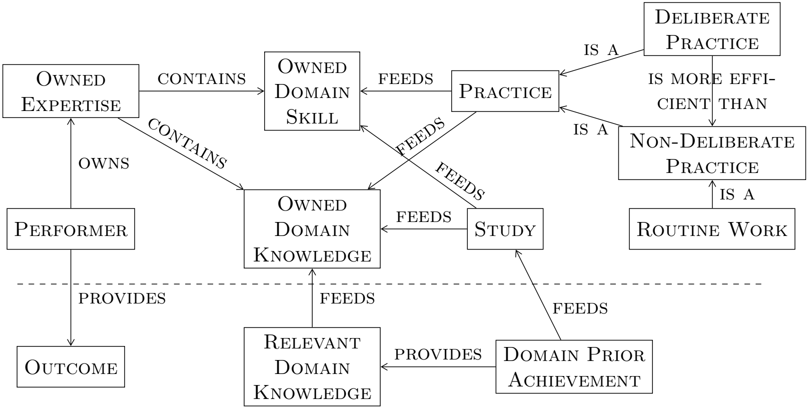


(adapted from Ericsson [2006])

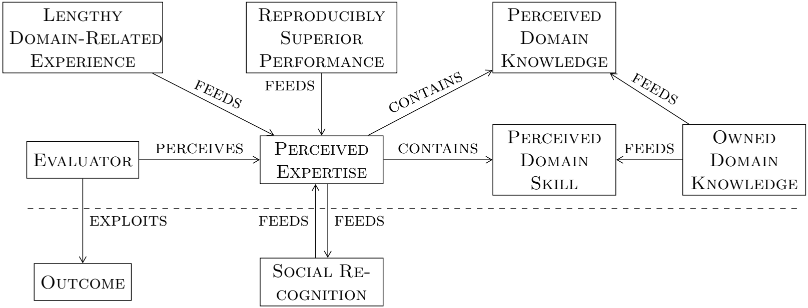
Meta-model: Domain



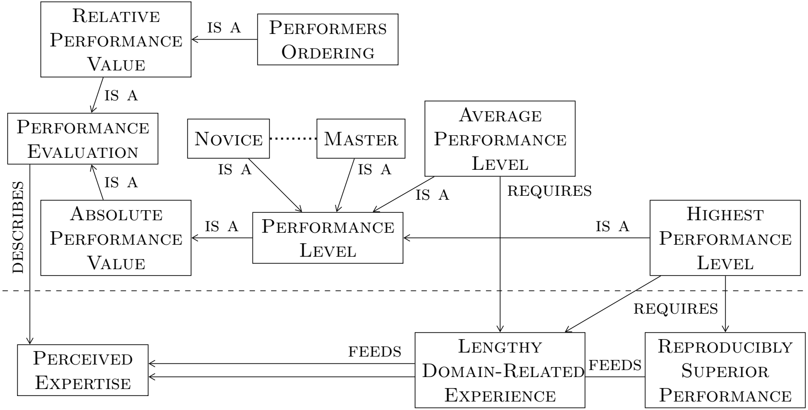
Meta-model: Performer



Meta-model: Evaluator



Meta-model: Performance Evaluation



Weighting Policies

Which value for the weights?

- Amount of evidence: $w_{ab} \in \mathbb{R}^+$
- $w_{ab} = 0 \Rightarrow$ no evidence
- $w_{ab} = 5, w_{cd} = 10 \Rightarrow$ evidence for c-d $= 2 \times$ evidence for a-b
- Value unit depends on the interpretation of evidence
  - *Lim et al. [2010]: salience elicited from stakeholders*
  - *Castro-Herrera and Cleland-Huang [2010]: normalized term frequencies*
- Each type of relation can have its own unit if enough independence is maintained.

Ranking Metrics: Fundamental Problems

R	R_{ref}	Problem
s_1 s_2 s_3 s_4	s_1 s_2, s_3 s_4	s_2 and s_3 have equal rank in R_{ref}, not in R, leading to disagreement instead of indifference.
s_1 s_2, s_3 s_4	s_1 s_2 s_3 s_4	P@k, R-precision, AveP, MAP, CG_k, DCG_k, $NDCG_k$ inapplicable as is: iteration require total order for R or arbitrary choice.
s_1 s_2 s_3 s_4	s_1 s_2 s_4	s_3 not in R_{ref}: whether the different ranks lead to unmotivated disagreement, whether workaround measures are needed like removing s_3 from R.

Metrics Overview

Two ranking representations:

Ranking	Ordering
1 : s_1	$s_1 > s_2$
2 : s_2, s_3	$s_1 > s_3$
3 : s_4, s_5	$s_2 ? s_3$
4 : s_6	$s_2 > s_4$
...	...

Orderings provide:

- Intuitive notion of (dis)agreement
- Explicit use of order
- Easy building of centroids

In our formalisation of rankings:

- Orderings distances: evaluate stability of EF technique
- Orderings compliance: evaluate correctness of EF technique
- Ordering centroid: compute representative ranking for a set

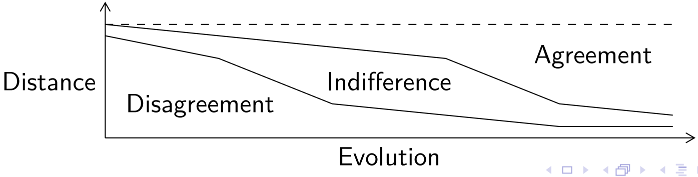
Disagreement Distances for Stability

Build on agreement concepts:

- A $s_1 > s_2$ vs. $s_1 > s_2$ = Agreement
- D $s_1 > s_2$ vs. $s_1 < s_2$ = Disagreement
- U $s_1 > s_2$ vs. $s_1 ? s_2$ = Indifference

Distances based on disagreement:

- Optimistic DD: $ODD = \frac{D}{A+U+D}$
- Pessimistic DD: $PDD = \frac{U+D}{A+U+D}$
- Combination provides rich evaluation:



Compliance Measures for Correctness

Basic measures:

o_1	o_2	Measures
$s_1 > s_2$	$s_1 > s_2$	$Orders(o_1, >) = 3$
$s_1 > s_3$	$s_1 > s_3$	$Orders(o_1, ?) = 0$
$s_2 > s_3$	$s_2 ? s_3$	$Shares(o_1, o_2, >) = 2$

Compliance measures:

- $TotalComp(\hat{o}, o) = \frac{Shares(\hat{o},o,>)+Shares(\hat{o},o,?)}{Orders(\hat{o},>)+Orders(\hat{o},?)}$
- $OptimComp(\hat{o}, o) = \frac{Shares(\hat{o},o,>)+Orders(\hat{o},?)}{Orders(\hat{o},>)+Orders(\hat{o},?)}$
- $OrderComp(\hat{o}, o) = \frac{Shares(\hat{o},o,>)}{Orders(\hat{o},>)}$

Centroid of Orderings

Centroid building:

o_1	o_2	o_3	$c(o_1, o_2, o_3)$
$s_1 > s_2$	$s_1 > s_2$	$s_1 > s_2$	$s_1 > s_2$
$s_1 > s_3$	$s_1 < s_3$	$s_1 < s_3$	$s_1 < s_3$
$s_2 ? s_3$	$s_2 ? s_3$	$s_2 ? s_3$	$s_2 ? s_3$
$s_2 > s_4$	$s_2 ? s_4$	$s_2 < s_4$	$s_2 ? s_4$

Particular care:

- Loop-free o_i do not guarantee loop-free centroid.
  $\rightarrow$ Remove loops to build proper ranking
- Balanced disagreements leads to loose orders.
  $\rightarrow$ Pay attention to centroid Unordereds
- Orderings can have sparse ordered pairs.
  $\rightarrow$ Add arbitrary pairs to build a proper ranking.

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Scenarios Datasets

Synthetic data:

- 18 S, 5 R, 5 T, 10 C
- 485 relations

Cuisine discussions:

- 3 S, 0 R, 3 T, 293 C
- 1767 relations

OSS mailing list:

- 18 S, 0 R, 42 T, 969 C
- 59k relations

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