

# Trust-Based Service Discovery in Multi-Relation Social Networks

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# Outline

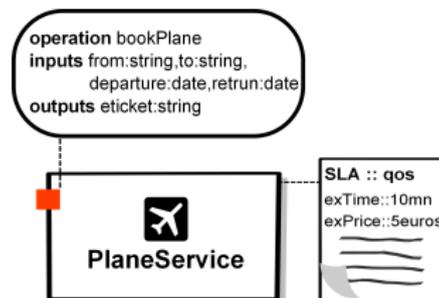
- 1 Composition in Web Service Context
- 2 Trust-Based Service Discovery in MRSN
- 3 Conclusion

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# Web Service Context

- Service-Oriented Architecture (SOA) and Service Computing (SOC) promote the construction of added-value composite systems out of reusable, loosely coupled, distributed entities called **services**
- **Web services** possibly described using three level interfaces:
  - 1 Signature (operations)
  - 2 Semantic (capabilities)
  - 3 Non-fuctional (quality of service)



# Web Service Composition Goals

- Composing **automatically** services from requirements:
  - ▶ **Satisfy** non-functional and semantic **user requirements**
  - ▶ Support **different** service and user need **description levels**

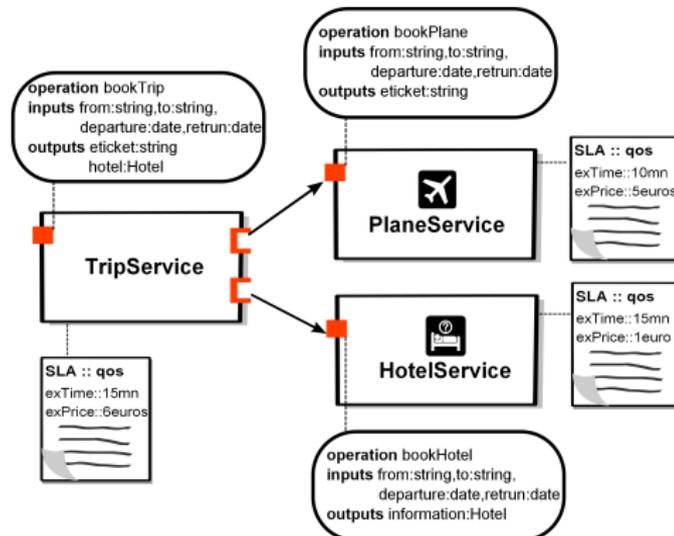
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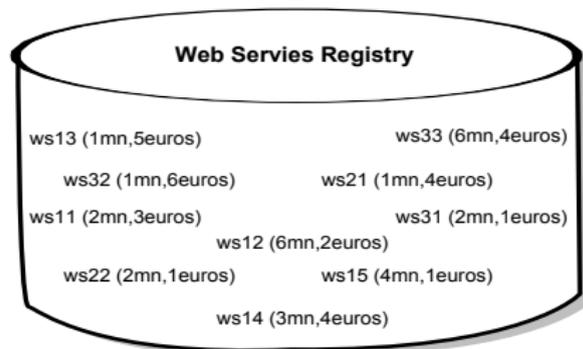
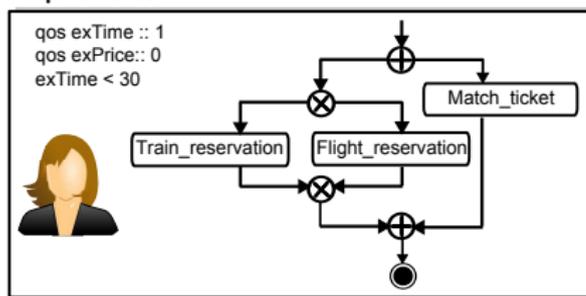
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# Web Service Composition Process

## Requirements



- **Discovery**: search for sets of semantically similar Web services for tasks of the requirement
  - ▶ Why? semantic of services correspond to the tasks of the requirement
  - ▶ How? semantically annotated registry

## Example

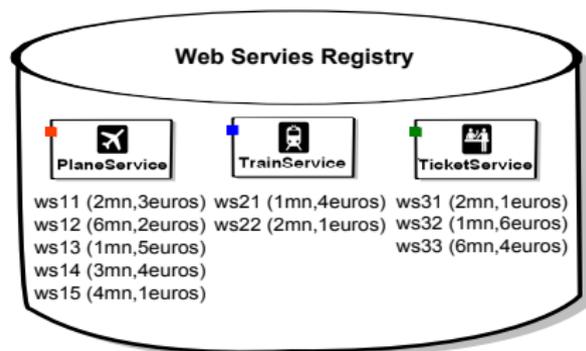
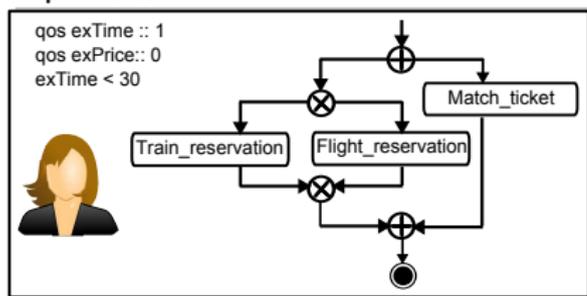
Reservation of a flight ticket for 2014 FIFA World Cup in Brasil, from 12/06 till 12/07:

- Task (activity): reservation of a ticket on a flight
- Web services? Air France, TAP Portugal, British Airways, ...



# Web Service Composition Process

## Requirements

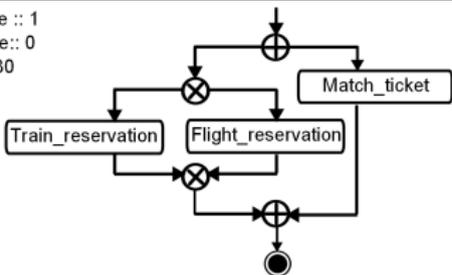


- **Selection:** obtain one candidate for each task of the requirement and under precise constraints
  - ▶ Why? Because **discovered Web services have the same functionality**. In our example, several Web services (companies) do the connection Paris-Rio De Janeiro (Air France, TAP, ...)
  - ▶ How? **Non-functional properties** such as Quality of Service (execution duration, availability, ...)

# Selection Step

## Requirements

qos exTime :: 1  
qos exPrice:: 0  
exTime < 30



## Web Services Registry

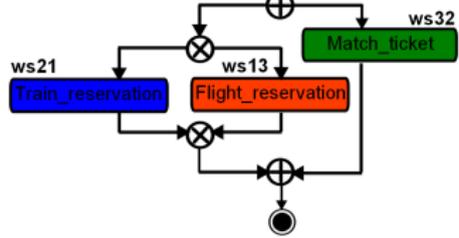


- |                   |                   |                   |
|-------------------|-------------------|-------------------|
| ws11 (2mn,3euros) | ws21 (1mn,4euros) | ws31 (2mn,1euros) |
| ws12 (6mn,2euros) | ws22 (2mn,1euros) | ws32 (1mn,6euros) |
| ws13 (1mn,5euros) |                   | ws33 (6mn,4euros) |
| ws14 (3mn,4euros) |                   |                   |
| ws15 (4mn,1euros) |                   |                   |

## Planner Engine



## Web Services Compositon



# Selection Step

- 1 User requirements: workflow (abstract) of capacities + weights over QoS criteria
- 2 Services: functionality (capabilities) + QoS values
- 3 Instantiation of workflow: selection of **the best QoS** component Web services that satisfies the user's QoS preferences
  - ▶ The set of possible execution plans is **combinatorial**
  - ▶ QoS-aware Web service selection problem for workflow realization is a **combinatorial optimization** problem (MCKP)
  - ▶ Local optimization [El Haddad et al., ICWS 2008, IEEE TSC 2010]
  - ▶ Global planning [El Haddad et Spanjaard, ROADEF 2009]
  - ▶ ANR JCJC PERSO (2007-2010)  
([http://pagesperso-systeme.lip6.fr/Pascal.Poizat/ANR\\_PERSO](http://pagesperso-systeme.lip6.fr/Pascal.Poizat/ANR_PERSO))

# Issues

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  - ▶ What about **human services**?

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- 3 The quality of Web services is known
  - ▶ What about **quality of providers**?

# Issues

- 1 Registry-based SOA deals only with automatic (Web) services
  - ▶ What about **human services**?
- 2 Emergence of Web 2.0 and especially **social networks**
  - ▶ How to take into account the **social dimension**?
- 3 The quality of Web services is known
  - ▶ What about **quality of providers**?
- 4 Web services ignore past interactions
  - ▶ How to keep **track of past interactions**?

## Goal

Melt social aspect into service discovery and selection

*PhD of Amine Louati, co-advised with Suzanne Pinson*

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# Trust-based Service Discovery Problem

- How to determine trustworthy providers before using their services ?
- What information needs to be captured from service requester's multi relation social network ?



[Bansal et al. 2010]

- A **trust-based** dynamic Web service composition in **single-relation social networks**
- Trust rating based on **centrality measure** to select Web services provided by trustworthy providers
- ⊖ Trust representation is **limited to one measure**
- ⊖ **The multi-relation aspect** of social networks is **ignored**

# Trust-based Service Discovery Problem

- How to determine trustworthy providers before using their services ?
- What information needs to be captured from service requester's multi relation social network ?



[Maaradji et al., 2010]

- Composition based on a **recommendation confidence** in **single-relation social networks**
- The recommendation confidence is the combination of 3 ratings: **number of times** a service is used, **social proximity** between requester and recommender and, **expertise** of the recommender
- ☹ The approach is limited to **automatic services**
- ☹ **The multi-relation aspect** of social networks is **ignored**

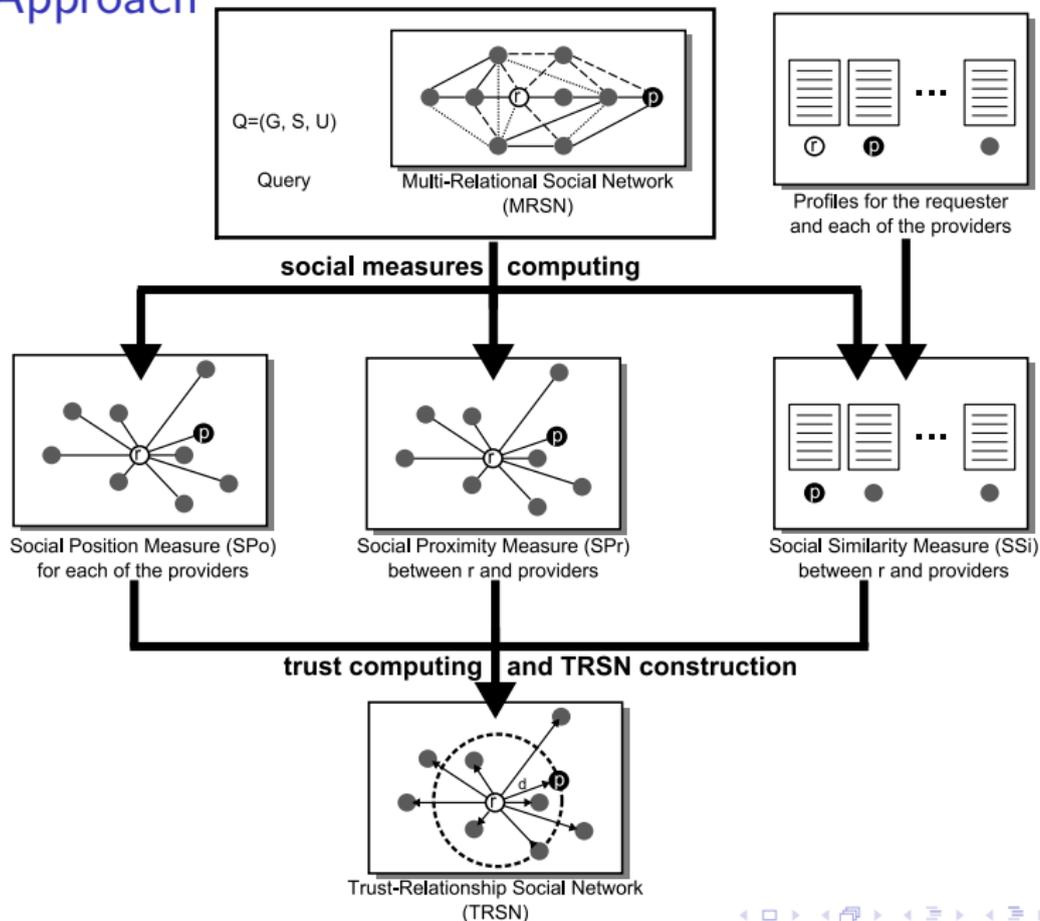
# Trust-based Service Discovery Problem

## Our contribution

A **service provider discovery** approach based on **social trust** measure between service's requester and providers

- Human service as well as automatic service
- Social trust measure computed over the service's requester **multi-relation social network**
- Social trust measure handles a **multi-dimensional rating** established from structural as well as semantic information

# Our Approach



# Our Model

## Multi-Relation Social Network (MRSN)

An undirected graph  $G = (V, E)$ , where  $V$  is the set of nodes (users) and  $E = \{E_1, \dots, E_r\}$  is the set of edges where  $E_i$  is the set of edges with respect to the  $i$ th relationship

## Neighborhood

Given a MRSN graph  $G$ , the neighborhood of a node  $u$  regarding a type of relationship  $R_i$  is defined as  $N_{R_i}(u) = \{v \in V \mid (u, v) \in E_i\}$

## User query

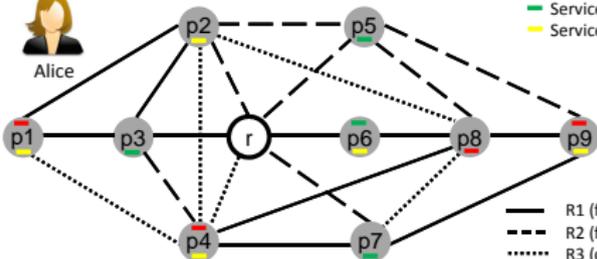
$Q = (G, S, U)$ , where  $G$  is a MRSN graph,  $S$  a requested service, and  $U$  a utility function expressing the service requester preferences over types of relationships

# Example

Query Q = (G, -, R1>R2>R3)



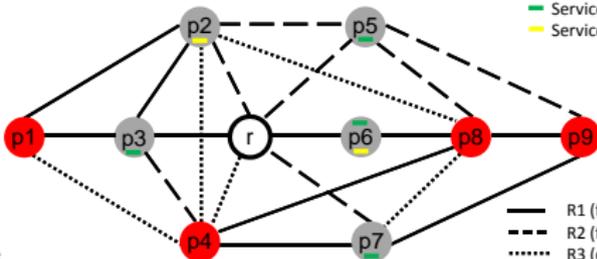
Alice



— Service S  
 - - Service S'  
 ···· Service S''

— R1 (family)  
 - - R2 (friend)  
 ···· R3 (colleague)

U(R1) = 1, U(R2) = 2, U(R3) = 4



— Service S  
 - - Service S'  
 ···· Service S''

— R1 (family)  
 - - R2 (friend)  
 ···· R3 (colleague)

$$Q_{Alice} = (G, babysitting, family \succeq friend \succeq colleague)$$

# Step1: Social Measures Computing

Three measures are computed:

- **Social Position** Measure (SPo)
- **Social Proximity** Measure (SPr)
- **Social Similarity** Measure (SSi)
  - ▶ **Profile** Similarity (PS)
  - ▶ **Neighborhood** Similarity (DS)

# Step1: Social Position Measure (SPo)

## Definition

$SPo(p) = \sum_{i=1, \forall p' \in V}^{|R|} w_i \cdot a^i(p, p')$  where  $a^i(p, p') = 1$  iff  $p$  and  $p'$  are directly connected with an edge of a relation type  $R_i$ , 0 otherwise;  $w_i = \frac{1}{U(R_i)}$

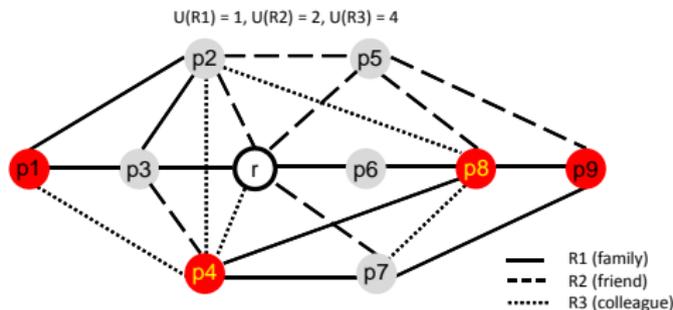


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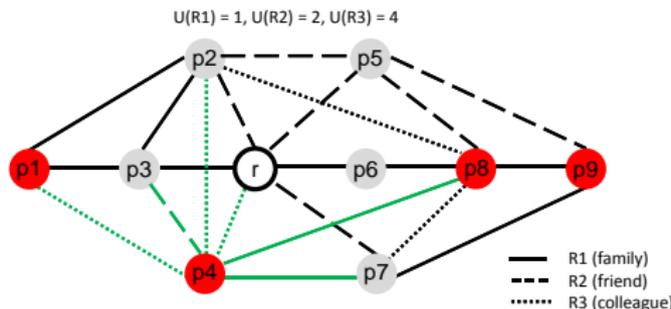
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## Example

-  $SPo(p_4) = 1 \times 2 + \frac{1}{2} \times 1 + \frac{1}{4} \times 3 = 3.25$



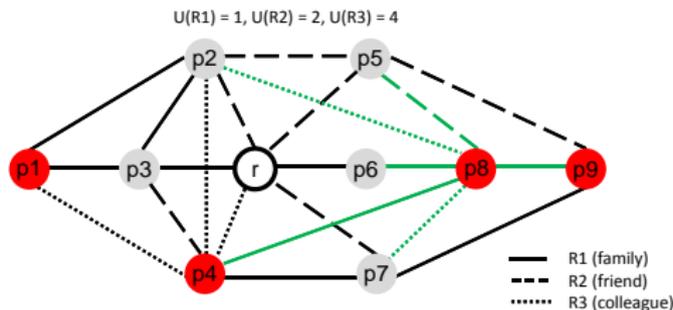
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## Example

- $SPo(p_4) = 1 \times 2 + \frac{1}{2} \times 1 + \frac{1}{4} \times 3 = 3.25$
- $SPo(p_8) = 1 \times 3 + \frac{1}{2} \times 1 + \frac{1}{4} \times 2 = 4$



# Step1: Social Proximity Measure (SPr)

## Definition

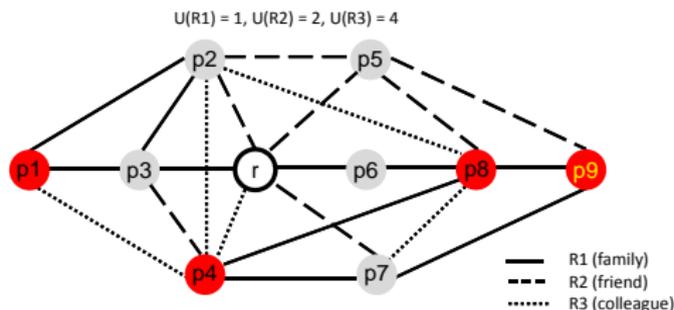
$$SPr(r, p) = \frac{\sum_{i=1}^k U((x_i, x_{i+1}))}{k-1}$$

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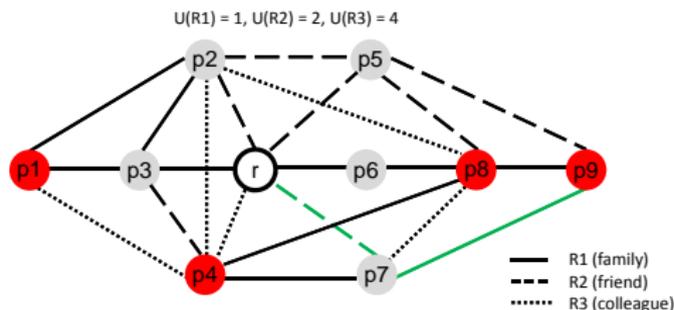
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- $path_1 = (r, p_7, p_9)$  and  $cost = \frac{3}{2} = 1.5$



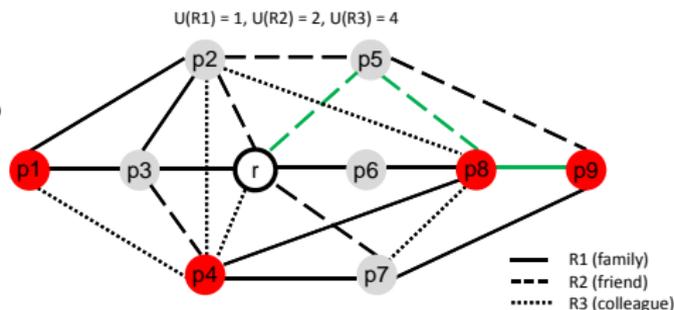
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- $path_2 = (r, p_5, p_8, p_9)$  and  $cost = \frac{5}{3} = 1.66$



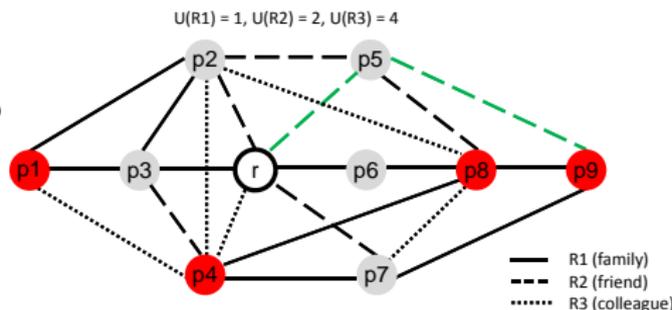
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- $path_3 = (r, p_5, p_9)$  and  $cost = \frac{4}{2} = 2$





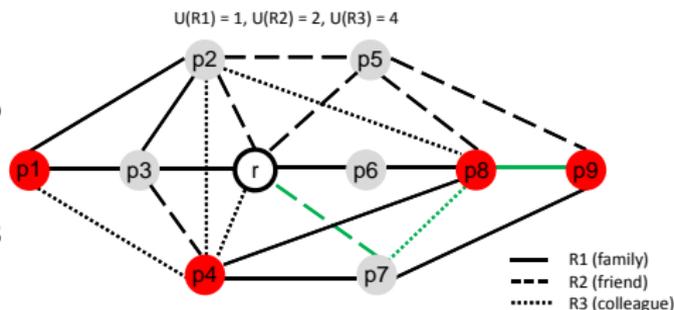
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- $path_3 = (r, p_5, p_9)$  and  $cost = \frac{4}{2} = 2$
- $path_4 = (r, p_7, p_8, p_9)$  and  $cost = \frac{7}{3} = 2.33$



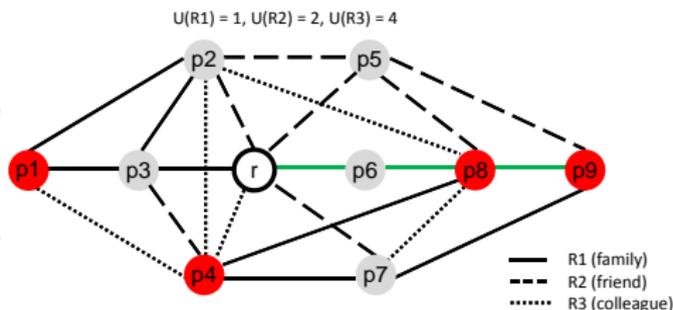
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- $path_3 = (r, p_5, p_9)$  and  $cost = \frac{4}{2} = 2$
- $path_4 = (r, p_7, p_8, p_9)$  and  $cost = \frac{7}{3} = 2.33$
- $path_5 = (r, p_6, p_8, p_9)$  and  $cost = \frac{3}{3} = 1$



## Step1: Social Similarity Measure (SSi)

### Definition

$$SSi = DS \times PS$$

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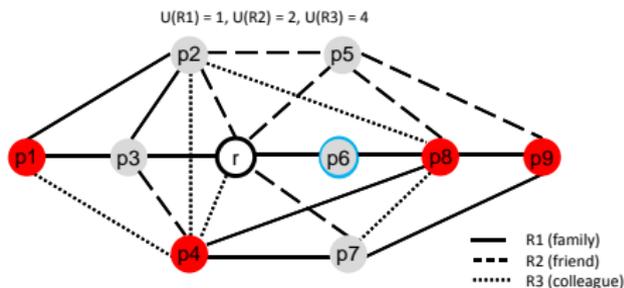
$$SSi = DS \times PS$$

## Degree Similarity (DS)

$DS(r, p) = \sum_{i=1}^{|R|} w_i \cdot \delta^i(r, p)$  with  $\delta^i(r, p) = \frac{1}{1+dist^i}$ ,  $w_i = \frac{1}{U(R_i)}$ ; and  $dist^i = \frac{b_i+c_i}{a_i+b_i+c_i}$  is the Jaccard distance between  $r$  and  $p$  according to the relationship  $R_i$

## Example

	family	friend	colleague
(r,p8)	a=1		



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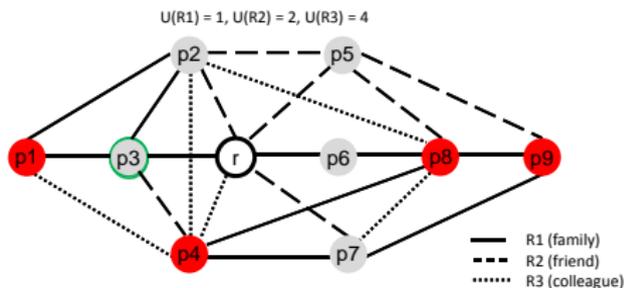
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## Example

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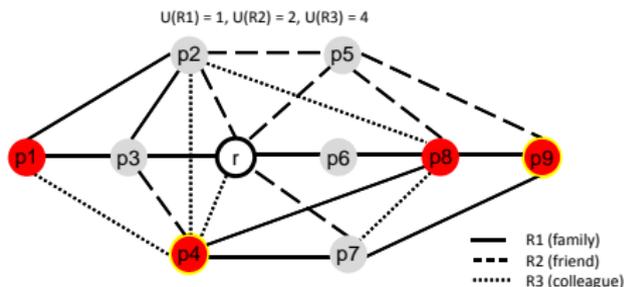
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## Example

	family		friend	colleague	
(r, p8)	a=1	b=1			
	c=2				



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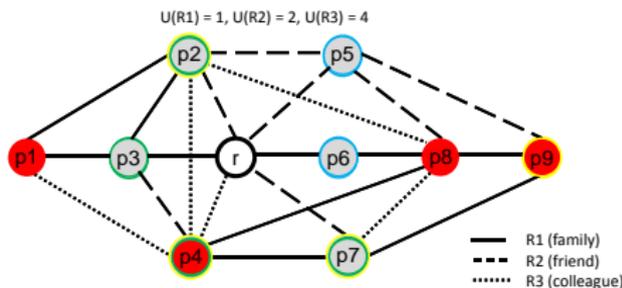
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## Example

	family		friend		colleague	
(r, p8)	a=1	b=1	1	2	0	1
	c=2		0		2	

$$DS(r, p_8) = 1 \times \frac{1}{1+\frac{3}{4}} + \frac{1}{2} \times \frac{1}{1+\frac{2}{3}} + \frac{1}{4} \times \frac{1}{1+\frac{3}{3}} = 0.9$$



# Step1: Social Similarity Measure (SSi)

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$$SSi = DS \times PS$$

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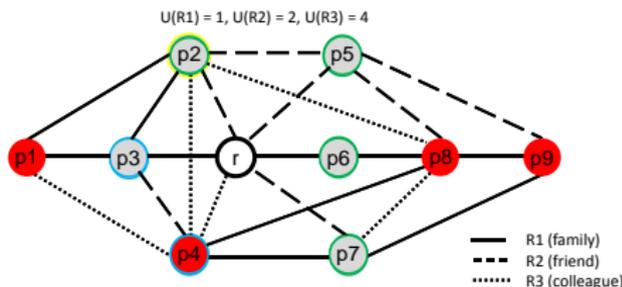
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	family		friend		colleague	
(r, p1)	1	1	0	3	1	0
	1		0		0	

$$DS(r, p_1) = 1 \times \frac{1}{1+\frac{2}{3}} + \frac{1}{2} \times \frac{1}{1+\frac{1}{3}} + \frac{1}{4} \times \frac{1}{1+\frac{0}{1}} = 1.1$$





# Step1: Social Similarity Measure (SSi)

## Profile Structure (P)

- $P = \text{Item}^+$
- $\text{Item} = \text{Field}^+$
- $\text{Field} = \text{value}^*$

General info	
 Alice	Sex: F Birthday: 12/11/2012 Living: Shanghai Langages: English, Chinese
Work	
Employer: society1 Type: consulting Post: manager	
Interests	
reading, travel, sport	

General info	
 Bob	Sex: M Birthday: 15/11/2012 Living: Shanghai Langages: French, Chinese
Work	
Employer: society1 Type: development Post: engineer	
Interests	
games, movies, football	

## Profile Similarity (PS)

$PS(r, p) = \frac{1}{|I|} \times \sum_{i \in I} \beta_i \cdot S_i(r, p)$  where  $I$  is the set of items,  $S_i(r, p)$  is the similarity between the  $i$ th items of  $r$  and  $p$ ; and  $\beta_i$  is a weight attributed to the item  $i$

## Item Similarity (IS)

$$S_i(r, p) = \frac{1}{|Fd|} \times \sum_{k=1}^{|Fd|} \frac{1}{|\mathcal{V}(Fd_k^r)|} \sum_{l=1}^{|\text{Max}B_k|} bur_l$$

where  $FD$  is the set of fields,  $\mathcal{V}(Fd_k)$  is the set of values taken by a multi-valued field  $Fd_k$ ,  $\text{Max}B_k$  is the set of the  $|\mathcal{V}(Fd_k^r)|$  biggest similarity values computed between all possible pairs of  $\mathcal{V}(Fd_k^r)$  and  $\mathcal{V}(Fd_k^p)$  and,  $bur$  is the **Burnaby similarity**

# Step1: Social Similarity Measure (SSi)

## Single-valued Field Similarity

$$Burnaby(X_k, Y_k) = \begin{cases} 1 & \text{if } X_k = Y_k \\ \frac{\sum_{q \in \mathcal{A}_k} 2 \log(1 - \hat{p}_k(q))}{\log \frac{\hat{p}_k(X_k) \hat{p}_k(Y_k)}{(1 - \hat{p}_k(X_k))(1 - \hat{p}_k(Y_k))} + \sum_{q \in \mathcal{A}_k} 2 \log(1 - \hat{p}_k(q))} & \text{otherwise} \end{cases}$$

## Example

$|Fd| = 3$ ,  $|\mathcal{V}(Fd'_k)| = 1$  and  $|MaxB_k| = 1$  (for all k)

work	Alice	Bob
employer	society1 (s1)	society1 (s1)
type	consulting (c)	development (d)
post	manager (m)	engineer (en)

$$\Rightarrow S_{work}(Alice, Bob) = \frac{1}{3} \times \left[ \frac{1}{1} \times Burnaby(s1, s1) + \frac{1}{1} \times Burnaby(d, c) + \frac{1}{1} \times Burnaby(en, m) \right]$$

# Step1: Social Similarity Measure (SSi)

<i>work</i>	10 profiles		
employer	society1 (s1) 5	society2 (s2) 3	society3 (s3) 2
type	development (d) 3	consulting (c) 4	audit (a) 3
post	engineer (en) 3	manager (m) 5	expert (ex) 2

$$- \text{Burnaby}(s1, s1) = 1$$

$$- \text{Burnaby}(d, c) = \frac{2(\log(1 - \frac{3}{10}) + \log(1 - \frac{4}{10}) + \log(1 - \frac{3}{10}))}{\log(\frac{\frac{3}{10} * \frac{4}{10}}{(1 - \frac{3}{10})(1 - \frac{4}{10}))}) + 2(\log(1 - \frac{3}{10}) + \log(1 - \frac{4}{10}) + \log(1 - \frac{3}{10}))} = 0.66$$

$$- \text{Burnaby}(en, m) = \frac{2(\log(1 - \frac{3}{10}) + \log(1 - \frac{5}{10}) + \log(1 - \frac{2}{10}))}{\log(\frac{\frac{3}{10} * \frac{5}{10}}{(1 - \frac{3}{10})(1 - \frac{5}{10}))}) + 2(\log(1 - \frac{3}{10}) + \log(1 - \frac{5}{10}) + \log(1 - \frac{2}{10}))} = 0.75$$

$$\text{Thus, } S_{\text{work}}(\text{Alice}, \text{Bob}) = \frac{1}{3} \times [\frac{1}{1} \times 1 + \frac{1}{1} \times 0,66 + \frac{1}{1} \times 0,75] = 0.8$$

# Step1: Social Similarity Measure (SSi)

<i>work</i>	10 profiles		
employer	society1 (s1) 5	society2 (s2) 3	society3 (s3) 2
type	development (d) 3	consulting (c) 4	audit (a) 3
post	engineer (en) 3	manager (m) 5	expert (ex) 2

$$- \text{Burnaby}(s1, s1) = 1$$

$$- \text{Burnaby}(d, c) = \frac{2(\log(1-\frac{3}{10})+\log(1-\frac{4}{10})+\log(1-\frac{3}{10}))}{\log(\frac{\frac{3}{10} * \frac{4}{10}}{(1-\frac{3}{10})(1-\frac{4}{10})})+2(\log(1-\frac{3}{10})+\log(1-\frac{4}{10})+\log(1-\frac{3}{10}))} = 0.66$$

$$- \text{Burnaby}(en, m) = \frac{2(\log(1-\frac{3}{10})+\log(1-\frac{5}{10})+\log(1-\frac{2}{10}))}{\log(\frac{\frac{3}{10} * \frac{5}{10}}{(1-\frac{3}{10})(1-\frac{5}{10})})+2(\log(1-\frac{3}{10})+\log(1-\frac{5}{10})+\log(1-\frac{2}{10}))} = 0.75$$

$$\text{Thus, } S_{\text{work}}(\text{Alice}, \text{Bob}) = \frac{1}{3} \times [\frac{1}{1} \times 1 + \frac{1}{1} \times 0,66 + \frac{1}{1} \times 0,75] = 0.8$$

Using the same method:

$$- S_{gi}(\text{Alice}, \text{Bob}) = 0.81$$

$$- S_{\text{interest}}(\text{Alice}, \text{Bob}) = 0.17$$

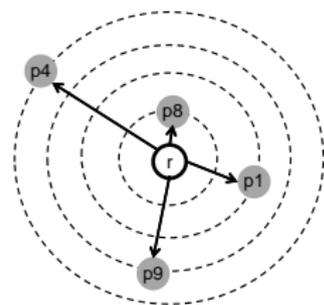
$$\Rightarrow PS(\text{Alice}, \text{Bob}) = \frac{S_{\text{work}}(\text{Alice}, \text{Bob}) + S_{gi}(\text{Alice}, \text{Bob}) + S_{\text{interest}}(\text{Alice}, \text{Bob})}{3} = 0.59$$

## Step2: Trust Computing and TRSN Construction

### Social Trust (ST)

$ST(r, p) = \sum_{j=1}^3 \lambda_j \cdot M_{pj}(r, p)$  where  $M_p = (SPo(p), SPr(r, p), SSi(r, p))$  and  $\lambda_j \in [0, 1]$  and  $\sum_{j=1}^3 \lambda_j = 1$ .

id	SPo	SPr	PS	DS	SSi	ST
1	0.125	1	0.59	1.1	0.651	<b>0.637</b>
4	0.625	0.5	0.417	0.875	0.335	<b>0.486</b>
8	1	1	0.74	0.966	0.764	<b>0.921</b>
9	0.25	1	0.512	0.925	0.513	<b>0.587</b>



Trust-Relationship Social Network (TRSN)

The outcome of the proposed approach is a weighted directed graph modeling a new social network that is service requester centered and based on a single relation, **the social trust relation**

# Outline

- 1 Composition in Web Service Context
- 2 Trust-Based Service Discovery in MRSN
- 3 Conclusion**

# Summing up

## Conclusion

- A service provider discovery approach based on social trust measure
- Social trust measure is the aggregation of three measures: social position, social proximity, and social similarity
- Social trust measure take into account both semantic and structural knowledge extracted from the multi-relation social network

## Perspectives

- Scalability in big graphs and pertinence on real data sets
- Exploiting feedback and history of service requester's experiences
- Extension of our trust model to perform a trustworthy composition

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