One-to-Many Multi-agent Negotiation and Coordination Mechanisms to Manage User Satisfaction

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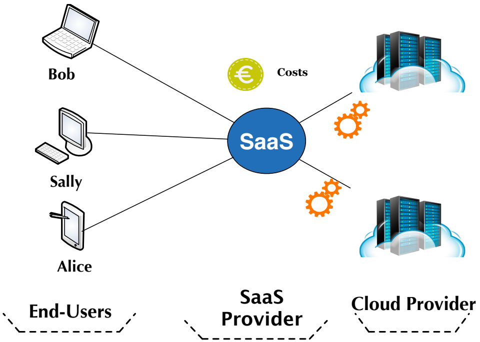
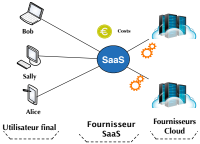
Satisfaction Management



Satisfaction Management (SM)

- The provider seeking a balance between:
  1. Minimizing its costs and use its resources efficiently
  2. Providing a (fine-grained) satisfactory service to its users

Satisfaction Management



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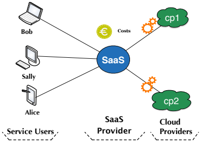

- Distributed & Dynamic Ecosystem
- Involves Multiple & Heterogeneous Actors

Satisfaction Management (SM)

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Problem!

In most of existing works, SM decision is taken unilaterally by the provider, the end-user preferences and her expectations are overlooked, inter-user differences are ignored

Proposition

A one-to-many negotiation architecture whose goals are:

Objectives

- Integrate the user's subjective evaluation of the service quality[Hoßfeld et al., 2016, Najjar, 2015]
- Equip the provider with a fine-grained control over end-user satisfaction while respecting its budget constraints

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In order to understand and model users' satisfaction and their subjective acceptability thresholds, we resorted to the literature of :

Related Domains

1. Customer expectation management [Zeithaml et al., 1993] and Psychophysics [Reichl et al., 2010]
2. Quality of Experience (QoE) [Möller and Raake, 2014]

Plan

Quality of Experience

- QoE: is the service quality estimated subjectively by the end-user (a subjective and user-centric measure)

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Most of existing works are *unilateral* and they rely on MOS (Mean Opinion Score). Yet, MOS hides infiormation about user diversity and ignores users evolution [Hoßfeld et al., 2011]

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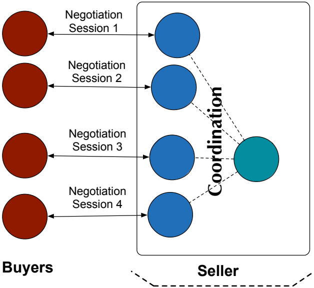
A Possible Solution

- Recent empirical studies on QoE recommend providers to rely on percentiles to evaluate the user satisfaction[Hoßfeld et al., 2016]
- Agents can integrate user's personal and evolving preferences and involve her in the decision-making process [Najjar et al., 2017, Najjar et al., 2016a]

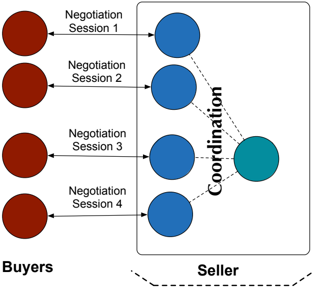
Plan

One-to-Many Negotiation



- Allows a seller *s* to negotiate simultaneously with several buyers [Nguyen and Jennings, 2004]
- Involves negotiation and coordination strategies [Rahwan et al., 2002]

One-to-Many Negotiation



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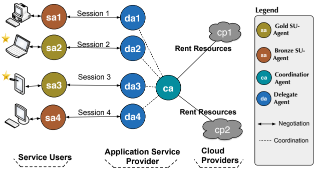
Challenges

- Most of existing works address atomic simultaneous negotiation sessions
- One agreement is required, all other sessions are aborted
  - Useful works in service composition [Mansour and Kowalczyk, 2014, Richter et al., 2012]

Agenda

AQUAMan Architecture



- Integrate the user into the loop [Najjar et al., 2016a]
- Allows for QoE-aware and personal elsaticity management [Najjar et al., 2016b]
- End-users have personalized utility functions and negotiation strategies
- Negotiation sessions are autonomous but they must respect their budget constraints *RC*
- Users can enter the system and leave at will (with variable influx)

AQUAMan*: User Satisfaction Management

During the negotiation process, user can accept/reject service depending on their expectations and subjective evaluation of its quality

AQUAMan's Adaptive Mechanism

- Goal: guarantee a predefined satisfaction goals while not exceeding *RC*, the average cost invested per user
- Solution: to do so, the provider must
  1. Construct a model of negotiation behavior of each user [Najjar et al., 2017, Baarslag et al., 2015]
  2. Adjust its negotiation strategy in order to restore user satisfaction to its predefined goals while *RC*

Formalization

Satisfaction Goals

- Enforce $Goal[k]$ how much percent of users receive a service of the satisfaction category k (e.g. *acceptable*, *good*, *excellent*, etc.)

Satisfaction Management as an Optimization Problem

$$\textbf{Minimize} \sum_{k=1}^{K} \sum_{i=1}^{N^t} C_i^k \cdot X_i^k \tag{1}$$

Subject to

$$\sum_{k=1}^{K} X_i^k \leq 1, \quad \forall i \tag{2}$$

$$\sum_{m=1}^{k} \left(\frac{\sum_{i=1}^{N^t} X_i^m + Already[m]}{\#TerminatedSessions} \right) \geq Goal[k], \quad \forall k \tag{3}$$

Heuristic Algorithm

Construct a list of users approaching their deadline

Sorting the list

1. $Cost_{First}$: users with cheaper *acceptability* requirements are put on top of the list
2. $Utility_{First}$ users with cheaper *satisfaction* on top
3. $Deadline_{First}$ the shorter the user's remaining time is, the upper in the list it is

Selecting Users from The list

1. *DISTANCE_TO_GOAL*: the category furtherest from achieving its satisfaction goals is prioritized
2. *CATEGORY_COST* the category the less costly is prioritized

Based on the user model, propose a tailored offer

Agenda

1. Context
2. Quality of Experience
3. One-to-Many Negotiation
4. Adaptive-QoE-Aware elasticity Management (AQUAMan*)
5. Evaluation

Optimal Solution vs Heuristic Algorithm

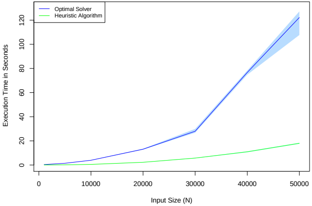


Table: Heuristic strategies vs. optimal cost

	Utility_First	*Cost_First*	*Deadline_First*
DISTANCE_TO_GOAL	+10.2%	+16.5%	+10.9%
CATEGORY_COST	+12.9%	+12.9%	+13.1%

Results

- The optimizer is intractable with high number of users
- Cost-wise, the best heuristic is 10% more expensive that the optimal solution

User Satisfaction & Cost

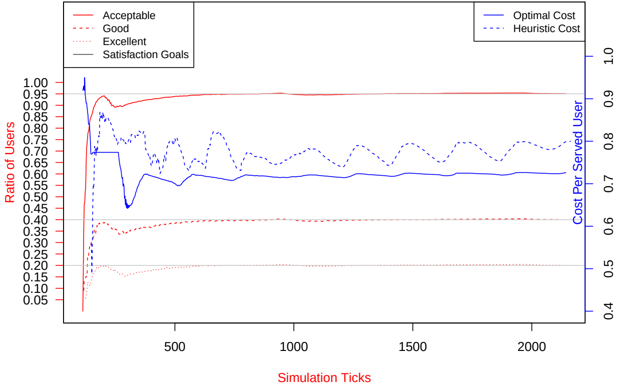


Figure: The user satisfaction achieved by the heuristic strategies (red curves) and their cost (blue dashed curve) compared with the optimal solution cost (blue solid curve).

Impact of User Feedback

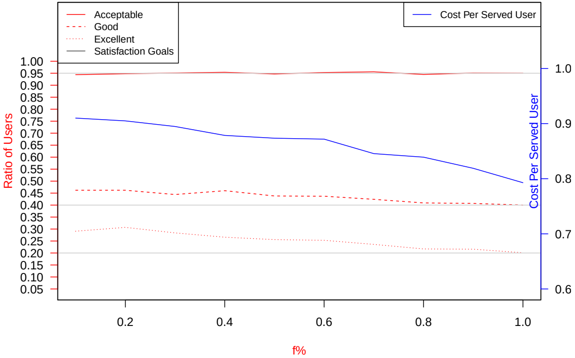


Figure: The impact of $f\%$ (x-axis) on the ratio of users assigned to each satisfaction category (left y-axis) and on the cost spent per served user (right y-axis).

Impact of BBC Users

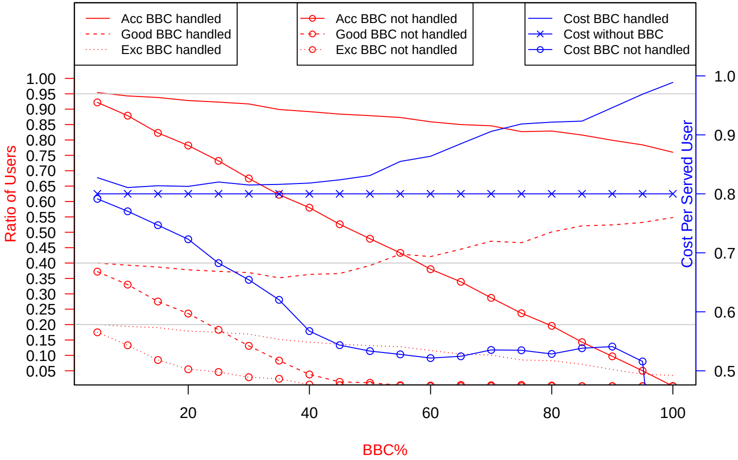


Figure: The Impact of BBC Users.

Conclusions & Future Works

Conclusions

- AQUAMan* equips the user with fine-grained control over user satisfaction
- Satisfies the provider cost constraints
- Executable in tractable time

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Future Works

- Study the relations among different satisfaction goals
- Introduce measures of *QoE fairness*
- Develop BBC Handling Strategies

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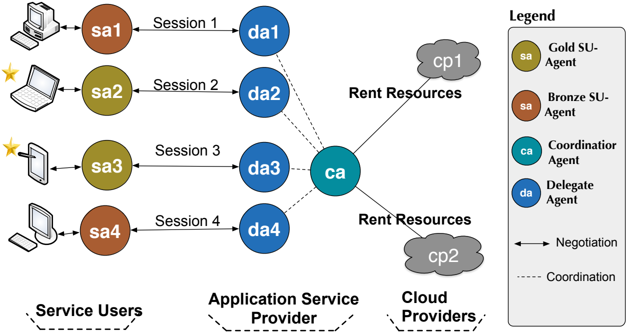
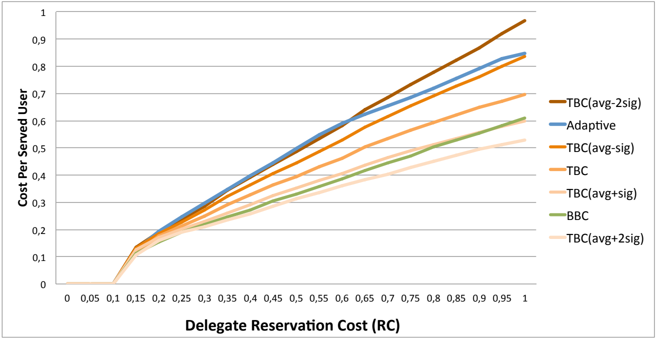
Limit of the Adaptive Mechanism



- We set $Goal = 100\%$ to push AQUAMan to accept as much user as possible in order to identify its limit

Costs of the Adaptive Mechanism



The cost spent per user of AQUAMan compared with other non-adaptive strategies

Elasticity Negotiation: Negotiation Object

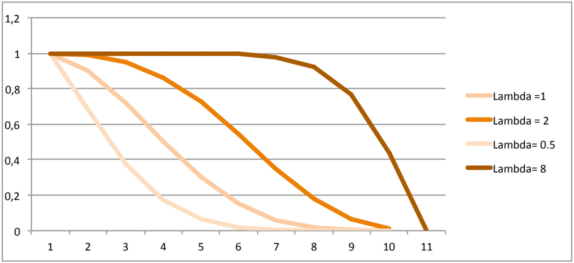
Offer

- The negotiation object is offer $o_i^t = \langle v_1, v_2, \cdots v_J \rangle$
- It assigns a value v_k $(k \in [1, J])$ to each of the service attribute

Example: in the transcoding service an offer is:

$$o_{da_i}^t = \langle HD, 10\ min, 24p \rangle$$

Concession Strategy



- sa_i make concessions by reducing their aspiration rate
- $\Delta AR_i^t = AR_i^t \cdot \left(\frac{t}{T_{sa_i}}\right)^{\lambda_i}$
- Then $AR_i^{t+1} = AR_i^t - \Delta AR_i^t$
- When T_{sa_i} is reached, sa_i quits the negotiation

λ controls the convexity of the concession curve

- $\lambda_i < 1$: Conciliatory
- $\lambda_i \approx 1$: linear
- $\lambda_i > 1$: Boulware

Linear User Utility functions

- sa_i rely on a utility function M derived from su_i preferences
- M is a weighted sum of $\mu_{sa_i,}$ linear attribute utility functions

$$\mu_{sa_i,at_j}(o^t_{da_i}[at_j]) = \frac{rv_{sa_i,at_j} - o^t_{da_i}[at_j]}{rv_{sa_i,at_j} - pv_{sa_i,at_j}} \tag{4}$$

- rv_{sa_i,at_j} and pv_{sa_i,at_j} are the preferred and reservation values of the attribute at_j
- sa_i's subsequent decision is based on the acceptance condition

QoE Influence Factors

QoE is a function of influence factors. Influence factors are the independent variables and QoE is dependent variable:

$$QoE_s = \Phi(IF_1, IF_2, .., IF_n)$$

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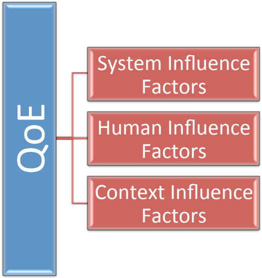


1. SIF:technical aspects of the system on which the user consumes the factors
2. HIF:user background, expectations, his personality and previous experience
3. CIF: the context when the user consumes the service

QoE-aware Agent Decision Model

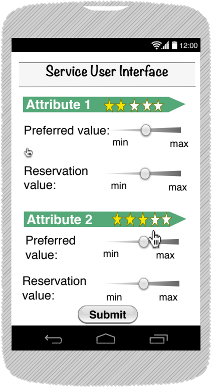
- The user agent seeks to maximize the subjective satisfaction of the user
- Therefore, it derives its decision model and utility function from the user preferences
  - Thus, for each attribute:

$$\mu_{sa_i,at_j} = \alpha_{sa_i,at_j} \cdot f(v_{at_j}) + \beta_{sa_i,at_j} \qquad (5)$$

  - The form of $f()$ depends on the attribute type
  - If the service involves multiple attributes:

$$M_{sa_i}(o) = \sum_{j=1}^{j=J} w^t_{sa_i,j} \cdot \mu_{sa_i,at_j}(o^t_{da_i}[at_j]) \qquad (6)$$

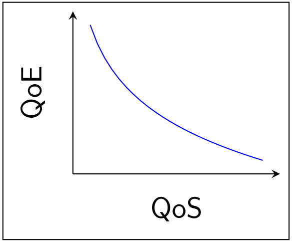
  - Where o is an offer received from the provider



The Logarithmic Hypothesis

- Derived from the Weber Fechner Law (WFL) of psychophysics
- Logarithmic relationship between *QoS* parameter and QoE:

$$QoE = -\alpha \cdot log(QoS) + \beta \quad (7)$$



- *QoS* should be perceivable by the user (e.g. waiting time)
- Validated and applied to various applications (file download, Email, etc.)

QoE-Aware Version: Decision Model

M becomes a weighted sum of logarithmic attribute utility functions:

$$M_{sa_i}(o^t_{da_i}) = \sum_{j=1}^{j=J} w^t_{sa_i,j} \cdot [-\alpha_{sa_i,at_j} \cdot ln(o^t_{da_i}[at_j]) + \beta_{sa_i,at_j}] \qquad (8)$$

Coefficients

- α_{sa_i,at_j}, β_{sa_i,at_j} are the personal coefficients of sa_i for at_j
- Derived from sa_i preferences:

$$\alpha_{sa_i} = \frac{1}{ln(rv_{i_{res}}) - ln(pv_{i_{res}})} \beta_{sa_i} = \frac{ln(rv_{i_{res}})}{ln(rv_{i_{jct}}) - ln(pv_{i_{res}})} \qquad (9)$$

Use-case scenario: Cloud-hosted Service

Provider (ASP) Side

- A SaaS provider whose service is compute-intensive
- Rents resources from a cloud provider (CP) (e.g. Amazon EC2) to fulfill the requests

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Provider (ASP) Side

- A SaaS provider whose service is compute-intensive
- Rents resources from a cloud provider (CP) (e.g. Amazon EC2) to fulfill the requests

User Side

- We suppose that all attributes of the service are directly perceivable by the user (e.g. execution time)
- Therefore, we consider that the logarithmic hypothesis applies to these attributes

$$\mu_{sa_i,at_j}(v_{at_j}) = -\alpha_{sa_i,at_j} \cdot ln(v_{at_j}) + \beta_{sa_i,at_j} \tag{10}$$

Coordination Protocol (1/2)

- States the rules of interaction between *ca* and da_i
- proposed to satisfy the specific requirements of elasticity management negotiation
- Illocutions sent from da_i to *ca* are different from those sent from *ca* to da_i

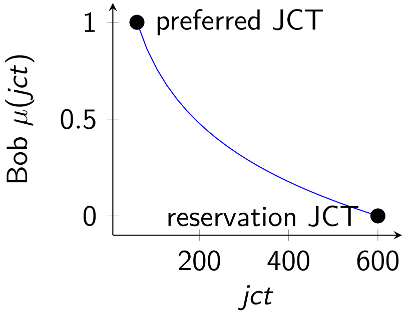
Illocutions ($da_i \rightarrow ca$)	**Description**
Inform(*event*)	da_i notifies the coordinator *ca* about an important *event*
RequestIntervention	da_i asks *ca* to intervene in its session *i* because the decision is beyond da_i capacities.

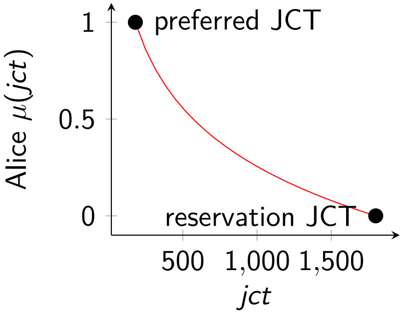
Coordination Protocol (2/2)

- The illocutions sent from the *ca* to da_i are *imperative*
- da_i cannot reject it

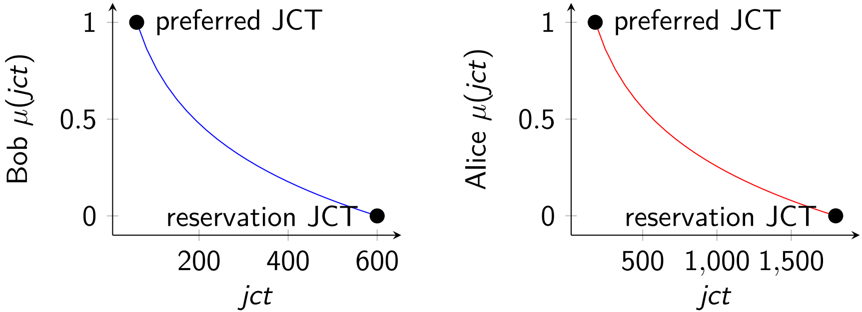
Illocutions ($ca \rightarrow da_i$)	**Description**
Spawn (Ω_{da_i})	*ca* spawns a delegate da_i to negotiate with sa_i
Modify($\Omega\prime_{da_i}$)	*ca* alters the negotiation strategy of da_i.
Suspend	*ca* orders the delegate da_i to suspend the negotiation process in the session i.
Kill	*ca* terminates the delegate da_i

Example


preferred JCT
reservation JCT
Bob $\mu(jct)$
1
0.5
0
200
400
600
jct

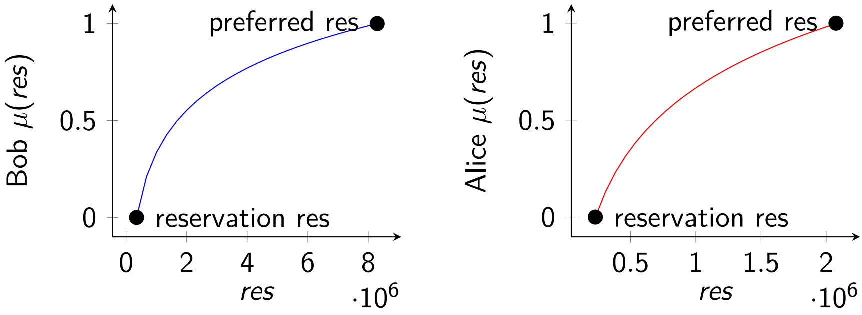

preferred JCT
reservation JCT
Alice $\mu(jct)$
1
0.5
0
500
1,000
1,500
jct

Example



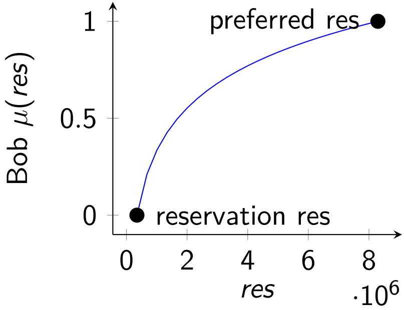
- $\mu_{sa_i,jct}$ is a decreasing logarithmic function
- Bob, gold SU, has lower reservation and preferred values
- Alice, bronze SU, has higher reservation and preferred values

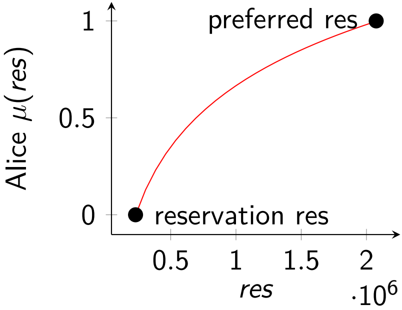
Example (2)



Bob $\mu(res)$
preferred res
reservation res
1
0.5
0
0
2
4
6
8
res
$\cdot 10^6$
Alice $\mu(res)$
preferred res
reservation res
1
0.5
0
0.5
1
1.5
2
res
$\cdot 10^6$

Example (2)





- $\mu_{sa_i,res}$ is an increasing logarithmic function
- Bob, gold SU, has higher reservation and preferred values
- Alice, bronze SU, has lower reservation and preferred values
- M_{sa_i}, the overall utility function, is a weighted sum of $\mu_{sa_i,res}$ and $\mu_{sa_i,jct}$

Performance Model Example

Simple example of a performance model of a transcoding service

t/q	SD	MD	HD
10 min	4	5	8
20 min	2	4	6
30 min	1	2	3

- Tradeoffs
- Faster process requires more cloud resources $\Rightarrow$ more costly for the ASP