Title: Intelligent agents and ecostructuring decisions in service journeys

Ralph D. Badinelli, Virginia Tech

Purpose:

The purpose of this paper is the derivation of design principles for smart Service Support Systems (SSS). An SSS is a personalized, intelligent decision support system for navigating a service journey (Badinelli 2021). The development of smart SSS's is a natural next step in the quest for more efficient and effective service systems (Barile & Polese 2010). The soon-to-be ubiquitous applications of artificial intelligence (AI) and big data analytics (BDA) in resource-aggregating service systems motivates an investigation into the benefits and limitations of these systems (Langley et al 2020).

The paper extends the author's previous research in the role of actor engagement decisions as the mechanism for determining the trajectory of an actor's service journey (Badinelli et al 2019). We model each engagement as an ecostructuring decision followed by a commitment decision. The focus of this paper is the joint support of the ecostructuring decision by the individual actor and the intelligent SSS.

Methodology:

The principal methodology of this research is decision analytics. Specifically, we begin with a model of an actor's service journey as a sequential decision process (SDP). This process incorporates the actor's opportunities to explore service ecostructures for their service potential and opportunities to exploit service ecostructures for value cocreation (Badinelli et al 2012). At each juncture of the SDP, the actor and the SSS agent must learn from previous engagements and adapt the ecostructure to the evolving value structure and knowledge base of the actor.

We examine the salient methodologies for decision support in SSS's to date. The multi-armed bandit (MAB) decision model has become a favorite of online service systems that present an actor with an assortment of options for the service ecostructure based on a probabilistic assessment of the actor's preferences. Similarly, Bayesian decision models are often used to describe rational sequential decision processes. We also consider heuristic decision rules as options for the actor. Computer simulation is a methodology that allows experimental testing of our theoretical results and conjectures.

Results:

We identify a potential learning gap between an actor and an SSS with the following implications.

- Synchronizing an actor's SDP and that of a smart SSS can be impossible in many cases.
- The actor's actions that are independent of the SSS make the actor's journey only partially observable to the SSS.
- The limitations of an SSS call into question the viability of micro services, aggregation services, intelligent service support systems (Barile & Polese 2010, Golinelli 2010).
- Overcoming the limitations of an SSS through more sophisticated analytics could introduce coupling across the stages of a service journey which could threaten the scalability, evolvability and observability of the SSS (DeBruyn 2014, Mannaert, H. and Verelst, J. 2009).

Research Limitations:

The research is theoretical and would benefit from empirical support.

Practical Implications:

This research provides recommendations for the future development and deployment of intelligent agents in smart service systems.

Originality/Value:

This paper presents an evaluation of smart service systems at an operational level. Benefits and limitations of intelligent agents in service support systems are revealed. Results are supported by analytical models of ecostructure decisions.

Key Words:

service ecostructure, service support system, decision analytics, Viable Systems Approach, subjective logic

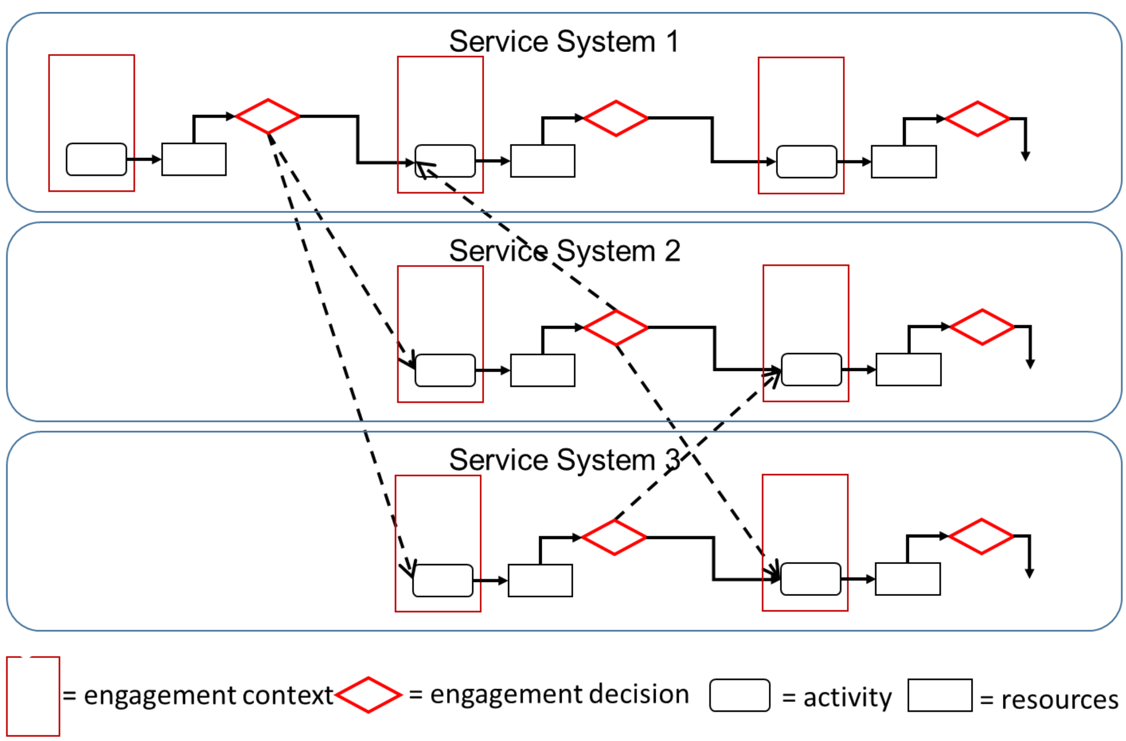
Paper Type:

Research paper – Service Science, Network and Systems Theory.

1 Introduction

This paper defines the concept of a service ecostructure as a precondition for the manifestation of the dynamics of a service ecosystem (Vargo and Lusch, 2016) and derives key features of ecostructures that engender viability of ecosystems (Wieland et al., 2012). To this extent, we build on a model of a service journey as a sequence of engagements (Badinelli 2015) integrating components of a service ecostructure. From this model, principles of subjective logic (Josang 2016) and the implementation of intelligent agents are introduced to the ecostructure model. A fundamental aspect of the research is the exposition of the effects of actor decision making on the service potential of an ecostructure. Badinelli (2015) establishes the role of actors' decision modeling as the subjective determinant of service trajectories through the ecostructure and the emergence of the ecosystem. See Figure 1. The viability of a service ecosystem (Golinelli, 2010; Barile and Polese, 2010) depends on the successful execution of decisions that engage actors in the structural elements of the system (Badinelli, 2015) . The paper introduces subjective logic as a robust tool for modeling engagement decisions that require abductive reasoning with the assistance of expert opinions that could be provided by an intelligent agent (IA).

Figure 1: A service journey via engagement decisions



This paper makes three contributions:

(i) We identify the ecostructure decision as a necessary action by each actor at each stage of the service journey.

(ii) We model the ecostructure decision using the theoretical construct of the multi-armed bandit problem (MAB) for exploration and exploitation.

(iii) We recognize the ecostructure decision as an application of abductive reasoning and we introduce subjective logic as a modeling tool that is uniquely applicable to the ecostructure decision.

We define ecostructure by examining the structure-system paradigm (Barile and Saviano, 2011) based on systems theories. The ecostructure of a service ecosystem is a network of elements that include:

- resources
- actors
- agents

Each element possesses properties relevant to an actor that are defined information variety (Golinelli, 2010). The information variety of each actor/agent consists of :

- categorical values (strong beliefs)
- interpretive schemes (specific of certain disciplines or more general)
- information units

These elements of information provide the actor with knowledge and perspective that assist in making engagement decisions. These elements derive from the experience and knowledge of the actor, which is modified by experience with the service journey. The scope of the actor's education, experience, participation in institutional arrangements (Scott, 2017, Vargo and Lusch, 2016, Siltaloppi et al., 2016) all contribute to and constrain the actor's information variety.

The word "system" is applied in a confusing way in the theory of systems. Every system consists of two aspects: the structure of the system and the transitions that move the system from one state to another. This dichotomy is referred to as the structure-system paradigm. In the literature, the word "system" is applied to both the system and the transition component of the system. To avoid this confusion, we adopt the use of the word "dynamics" to represent the transition aspect of the system. The dynamics, applied to an ecostructure completes the ecosystem. Hence, the service ecostructure is a precondition for the evolution of an ecosystem (Badinelli, Polese, Sarno 2019).

The foundation of this research can be summarized through the following arguments (Badinelli 2015):

- Service dynamics emerge from a service ecostructure through service-journey trajectories.
- Service trajectories consist of a sequence of service activities.
- Service activities are instigated by engagement decisions of actors and agents.
- All value co-creation is generated by service activities.
- Engagement decisions are based on the actor's a priori subjective assessment of the value that can be co-created .
- Therefore, the performance of a service in value co-creation is the outcome of engagement decisions made in the context of an ecostructure.

The methodology of this research integrates several theories and modeling perspectives: service science, Service Dominant Logic (SDL), Viable Systems Approach (VSA), decision modeling and subjective logic. The rest of the paper is organized as follows. In Section 2, features of ecostructure that frame the engagement decision. We probe the engagement decisions further and identify these decisions as two types: ecostructure decisions for exploration of the service landscape and activity engagement decisions for exploitation of value co-creating processes. Section 3 provides an overview of the applicability of a theoretical, decision-modeling framework known as the multi-armed bandit problem (MAB) for the engagement decisions. In Section 4, the basic principles of subjective logic in decision making are introduced in the context of ecostructure decisions supported by an intelligent agent. In Section 5, we apply the subjective logic to examples of ecostructure decisions to demonstrate the performance of an IA-supported decision support system.

2 Service Systems and Ecostructure Decisions

- We begin with some essential definitions. The ecostructure of a service journey is unique to each actor. For each actor we define different types of ecostructures, based on the relevance and accessibility of the ecostructure to the service that the Actor/Agent pursues. Associated with each ecostructure is its corresponding dynamics, these components together forming an ecosystem.
- The <u>**Extended Ecostructure**</u> (first instantiation DeBruyn 2014) is the general set of resources, actors, agents, platforms and information of all types that exist and are known to the Actor/Agent.
- The <u>**Accessible Ecostructure**</u> is the portion of the Extended Ecostructure that is accessible to a particular actor under the institutional and physical constraints that apply to the actor.
- The <u>**Relevant Ecostructure**</u> is the portion of the Accessible Ecostructure that is within the conscious environment of the actor that is judged to be relevant to the service journey of the actor.

- The **<u>Engaged Ecostructure</u>** is the portion of the Relevant Ecostructure that the actor engages for a particular service activity (second instantiation DeBruyn 2014).

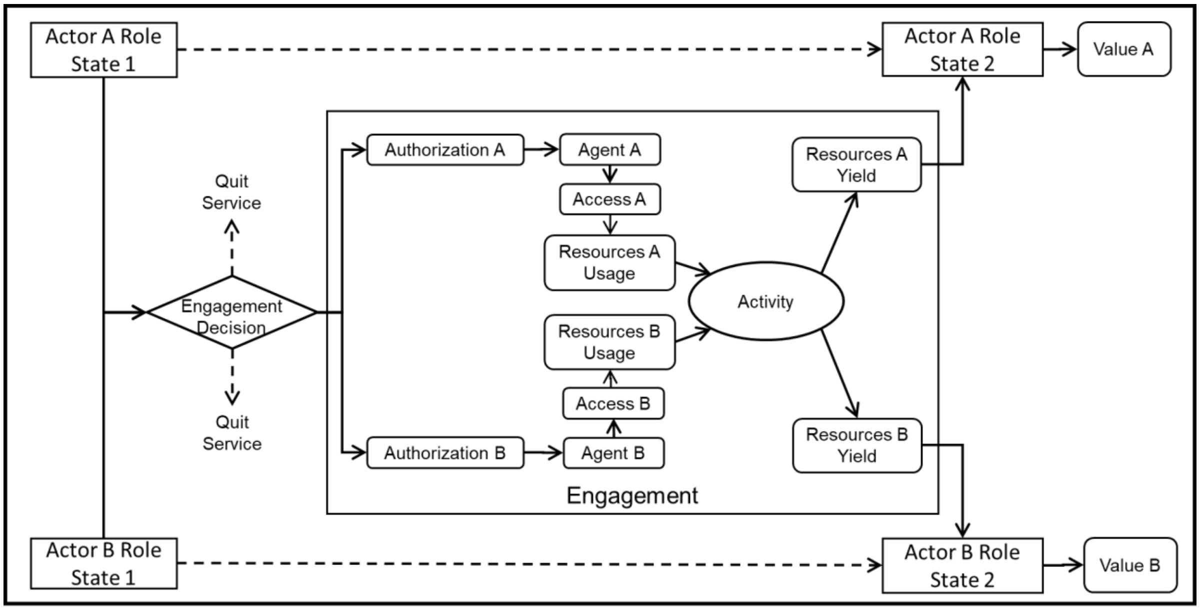
These definitions of ecostructure point out an important aspect of service systems. The Accessible Ecostructure is part of the Extended Ecosystem and the lower levels of ecostructures are parts of subsystems of the Extended Ecosystem. Hence, the Extended Ecosystem represents a system of systems. At each stage of an individual actor's service journey a subsystem of a larger system is engaged. The relevant ecostructure can change at each stage as the requirements of each stage are unique. Furthermore, the fact that the actor in a service ecosystem is intelligent and have the potential to learn, adapt and decide to engage a different ecostructure at each juncture of the service journey.

The service journey for any actor is a sequence of resource-integrating co-creative activities (Badinelli 2015). Each of these activities is initiated by a joint decision of the participating actor/agents to engage in the activity. This engagement can occur only if the Relevant Ecostructures of the participating Actor/Agents intersect as illustrated by Figure 2. For example,

- A student's relevant ecostructure for a given module of a course can consist of a textbook chapter, instructor meetings, YouTube videos, fellow students and web sites.
- A patient's relevant ecostructure for the stage of seeking a diagnosis can consist of several medical web sites, a visit to a physician, advice from friends and family and self-help books.
- A tourist's relevant ecostructure for the stage of planning an itinerary can consist of travel agent consultation, tour-guide publications, airline and hotel web sites, travel reservation web sites and advice from family and friends.

Upon completion of a service activity, each actor receives output resources from which value is extracted. Before the next stage of the journey is engaged, each Actor/Agent has the opportunity to evaluate the activity just completed and learn from it. Actor, possessed of intelligence and value categories, have the opportunity to evaluate the outcomes of each activity in terms of their individual motives, interpretive schema and values. Furthermore, the information units of each actor are expanded with each activity. Hence, the actor can possess new data, information and knowledge with which to continue the service journey. This learning opportunity informs the subsequent engagement decision. In effect, the actor's Relevant and Accessible ecostructures can be modified by the experience of the activity just completed. Accordingly, the actor has the opportunity to re-define these ecostructures prior to the next stage of the service journey.

Figure 2: Engagement among intersecting relevant ecostructures



The Relevant Ecostructure can be specified in terms of service platforms. A service platform is an integration of resources and actor/agents that are enabled, coordinated and constrained by institutional arrangements. Examples of service platforms are a health care clinic, a university, a travel reservation web site, etc. Transitions from one platform to another are made through the actor ecostructuring decisions. Therefore, we extend the model of engagement by breaking down the engagement decision into three generic steps: Engage>Learn>Re-structure. Hence, each stage of a service journey begins with an ecostructuring decision to explore the options of the relevant ecostructure. Once the actor has selected an option, then the engagement decision commits the actor's resources to a service activity.

Restructuring as part of a service journey stage can be considered a co-creative innovation of a service. The restructuration decision by any actor reflects the information units and interpretive schema of the actor as these elements are updated through the experience of a resource-integrating, co-creative activity. Restructuration can result in either a narrowing or broadening of the relevant ecostructure of each actor that participated in the activity. In effect, ecostructuring is adaptation in context. Therefore, the modeling of ecostructuring decisions provides a fertile ground for service research.

At any given stage of the service journey, after the ecostructure is co-created, the execution of the service activity occurs. The service activity represents the dynamic, resource-integrating interactions of the engaged ecostructure. The service ecostructure that executes the service activity can be re-defined and re-created at each stage of the journey.

The significance of this view is the paradigm change that it represents. Instead of viewing a service journey as the evolution of a service ecosystem, we view the service journey as the evolution of service ecostructures with embedded evolution of service ecosystems. In other words, there is a two-level hierarchy of systems or a system of systems. DeBruyn (2014) refers to this hierarchy in terms of the re-structuring decision as a first instantiation and the ecosystem engagement as the second instantiation.

Our interest is in the first level of the hierarchy. The evolution of service ecostructures involves a complicated interactions among information resources. Furthermore, these interactions are complex due to the fact that they involve decision making by actors and agents. Therefore, we must make decision models the core of the ecostructure evolution model.

3 The multi-armed bandit problem

The MAB problem is a classic decision model for cases of an actor who face multiple options, known as arms from the analogy of a gambler faced with multiple slot machines, for repetitive engagements. Each engagement holds the possibility of value cocreation, but the actor does not possess perfect information of the potential of each option. The only way to learn the potential of an option is to engage the option. Consequently, the optimal journey for the actor is a combination of exploration and exploitation. The strategy for the sequential decision process of selecting options involves a tradeoff between exploration and exploitation. The standard MAB model is presented below.

Notation:

$t \coloneqq$ ***round*** number of engagements of a journey

$e \coloneqq$ index for the number of engagements in an alternative

$E \coloneqq$ ***environment*** class = the set of bandits = the relevant ecostructure

$k \in K \coloneqq$ set of ***alternative*** systems (aka arms) for ***engagement***s for the ***Actor***.

For a service journey, $K_t \in E$ is a function of t because the accessible, relevant ecostructures change during the service journey as the actor learns and adapts.

$X_{k,e} :=$ random variable for the ***reward*** (***value)*** of engaging in alternative k for the e^{th} time.

Note: For a service journey $X_{k,e}$ is a vector.

Assumption 1: Alternative systems are assumed independent. The reward in any alternative is independent of the rewards for all other alternatives.

Note: For a service system, rewards across arms are likely to be correlated as they represent the value co-created with the actor.

Assumption 2: The reward function for any given alternative is stationary in the round t and engagement e. The actor's estimates of the probability distribution of the rewards changes through Bayesian learning, but the reward function does not change.

Note: For a service system, rewards for successive engagements change.

Assumption 3: The actor learns and modifies the probability distribution of the reward of an alternative with each engagement in that alternative. Hence, the sequence of estimated values for a system is autocorrelated in the number of engagements but is independent of the number of rounds.

X_t ≔ random variable of the value of the engagement of round t

a_i ≔ the action (decision) made by the Actor in round i

$H_{t-1} = \{a_1, x_1, a_{2,} x_2, \ldots a_{t-1}, x_{t-1}\}$ ≔ **history** of the bandit policy up to round t

$\pi = \{\pi_1, \pi_2, \pi_3, \ldots\}$ ≔ **policy** for a sequence of engagements

$\pi_t(H_{t-1}) = a_t$ for all $t > 0$ where $a_t = k$ for some $k \in K$

Π ≔ set of available policies called the ***competitor class***

A policy describes a sequential decision process (SDP). A policy embodies *learning* and *adaptation*, *exploration* and *exploitation.* Learning changes the probability distribution of $X_{k,e}$.

$s_k(\pi)$ ≔ ***stopping rule*** for alternative k = the number of consecutive times that alternative k starting at iteration $t = 1$ is chosen before switching.

The analogy of the MAB problem to the engagement decisions of the service journey is apparent. However, the service journey introduces some complications to the MAB. First, a service engagement can take place at two different levels: an exploratory engagement to discover the requirements and capabilities of the option and a resource commitment to performing an activity with the option. The classic MAB recognizes only one type of engagement with each option. The ecostructuring engagement is for the purpose of learning and adaptation. Second, as the journey progresses, the ecostructuring decision must be repeated as the journey leads to expanding knowledge of the actor and changing requirements and capabilities of the options. In the classic MAB, the options are stationary in terms of their costs and benefits. Third, the cost of exploratory engagements, such as perusing a web site or visiting a professional service provider, includes the actor's time and, potentially, out-of-pocket expense. In the classic MAB, these costs are considered low enough to allow many repeated engagements, but in typical service journeys, actors usually can endure only a few exploratory attempts at each stage.

4 Subjective Logic

Exploratory engagements, by definition, are learning processes. As the actor does not have sufficient knowledge of the upcoming stage of the service journey and the capabilities and requirements of the optional platforms for the engagement, the actor is charged with the fundamental procedures of the scientific method: abductive reasoning for hypothesis generation, inductive reasoning for hypothesis validation and deductive reasoning for application of the validated hypothesis.

Deductive inference is the logical kind of inference found in mathematics and arguments that justify a conclusion and can be stated as follows. Proposition *a* ***implies*** proposition *b,* proposition *b* is derived from proposition *a,* because of an established law that makes proposition *b* a consequence of proposition *a*. In a probabilistic sense, we can claim $P(b|a) = 1$. Deduction can take the form of a statement about a sample *(b)* from knowledge of a population *(a).*

Inductive inference is based on empiricism and establishes belief in a hypothesis based on the statistical measures of a sample and can be stated as follows. Proposition *a* (hypothesis) ***infers*** proposition *b* (sample statistic) because empirical evidence correlates *b* with *a*. $P(b|a)$ measures our belief in *a*, according to classical statistics. Induction can be a statement about a population based on knowledge of a sample.

Hypothesis generation, is the basic process of the ecostructure decision. Abduction begins with a ***hypothesis*** that is derived from an ***explanation***. The explanation can be based on data, intuition, judgment. The explanation is not known to be true or correct. When there is more than one explanation, we have multiple hypotheses. Proposition *b* (examples, case, intuition, analogy, explanation, base state) ***abduces*** proposition *a* (hypothesis) because our intuition about proposition *a* indicates that it is possible. $P(a|b)$ measures our belief in *a*, according to Bayesian statistics or belief functions. Abductive reasoning commits the fallacy of the converse, converse error, affirming the consequent, assuming sufficiency from necessity. Abduction can be a statement about a population based on knowledge of a similar population, cursory knowledge or intuition.

The nature of uncertainty separates abductive reasoning from inductive and deductive reasoning. We review the different forms of uncertainty below:

- Determinism: The absence of uncertainty, sometimes referred to known-knowns.
- Alearatic uncertainty: Conventional, statistical uncertainty due to natural randomness of a process, hidden variables, unexplained variation/variability, sometimes referred to as known-unknowns. The nature of the randomness is known, so the probability distribution is known. The model specification is not in question.

- Epistemic uncertainty: Uncertainty due to fuzziness or lack of knowledge about the process that gave rise to data, sometimes referred to as unknown-knowns. Assumptions about the probability distributions cannot be made. More specifically, model epistemic uncertainty is the error due to ground truth not being within the hypothesis set. It is the part of epistemic uncertainty due to lack of knowledge about the model that generates the data. There is no single specification/identification of the model for the random variable in question, and the modeler is unaware of the correct model. Approximation epistemic uncertainty is the part of epistemic uncertainty due to inaccuracy in selecting the hypothesis/model due to sampling error or bias.
- Knightian Uncertainty refers to the case of unknown-unknowns and reflects ignorance of one's ignorance.

The Johari window in Table 1 summarizes the forms of uncertainty.

Table 1: Johari Window

Linguistic Precision\Artifact	**Measured**	**Not Measured**
Precise	Known-Known	Known-Unknown
Fuzzy, unknowable	Unknown-Known	Unknown-Unknown

The only difference between aleatory and epistemic is model validation. If a model is not validated, then there can exist multiple models of the phenomenon. If a model is validated, then there is only sampling error in the estimation of the parameters of the model. However, model validation always carries hypothesis risk (Type 1 error). Therefore, there is always some epistemic uncertainty.

Subjective logic is a generalization of probabilistic logic. The logic is based on subjective opinions about the actor's options instead of probabilities. In this context, the options are hypotheses about the value of available engagements in the relevant ecostructure. Subjective logic can be used for modeling abductive reasoning, Bayesian networks, Trust networks and decision making under uncertainty and vagueness. The atomic formula of subjective logic is the opinion. An opinion consists of an actor's belief distribution, uncertainty and a source of relevant knowledge known as the base rate distribution. The base rate is the role played by an intelligent agent.

Uncertainty in subjective logic can be both aleatory and epistemic. The uncertainty occurs at two levels. First order uncertainty is the typical aleatoric uncertainty about the hypothesis. Second order uncertainty represents the vacuity of evidence:

- Aleatory uncertainty regarding the lack of evidence to support the hypothesis.

- Epistemic uncertainty about the knowledge behind the explanation of the hypothesis.
- Trust in the source of evidence or explanation for the hypothesis.

A subjective opinion incorporates second order uncertainty applied to the first order uncertainty. In other words, the subjective opinion is expressed as a probability distribution of a probability distribution.

Basic structure of an opinion

$\mathcal{H} \coloneqq$ a domain of hypotheses, a discrete state space of states, propositions, hypotheses or model specifications. The elements of the domain are mutually exclusive and collectively exhaustive. The elements of the domain are assumed to be crisp.

$\mathcal{P}(\mathcal{H}) \coloneqq$ the power set of $\mathcal{H}$

$\mathcal{R}(\mathcal{H}) = \mathcal{P}(\mathcal{H})\backslash\{\{\mathcal{H}\},\{\emptyset\}\} \coloneqq$ the hyperdomain of $\mathcal{H}$

$\mathcal{C}(\mathcal{H}) = \{h \in \mathcal{R}(\mathcal{H}): |h| > 1\} \coloneqq$ the composite set of $\mathcal{H}$

Default Base Rate (aka Relative Atomicity) of a composite value $\coloneqq \frac{|\mathcal{C}|}{|\mathcal{H}|}$

Variable over the hypotheses

$X \coloneqq$ the name of the random variable over the hypotheses in $\mathcal{R}(\mathcal{H})$

$\mathcal{X} \subseteq \mathbb{R} \coloneqq$ the domain of X

$x \in \mathcal{X} \coloneqq$ a value of X

Subjective Opinion

$b_X \coloneqq$ subjective joint belief mass distribution over the possible states , the belief that that x is true, membership function, truth measure.

Belief mass expresses support for the truth of any one of the singleton values in a composite value.

Sharp Belief: Belief mass for a singleton

Vague Belief: Belief mass for a composite value

$a_X \coloneqq$ joint base rate distribution, the non-informative prior probability distribution of X, expert opinion based on background information, data, theory, intuition. Non-informative means that there is no direct empirical support for the base rate, but there can be more general support for the subject domain

$a_X \in [0,1]$

$\sum_{x\in\mathcal{X}} a_X(x) = 1$

$a_X(x|x_i) = \frac{a_X(x\cap x_i)}{a_X(x_i)},\ x, x_i \in \mathcal{R} \coloneqq$ Relative Base Rate

u_X ≔ scalar uncertainty mass, epistemic uncertainty about the opinion, a measure of the vacuity of evidence, the lack of confidence in probabilities about the states $x \in \mathcal{X}$

$u_X \in [0,1]$

$b_X(x), u_X, a_X(x) \in [0,1]$

A ≔ a source of an opinion. All sources have a common semantic understanding of the domain.

w_X^A ≔ an opinion of actor A over the variable X

$w_X^A = (b_X, u_X, a_X)$ a tuple

The subjective logic model:

$u_X + \sum_{x \in \mathcal{H}} b_X(x) = 1$

$\sum_{x \in \mathcal{H}} a_X(x) = 1$

Vacuous opinion ≔ $u_X = 1$

Uncertain opinion ≔ $0 < u_X < 1$

Dogmatic opinion ≔ $u_X = 1$

Absolute opinion ≔ $u_X = 1$ and $b_X(x) = 1$ for some single value x

Aleatory opinion: an opinion that is based on aleatory uncertainty

Epistemic opinion: an opinion based on epistemic uncertainty

First order probabilities

p_X ≔ probability distribution over the singleton states $x \in \mathcal{X}$.

$p_{\mathcal{R}}$ ≔ probability distribution over the composite states $x \in \mathcal{R}$

$p_X(x) = \sum_{x_i \in \mathcal{R}} a_X(x|x_i) p_R(x_i)$

Projected Probability Distribution

A projection of an opinion adds or removes uncertainty according to the balance of belief and disbelief of the base rate distribution. Projected Probability Distribution = Uncertainty Minimizing Opinion: The projected opinion that has zero uncertainty. The projected probability distribution represents how the actor's beliefs would be translated to a state of no uncertainty – the translation being consistent with the probability distribution of the base rate.

$P_X :=$ projected probability distribution of x after updating the opinion with knowledge of base state (prior, expert opinion) and exploratory data.

$P_X(x) = b_X(x) + a_X(x)u(x), \forall x \in X$

Uncertainty Maximizing Opinion: The opinion with the highest uncertainty that still projects onto P_X. The Uncertainty Maximizing opinion is found by increasing uncertainty until one of the belief masses for one of the singleton values is zero. Epistemic opinions (which cannot be supported by data) must be uncertainty maximizing opinion.

<u>Second-order probabilities</u>

The second-order probabilities are probability distributions. The parameter $p_X(x)$ for each Bernoulli random variable for each $x \in X$ has a distribution due to the aleatoric or epistemic uncertainty in this parameter. This distribution is the second-order distribution. We assume that the projected probability distribution is assumed to be the mean values of the probability distribution of the second-order probability distribution over the probabilities of the singleton state probabilities. Second-order probability is a pdf over the first-order pdf. For each opinion there is a unique secondary pdf. The Dirichlet probability distribution is uniquely suited to representing the second-order probabilities.

<u>Dirichlet Distribution</u>

Strength Parameters: Dirichlet Distribution has a distribution of parameters $\alpha_X(x), \forall x \in X$

$Dir(p_X; \alpha_X) :=$ Dirichlet Distribution = the second-order probability distribution of belief

$$Dir(p_X; \alpha_X) = \frac{\Gamma(\sum_{x \in X} \alpha_X(x))}{\prod_{x \in X} \Gamma(\alpha_X(x))} \prod_{x \in X} p_X(x)^{(\alpha_X(x)-1)}$$

$$E_X(x) = \frac{\alpha_X(x)}{\sum_{x_i \in X} \alpha_X(x_i)}$$

$$Var_X(x) = \frac{\alpha_X(x)\left(\sum_{x_i \in X} \alpha_X(x_i) - \alpha_X(x)\right)}{\left(\sum_{x_i \in X} \alpha_X(x_i)\right)^2 \left(\sum_{x_i \in X} \alpha_X(x_i) + 1\right)}$$

If the actor is aware of the base rate and the projected distribution, then the actor is motivated to investigate the options according to the projected distribution as it represents a compromise between the actor's beliefs and the base rate. As the actor explores options, the actor accumulates evidence with which the actor updates the belief distribution and reduces uncertainty.

$W :=$ unit of evidence weight, $W \approx 2$

$r_X :=$ evidence vector

$\alpha_X(x) = r_X(x) + a_X(x)W, \forall x \in X$

$Dir^e(p_X; r_X, a_X(x)) :=$ evidence-based Dirichlet distribution = the Dirichlet distribution with α_X evaluated according to the updating expression above.

$$P_X(x) = E_X(x), \forall x \in X$$

$$\Rightarrow b_X(x) + a_X(x)u_X = \frac{\alpha_X(x)}{\sum_{x_i \in X} \alpha_X(x_i)} = \frac{r_X(x) + a_X(x)W}{\sum_{x_i \in X} r_X(x_i) + W}$$

$$\Rightarrow b_X(x) = \frac{r_X(x)}{\sum_{x_i \in X} r_X(x_i) + W}, \forall x \in X \, , u_X = \frac{W}{\sum_{x_i \in X} r_X(x_i) + W}$$

and

$$u_X + \sum_{x \in \mathcal{H}} b_X\,(x) = 1$$

$$\sum_{x \in \mathcal{H}} a_X\,(x) = 1$$

The procedure for performing exploration with the assistance of an intelligent agent providing the base rate follows. We assume that the actor has a fixed budget for number of explorations, and wishes to minimize uncertainty through exploratory, ecostructuring decisions.

Ecostructuring procedure

1. Abductive, find support for alternate hypotheses
2. Enter beliefs
3. Engage IA for base rate
4. Calculate projected probability as best abductive probabilities that combine beliefs and base rate
5. Explore based on the highest projected probability. EMV criterion
6. Decision tree: outcome is binary, cost to explore, learning incorporated in data, update priors, update beliefs, reduce uncertainty
7. If uncertainty < threshold or number of explorations = limit, then exploit option with highest belief.
8. Else, go to step 4

5 Conclusions

This paper provides an exposure to subjective logic as a modeling tool for service ecostructuring decisions. Clearly, this paper has only scratched the surface of subjective logic and its potential for modeling service journeys. We conclude with some examples that illustrate the application of subjective logic and the manner in which the intelligent assistant and the actor use this logic to arrive at a satisfactory ecostructuring decision. Table 2 shows the evolution of opinion assisted by an IA.

The initial condition shows the base rate and the actor's belief distribution over three options. We assume that the actor's beliefs are supported by some kind of data, information, intuition or experience that we represent as the prior support for the actor's beliefs. The reader can see how the projected probability distribution represents a zero-uncertainty opinion that is a compromise between the base rate and the actor's belief distribution. Exploring the option with the highest projected probability, the actor records the experience with this engagement. In this example, we simulate the actor having had a negative experience, and updates the information state accordingly. The belief distribution is updated accordingly, and the uncertainty is reduced. The updated projected probability now indicates that the second option is most preferred. After exploring the second option, we simulate the actor having had a positive experience. Finally, when the uncertainty is reduced to 25%, the actor is satisfied with choosing the second option.

Table 2: Scenario of the ecostructuring procedure

		Option 1	Option 2	Option 3	Uncertainty/ Information State	Base Norm/ Projection Norm
	Base Rate	0.50	0.30	0.20		
Initial Condition	Actor Prior Support	1.00	1.00	1.00	3.00	
	Belief	0.20	0.20	0.20	0.40	0.333
	Projected Probability	0.40	0.32	0.28		0.133
Exploration 1	Actor Priors	0.50	1.75	1.75	4.00	
option1	Belief	0.08	0.29	0.29	0.33	0.746
bad experience	Projected Probability	0.25	0.39	0.36		0.246
Exploration 2	Actor Priors	1.25	1.96	1.79	5.00	
option 2	Belief	0.18	0.28	0.26	0.29	0.507
	Projected Probability	0.32	0.37	0.31		0.147
Exploration 3	Actor Priors	1.93	2.19	1.88	6.00	
option 2	Belief	0.16	0.37	0.22	0.25	0.573
	Projected Probability	0.28	0.45	0.27		0.133

An interesting approach to evaluating the progress of the ecostructuring procedure is the comparison of the actor's belief distribution to the base rate distribution and the projected probability distribution. To make this evaluation we define two norms. The base rate norm (BRN) measures the distance between the actor's belief distribution, normalized to a probability distribution for uncertainty, and the base rate distribution. The projected probability norm (PPN) measures the distance between the actor's belief distribution, normalized to a probability distribution for uncertainty, and the projected probability distribution. These norms reflect the extent to which the actor is consonant with the advice from the IA.

$$\|BRN\| = \sum_{x_i \in X} \left| a_X(x_i) - \frac{b_X(x_i)}{1-u_X} \right|$$

$$\|PPN\| = \sum_{x_i \in X} \left| P_X(x_i) - \frac{b_X(x_i)}{1-u_X} \right|$$

A simulation of the example of Table 2 that generated 1000 values of the actor's updated information state for option 1. Figure 3 shows the variety of values for the norms as a function of the actor's updated information state after exploring the first option in the first exploration. In this example, a value above one for the experience indicates a positive experience with the option and a value below 1 indicates a negative experience.

Figure 3: Norms as a function of option 1 information state update

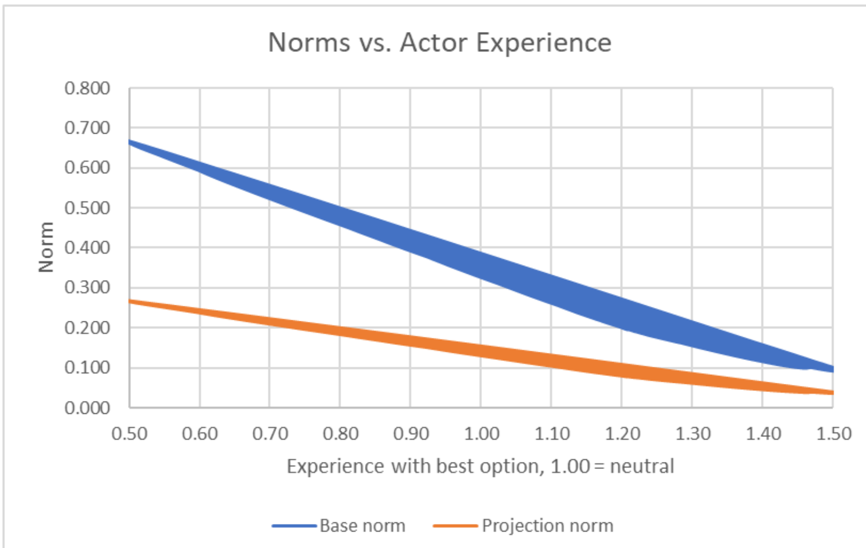
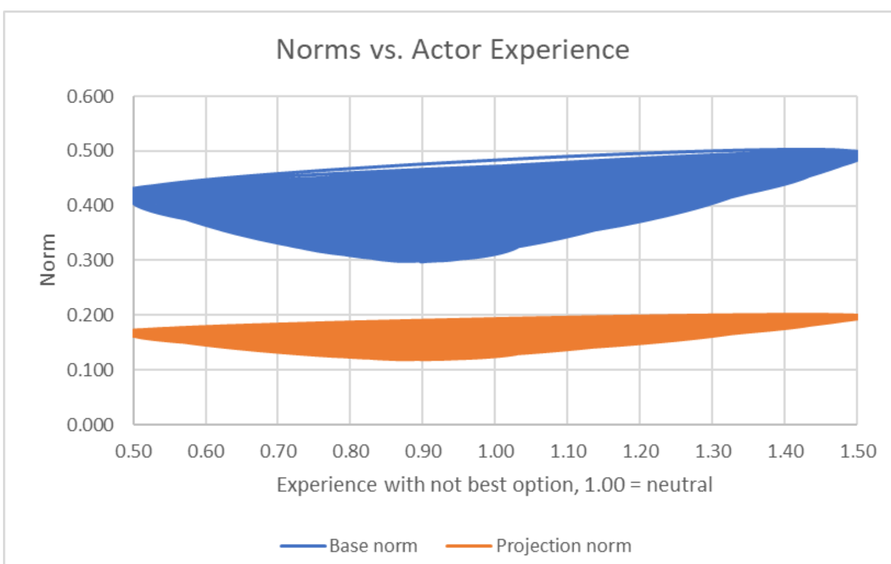


Figure 4: Norms as a function of option 2 information state update



References

Badinelli, R., (2021). “Service Support Systems for Ecostructuring Decision Support”, to appears in Research Handbook for Services Management, Mark Davis, Ed., Elgar Publishing.

Badinelli, R. 2015. Modeling Service Systems, Business Expert Press.

Badinelli, R. (2013). “Viability and service evolution”, presented in invited session at the INFORMS Annual Meeting, Minneapolis, MN.

Badinelli, R. (2012). “Fuzzy modeling of service system engagements”, *Service Science*, Summer, vol. 4, pp. 135-146.

Badinelli, R., Polese, F., Sarno, D. (2019). “The emergence of service ecosystems from service ecostructure”, working paper.

Badinelli, R., Barile, S., Ng., I., Polese, F., Saviano, M., Di Nauta, P (2012). “Viable Service Systems and Decision Making in Service Management”, *Journal of Service Management ,* Vol. 23 Iss: 4, pp.498 - 526.

Barile, S. and Polese, F. (2010), “Smart Service Systems and Viable Service Systems”, *Service Science*, Vol. 2 No.1, pp. 21-40.

De Bruyn, P. (2014). Generalizing normalized systems theory: Towards a foundational theory for enterprise engineering, Ph.D. dissertation, University of Antwerp.

Golinelli, G. M. (2010). *Viable Systems Approach (VSA) Governing Business Dynamics*. Milan, Wolters Kluwer Italia Srl.

Josang, Audun (2016). Subjective Logic: A Formalism for Reasoning Under Uncertainty, Springer, Switzerland.

Langley, D., van Doorn, J., Ng, I., Stieglitz, S., Lazovik, A., Boonstra, A. (2020). “The Internet of Everything: Smart things and their impact on business models”, *Journal of Business Research*, https://doi.org/10.1016/j.jbusres.2019.12.035

Lattimore, T., Szepesvari, C., *Bandit Algorithms*, https://tor-lattimore.com/downloads/book/book.pdf, accessed June, 2021.

Mannaert, H. and Verelst, J. (2009). Normalized systems: re-creating information technology based on laws for software evolvability, Koppa.

Polese, F. (2018). Successful Value Co-creation Exchanges: A VSA contribution, in Barile, S., Pellicano, M. and Polese, F. (eds.), Social Dynamics in a Systems Perspective, New Economic Windows, Springer, Cham, 19-37.

Polese, F., Pels, J., Tronvoll, B., Bruni, R. and Carrubbo, L. (2017). A4A relationships, Journal of Service Theory and Practice, 27, 5.1040-1056.

Siltaloppi, J., Koskela-Huotari, K. and Vargo, S.L. (2016). Institutional complexity as a driver for innovation in service ecosystems, Service Science, 8, 3.333-343.

Vargo, S.L. and Lusch, R.F. (2008). Service-dominant logic: continuing the evolution, Journal of the Academy of marketing Science, 36, 1.1-10.

Vargo, S.L. and Lusch, R.F. (2011). It's all B2B… and beyond: Toward a systems perspective of the market, Industrial marketing management, 40, 2.181-187.

Vargo, S.L. and Lusch, R.F. (2016). Institutions and axioms: an extension and update of service-dominant logic, Journal of the Academy of Marketing Science, 44, 1.5-23.

Vargo, S.L. and Lusch, R.F. (2017). Service-dominant logic 2025, International Journal of Research in Marketing, 34, 46-67.

Wieland, H., Polese, F., Vargo, S.L. and Lusch, R.F. (2012). Toward a service (eco)systems perspective on value creation, International Journal of Service Science, Management Engineering, and Technology, 3, 3.12-25.

Yi, Y. and Gong, T. (2013). Customer value co-creation behaviour: scale development and validation, Journal of Business Research, Vol.