

An AI Aid for General Decision-Making Assistance

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Abstract

This paper introduces a human-AI collaborative system for decision making. Our AI aid acts as a decision-making assistant and guide, engaging in a well-structured natural language dialogue with nonprofessional stakeholders. It guides users through evaluating either multiple alternatives, such as selecting the most suitable among several cars or homes, or a single option, like assessing the suitability of a specific job offer. In all cases, our goal is to create a scalable and intuitive human-AI partnerships across diverse application domains. In its role as a decision-making assistant, the AI aid can also serve as a personalized recommender/advisor. The functionality of the proposed decision-making aid can be used for the development of an independent AI agent, capable of providing decision-making support to humans and other AI agents.

Introduction

Human commonsense decision making is observable, measurable, modelable, and explainable. It consists of identifying a set of alternatives/objects, evaluating each alternative, and selecting the most suitable alternative. Each alternative is characterized by a set of suitability attributes. Then, each attribute is separately evaluated, creating a graded percept of satisfaction. All such graded percepts are logically aggregated resulting in the aggregated percept of the overall suitability. That is the compound overall degree of satisfaction of stakeholder's requirements. So, the natural human logic processes graded percepts and it is a fundamental observable component of human commonsense decision making.

The observable and measurable process of human natural commonsense logical reasoning is used to develop the mathematical infrastructure called Graded Logic (Dujmović). This infrastructure is used as the essential component of the LSP (Logic Scoring of Preference) evaluation method (Dujmović 2018). Both the Graded Logic and the LSP method are used for solving a spectrum of professional evaluation, optimization, and selection problems. Unsurprisingly, such methodology requires professional preparation and is not accessible to nonprofessional users.

Since the LSP methodology is derived from observable human reasoning, it should be possible to create AI tools that make this methodology accessible to general nonprofessional users. An initial step in that direction is made in personalized hotel recommender systems (Solano-Barliza at al. 2024). This system is limited to hotel recommendations and based on a fix structure of the LSP criterion.

In this paper, our goal is to propose a general decision-making aid that can be used by nonprofessional users. Our system (called LSPrec) is based on the LSP method, but uses strictly verbalized queries, accessible to all users. We first present a short survey of properties of Graded Logic, and then present the functionality of LSPrec using a simple example of a job selection process.

Graded Logic

Graded Logic (Dujmović, Dujmović 2018, Dujmović 2019) is a fully continuum-valued propositional logic. It is modeling the natural human commonsense logic where the fundamental logic percepts are truth, importance, simultaneity, and substitutability. These percepts are graded, i.e., they all belong to the standard unit interval $[0,1]$. The intensity of these percepts is usually identified using linguistic labels. The intensity of importance can be selected from the rating scale [lowest < low < medium < high < highest]. The percepts of truth, satisfaction, and suitability usually belong to the scale [unacceptable < very poor < poor < below average < average < above average < good < very good < excellent].

The intensity of simultaneity (conjunction) is defined as the conjunction degree or andness (α), where the pure conjunction $x_1 \wedge \dots \wedge x_n = \min(x_1, \dots, x_n)$ has the andness $\alpha = 1$ (Dujmović 2018, Dujmović and Torra 2023). The intensity of substitutability (disjunction) is defined as the disjunction degree or orness (ω), where the pure disjunction $x_1 \vee \dots \vee x_n = \max(x_1, \dots, x_n)$ has the orness $\omega = 1$. Andness and orness are complementary: $\alpha + \omega = 1$. The arithmetic mean $(x + y)/2 = [(x \wedge y) + (x \vee y)]/2$ is located in the

middle point between the pure conjunction and the pure disjunction and has the andness equal to orness: $\alpha = \omega = 0.5$. That indicates the simultaneous presence of graded conjunction and graded disjunction in human reasoning. Operators that have predominantly conjunctive properties satisfy $\alpha > 0.5 > \omega$ and operators that have predominantly disjunctive properties satisfy $\alpha < 0.5 < \omega$.

In the graded propositional calculus, we use a general logic function called Graded Conjunction/Disjunction, $GCD(\mathbf{X}; \mathbf{W}, \alpha)$, $\mathbf{X} = (x_1, \dots, x_n)$, $\mathbf{W} = (w_1, \dots, w_n)$, $0 \leq x_i \leq 1$, $0 < w_i < 1$, $i = 1, \dots, n$, $n > 1$, and $w_1 + \dots + w_n = 1$. GCD unifies conjunctive and disjunctive logic properties and enables continuous transition from conjunction to disjunction based on the value of andness α . This property is called andness-directedness (Dujmović and Torra 2023).

The GCD function is used in logic structures of aggregation of suitability degrees. There are seven types of basic logic aggregators: five of them are the special cases of GCD, and two are the partial absorption aggregators. The special cases of GCD are: the hard graded conjunction ($\alpha \geq 0.75$) denoted HC, the soft graded conjunction ($0.5 < \alpha < 0.75$) denoted SC, the logic neutrality ($\alpha = 0.5$) denoted A, the soft graded disjunction ($0.25 < \alpha < 0.5$) denoted SD, and the hard graded disjunction ($\alpha \leq 0.25$) denoted HD. Hard aggregators support annihilators: HC gives the result 0 if any input is 0, and HD gives the result 1 if any input is 1. Soft aggregators do not support annihilators. Each of basic GCD aggregators has three levels of intensity: low is denoted “-”, and high is denoted “+”. These aggregators have the following simple verbal interpretations:

- HC+, HC, HC- : we must have *all* input requirements highly satisfied (this is a high level of simultaneity).
- SC+, SC, SC- : it is desirable to have (but not necessary) *most* inputs highly satisfied.
- A: we want inputs satisfied in a balanced way where simultaneity and substitutability are equally present.
- SD-, SD, SD+ : it is desirable to have *some* highly satisfied inputs.
- HD-, HD, HD+ ; it is enough to have *any* input highly satisfied (this is a high level of substitutability)

These aggregators are used to compose the conjunctive partial absorption (CPA) and the disjunctive partial absorption (DPA). Both CPA and DPA have two inputs denoted primary (x) and secondary (y). In the case of CPA, the primary input is mandatory (must be satisfied) and the secondary input is optional (desirable but not mandatory). In the case of DPA, the primary input is sufficient to satisfy user requirements, and the secondary input is optional (desired, but not sufficient to satisfy requirements). In both cases, if the primary input is partially satisfied ($0 < x < 1$), then the secondary input $y = 0$ causes a penalty P (Output = $x - P$). Similarly, if the primary input is partially satisfied

($0 < x < 1$), then the secondary input which is completely satisfied ($y = 1$) causes a reward R (Output = $x + R$). The desired values of penalty and reward are the regulating parameters that the user selects to adjust desired logic properties of the CPA and DPA aggregators.

LSP Method and a General Decision-Making Aid and Recommender

The LSP method, supported by the LSP.NT software tool, consists of 5 steps: (1) the identification of stakeholder and the object of evaluation, (2) the development of suitability attributes, (3) the specification of attribute criteria, (4) the specification of graded logic aggregation structure for computing the overall suitability of the evaluated object, and (5) the cost/suitability analysis (Dujmović 2018).

The functionality of the proposed LSPrec decision-making aid and recommender system is presented in Figs. 1-4 and Tables 1-5 using a simplified example of job selection. We assume that the stakeholder is an employee who has a current salary which is insufficient and unacceptable. The stakeholder is looking for a new job that could provide up to 50% increase of the starting salary,

The development of the suitability attribute tree is shown in Fig. 1. The job offer evaluation model consists of two basic components: the monetary compensation, and the main characteristics of the offered job. Each of these components is further decomposed until the user reaches components that cannot be further decomposed. These are the leaves of the suitability attribute tree, or the suitability attributes shown in Fig 2.

For each suitability attribute it is necessary to create an evaluation criterion, and five such criteria are shown in Table 1. Each criterium must have a precise specification of the evaluation process. For example, the criterion 1211 (average work week) shows that the stakeholder is fully satisfied with the work week that is less than or equal to 40 hours. In the case of 50 hours, the degree of satisfaction is 80%; so, in this case, the degree of truth of the statement “I am fully satisfied with the work week” would be 0.8. Finally, the work week of 72 hours or more is completely unacceptable. This criterion can be graphically presented as shown in Fig. 3. We can also use a very compact vertex notation, which is based on the sequence of breakpoints based on increasing values of the attribute value: $\text{Crit}(\text{Average work week [h]}) = \{(40, 100), (50, 80), (72, 0)\}$. Of course, for all values between the breakpoints we use the linear interpolation (e.g., for the average work week of 45 hours, the stakeholder satisfaction would be 90%). The presented attribute criteria yield 5 degrees of truth that must be aggregated, as shown in Table 2 and Fig. 4.

1 JOB

11 Monetary compensation

111 Offered starting salary [%]

112 Anticipated 3-year salary [%]

12 Main characteristics of the job

121 Total time at work

1211 Average work week [h]

1212 Daily commute time [min]

122 Attractiveness of job [0..8]

Figure 1. The suitability attribute tree

1. Offered starting salary [%]
2. Anticipated 3-year salary [%]
3. Average work week [h]
4. Daily commute time [min]
5. Attractiveness of job [0..8]

Figure 2. The list of suitability attributes

111		Offered starting salary [%]
Value	%	Evaluation is based on the following relative salary: Srel = 100*Snew/Sold where: Snew = offered new starting salary Sold = salary at the current job
100	20	
150	100	
112		Anticipated 3-year salary [%]
Value	%	Evaluated as the following relative anticipated salary: RAS = 100*A/Snew where: A = anticipated 3-year salary Snew = the offered starting salary
100	0	
130	100	
1211		Average work week [h]
Value	%	Average work week time, measured in hours: Time <= 40 : standard workload 50 h = high load: 5 days * 10 hours 72 h = startup mode: 6 days * 12 hours
40	100	
50	80	
72	0	
1212		Daily commute time [min]
Value	%	Total average daily commute time measured in minutes: 0 = working online from home 30 min = 2 * 15 min (working close to home) 90 min = 2 * 45 min (not acceptable)
0	100	
30	80	
90	0	
122		Attractiveness of job [0..8]
Value	%	Evaluated using the following rating scale: 0 = lowest, 1 = very low, 2 = low, 3 = medium-low, 4 = average, 5 = medium-high, 6 = high, 7 = very high, 8 = highest
0	0	
8	100	

Table 1. Suitability attribute criteria in detailed LSP.NT form (Dujmović 2018)

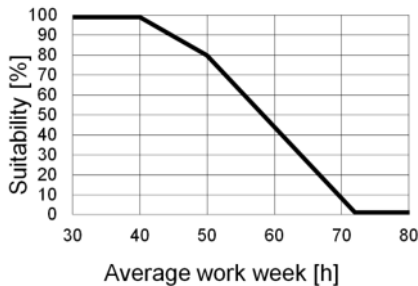


Figure 3. Graphic form of the average work week criterion

111	Starting salary [%] {(100, 20), (150, 100)}	M	11 Monetary compensation		55	Job
112	Anticipated 3-year salary [%] {(100, 0), (130, 100)}	O	CPA: P=20%, R=10%			
1211	Average work week [h] {(40, 100), (50, 80), (72, 0)}	75	121 Total time at work	M	45	HC
1212	Daily commute time [min]: {(0, 100), (30, 80), (90, 0)}	25	HC-			
122	Attractiveness of job [0..8] {(0, 0), (8, 100)}		O	CPA: P=20%, R=10%		

Table 2. The complete LSP criterion in a tabular form

1 [HC] JOB

11 [55%; CPA: P=20%, R=10%] Monetary compensation

111 [MAN] Offered starting salary [%]: {(100,20), (150,100)}

112 [OPT] Anticipated 3-year salary [%]: {(100,0), (130,100)}

12 [45%; CPA: P=20%, R=10%] Main characteristics of the job

121 [MAN; HC-] Total time at work

1211 [75%] Average work week [h]: {(40,100), (50,80), (72,0)}

1212 [25%] Daily commute time [min]: {(0,100), (30,80), (90,0)}

122 [OPT] Attractiveness of job [0..8]: {(0,0), (8,100)}

Figure 4. The LSP criterion in the compact LSP.NT form

Id	Attribute	NewJob1	NewJob2	OldJob
	Cost	1.0500	1.1000	1.0000
111	Offered starting salary [%]	115	135	100
112	Anticipated 3-year salary [%]	120	120	100
1211	Average work week [h]	45	50	48
1212	Daily commute time [min]	0	40	30
122	Attractiveness of job [0..8]	5	6	2

Table 3. The values of suitability attributes

Evaluation results (all values expressed as percentages)
Missingness penalty: 0 %

Id	Attribute	NewJob1	NewJob2	OldJob
1	JOB	55.72	75.13	19.71
11	Monetary compensation	47.30	74.47	16.01
12	Main characteristics of the job	87.21	75.96	72.22
121	Total time at work	92.29	76.14	82.96
122	Attractiveness of job [0..8]	62.50	75.00	25.00
1212	Daily commute time [min]	100.00	66.67	80.00
1211	Average work week [h]	90.00	80.00	84.00
112	Anticipated 3-year salary [%]	66.67	66.67	0.00
111	Offered starting salary [%]	44.00	76.00	20.00

Table 4. The values of suitability attributes and the overall suitability results

Overall value: $100 * (\text{Score}_i / \text{Score}_{\max})^w (\text{Cost}_{\min} / \text{Cost}_i)^{1-w} [\%]$

System	Cost	Relative importance of high score (w)										Overall score [%]	
		0%	10%	20%	30%	40%	50%	60%	70%	80%	90%		100%
NewJob1	1.0500	95.24	92.89	90.59	88.36	86.18	84.05	81.97	79.95	77.97	76.05	74.17	55.72
NewJob2	1.1000	90.91	91.78	92.66	93.55	94.44	95.35	96.26	97.18	98.11	99.05	100.0	75.13
OldJob	1.0000	100.0	87.48	76.52	66.94	58.56	51.23	44.81	39.20	34.29	30.00	26.24	19.71

Table 5. The overall values (the cost/suitability analysis)

Analyzed item: Job
Please enter up to 5 components of this item

COMPONENT NAME	WOULD YOU FURTHER DECOMPOSE THIS?
Monetary compensation	Yes
Main characteristics of the job	Yes
Component 3 name	Please select
Component 4 name	Please select
Component 5 name	Please select

Continue

Evaluated item: Offered starting salary [%]
Please select one of the following 5 options.

- I prefer high values of this item
- I prefer low values of this item
- I prefer a specific range of values
- I will specify a table of requirements
- I will select suitability from your table

Evaluated item: Offered starting salary [%]
Please specify your requirements, keeping in mind that the first value should always be less than the second.

Description of requirements	Your (numeric) values
It is unacceptable if the given value is less than	100
I am fully satisfied if the value is greater than	150

Continue

Figure 5. Three examples of the user-LSPrec query

The tabular form of the complete LSP criterion shown in Table 2 includes four logic aggregators. The aggregators 11 and 12 are conjunctive partial absorptions with the penalty of 20% and the reward of 10%. Consequently, in this example, the attributes 112 (anticipated 3-year salary) and 122 (the attractiveness of job) are optional, while the remaining inputs (the starting salary, the average work week, and the daily commute time) are mandatory. All mandatory requirements must be satisfied and if any of them are not satisfied, such a job offer is rejected. That is achieved using the hard graded conjunction: the week form HC- is used in the aggregator 121 and the average form HC is used in the final aggregator 1. The complete criterion can also be presented in the LSP.NT compact form shown in Fig. 4.

The competitive job offers NewJob1 and Newjob2, compared with the OldJob, are shown in Table 3. The cost values reflect the situation where the cost of living in locations of the offered jobs is not the same as the cost of living in the location of the current job. The NewJob1 has the commute time 0, which means that the work is done from home.

The results of the presented evaluation are shown in Tables 4 and 5. The most suitable job is NewJob2, which satisfies 75.13% of user requirements, and represents a significant improvement, compared to the current job.

All communication between the nonprofessional user and the LSPrec tool is strictly verbal, and it does not require any user preparation. Three examples of LSPrec queries are shown in Fig. 5. The first example illustrates the beginning of building the suitability attribute tree. This query repeats as long as the user has items that can be further decomposed. The second query illustrates options for building a typical attribute criterion. E.g., if the user selects the “preferred high values” option, then this choice activates the specification of requirements exemplified in the third query in Fig. 5.

Conclusions

The LSP method which is used in professional evaluation decision studies can be verbalized and adapted for use by general nonprofessional users. Our decision-making tool LSPrec provides a sequence of simple queries that guide the user to systematically specify the requirements that reflect the stakeholder’s goals. Even in the case of a small number of inputs (in our example 5) it is necessary to use subtle logic relationships that are provided by the Graded Logic. The presented decision process helps users to systematically build criteria for evaluation problems of complexity much higher than the complexity of problems that can be intuitively solved. Such AI tools provide valuable recommendations and could be made widely available and implemented in the form of AI agents.

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