Proceedings of the 15th IFIP WG 8.3 International Conference on Decision Support Systems (DSS) 2010

Visualization methods for multi-criteria portfolio selection – an empirical study

Rudolf VETSCHERA [a], Johannes GETTINGER [b], Elmar KIESLING [a], Christian STUMMER [a]

[a] *University of Vienna, Vienna, Austria*
[b] *Vienna University of Technology, Vienna, Austria*

Abstract. We conducted an experiment comparing two different visualization methods for multi-criteria portfolio selection methods: heat maps and parallel coordinates. The two methods were compared both in terms of subjective user evaluations and objective measures. Users found the coordinate view subjectively more easy to use, although objectively, they performed more iterations using that view. In contrast, parallel coordinates led to more backtracking behavior in the search process. We also found a strong impact of decision making styles on users' attitudes towards the DSS.

Keywords. Visualization; multi-criteria portfolio selection; user attitudes; search process

Introduction

Portfolio selection problems involving multiple criteria constitute an important application of Decision Support Systems (DSS), because they involve complex computational tasks as well as subjective judgment by the decision maker (DM). Interactive solution methods allow decision makers to deal with such problems in an effective way, without having to perform an extensive preference elicitation process. These methods require a constant flow of information between user and DSS, so the choice of suitable problem representations becomes an important topic in the design of DSS for these problems. While research on the presentation of information to users has a long tradition in the area of management information systems (MIS), the design of suitable representations for user interaction in DSS is less well understood. This is particularly true for the specific situation of DSS for multi-criteria portfolio selection, in which users have to deal with a potentially large number of Pareto-optimal portfolios.

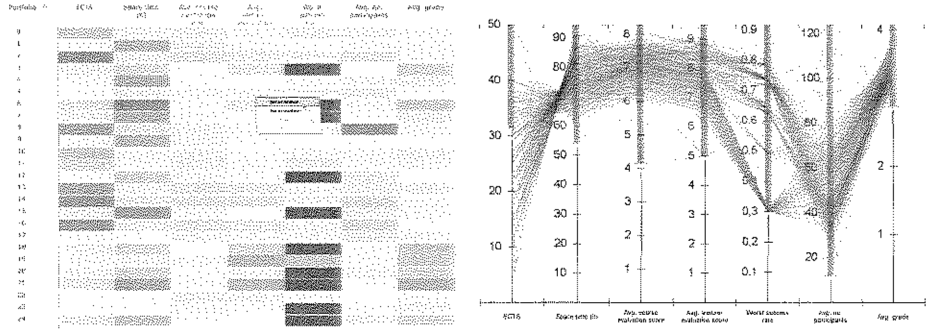
The present paper compares two visualization methods, which can be used to support decision makers in interacting with DSS for portfolio selection using aspiration levels. The DSS used in these experiments implements an unstructured search process on the set of efficient portfolios. It allows the DM to freely explore the solution space by interactively changing the upper and lower bounds for each criterion. Portfolios which fall within these bounds for all criteria are referred to as *admissible portfolios.* The search process reduces the set of admissible portfolios until the user is able to select one portfolio. This unstructured search process does not require any assumptions about the decision maker's preference structure, other than that preferences are a monotone function of the achievements for each criterion.

In our experiments, we compared two visualization methods: (a) interactive heat maps, and (b) interactive parallel coordinate plots. Heat maps (Figure 1a) are organized in a similar way as classical tables, each row in the table represents a portfolio and each column a criterion. Different colors are used to represent the value of a criterion for a particular portfolio. Compared to tables, this representation provides a higher information density and makes it easier to identify patterns such as correlations and trade-offs between criteria. This representation allows the DM to sort portfolios by each criterion, and/or to set upper and lower bounds for any criterion via a context menu.

Within parallel coordinate plots (Figure 1b), criteria are represented on separate parallel axes and portfolios are shown as profile lines. This representation emphasizes geometric interpretability and provides a good overview of the distribution of values, given that the number of efficient portfolios remains moderate. The mechanism for setting upper or lower bounds for criteria is based on dragging bars to mark the aspired intervals and indicates which portfolios will be eliminated during dragging operations.

We compare these two visualization methods with respect to both subjective and objective criteria. Subjective criteria evaluate the subjects' attitudes towards the DSS, the solution process and outcomes. Objective measures represent both the actual effort exerted by subjects and the structure of the search process.

In addition to the main experimental factor of different visualization methods, we also study the effect of problem complexity and user characteristics on both subjective and objective outcome measures. Problem complexity was manipulated by posing two different portfolio selection problems, which differed in the number of criteria used and consequently also in the number of efficient portfolios that could be considered. User characteristics involved demographic characteristics (in particular gender), as well as the users' decision making styles.



(a) Heatmap visualization (b) Parallel coordinate visualization

Figure 1. Screen captures of both visualizations

Experiments and Measurement

The experiments were conducted using 96 students at the University of Vienna as subjects. Table 1 provides an overview of the sample composition and treatments. Subjects were recruited from various classes in the undergraduate and graduate programs of Business Administration at the University of Vienna. As incentive to participate, a lottery was held in which 12 iPods were distributed among the participating students.

Problem	Simple			Complex		
Mode \ Participants	m	f	Total	m	f	Total
Heat map	9	14	23	12	16	28
Coordinates	10	11	21	10	14	24

Table 1. Sample composition and treatments

In order to provide a realistic setting, we used a portfolio selection problem familiar to the subjects, namely the selection of courses for the forthcoming semester. In the "Simple problem" treatment, three criteria were used: Total number of ECTS points (maximize), total course hours (minimize), and average evaluation of the course (maximize). This scenario contained 331 efficient portfolios. In the "Complex problem" treatment, four additional criteria were used: Average evaluation of lecturer (maximize), minimal success rate of courses (maximize), average number of participants in course (minimize), and average grade obtained in course (maximize). This setting contained 999 efficient portfolios.

Established scales were used both for user characteristics and the subjective outcome measures. Decision making styles were evaluated using the decision making style scales of Scott and Bruce [3]. This instrument contains five scales, which measure an individual's propensity to follow a Rational, Intuitive, Dependent, Avoidant or Spontaneous decision making style, respectively.

System-oriented subjective output measures included perceived ease of use (*PercEase*) and perceived usefulness (*PercUse*) of the system. These two constructs were taken from the widely used Technology Acceptance Model (TAM) by Davis [2]. The subjective evaluation of the decision process involved both the perceived decisional conflict (*DecConf*) and the perceived effort measured (*PercEff*), each measured on a scale developed by Aloysius et al. [1]. As a subjective measure of decision quality, we used the perceived accuracy (*PercAcc*), also measured on a scale developed by Aloysius et al. [1].

Objective measures considered both the effort involved in solving the problem, and the path by which subjects arrived at their most preferred solution. Effort was measured using two indicators: The total time elapsed between the user's first interaction with the system and the time at which they indicated completion of the problem (*TotTime*), and the total number of filtering steps (*Steps*), i.e. the number of times a user changed the aspiration level for an attribute.

Subjects followed widely different paths in reaching their most preferred solutions. While some users continuously tightened their aspiration levels and thus reduced the number of admissible portfolios, others quite often backtracked in their search process by loosening the aspiration levels. To capture these differences in search behavior, we calculated the number of filtering steps which led to an increase, rather than a decrease, in the number of admissible portfolios (*RevAbs*). A low value of *RevAbs* thus indicates a smooth convergence. To study the speed of convergence in different stages of the search process, we also looked at the average number of admissible portfolios in the first and last third of the process (*Avg1* and *Avg3*). In order to make these values comparable across the simple and complex problem treatments, they were standardized by the total number of portfolios.

Results

We performed linear regression analyses to test the impact of the various factors under study on the outcome dimensions. Table 2 shows the results of regressions for subjective outcome measures. With the exception of perceived accuracy, all regressions exhibit a reasonably good fit as represented by the adjusted R^2 values.

Variable		*PercUse*	*PercEase*	*DecConf*	*PercEff*	*PercAcc*
(Intercept)	Coeff	-2.6515	0.0784	*** 12.2935	*** 9.9349	* 8.0964
	t	-0.4826	0.0098	3.7295	4.6448	2.3203
Coordinate View	Coeff	3.0459	** 8.4951	*** -4.5012	* -2.0852	0.8674
	t	1.4467	2.7804	-3.5635	-2.5440	0.6487
Complex Problem	Coeff	-0.3545	2.7228	-2.0310	-0.3044	0.6290
	t	-0.1805	0.9554	-1.7237	-0.3981	0.5043
Gender	Coeff	-1.0258	-3.3545	0.7173	0.2125	-1.5939
	t	-0.7013	-1.5804	0.8174	0.3731	-1.7158
Rational DS	Coeff	*** 0.5964	*** 0.7462	* -0.1866	-0.0788	0.1338
	t	4.5057	3.8850	-2.3499	-1.5289	1.5921
Intuitive DS	Coeff	0.2105	0.0826	-0.0291	-0.0157	-0.0500
	t	1.4470	0.3912	-0.3337	-0.2767	-0.5410
Dependent DS	Coeff	0.1783	0.2028	0.0859	-0.0324	0.0543
	t	1.5007	1.1766	1.2046	-0.7008	0.7198
Avoiding DS	Coeff	-0.0280	-0.0594	0.0293	* 0.1001	-0.0348
	t	-0.2596	-0.3789	0.4524	2.3820	-0.5072
Spontaneous DS	Coeff	0.0991	0.1401	0.1077	-0.0610	0.0837
	t	0.6319	0.6152	1.1444	-0.9980	0.8404
View × Criteria	Coeff	-2.4464	-5.7447	** 5.4738	1.5343	-1.6906
	t	-0.8602	-1.3919	3.2079	1.3856	-0.9359
R^2		0.2226	0.1942	0.2026	0.1044	0.0168

Table 2. Regression analysis - Subjective outcome variables

The visualization method used had a considerable impact on the subjective evaluation by users. Users considered the coordinate view to be considerably easier to use than the heat maps, and also indicated that they experienced less decisional conflict and considered the effort involved to be lower when using this problem representation.

Our results also indicate that the appreciation of DSS depends on the users' individual decision making styles. Subjects who scored high on the Rational decision style scale perceived the system both as more useful and as easier to use and also experienced less decisional conflict in solving the problem.

Contrary to our expectations, problem complexity did not have a significant impact on the subjective measures. However, it is a mediating variable on the impact of the visualization method on perceived decisional conflict. This interaction effect can best be illustrated by considering the distribution of this outcome dimension for the different experimental groups as shown in Figure 2. While for the low complexity group (3 criteria), subjects using the coordinate view experienced a considerably lower decisional conflict than subjects using the heat maps, this difference vanishes for the more complex problems involving seven criteria.

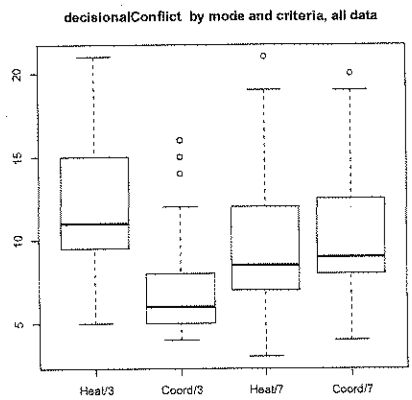


Figure 2. Distribution of decisional conflict for the treatment groups

Table 3 reports on the regression analyses for objective outcome variables. We again find a considerable impact of visualization methods. In particular, users of the coordinate view performed a much larger number of filtering steps than heat map users, although they completed the process in approximately the same time. Time was, however, influenced by problem complexity. As could be expected, subjects who had to solve the more complex problem took somewhat longer than subjects who dealt with the simpler problem. The search process of heat map users was smoother than for the coordinate view. However, users of the coordinate view achieved a significantly larger reduction in the number of admissible portfolios already in the first third of the search process, and maintained that lead until the last third.

Conclusions

Our results indicate that the choice of visualization methods in DSS has a considerable impact on both the users' subjective experiences when using the system, and their objective performance. For the problem we were studying – a free

Variable		*Steps*	*TotTime*	*RevAbs*	*Avg1*	*Avg3*
(Intercept)	Coeff	15.1927	* 385.4339	7.1584	*** 0.5203	0.1430
	t	0.6295	2.3571	1.2864	3.4422	1.1549
Coordinate View	Coeff	*** 37.2515	-116.6639	** 7.0584	*** -0.2249	*** -0.1894
	t	4.0276	-1.8618	3.3099	-3.8832	-3.9911
Complex Problem	Coeff	4.2691	* 137.6545	-0.2368	* -0.1373	-0.0460
	t	0.4948	2.3550	-0.1191	-2.5416	-1.0381
Gender	Coeff	3.7594	** 118.0890	1.9398	-0.0147	0.0288
	t	0.5851	2.7126	1.3093	-0.3646	0.8724
Rational DS	Coeff	0.0520	5.2872	-0.0086	0.0025	0.0033
	t	0.0894	1.3421	-0.0641	0.6792	1.0906
Intuitive DS	Coeff	0.4193	7.8104	0.0524	−0.0072	0.0046
	t	0.6561	1.8037	0.3555	−1.7987	1.3952
Dependent DS	Coeff	-0.4623	* -8.0221	-0.1737	0.0047	-0.0043
	t	-0.8858	-2.2690	-1.4435	1.4397	-1.6012
Avoiding DS	Coeff	0.5160	* 7.2165	0.0864	-0.0016	-0.0006
	t	1.0880	2.2461	0.7904	-0.5255	-0.2416
Spontaneous DS	Coeff	-0.6701	-8.1022	-0.1404	0.0039	-0.0010
	t	-0.9722	-1.7351	-0.8833	0.9000	-0.2839
View × Criteria	Coeff	9.5208	-31.4676	-0.9777	0.1065	0.0154
	t	0.7620	-0.3718	-0.3394	1.3604	0.2402
R^2		0.3210	0.1893	0.1731	0.1991	0.2350

Table 3. Regression analysis - Objective outcome variables

search among efficient portfolios using an aspiration-based approach – the parallel coordinates view turned out to be superior to heat maps. However, since we have already observed that problem characteristics can diminish or in some cases even eradicate the effect of graphical representations, future studies in this direction are necessary.

We have also demonstrated that user characteristics can have a strong impact on subjective evaluation, and thus on the acceptance of decision support methods. Establishing the right fit between problem representation, support tools and the users' cognitive style is therefore an important task for DSS designers, for which studies like ours can provide guidelines.

References

[1] J. A. Aloysius, F. D. Davis, D. D. Wilson, A. R. Taylor, and J. E. Kottemann, User Acceptance of Multi-Criteria Decision Support Systems: The Impact of Preference Elicitation Techniques, *European Journal of Operational Research* **169** (2006), 273–285

[2] F. D. Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, *MIS Quarterly* **13** (1989), 318–340.

[3] S. G. Scott and R. A. Bruce, Decision-Making Style: The Development and Assessment of a New Measure, *Educational and Psychological Measurement* **55** (1995), 818–831.