

Using the Lens Model Framework to Characterize Compensatory and Noncompensatory Decision Making Strategies

Ling Rothrock, Jing Yin

The Pennsylvania State University
310 Leonhard Building
University Park, PA 16802
{jxy178, lrothroc} @psu.edu

Alex Kirlik

University of Illinois at Urbana-Champaign
#1 Airport Road
Savoy, IL 61874
kirlik@uiuc.edu

Abstract

This paper presents an effort to use the Lens Model Framework, as originally conceived by Egon Brunswik to characterize a functional relationship between a decision maker and his environment which is mediated through the lens of probabilistic variables in the environment. In particular, the authors are interested in using the Lens Model to explore the hypothesis that human judgments oscillate between compensatory and noncompensatory decision making strategies. We submit that a continuum can be constructed to characterize this oscillation. Our claim for the existence of a continuum is motivated by psychological research which suggests that humans tend to adjust their decision strategies to cope with the change of information demands and time available. We propose a framework within which to investigate strategy shifts. A cornerstone of our framework is a rule-based formulation of the lens model called the noncompensatory lens model (NLM) to investigate decision strategies under time-stressed and information-rich task environments. In addition to the NLM, we also discuss the development and expansion of a noncompensatory policy capturing algorithm to complement the traditional multiple-linear regression-based implementation of the Lens Model. We conclude the paper with a discussion of a planned empirical investigation to validate our framework.

We submit that, while the models discussed in this paper do not directly concern human-computer interaction (HCI), the outcomes of the research program can have broad implications. By providing HCI practitioners with means to determine the salient perceptual cues for decision making as well as to find whether a decision maker is consistent with a compensatory versus noncompensatory mode of judgment, the development of adaptive interfaces which provide the correct information at the appropriate time may be within reach.

1 Introduction

This paper presents an effort to use the lens model framework, as originally conceived by Brunswik (1955), to characterize a functional relationship between a decision maker and his environment which is mediated through the lens of probabilistic variables in the environment. The purpose of the research is to develop a theoretical account of human decision making under varying task and environmental conditions. For the traditional formulation of the Lens Model (Hursch et al., 1964), which we call the Compensatory Lens Model (CLM), the formulation of the model relies heavily on multiple linear regression models to determine the fitness of human judgments relative to constraints in the task environment. While this formulation has been widely used, its success is tempered by occasions in which judgment is driven by noncompensatory strategies. Although some have attempted to extend the CLM to account for noncompensatory strategies (Einhorn, 1970; Cooksey, 1996), a framework which is able to fully model both compensatory and noncompensatory decisions has not been developed.

The CLM framework is illustrated in Figure 1. R_e , also called environmental predictability, measures the coherence between the model of the environmental and the actual criterion value. Correspondingly, human control, R_s , represents the coherence between the model of the judge and actual human judgments. Modeled knowledge, G , represents the correspondence between the model of the environment and the model of the judge. C , common called unmodeled knowledge, captures systematic regularities between the errors of the ecological and judge models. The remaining term, r_a , represents the correspondence between human judgments and the actual value of the environmental criterion. In CLM, R_e , R_s , G , and C are calculated using the Pearson product-moment correlation

coefficient. r_a , is the centerpiece of the CLM, and its equation is called the Lens Model Equation (Hursch et al., 1964; Tucker, 1964):

$$r_a = GR_e R_s + C\sqrt{(1-R_e^2)}\sqrt{(1-R_s^2)} \quad (1)$$

The Lens Model Equation (LME) formulates a judge's performance (or achievement) in a task in terms of components that account for linear ($GR_e R_s$) and non-linear ($C\sqrt{(1-R_e^2)}\sqrt{(1-R_s^2)}$) correlations.

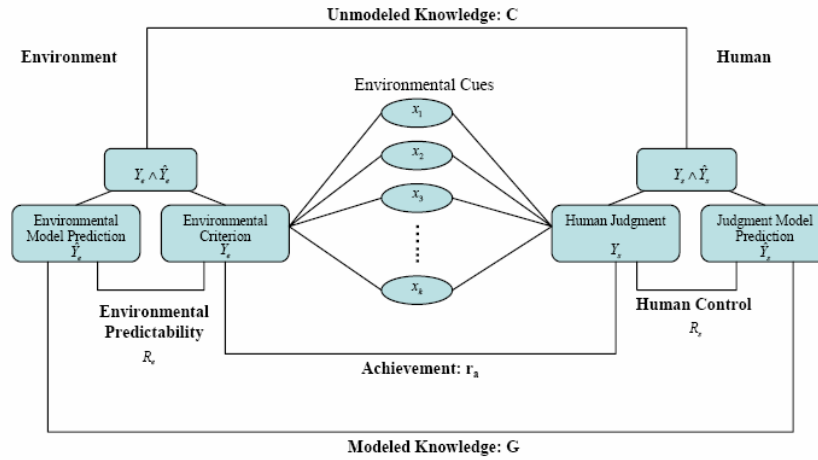


Figure 1. The Lens Model.

An implicit assumption when using the LME is that it is broadly applicable to varying decision processes under different task environments. We submit that, while the conceptual model framed by Brunswik (1955) is broadly applicable, the narrowly formulated LME should be applied only when judgment behavior is compensatory. Under a compensatory mode of decision making, information is processed exhaustively and trade-offs need to be made between attribute values. Compensatory modes of decision strategies are contrasted against noncompensatory modes (Payne, 1976; Einhorn, 1970; Svenson, 1979) where, typically, not all available information is used. An exemplar of a noncompensatory strategy is the *Take the Best* heuristic in which a decision maker uses a sequence of simple rules to choose an alternative in the face of uncertain knowledge (Gigerenzer, 1996).

Motivated by the psychological research that humans tend to change decision strategies based on the amount of information demands (Payne, 1976) and time available (Wright, 1974), we speculate that there exists a continuum between compensatory decision strategies at one extreme and noncompensatory strategies at the other. Furthermore, we hypothesize that this continuum can be characterized via cue-criteria relationships for the human judgment system. Our paper will first discuss a percentage-match formulation of the Lens Model, which we call the Noncompensatory Lens Model (NLM). In addition to the NLM, we also discuss the development and expansion of a noncompensatory policy capturing algorithm to complement the traditional multiple-linear regression-based implementation of the Lens Model. We conclude the paper with a discussion of a planned empirical investigation to validate our framework.

2 The Noncompensatory Lens Model

While LME exists to assess the correspondence of human judgments and environmental criteria in a linear-additive way, no such tool exists in situations where noncompensatory relationships occur. We observe that there are two fundamental modeling differences between the CLM and the NLM. The first is the relationship that is modelled. While linear models often provide a sufficient approximation to non-linear relationships, a more desirable alternative is to provide a non-linear (e.g., noncompensatory) modeling approach. The second is the measurement scale which best fits a compensatory versus a noncompensatory model. A standard way of measuring the linear (e.g., compensatory) relationship is represented by calculating the correlation coefficient. The most commonly used

measure of correlation for variables that have been measured on interval or ratio scales is Pearson's product-moment correlation coefficient (r), which makes the implicit assumption that the two variables are jointly normally distributed. When this assumption is not justified, a non-parametric measure such as the Spearman's Rank Correlation Coefficient or Kendall's τ which is closely related to probability theory might be more appropriate (Lordahl, 1967); yet even these methods require the data to at least be ordered.

When modeling noncompensatory strategies and ecologies, the data used to represent environmental cues, judgments and criteria are discrete and categorical. As such, the numbers assigned to them are on nominal scales. This means the assignment is arbitrary, as the numbers are merely labels (Lordahl, 1967). Thus, it makes no sense to apply interval or ratio scale operations and use the correlation coefficient as a measure of the correspondence between either data or fitted model components. Therefore, to create the Noncompensatory Lens Model (NLM), we consider the a percent-match framework which was first proposed in Yin and Rothrock (submitted) to compare the results of fitted models of both judgment strategies and the task ecology:

Assuming the ecological criterion to be judged is Y , which takes the categorical values on nominal scale. Let $\{Y_1, Y_2, Y_3, \dots, Y_p\}$ be the set of discrete values that Y can take. For instance i , $1 \leq i \leq n$

Let Y_{ei} represents the actual environmental criterion value;

\hat{Y}_{ei} represents the predicted criterion value from the environmental rule-based model;

Y_{si} represents the human judgment value;

\hat{Y}_{si} represents the predicted judgment value from the human judgment rule-based model;

$$\begin{aligned} \text{Define } I_{ei} &= \begin{cases} 1 & \text{if } Y_{ei} = \hat{Y}_{ei} \\ 0 & \text{otherwise} \end{cases} & \text{then } R_e &= \sum_{i=1}^n I_{ei} / n \\ I_{si} &= \begin{cases} 1 & \text{if } Y_{si} = \hat{Y}_{si} \\ 0 & \text{otherwise} \end{cases} & \text{then } R_s &= \sum_{i=1}^n I_{si} / n \\ I_{ri} &= \begin{cases} 1 & \text{if } Y_{ei} = Y_{si} \\ 0 & \text{otherwise} \end{cases} & \text{then } r_a &= \sum_{i=1}^n I_{ri} / n \\ I_{Gi} &= \begin{cases} 1 & \text{if } \hat{Y}_{ei} = \hat{Y}_{si} \\ 0 & \text{otherwise} \end{cases} & \text{then } G &= \sum_{i=1}^n I_{Gi} / n \\ I_{Ci} &= \begin{cases} 1 & \text{if } I_{ei} = I_{si} = 1 \\ 0 & \text{otherwise} \end{cases} & \text{then } C &= \sum_{i=1}^n I_{Ci} / n \end{aligned}$$

The interpretation of the lens model parameters for the noncompensatory case is analogous to the linear case (see Figure 1). r_a represents the correspondence between human judgments and the actual value of the environmental criterion. R_e measures how well the noncompensatory environmental model can be used to predict the criterion value. R_s indicates how well the noncompensatory judgment model captures actual human judgments. G represents how well the noncompensatory model of the environment maps onto the noncompensatory model of the human judgments strategy. Finally, C captures systematic regularities between the errors of the noncompensatory ecological and judgment models.

2.1 Simulation Study and Result Discussion

To explore the impact of a change in decision making behavior due to time stress and task load fluctuations, we simulated human judgments along a continuum between purely compensatory and purely noncompensatory strategies. In a simulated domain, we created instances of judgment by mixing the data generated by specified linear-based and rule-based generators. We ordered all instances on the proportion of judgment data generated by the linear generator, which we called p . Therefore, the left-hand side extreme represents cases in which the human uses purely noncompensatory strategies (i.e., $p=0$) to make decision while the right-hand side extreme indicates that

the human uses purely compensatory strategies (i.e., $p=1$). Points between the extremes represent instances where a mixture of strategies exists. Note that all the environmental criteria values are created by the linear generator, which does not change along the continuum. The NLM and CLM analyses are then applied to get two set of lens model parameters. By examining the results, we expected to detect trends as p increases.

The results of the simulation suggest that noncompensatory C , unmodeled knowledge, is most diagnostic toward explicating the relationship between the NLM and the CLM. In fact, there exists a high positive correlation ($R^2 \sim 1$) between C under NLM analysis and p . Our findings support the claim that unmodeled knowledge in NLM increases with the proportion of linear generated decision data. More details of the simulation can be found in Yin and Rothrock (submitted).

3 A Noncompensatory Method to Infer Decision Strategies: Alternative Formulations

The Lens Model Equation developed by Hursch, Hammond, and Hursch (1964) can be viewed as a coherent modeling methodology which links together a regression-based policy capturing model and a regression-based criterion model for comparison between the human judgment and ecological systems (Cooksey, 1996). However, no complete formulation exists for the Noncompensatory Lens Model. An initial step has been taken toward the development of a rule-induction model, called Genetics-Based Policy Capturing (GBPC) (Rothrock & Kirlik, 2003) as a noncompensatory complement to the regression-based policy capturing model.

A central element of the GBPC is the multi-objective fitness evaluation function. In LME, both the human judgment model and the ecological model are fit by least-squares. In moving to a noncompensatory approach to judgment modeling, one must define an alternative to least-squares for measuring the goodness or fitness of a rule set. In Rothrock and Kirlik (2003) the fitness of a rule set was taken to be the ability to classify a set of exemplars (i.e., human judgment data) in a manner consistent with bounded rationality. Therefore, a rule set should not only match a set of exemplars, but it should also resemble economical, noncompensatory judgment strategies. This is done in the GBPC by a multi-objective function that evaluates fitness along three dimensions: completeness, specificity, and parsimony. The completeness dimension is based on work by DeJong et al. (1993), reflecting how well a rule set matches the entire set of exemplars. The specificity dimension was first suggested by Holland et al. (1986), and reflects how specific a rule set is with respect to the number of wild cards (match-anything conditions) it contains. Rule sets with less wild card characters are classified as more specific. The parsimony dimension reflects the goodness of a rule set in terms of necessity. In a parsimonious rule set, there are no unnecessary rules. The ideal rule set, therefore, will match all behavioral data, will be maximally specific, and maximally parsimonious. Therefore, the general formulation of the global fitness function, g , is:

Maximize $g(c, s, p)$

subject to

$$0 \leq c \leq 1$$

$$0 \leq s \leq 1$$

$$0 \leq p \leq 1, \text{ where } c \text{ is completeness, } s \text{ is specificity, and } p \text{ is parsimony.}$$

For details of a mathematical solution to the multi-objective problem see Rothrock, Ventura and Park (2003). We submit that it is difficult to establish a necessary condition using completeness, specificity, and parsimony for noncompensatory strategies that are consistent with human judgment behavior. That is, a high global fitness necessarily leads to noncompensatory behavior. It is entirely possible that alternative dimensions, such as *frugality* (Gigerenzer and Goldstein, 1996), may add to the global fitness of the model. We intend to explore such alternatives in future work.

4 Model Validation

Although our simulation study (Yin and Rothrock, submitted) provided encouraging results, we realize that merely fitting the data in a simple simulated domain is not sufficient to validate the model in dynamic decision contexts

where noncompensatory behavior is induced under time stress and high task load. Therefore, an empirical assessment of the NLM is necessary. We plan to run a series of experiments using a human-in-the-loop simulation called the Team Aegis Simulation Platform (TASP). The task is a continuous-time simulation in which participants must identify aircraft based on perceptual information available through a simulated radar scope. The aircraft identification task has been used by researchers to investigate dynamic decision making (Adelman, Christian, Gualtieri, & Bresnick, 1998; Bisantz et al., 2000; Campbell, Buff, Bolton, & Holness, 2001; Rothrock & Kirlik, 2003). The task is based on an existing simulation developed by the investigators (Bhandarkar, Thiruvengada, Rothrock, Campbell, & Bolton, 2004; Kirlik, Fisk, Walker, & Rothrock, 1998).

Our proposed research is motivated by the hypothesis that there exists an oscillation between compensatory and noncompensatory decision strategies in dynamic task environments and such shift of strategies is influenced by factors such as the cue-criterion structure of the task ecology, time pressure, and task load. Based upon that, we plan to validate the modeling technique in the laboratory decision task by manipulating task features such as cue-criterion structure, workload, and time-pressure to determine if the NLM provides a better fit to behavioral data under conditions which are believed to prompt the use of, or transition to, noncompensatory decision strategies.

Using the aircraft identification task, we propose to analyze the effects of cue structure on subject judgment strategies. By varying the relationship between the cues and the true aircraft identity from linear-additive to nonlinear and noncompensatory, we intend to examine the possible impact of this manipulation on the nature of the judgment strategy induced by the cue structure, by analyzing the data by both CLM and NLM. We will create two versions of the task; one in which cue-criterion relations (the task ecology) are linear-additive (compensatory), and one in which these relationships are noncompensatory. We predict that at high levels of adaptation or performance, the behavioral data generated by participants performing the first version of the task will be better described by the CLM, while the data from the second version will be better described by our noncompensatory formulation. We also intend to introduce varying levels of time stress (the speed of the aircraft) and task load (the number of aircraft to be identified) to assess the possible effects of these manipulations on decision strategies. We predict that, even for participants performing the linear additive (compensatory) version, increasing workload (number of aircraft) and time stress (speed across the display) will promote a shift from compensatory to noncompensatory strategies. We expect to diagnose this shift using both classical and GBPC. In addition to serving the goal of evaluating and guiding the further development of the NLM, the proposed empirical investigations have the dual goal of providing additional findings on the degree and manner to which humans adapt to ecological structure, time-stress, and task load in dynamic decision environments. We expect this work to make a valuable contribution toward understanding decision making in complex, dynamic environments.

5 Concluding Remarks

In summary, this paper presents an effort to use the Lens Model Framework as originally conceived by Egon Brunswik. Three research goals are presented to within our research framework to broaden the applicability of the Lens Model to both compensatory and noncompensatory decision processes. As our starting point, we used a simulation study to illustrate the behavior of NLM and CLM under varying conditions. The results from our simulation study suggest encouraged us to continue our investigation. Moreover, the NLM work (Yin and Rothrock, submitted) was done in isolation from the development work on the GBPC (Rothrock and Kirlik, 2003) and thus required an integration effort.

Much of this paper discusses planned work based on existing findings. We propose that a generalized framework which uses both CLM and NLM can be an invaluable tool to HCI practitioners by informing the development of adaptive interfaces which anticipate real-time demands of users in work contexts with varying time pressure and task load. Moreover, the framework can give us deeper insights on why humans change judgment strategies to cope with changes in the environments.

References

- Adelman, L., Christian, M., Gualtieri, J., & Bresnick, T. A. (1998). Examining the Effects of Communication Training and Team Composition on the Decision Making of Patriot Air Defense Teams. *IEEE Transaction on Systems, Man, and Cybernetics--Part A: Systems and Humans*, 28(6), 729-741.

- Bhandarkar, D., Thiruvengada, H., Rothrock, L., Campbell, G. E., & Bolton, A. E. (2004, May 15-18, 2004). *TASP: A Toolkit to Analyze Team Performance in a Complex Task Environment*. In Proceedings of the Annual Conference of the Institute of Industrial Engineers, Houston.
- Bisantz, A. M., Kirlik, A., Gay, P., Phipps, D., Walker, N., & Fisk, A. D. (2000). Modeling and Analysis of a Dynamic Judgment Task Using a Lens Model Approach. *IEEE Transaction on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 30(6), 605-616.
- Brunswik, E. (1955). Representative design and probabilistic theory in a functional psychology. *Psychological Review*, 62, 193-217.
- Brunswik, E., 1956. Perception and the representative design of psychological experiments. Berkeley, Calif.: Univ. of California Press.
- Campbell, G. E., Buff, W. L., Bolton, A. E., & Holness, D. O. (2001). *The Application of Mathematical Techniques for Modeling Decision-making: Lessons Learned from a Preliminary Study*. In Proceedings of the Fourth International Conference on Cognitive Modeling, Fairfax, VA, 49-54.
- Cooksey, R. W. (1996). Judgment Analysis: Theory, Methods, and Applications. San Diego: Academic Press, Inc.
- DeJong, K. A., Spears, W. M., & Gordon, D. F. (1993). Using Genetic Algorithms for Concept Learning. *Machine Learning*, 13(2-3), 161-188.
- Einhorn, H. J. (1970). The Use of Nonlinear, Noncompensatory Models in Decision Making. *Psychological Bulletin*, 73(3), 221-230.
- Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the Fast and Frugal Way: Models of Bounded Rationality. *Psychological Review*, 103, 650-669.
- Holland, J. H., Holyoak, K. F., Nisbett, R. E., & Thagard, P. R. (1986). *Induction*. Cambridge, MA: The MIT Press.
- Howell, D. C. (1985). *Fundamental Statistics for the Behavioral Sciences*. Boston, MA: Duxbury Press.
- Hursch, C. J., Hammond, K. R., Hursch, J.L. (1964). Some methodological considerations in multiple-cue probability studies. *Psychological Review*, 71(1), 42-60.
- Kirlik, A., Fisk, A. D., Walker, N., & Rothrock, L. (1998). Feedback Augmentation and Part-Task Practice in Training Dynamic Decision-Making Skills. In J. A. Cannon-Bowers & E. Salas (Eds.), *Making Decisions Under Stress: Implications for Individual and Team Training* (pp. 91-113). Washington, D.C.: American Psychological Association.
- Lordahl, D. S. (1967). *Modern Statistics for Behavioral Sciences*, New York, Ronald Press.
- Payne, J. W. (1976). Task complexity and contingent processing in decision making: an information search and protocol analysis. *Organizational Behavior and Human Performance*, 16, 366-387.
- Rothrock, L., and Kirlik, A. (2003). Inferring rule-based strategies in dynamic judgment tasks: toward a noncompensatory formulation of the lens model. *IEEE Transactions on Systems, Man, and Cybernetics, Part A*, 33(1), 58-72.
- Rothrock, L., Ventura, J., & Park, S. (2003). *An Optimization Methodology to Investigate Operator Impact on Quality of Service*. In Proceedings of the Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC), Orlando, FL,
- Schneider, L. G., Selling, T. I. (1996). A comparison of compensatory and noncompensatory models of judgment: effects of task predictability and degree of freedom. *Accounting, Organizations and Societ*, 21(1), 3-22.
- Tucker, L. R. (1964). Suggested alternative formulation in the developments by Hursch, Hammond, and Hursch, and by Hammond, Hursch, and Todd. *Psychological Review*, 71(6), 528-530.
- Wright, P. (1974). The harassed decision maker: time pressures, distractions, and the use of evidence. *Journal of Applied Psychology*, 59(5), 555-561.
- Yin, J., & Rothrock, L. (Submitted). Investigating the Continuum between Compensatory and Noncompensatory Decision Making Strategies: Towards a Generalized Formulation of the Lens Model. *International Journal of Industrial Ergonomics*(Special Issue on New Insights on Human Performance and Decision Making).