Comparing performance of discrete choice models in stated choice methods: A prediction-based approach using preference order data

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1. Motivation and Research Questions

Random parameter logit (RPL), latent class logit (LCL), and random parameter latent class logit (RPLCL) are three of the most widely used models in stated choice analysis. However, how to select the most appropriate model among these three to study the underlying preference structure is still an ongoing discussion. In this paper, we propose a model assessment strategy using data solely from stated choice survey to examine the prediction performances of the three competing models.

The RPL model (or mixed logit) is considered the most dominant model in discrete choice analysis, known for its flexibility and ability to capture preference heterogeneity (Hensher and Greene, 2003; Hoyos, 2010). RPL assumes that the marginal utilities of attributes, due to unobserved individual heterogeneity, have some continuous distributions such as normal, lognormal, triangle, or uniform. Often, however, these specified distributions of marginal utilities could not represent the true underlying preference accurately. For instance, if there is a multi-mode distribution of marginal utility or if attribute non-attendance (or attribute ignoring) is present, the assumption of continuously distributed marginal utility will fail. Attribute non-attendance refers to respondents' tendency to be unconcerned with certain attributes in the choice tasks. That is, if a respondent is not paying attention to a particular attribute, her overall utility of a choice alternative will not be affected no matter how the level of that attribute is changed. Respondents who actually practice attribute non-attendance have a discontinuous preference for the ignored attributes, and the discontinuity of preference will cause problems to the models based on the assumption of continuous utility functions. This issue can have serious impacts on the estimates of willingness-to-pay (Scarpa et al., 2009).

The LCL incorporates the idea of latent class analysis, which is widely used in other disciplines such as Marketing and Psychology, and is another favorable approach currently being used to analyze stated choice data. Assuming the population falls into a finite number of classes, each class having homogenous preference, the LCL model uses discrete distributions to capture preference heterogeneity among individuals (Boxall and Adamowicz, 2002; Greene and Hensher, 2003). For each individual, belonging to a specific class is probabilistic, and determined by individual characteristics. That is to say, individual characteristics indirectly determine the choice respondents make through their class membership. Compared to RPL, while the assumption of homogenous preference within groups makes LCL less flexible, LCL is able to capture the variation when the marginal utility is discretely distributed. A couple of studies have found that a significant portion of respondents ignore attributes (Scarpa et al., 2009; Campbell et al., 2012), and LCL is ideal for dealing with this issue by modeling respondents ignoring attributes as an attribute non-attendance class. Additionally, computational simplicity is another advantage of LCL over RPL. Several studies have investigated and compared the performances of RPL and LCL using relative model fit measures such as AIC, BIC, and likelihood ratio, while the results are mixed (Hynes et al., 2008; Shen, 2009; Yoo and Ready, 2014).

Recently, several studies extended LCL to allow within-class heterogeneity by specifying the parameters associated with each class to be randomly distributed, which is usually called random parameter latent class logit model (RPLCL), and it has been shown that RPLCL outperforms RPL and LCL in terms of model fit (Greene and Hensher, 2013). In addition, studies find that, by using RPLCL, the share of attribute non-attendance class drops significantly compared to the estimates by LCL (Hensher et al., 2013; Hess et al., 2013). These results suggest that those respondents who were classified as practicing attributes non-attendance might not be truly ignoring some certain attributes, instead just have some very low utilities on certain attributes. Therefore, simply applying a LCL to fit the data is likely to overestimate the portion of respondents practicing attribute non-attendance (Hess et al., 2013). In sum, RPLCL not only provides an alternative approach to accommodate the issue of attribute non-attendance, which RPL is unable to tackle with, but also allows more flexible specification than LCL does. RPL and LCL indeed are two special cases of RPLCL, i.e., RPL is the case with only one class, while LCL is the case with all parameters as fixed. As RPL and LCL are nested in RPLCL, theoretically RPLCL should outperform the two special cases in terms of model fit.

Despite the fact that relative model fit measures can provide guidance for model selection, what researchers really care about is if a model can correctly identify the underlying preference structure, i.e., whether the estimates of marginal utility of attributes or willingness to pay are unbiased. Provencher and Bishop (2004) examined the out-of-sample forecasting performances of RPL and LCL using recreational fishing behavior data, and the results indicate that both models perform equally well. Their results also emphasize a caution for heavily-parameterized models. If a choice model is misspecified, the additional parameters for modeling the heterogeneity of preference would potentially ‘‘absorb’’ specification errors and generate models inferior, in terms of forecasts and welfare estimates, to those of a simpler model, despite the better model fit. We argue that this prediction/forecasting based approach is more appealing to assess model performance than model fit measures, because we can tell which model is better in capturing the actually behavior or the underlying preference. Based on our literature review, no study has evaluated the predictive performances of models in the context of stated choice methods. One obstacle of this approach could be that no proper revealed preference data are available at the time when a state choice experiment being conducted.

This study proposes a prediction-based model assessment strategy to examine the performances of the two most dominant models in stated choice methods, RPL and LCL, and their recent extension, RPLCL. The strategy is applied to the data retrieved from a survey on the values of non-hydrological landscape amenities accompanied with green infrastructure. Prior to the choice questions, the survey describes the four attributes we are interested in, i.e., variety in plant species, presence of water, percentage of mowed area, and natural versus designed appearance of landscape. The description of each attribute is followed by a question asking respondents to rank the levels of each attribute in their preferred order. The candidate models are estimated with the stated choice data, and we evaluate how well these models predict the actual preference order at both the aggregate and individual levels. We expect this study provides a convincing and easy-implemented approach for model selection in stated choice methods.

2. Methods

2.1. Data

The data was collected from a survey to measure the values of non-hydrological landscape amenities accompanied with GI. The survey instrument demonstrates the choice scenarios with both computer-rendered 3D images and text description. The background context of the choice scenarios is asking the respondents to imagine that they have decided to move to a new home and are choosing where to live. Each choice question asks respondents to choose between a pair of neighborhoods that have varied attributes. The attributes for the choice scenarios and their levels were identified with discussions with professors and graduate students of landscape architecture. The four attributes - variety in plant species, presence of water, percentage of mowed area, and natural vs. designed appearance of landscape (level of geometry) - are some of the core elements in designing green infrastructure. The levels of attributes are listed in Table 1. Cost is also included in the form of a home association fee. Throughout the survey, we use a more general term "green spaces" to replace GI to avoid the perception that new development will occur. The survey provides respondents with background information about green spaces and the four attributes. Following the information on each attributes, we ask respondents to rank the levels of each attribute in their preferred order. We call information obtained from these questions as the "preference order data," in contrast to the "choice data" retrieved from choice questions. The research question is, then, how well do the different choice models predict the preference order data collected from the same respondents?

Twelve choice questions are then presented.[1] We offer three levels of housing density for respondents to choose from, so the images describing the choice scenarios can better meet the

[1] We randomize the order of choice questions to reduce potential bias led by ordering effect and respondent fatigue.

expectation of respondents. We leave the attribute, natural vs. designed appearance of landscape, to be explained by images solely, because it is unlikely to be clarified given the limited length of survey. A confusing definition of the attribute and its level would invite a potential bias among the users in the survey in terms of choosing words instead of the landscape they find visually pleasing. The choice questions are followed by several questions about attitude toward green spaces, for instance, potential concern and general expectation. The survey begins with questions regarding the place that the respondents currently live in and important characteristics for choosing a new neighborhood.

Computer-rendered images are generated in a program called Visual Nature Studio (VNS). The terrain of the neighborhood is exported to VNS from GIS. For each scenario, the images are chosen to represent the landscape from three different angles to give an idea of the place as a whole. The four attributes and building style can be controlled in the VNS interface and desired images are then rendered. The rendered images from three different angles are composed into a single composite image used in the survey. An example of choice task is shown below in Figure 1.

The participants are recruited through the KnowledgePanel, a web-panel service provided by GfK Knowledge Networks,[2] and a total of 170 complete samples are collected. The participants are possible home buyers who live in suburban area of Chesapeake and Delaware Watersheds, and all survey candidates must be between the ages of 25-64 years old. In order to ensure the survey setting to be familiar and understandable to respondents, we further filter the survey regions by population density in zip code level. Only people live in the zip code regions with population

[2] The households in KnowledgePanel are randomly chosen and the number of surveys they are allowed to participate in is limited. In addition, KnowledgePanel provides computer and internet service for households without home internet access. These features allows KnowledgePanel to cover more than 95% of US households, and thus the sample representativeness is comparable to that using random digit dialing with cellphone sample. It can also provide detail demographic information

density per square miles from 500 to 5000 are targeted for recruiting. In addition, we exclude regions in Washington D.C., the eastern shore area of Maryland, and with area smaller than 0.05 square miles or less than 10 households. In the case of some regions are partly inside the two watersheds, only regions with at least 50% land area inside any one of the two watersheds are selected. In terms of the age selection criterion, residents younger than 25 years old are excluded because they are unlikely to soon purchase a home. Residents older than 64 years old are excluded because they typically face a different household budget constraint. Detail socio-demographic information of respondents, such as income, education, employment status, and marital status, are provided through the database of KnowledgePanel.

2.2. Econometric and Model Performance Assessment Methods

In this section, we summarize three candidate discrete choice models and propose a strategy to assess the performances of the three competing models based on their ability to predict preference orders in both population and individual level. The individual level strategy exploits the estimation results of discrete choice models to predict preference orders of individual, while the population level strategy uses the same results to predict the portions of each preference order of entire sample.

2.2.1. Discrete Choice Model Specifications

The conceptual framework of state choice experiment is based on random utility maximization model (Holmes and Adamowicz, 2003). In this model, people are assumed to assess the utility generated by each alternative in a given choice set as a function of attributes attached, and choose the alternative which gives the respondents the highest utility. Under this setting, a person's utility for a certain scenario is a function of attributes and an unobserved random component. The utility (U) from scenario q is given by:

$$U_q = \alpha A_q + \varepsilon_q \tag{1}$$

where A_q is the vector of the attributes of scenario q, α is the vector of marginal utilities of each attributes, and ε_q is an unobserved, random component. When cost is included as an attribute, the monetary value, or marginal willingness to pay, of other attributes can be calculated as the ratio of the marginal utility of a certain attribute t divided by the negative marginal utility of cost attribute, i.e., $-(\alpha_t/\alpha_{cost})$.

In a random parameter logit model, if the random component in utility, ε, follows a Type I extreme value distribution, then the conditional (L_{iq}) and unconditional probability (P_{iq}) of an individual i choosing alternative q among all Q scenarios in a choice question can be shown respectively by:

$$L_{iq} = \frac{\exp(\beta_i x_{iq} + \gamma z_{iq})}{\sum_{q'=1}^{Q} \exp(\beta_i x_{iq'} + \gamma z_{iq'})} \text{ and } P_{iq} = \int L_{iq} f(\beta) d\beta \tag{2}$$

where x_{iq} is the vector of attributes of alternative q with random marginal utility, while z_{iq} is the vector of attributes with fixed marginal utility. β_i and γ are the marginal utilities for corresponding attributes, and β_i varies across individuals following some continuous distributions $f(\beta)$. The unconditional probability generally cannot be calculated because the integral does not have closed form but can be approximated using simulation. The simulated probability over R draws from $f(\beta)$ is given by:

$$\check{P}_{iq} = \frac{1}{R} \sum_{r=1}^{R} L_{iq}(\beta^r) \tag{3}$$

where r represents the r^{th} draw. See Train (2009), Ch. 6, for more detail on estimation strategy.

On the other hand, the random utility maximization model gives the conditional probability ($L_{iq|c}$) of an individual i, who belongs to class c, choosing alternative q among all Q scenarios in a choice question for a latent class logit model by:

$$L_{iq|c} = \frac{\exp(\beta_c x_{iq})}{\sum_{q'=1}^{Q} \exp(\beta_c x_{iq'})} \tag{1}$$

where x_{iq} is the vector of attributes of alternative q, β_c is vector of the marginal utilities for associated attributes. In contrast to RPL, β_c varies across classes but not individuals, i.e., it is fixed given its class. Given that the probability of individual i being in class c, H_{ic}, is a function of individual characteristics (k_i), the unconditional probability (L_{iq}) can be denoted by

$$L_{iq} = \sum_{c=1}^{C} L_{iq|c} H_{ic} \text{ and } H_{ic} = \frac{\exp(\theta_c k_i)}{\sum_{c'=1}^{C} \exp(\theta_{c'} k_i)} \tag{2}$$

and thus the likelihood is followed by

$$\mathcal{L} = \sum_{c=1}^{C} \left[H_{ic} \prod_{q=1}^{Q} L_{iq|c} \right] \tag{3}$$

In order to incorporate within-class heterogeneity, an individual specific random component, w_i, is introduced, and the conditional probability of randon parameter latent class logit can be written as

$$P_{iq|c} = \frac{\exp[(\beta_c + w_i) x_{iq} + \gamma_c z_{iq}]}{\sum_{q'=1}^{Q} \exp[(\beta_c + w_i) x_{iq'} + \gamma_c z_{iq'}]} \tag{4}$$

Similar to the specification of RPL denoted in section 1.2.2, x_{iq} is the vector of attributes of alternative q with random marginal utility, while z_{iq} is the vector of attributes with fixed marginal utility. β_c and γ_c are the marginal utilities for corresponding attributes following some discrete distributions given individual i being in class c, and w_i varies across individuals following some continuous distributions $g(\varphi)$ with zero mean and standard deviation σ_w, which is independent from all exogenous data in the sample. Accordingly, the probability of individual i making choices across all choice tasks can be given by

$$f[y_{i,t}|c] = \frac{\exp\{\sum_{q'=1}^{Q} y_{iq',t}[(\beta_c+w_i)x_{iq',t}+\gamma_c z_{iq',t}]\}}{\sum_{q'=1}^{Q}\exp[(\beta_c+w_i)x_{iq'}+\gamma_c z_{iq'}]} \tag{5}$$

where the subscript t stands for each choice task, and $y_{iq',t}$ = 1 if individual i chooses alternative q' for choice task t and 0 for all others. This probability can be approximated using simulation, and the simulated likelihood function can be expressed as

$$\mathcal{L} = \prod_{i=1}^{N}\sum_{c=1}^{C} H_c(\theta)\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T} f[y_{i,t}|c] \tag{6}$$

Noted that R is the number of draws in simulating the likelihood on the domain of random variable w_i.

2.2.2. Prediction Strategy in Population Level

The preference order data will give us the portions of population which have a specific order of each attribute. Also, by estimating models with choice data, we will have the distributions of marginal utility for each attribute level. Given the distributions of all levels of each attribute resulting from our three competing models, we calculate the percentages of population having a particular order of levels predicted by each model, and compare the predicted percentages to the percentages obtained from the preference order questions. The derivation of the predicted portions of population of possible orders for LCL is trivial. The estimation results of LCL will provide class prevalence and the coefficients of each class, and thus the percentage of respondents having a certain preference order over an attribute is simply the sum of prevalence of classes with that preference order.

For RPL, the predicted portions can also be calculated straightforwardly with some probabilistic computation. Given the distributions of each level of an attribute, we are able to compute or simulate the probabilities of the marginal utility of a certain level that is greater than that of the other levels. For instance, we can compute the probability of a draw from parameter $\beta_1 \sim N(1,1)$ is greater than that from $\beta_2 \sim N(0,1)$ and $\beta_3 \sim N(-1,1)$. Similarly, the predicted portions of respondents having a certain preference order resulting from RPLCL can be computed by the same procedure used for RPL with some additional work: one class at a time and then weighted by class prevalence.

2.2.3. Prediction Strategy in Individual Level

Revelt and Train (2000) proposed a maximum-likelihood-based "conditioning on individual tastes" (COIT) procedure to derive the distribution of preference in an individual level. The parameters of the preference distributions of each respondent can be obtained conditional on the choices a respondent have made. Given the context of RPL, the individual-specific parameters of individual i ($\bar{\beta}_i$) can be given by

$$\bar{\beta}_i = \frac{\int \beta P(y_i|x_i,\beta) f(\beta|\varphi) d\beta}{P(y_i|x_i,\beta)} \tag{7}$$

where y_i is the sequence of choices individual made, x_i is the vector of attributes of each choice scenario that individual experienced, and β is the vector of marginal utility with parameter φ.

Revelt and Train (2000) estimated a RPL model using choice data obtained in all choice questions but the last one, and derived the preference distribution of each individual.[3] The

[3] This unpublished manuscript was later comprised in Train's "*Discrete Choice Methods with Simulation*" as the Ch.11, Individual-Level Parameters. See its section 11.2 for the complete procedure for deriving conditional distribution.

distributions of individual-specific preference are then utilized to predict the choice made in the last choice question. While they explain the procedure in the context of a RPL model, it applies to any model that incorporates random parameters, for example, RPLCL. The authors pointed out one caution for using this approach. If the last choice situation includes trade-off which is fairly different from those in previous situation, even though the average predictions accuracy by their COIT procedure will be improved, the predictions for some individuals can be deteriorated comparing to the predictions made by point estimates of population parameters.

In light of Revelt and Train's caution, the strategy proposed for individual level prediction in this study renovates their approach by using all choice data to predict the preference order data. The premises of the potential strength of our strategy are, 1) preference order questions are cognitively easier to answer than choice questions are, because the former does not require respondents to evaluate multi-dimensional trade-offs; and 2) the choice made in the last choice question might be inconsistent due to fatigue effect, while preference order data does not suffer from the same problem. Hence, we can derive the individual specific distributions for each level of each attribute following COIT procedure, and compare model performance by two criteria: first, the percentages that the preference orders generated by point estimates of individual parameters matches the actual orders in preference order data. Another criterion can be obtained by a procedure similar to that proposed in population level, i.e., the probabilities that a certain individual specific distribution correctly predicts the stated order. This COIT procedure only applies to RPL and RPLCL simply because of the within-class homogeneity assumption of LCL. A Hierarchical Bayes analog to the COIT has also been commonly performed to achieve the same goal, and will provide essentially the same results with sufficiently large sample size[4].

[4] For detail on Bayesian procedures to derive individual level parameters, see Ch.12 in Train (2009).

Lastly, it is worthwhile to run a conditional logit model with interactions, which is essentially a special case of RPL where all parameters are fixed or an LCL with only one class, and assess its performance using this prediction-based approach. This will allow us to examine if the lesson, a heavily-parameterized but misspecified model will actually be inferior to some sparse models, is true in a state choice context.

3. Results

We ran a RPL model with following specification: 1) non-random cost attribute, 2) all others attributes being normally distributed, 3) no correlation between parameters, and 4) 200 Halton draws. The estimation results are then used to simulate the percentages of population having a particular order of levels for each attribute. The numbers are reported in the third column of Table 3. The individual estimates of marginal utility are derived using COIT procedure, and the resulting percentages are shown in the sixth column. Similarly, the predicted percentages from a 3-class LCL model are reported in the fourth and the seventh column of Table 3, respectively. Note that we do not specify any variable to be person specific, i.e., no variable is used for determining the class assignment of each respondent. The regression results of the two discrete choice models are shown in Table 2.

We calculated the differences between the predicted and stated percentages for each attribute level in absolute value. The total and average differences are listed at the end of Table 3 as indices for comparing the prediction accuracy. Despite the inferior model fit, the RPL model produces more accurate overall prediction than LCL does. The COIT for RPL gives less heterogeneous prediction but somewhat surprisingly deteriorates the overall prediction performance, while the COIT for LCL slightly improves the prediction compared to that solely based model estimates.

By demonstrating the prediction performances on stated preference orders in both population and individual levels, the results will provide new evidence on the abilities to capture the underlying preference heterogeneity of three competing models - random parameter logit, latent class logit, and random parameter latent class logit - serving state choice methods. Thus researchers can be better informed when they come to the question of model selection: if they should go for the classic RPL, LCL for less computational burden, or RPLCL for its complete flexibility. Ambitiously, we expect that this prediction-based model assessment approach would become a standard in stated choice methods, given its minor cost for obtaining preference order data. Researchers do not need extra data source other than the survey itself to assess the models in terms of their prediction performance. We consider that there is no certain model that can fit all different underlying preference structure, so our goal is proposing a powerful tool for model selection, in addition to relative model fit measures.

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Table 1: Attribute Levels

Attributes	Variety in Plant Species	Presence of Water	Percentage of Mowed Area	Level of Geometry	Cost
Levels	High Medium Low	Always Sometimes Never	100% 70% 30% 0%	High Medium Low	$100 $50 $0

Figure 1: Example of Choice Question

Table 2: Discrete Choice Model Results

	RPL		LCL (3-class)		
Log-likelihood	-923.84		-835.94		
Class Prevalence			37.57%	23.93%	38.5%
	Means	S.D.s	Means of Class 1	Means of Class 2	Means of Class 3
Geometry					
Low	-0.077 (0.113)	0.046 (0.178)	-0.800 (1.744)	-0.642 (0.406)	0.176 (0.145)
High	-0.028 (0.139)	0.136 (0.157)	1.486 (3.115)	-0.490 (0.477)	0.274 (0.201)
Variety in Plant Species					
Low	-1.390 (0.199)	1.730 (0.208)	0.278 (1.687)	-0.171 (0.379)	-1.372 (0.163)
High	0.175 (0.141)	0.386 (0.322)	2.137 (4.732)	-0.822 (0.526)	0.639 (0.171)
Presence of Water					
Never	0.334 (0.141)	1.259 (0.170)	1.299 (1.553)	0.760 (0.466)	-0.575 (0.168)
Always	-2.518 (0.277)	2.227 (0.262)	-4.487 (3.428)	-0.849 (0.393)	-0.866 (0.169)
Percentage of Area Mowed					
0%	-0.356 (0.153)	0.839 (0.201)	1.181 (3.142)	-1.146 (0.399)	0.159 (0.163)
70%	0.181 (0.126)	0.370 (0.190)	2.622 (4.817)	0.165 (0.292)	0.008 (0.151)
100%	-0.462 (0.181)	0.270 (0.298)	-0.062 (3.016)	-0.268 (0.328)	-0.617 (0.279)
Cost	-0.019 (0.002)		0.002 (0.008)	-0.043 (0.007)	0.00012 (0.002)

Note: Standard errors are in parenthesis.

Table 3: Stated and Predicted Preference Orders

	Stated	Model Prediction			COIT		
		RPL	LCL	RPLCL	RPL	LCL	RPLCL
Level of Geometry							
Low > Medium > High	27.98%	2.72%	0%		0%	0.00%	
Low > High > Medium	1.79%	0.24%	0%		0%	0.00%	
Medium > Low > High	16.07%	33.65%	0%		3.09%	0.00%	
Medium > High > Low	21.43%	21.77%	24.70%		80.25%	21.60%	
High > Low > Medium	0.60%	1.68%	38.50%		0%	35.19%	
High > Medium > Low	32.14%	39.95%	36.70%		16.67%	43.21%	
Variety in Plant Species							
Low > Medium > High	11.38%	6.91%	0%		3.70%	0.00%	
Low > High > Medium	0.60%	10.48%	0%		6.17%	0.00%	
Medium > Low > High	8.98%	1.51%	24.70%		0%	20.37%	
Medium > High > Low	21.56%	24.13%	0%		6.79%	4.94%	
High > Low > Medium	2.99%	3.71%	36.70%		2.47%	36.42%	
High > Medium > Low	54.49%	53.26%	38.50%		80.86%	38.27%	
Presence of Water							
Never > Sometimes > Always	41.42%	52.69%	61.50%		68.52%	62.96%	
Never > Always > Sometimes	2.96%	4.17%	0%		0.62%	0.00%	
Sometimes > Never > Always	26.63%	29.92%	38.50%		20.37%	37.04%	
Sometimes > Always > Never	10.65%	4.47%	0%		4.32%	0.00%	
Always > Never > Sometimes	1.18%	3.67%	0%		0.62%	0.00%	
Always > Sometimes > Never	17.16%	5.08%	0%		5.56%	0.00%	

Table 3. (Continued)

	Stated	Model Prediction			COIT		
		RPL	LCL	RPLCL	RPL	LCL	RPLCL
Area Mowed							
0% > 30% > 70% > 100%	12.50%	8.01%	0%		5.56%	0.00%	
0% > 30% > 100% > 70%	0.60%	2.06%	0%		0%	0.00%	
0% > 70% > 30% > 100%	0.60%	13.43%	38.50%		4.94%	34.57%	
0% > 70% > 100% > 30%	0.00%	0.46%	0%		0%	0.00%	
0% > 100% > 30% > 70%	0.00%	0.39%	0%		0%	0.00%	
0% > 100% > 70% > 30%	0.00%	0%	0%		0%	0.00%	
30% > 0% > 70% > 100%	10.71%	1.97%	0%		0.62%	0.00%	
30% > 0% > 100% > 70%	0.00%	0.74%	0%		0%	0.00%	
30% > 70% > 0% > 100%	11.90%	3.95%	0%		2.47%	0.00%	
30% > 70% > 100% > 0%	14.88%	9.81%	0%		1.85%	0.00%	
30% > 100% > 0% > 70%	0.60%	0.52%	0%		0%	0.00%	
30% > 100% > 70% > 0%	0.60%	2.85%	0%		0%	0.00%	
70% > 0% > 30% > 100%	1.19%	8.69%	36.70%		6.17%	38.27%	
70% > 0% > 100% > 30%	0.00%	0.28%	0%		0%	0.00%	
70% > 30% > 0% > 100%	2.38%	14.70%	0%		47.53%	1.23%	
70% > 30% > 100% > 0%	13.69%	28.96%	24.70%		30.25%	25.93%	
70% > 100% > 0% > 30%	0.00%	0.09%	0%		0%	0.00%	
70% > 100% > 30% > 0%	10.71%	1.66%	0%		0%	0.00%	
100% > 0% > 30% > 70%	0.00%	0.06%	0%		0%	0.00%	
100% > 0% > 70% > 30%	0.00%	0.02%	0%		0%	0.00%	
100% > 30% > 0% > 70%	0.60%	0.15%	0%		0%	0.00%	
100% > 30% > 70% > 0%	1.79%	0.75%	0%		0%	0.00%	
100% > 70% > 0% > 30%	1.19%	0.02%	0%		0%	0.00%	
100% > 70% > 30% > 0%	16.07%	0.32%	0%		0.62%	0.00%	
Total Absolute Difference (%)		223.95	423.37		377.77	411.78	
Average Difference per Item (%)		5.33	10.08		8.99	9.80	