The Information Product Methods: A Unified Approach to Dual-Purpose Computerized Adaptive Testing

Applied Psychological Measurement

2018, Vol. 42(4) 321–324

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DOI: 10.1177/0146621617730392

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Chanjin Zheng¹, Guanrui He¹, and Chunlei Gao¹

Abstract

This article gives a brief summary of major approaches in dual-purpose computerized adaptive testing (CAT) in which the test is tailored interactively to both an examinee's overall ability level, θ , and attribute mastery level, α . It also proposes an information product approach whose connections to the current methods are revealed. An updated comprehensive empirical study demonstrated that the information product approach not only can offer a unified framework to connect all other approaches but also can mitigate the weighting issue in the dual-information approach.

Keywords

dual-purpose CAT, information product approach, dual-information method, ASI, ARI, dapper-ness with information

The new federal grant program known as “Race to the Top” (RTTT) has led into a new era of K-12 assessments which emphasized both accountability and instructional improvement (Chang, 2012). In light of this, researchers began to consider to develop a computerized adaptive testing (CAT) in which the test is tailored interactively to both an examinee's overall ability level, θ , and attribute mastery level, α .

Four major approaches to address item selection in dual-purpose CAT can be summarized as the two-stage method (McGlohen & Chang, 2008), the weighted item selection (WIS) approach (Wang, Chang, & Douglas, 2012), the dual-information method (DIM; Cheng & Chang, 2007) which was further developed by Wang, Zheng, and Chang (2014), and the dapperness with information (DWI) index (Dai, Zhang, & Li, 2016). This brief report is to propose an information product approach which can take DWI as a special case, reveal its connections to the current methods, and then conduct an updated empirical study. The information product approach not only can offer a unified framework to connect all other approaches but also can mitigate the weighting issue in the dual-information approach.

¹Jiangxi Normal University, Nanchang, China

Corresponding Author:

Chunlei Gao, School of Psychology, Jiangxi Normal University, 99 Ziyang Ave., Nanchang 330022, Jiangxi, China.

Email: gaochunlei51@163.com

The Information Product Approach

The information product approach can be considered as a natural extension of WIS. A brief review of WIS will be presented below which leads to the development of the information product approach.

Wang et al. (2012) developed the WIS approach by borrowing the idea of the maximum priority index from CAT and proposed three variant priority indices for cognitive diagnostic CAT (CD-CAT). The generic formula is

$$objective = P_j \times KL_j(\theta_i),$$

in which P_j is the priority index in cognitive diagnostic models (CDMs) and $KL_j(\theta_i)$ is the KL (Kullback–Leibler) information index for item j in item response theory (IRT). P_j takes three different forms which can be regarded as a progression from no item discrimination to the coarse classic test theory (CTT) item discrimination index to the more refined KL-based item discrimination index. It can be expected that the KL-based index will outperform the other two counterparts with respect to the measurement precision which is confirmed by the simulation study (Wang et al., 2012).

This perspective can afford to offer the possibility that some new item algorithms can be readily proposed by further extending this progression. Any of the response distribution-based item selection algorithms (Zheng & Chang, 2016) such as posterior weighted attribute-level CDM discrimination index (PWACDI) can serve as a priority index. By such a line of reasoning, DWI, whose formulation is $DWI_j = KL_j(\theta_i) / SHE_j(\alpha_i)$, can be considered as a special case of the information product approach since $1 / SHE_j(\alpha_i)$ can be perceived as the priority index (the weight). And it can expect that the new methods will outperform the methods in WIS since the new weight carries more information for CDMs while the IRT part remains unchanged. It is better to perceive the “weight” as an equal counterpart of the IRT information indices and, thus, a new term, *information product approach*, is more appropriate.

Its Connection to the Dual-Information Approach

The information product methods can be considered as members of DIM. DIM is a weighted linear sum of the objectives:

$$Objective = wPWKL_j(\alpha_i) + (1 - w)KL_j(\theta_i),$$

where w is the weight and $PWKL_j(\alpha_i)$ is the posterior weighted KL information. To resolve the noncomparability of the two information indices resulted from the number of quadrature points for the integration of θ and the arbitrary selection of weight, Wang et al. (2014) proposed two modifications using two transformations of information indices: aggregate ranked information index (ARI) and aggregate standardized information index (ASI).

A simple trick can reveal the connection between the *information product algorithms* and the linear combination methods. The authors may apply the logarithm operation to the information product methods and then have the sum of the logarithm of two information pieces. Although both of them can mitigate the incompatibility issue, ASI and ARI have some defects. Ranking transformation for ARI is the easiest but suffers from the most information loss among the three, and it can also easily be influenced by the item bank size. The Z-score type standardization transformation can be easily influenced by extreme values. By contrast, the logarithm transformation can reduce magnitude difference but is free from any influence from item bank size or extreme values.

Table 1. RMSE and PCCR for the Seven Algorithms.

	11 quadrature points				31 quadrature points			
	30 items		60 items		30 items		60 items	
	RMSE	PCCR	RMSE	PCCR	RMSE	PCCR	RMSE	PCCR
Mlinfor	0.50	0.48	0.33	0.80	0.44	0.46	0.32	0.73
PWKL + KL	0.44	0.73	0.28	0.95	0.42	0.39	0.30	0.82
PWACDI + KL	0.63	0.29	0.43	0.42	0.51	0.23	0.36	0.45
ASI (PWKL + KL)	0.49	0.78	0.33	0.94	0.50	0.78	0.36	0.98
ASI (PWACDI + KL)	0.51	0.81	0.41	0.96	0.55	0.74	0.42	0.97
PWKL $\times$ KL	0.40	0.69	0.29	0.96	0.36	0.73	0.27	0.96
PWACDI $\times$ KL	0.41	0.73	0.28	0.96	0.38	0.76	0.27	0.96

Note. RMSE = root mean square error; PCCR = pattern correct classification rate; PWKL = posterior weighted KL information; KL = Kullback–Leibler; PWACDI = posterior weighted attribute-level CDM discrimination index; ASI = aggregate standardized information index.

Simulation Study

A simulation study was conducted to evaluate the performance of the new methods under various conditions. The item bank is identical to Study 2 in Wang et al. (2014). The authors had a fully crossed design resulting in 28 conditions: seven item selection methods $\times$ two test lengths (30 vs. 60) $\times$ two quadrature points (11 vs. 31).

The KL index is used for IRT, while PWKL and PWACDI are used for CDM. Specifically, the seven algorithms are maximum information weighed by the KL-based priority index (Mlinfor), two DIM algorithms (PWKL + KL and PWACDI + KL) and their ASI variants with empirical weights, and two information product algorithms (PWKL $\times$ KL and PWACDI $\times$ KL). The criterion for measurement accuracy is root mean square error (RMSE) for θ and pattern correct classification rate (PCCR) for α .

Results

The results are summarized in Table 1. The two information product methods outperform all other methods for both IRT and CDM. And, more importantly, they obtain stable results across different quadrature points for θ and α without any weighting scheme. The other methods underperform for various different reasons. For DIM, PWKL + KL demonstrates a negative effect of the quadrature points; PWACDI + KL produces particularly poor PCCR because PWACDI is in a much smaller magnitude than KL which makes the index solely dominated by KL. Both ASIs are, at the best, comparable with the two information product methods even with fine-tuned weights.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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