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Editorial

Editorial on developments in systems factorial technology: Theory and applications

Systems factorial technology (SFT), developed and refined by James Townsend and his colleagues over the past 25 years (Little, Altieri, Fifić, & Yang, 2017; Townsend & Nozawa, 1995) has stood out within mathematical psychology as one of the relatively few approaches that focuses on testing general model properties using qualitative evaluation. This is both an advantage for the methodology, as the conclusions drawn from its application are general and decisive, and a disadvantage in the sense that the constraints required for its application can be restrictive and difficult to verify. The special issue introduces recent advances in both methodology and application of SFT. We will shortly present the key contributions.

The fundamentals of identifying processing characteristics

For readers who are unfamiliar with SFT, it is an approach to studying information-processing systems in which two or more sources of information may be combined for a decision or action. The framework breaks down the fundamental properties of these types of systems across four dimensions: architecture (the temporal structure of information processing; e.g., processing one source at a time or all sources in parallel), stopping-rule (the function determining how the processed sources of information are jointly mapped onto a response, e.g., responding based on the first completed process or waiting until all relevant information are processed), the interdependencies among the processes, and the workload capacity, (i.e., the influence of the number of information sources on the processing).

One of the original motivations of SFT was that when each of these four properties is left free to vary, it can become impossible to determine them. For example, in one well known paradigm, the response times to a single target source of information are measured as a function of adding more distracting sources of information, and the change in response time across the number of sources is used to infer processing architecture. The (incorrect) argument is that, in a parallel processing system the number of additional distracting sources of information will have no influence on the target processing time whereas in a serial system the response time would increase. One significant issue with this argument is that it confounds workload capacity with architecture. That is, a parallel system that slows down with more items due to limitations in processing capacity (i.e., limited resources stretched across several subprocesses) could produce the same data pattern predicted by the serial model. In fact, Townsend has shown that the inability to discriminate serial from parallel processing without making assumptions about capacity and dependence is quite extensive (Townsend, 1990; see also Townsend & Ashby, 1983). Here, Zhang, Liu, and Townsend (2019) contribute new work to the general theory of parallel/serial identifiability. In particular, they demonstrate that with added assumptions of independence and invariance of each processing time distribution with respect to the presence or absence of the other processes, serial and parallel systems cannot perfectly mimic each other.

The core metrics and empirical methodologies of SFT are targeted at examining some or all of the aspects of information-processing systems while minimizing possible confounds of other aspects. The capacity coefficients and assessment functions (Townsend & Altieri, 2012) target the workload capacity and interdependencies under assumed architecture and stopping rules. The resilience functions (Little, Eidels, Fifić, & Wang, 2015) are similar, in that they examine the dependency and workload, but are focused on the effect of conflicting information. The resilience functions can also be contrasted across levels of salience, referred to as the conflict contrast function, of the information sources to inform inferences about architecture and stopping rule. The survivor interaction contrast (SIC) and mean interaction contrast (MIC) target the system architecture and stopping rule while attempting to minimize the influence of interdependency and removing workload variation. The idea is to examine the interaction between manipulations that selectively influence the processing of each source of information. If such selective influence manipulations can be found and if the influence is strong enough to be detected in the response time distributions, many architecture/stopping-rule combinations yield distinctive SIC/MIC patterns. This allows for broad qualitative distinctions. For example, whenever an SIC is observed with any negative portion of the function (beyond that what occurs due to measurement noise), then all independent parallel and serial first-terminating process models can be rejected, regardless of processing specifics such as processing time distribution or other parametric properties.

Thomas, Fan, and Gamble (2019) extend the SIC and MIC analyses to nested architectures. They demonstrate through analytically proven theorems and simulation-based conjectures that combinations of serial and parallel information processing across levels, for example, two serial-first terminating processing systems operating in parallel with a self-terminating stopping rule, yield specific SIC and MIC patterns under selective influence manipulations.

Selective influence and identifying processing characteristics

From the preceding paragraphs, it is clear that selective influence plays a fundamental role in SFT, particularly for identifying

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architecture and stopping rule. Indeed, many of the articles in this special issue are targeted at aspects of selective influence. In most applications of SFT, selective influence is assumed as long as the estimated response time distributions are approximately ordered. In particular, if selective influence holds, the probability that a process is finished at one level of the selective influence manipulations is always higher than the probability at another level. Thus, the standard approach of testing distribution orderings is a necessary condition but not a sufficient condition. That this is the standard approach is due in part to the lack of general, testable, sufficient conditions for selective influence. However, theoretical work by Dzhafarov and Kujala (2010, 2012) has demonstrated sufficient conditions when each of the subprocesses can be observed. In their article Zhange, Yang, and Kujala (2019) describe a sophisticated empirical design that allows for the application of Dzhafarov and Kujala's theoretical work as well as the SIC analysis.

Schweickert and Zheng (2019) also focus on selective influence and its relationship to stochastic dominance in examining the underlying architecture of multinomial processing trees. In doing so, they build the theory to include another theme that emerged in this special issue: leveraging incorrect responses and response times for improved model identifiability.

Cox and Criss (2019) develop a parametric model to examine architecture and stopping rule combinations along with the potential for coactivation, i.e., an extreme failure of selective influence. They develop a hierarchical model that includes both the architecture-stopping rule combination and the model parameters at a group and individual level. To define this model, they rely on systems of linear ballistic accumulator models (Brown & Heathcote, 2008), which in turn allows them to make use of accuracy information and error response times. Further, they demonstrated a Bayesian implementation of their approach.

Glavan, Fox, Fifić, and Houpt (2019) address another aspect of the selective influence manipulation: the magnitude of its effect. The normal approach to determining the correct magnitude of a salience manipulation is based on extensive piloting to establish levels that are fixed across individuals. Experimental factors can influence different people to different degrees, so that the approach often leads to insufficiently effective manipulations for some of the participants. Glavan et al. adapt an approach from psychophysics to determine an accuracy-based criterion at the individual participant level for good selective influence levels and compare it to a method based on accumulator models to determine a criterion based jointly on response time and accuracy.

Strategy variation and errors

SFT has tended to focus on the correct response times only. Townsend and Altieri (2012) extended the capacity coefficients to incorporate incorrect responses to measuring workload and dependence, using models like the models in Schweickert and Zheng (2019). There has been much less progress on the appropriate use of incorrect response times for the survivor interaction contrast. The parametric models explored by Cox and Criss are one approach, although their inferences are limited to processes that are well represented by the linear ballistic accumulator model. Gondan's (2019) paper in this special issue proposes an alternative approach to including incorrect response times in architecture and stopping rule analysis using nonparametric approaches.

Another assumption for the SIC and MIC, and to some degree for capacity analysis, is that the participant's strategy (i.e., architecture and stopping rule) are consistent throughout a task. While this may hold for the more traditional psychophysical and simple cognitive applications, strategy switching is quite plausible in more complex tasks. When multiple processing strategies underlie the observed responses, a common, effective way of representing behavior is via mixture models. In such models, the observed distribution of responses is represented as a mixture of distributions of the multiple underlying strategies. To-date, little was known about how mixtures of strategies affect the diagnosticity of the SFT measures. Important theoretical developments introduced in this special volume fill in that gap. Both Tillman and Evans (2019), and ourselves (Little, Eidels, Houpt, Garrett, & Griffiths, 2019) examine how SFT metrics reflect mixtures of processing strategies. Tillman and Evans investigate SIC patterns for different combinations of architecture and stopping rules, and propose two types of hierarchical Bayesian models for detecting mixtures of processing. In addition to response times, their approach can also leverage incorrect response times for better identifiability. We also use a simulation study to examine patterns in the SFT measures, including the SIC as well as the capacity coefficients and conflict contrast function (Little et al., 2015; Little, Eidels, Fifić, & Wang, 2018). Further, we present analytic results for the form of the SFT functions predicted by mixtures of models and explore the nonparametric methods for distinguishing between channel interactions and mixtures.

Applications of SFT

To round out the special issue, we included a number of novel and exciting applications of SFT. Burns (2019) examines the use of tactile cues to support balance with an eye toward reducing falls in elderly populations. He does so by estimating SICs and capacity coefficients for individuals' latencies when shifting their balance in response to visual, tactile, and redundant visuo-tactile cues. Yang, Hsieh, Hsieh, Fifić, Yu, and Wang (2019) examine and report how older adults process information relative to younger counterparts. Their analysis suggests that age-related differences in processing could be due to degradation in attention control, along with more conservative decision criteria. They offered a possible model to account for the results that is based on parallel Poisson processes with inhibitory cross-channel interactions. Cooper and Hawkins (2019) apply SFT, for the first time, to consumer choices, and demonstrate how its assorted toolkit aids theory testing. Specifically, they show that many of the theories of consumer choices, which address the way people consider multiple attributes of products before making purchase decision, can be mapped as serial or parallel (based on the temporal consideration of the attributes) and thus tested using SFT measures. Finally, Garrett, Howard, Houpt, Landy, and Eidels (2019) apply SFT to study enumeration of multiple item-sets. Like other SFT applications in this issue, they explore an active area of science that can benefit from the rigor and formalism of mathematical psychology, in general, and SFT, in particular. They examine how people estimate quantities of simultaneously-presented items sets (colored discs, in their experiments) and show that despite the subjective ease with which people grossly estimate quantities, the underlying system is quite limited in its capacity.

Conclusions

To some readers, it may be surprising that a special issue on SFT would be warranted given the quite recent publication of a book dedicated to SFT. From our perspective, the fact that we were able to include a diverse set of papers with highly important contributions to the methodology, all of which are clear advances on the content in the book, is evidence of the vigor and rapidly accelerating pace of SFT research. As more researchers become familiar with the approach and its advantages, the rate of innovation within SFT and its contributions to psychology, in general, will continue to increase.

The general themes also highlight exciting future directions for work extending and applying systems factorial technology. In particular, we hope the research presented herein will inspire new developments, in general, nonparametric joint assessment of correct and incorrect responses, potentially even integrating general recognition theory (Ashby & Townsend, 1986) for a more methodical exploration of failures of selective influence. The opportunities for applications are vast and with the extensions to SFT in this issue, many new potential domains are available, including lifespan changes in how people combine multiple sources of information and the relationship between clinical disorders and information processing characteristics.

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