(discrimination, rather than detection), participants could again be presented with two target signals or just one (or none). In contrast to the 'distractor-free' example, however, other signals that are not the to-be-detected target could appear as well. For example, double target displays would again be XX, but single-target displays would be XO or OX and processing would be required to be focused only on the relevant target information. Thus, some displays could be accompanied by a distractor item that is irrelevant to the decision. This creates a challenge for the calculation and interpretation of the capacity coefficient: moving from one to two (or more) target-signals incurs more than just a change in load; it is also accompanied by changes in the distractor information. To calculate capacity one needs to take into account not only how efficiently the system processes two targets as opposed to just one target, but also potential effects due to the presence of distractors. For instance, superior performance with two targets (XX) vs. one target-one distractor display (XO) could mark efficient processing in the former condition, but could also be a consequence of slow-down in the latter due to the presence of the unhelpful (and possibly harmful) distractor item.

To date, research using the capacity coefficient has focused primarily on cognitive tasks in which the target is presented without distractors. In those studies that have used distractors as part of their design (e.g., Ben-David, Eidels, & Donkin, 2014) the capacity coefficient allowed only limited interpretation due to the competition between effects of load and distraction. The purpose of the current paper is to extend the applicability of the Townsend and Nozawa's (1995) capacity coefficient to cognitive tasks in which distracting information could be present along with target information.

Such an extension would expand the range of cognitive tasks that can be studied using this informative statistic to domains involving distractors. In particular, it would allow one to consider the role of distractor information (additional items or additional dimensions within an item) available in the standard designs of many psychological tasks, such as (but not limited to) categorization (Fific, Little, & Nosofsky, 2010; Little, Nosofsky, & Denton, 2011; Little, Nosofsky, Donkin, & Denton, 2013), recognition memory (Nosofsky, Little, Donkin, & Fific, 2011; Townsend & Fific, 2004), detection (Feintuch & Cohen, 2002; Mordkoff & Yantis, 1993), discrimination (Donkin, Little, & Houpt, 2014), and visual search (Ben-David & Algom, 2009; Fifić, Townsend, & Eidels, 2008; Thornton & Gilden, 2007). Furthermore, tasks that examine stimulus–response congruence, such as the Stroop (Stroop, 1935), Simon (Proctor & Vu, 2006; Simon & Rudell, 1967), and flanker (Eriksen & Eriksen, 1974) tasks, manipulate and measure the effects of conflicting sources of information in a way we can analyze using the machinery developed in this paper and that was not previously available. Like the initial development of the capacity coefficient (Townsend & Nozawa, 1995), our extension is derived for regimes involving near error-free performance.

The logic of our extension is illustrated with a simple case of one target and one distractor, as shown in Fig. 1. The figure illustrates the difference between distractor-free and distractor-present tasks. The left and middle panels of Fig. 1 show two variants of the (distractor-free) redundant-target detection task. The left-hand side panel depicts a task with an OR decision rule, where an observer should respond YES if she detects a target in the left *or* the right locations or both. The middle panel illustrates an AND decision rule, where an observer should respond YES only if targets appear on both the left *and* right locations. By contrast, the task depicted on the right-hand side panel requires discrimination of a target (low luminance dot) from distractors (high luminance dot).[1]

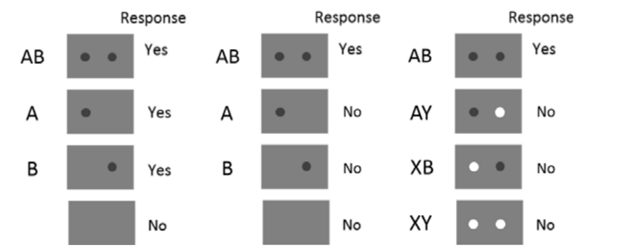

Fig. 1. Examples of detection (panels A and B) and discrimination (panel C) tasks.

Since the single- and null-target displays contain a non-target dot possibly alongside with the target information, accurate responding requires that the high-luminance target be discriminated from the low-luminance distractor. In the case where capacity is not unlimited, then processing the distractor information may occupy non-negligible processing time. Since the capacity coefficient is an RT-based measure, the presence of distractors can alter its value.

The influence of distractors on cognitive operations cannot be investigated separately from the role of *processing architectures* underlying those operations. A cognitive architecture defines how processes underlying cognitive operations are organized, in terms of processing order (serial, parallel), and stopping rule (whether it is possible to stop after a limited amount of information has been processed – self-terminating – or only after all information had been processed — exhaustive). Joint consideration of mental architectures and distractor information is critical in assaying the capacity function. For illustration, assume that a participant is using the *serial exhaustive system* to search for certain target items. In such a system, any two items (or more) are processed in a sequential fashion, and the processing is completed only when *both* are processed. Distractor items in such system will be mandatorily processed along with targets, since the cognitive system cannot stop upon the detection of the target. In contrast, a *serial self-terminating system* can make a decision as soon as a target was found, and before completing the processing of distractor information. Thus, two serial systems with different stopping rules will be affected by the presence of distractor information in different ways. The capacity coefficient statistic is sensitive to these differences as is revealed by the formal definition of the capacity coefficient provided in the next section.

Intuitively, the coefficient is expressed as a ratio between performance on the double-target condition and the minimum-time prediction derived from the single-target conditions. An unlimited capacity parallel model, which is used as the baseline comparison model, predicts that these quantities should be equivalent; hence, their ratio (the capacity coefficient, $C(t)$) should equal 1 across all observed response times (i.e., $C(t) = 1$). The presence of distractors may affect how quickly single-target trials are processed, and reduce or increase the minimum time predicted from the target + distractor trials. This, in turn, affects the inferences that one can derive from the capacity coefficient. For example, in the standard, distractor-free case (see Fig. 1, left and middle panels), limited capacity models predict $C(t) < 1$; however, the same limited capacity models can predict $C(t) = 1$ or $C(t) > 1$ when distractors are present in the display. Likewise, supercapacity models (such as coactive or facilitatory interactive models, e.g., Eidels, Houpt, Altieri, Pei, & Townsend, 2011), which exhibit double-target processing that is faster than the benchmark minimum-time prediction of independent single targets (i.e.,

[1] It should be noted that the high-luminance white dot is not "informationless" but provides positive evidence for a NO response (or, equivalently, negative evidence for a YES response). Consequently, whether or not an AND or an OR rule is applied depends on whether the observer frames the task as detecting two low luminance black dots on the left and the right or detecting a white dot on the left or the right.