Bounding Consideration Probabilities in Consider-Then-Choose Ranking Models

Extended Abstract

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ABSTRACT

A common theory of choice posits that individuals make choices in two steps, first selecting a subset of the alternatives to consider before making a choice from the resulting consideration set. However, inferring unobserved consideration sets (or item consideration probabilities) in this “consider then choose” setting poses significant challenges: even simple models of consideration with strong independence assumptions are not identifiable, even if item utilities are known. We consider a natural extension of consider-then-choose models to a top-$k$ ranking setting, where we assume rankings are constructed according to a Plackett–Luce model after sampling a consideration set. While item consideration probabilities remain non-identified in this setting, we prove that knowledge of item utilities allows us to infer bounds on the relative sizes of consideration probabilities. Additionally, given a bound on the expected consideration set size, we derive absolute upper and lower bounds on item consideration probabilities. We also provide an algorithm to tighten those bounds on consideration probabilities by propagating inferred constraints. Thus, we show that we can learn useful information about consideration probabilities despite their non-identifiability. We demonstrate our methods on a dataset from a prominent line of work in discrete choice suggests that selection of consideration sets (except in carefully controlled experimental settings) and cannot in general be identified from observed choice data [14, 31]. Perhaps as a result, consider-then-choose models have received comparatively little attention in the ranking literature.

In keeping with the framework of bounded rationality [27], a prominent line of work in discrete choice suggests that selection is a two-stage process, where individuals first narrow their options to a small consideration set from which a final selection is made [12, 26]. These “consider then choose” models have shown considerable promise [4, 24], but suffer from the unobservability of consideration sets (except in carefully controlled experimental settings) and cannot in general be identified from observed choice data [14, 31]. Perhaps as a result, consider-then-choose models have received comparatively little attention in the ranking literature.

Plackett–Luce with consideration: the PL+C model. Here, we study the natural consider-then-rank model obtained by augmenting top-$k$ Plackett-Luce with the independent-consideration rule [17], which we term PL+C. Each of the $n$ items in a universe $U$ has an item-specific consideration probability $p_i \in (0, 1]$ and a utility $u_i \in \mathbb{R}$. The two-stage choice unfolds as follows, for fixed $k \leq n$:

1. Consideration: Each item $i \in U$ advances to the second stage randomly and independently with probability $p_i$, yielding some consideration set $C \subseteq U$. (We do not observe cases...
We imagine making observations of many individuals’ rankings, with relatively mild assumptions—see (2), above—item occurrence (1) known item utilities and (2) a lower bound on expected consideration probabilities. In an existing psychology experiment about perceptions of U.S. history [23], participants were provided with a random set of 10 states and asked to rate their importance to U.S. history. We thus estimate utilities in the absence of consideration from the Random-10 data, and then estimate consideration from the Top-3 data, using the PL+C model and our bounds (implemented in Pytorch [21]).

The algorithms described above rely on the existence of pairs of states whose utilities and top-$k$ ranking rates are flipped. Interestingly, many such flips occur in this data, highlighting the apparent importance of consideration in the Top-3 question. Using our methods, we find that, e.g., $P_{Massachusetts} > P_{Virginia} > P_{Pennsylvania}$ and $P_{Virginia} > P_{New York}$. Combining our lower and upper bounds yields feasible intervals on consideration probabilities for each state, revealing that, if our assumptions are valid, most states are considered less than 30–40% of the time. Additionally, the bounds on consideration probabilities align with theories about why certain states were highly rated in the data [23].

Related work. Prior research on consideration focused on single choices rather than rankings. The approach most closely related to our work adds a consideration stage to random utility models [4, 5, 24, 31], following Manski’s formulation [16], but there are many alternative strategies [5, 7, 14, 17, 24]. Existing discrete choice approaches to handle non-identifiability of consideration probabilities use explicit item availability questions [5, 24, 28] online browsing data [11, 19], observations of “none of the above” outside options [14, 17], item features that change over time [1], and parametric models of consideration [4, 31]. Consideration has received only limited attention in the ranking literature [10, 20].

Discussion. We formalized a natural model of ranking with consideration, augmenting Plackett–Luce with an independent consideration model. Despite showing that consideration probabilities are not identified in general, we derived relative and absolute bounds that allow us to learn about possible ranges of consideration probabilities from observed ranking data. Our data application demonstrates how these bounds can be used in practice to gain insight into consideration behavior from ranking data.

There remains much to explore regarding the PL+C model, and ranking with consideration sets more generally. First, a thorough characterization of PL+C would be valuable, including its expressive power relative to other augmented Plackett–Luce models, such as the contextual repeated selection model [25]. Another interesting question concerns computing PL+C probabilities efficiently. If we know utilities and consideration probabilities, the direct approach to computing ranking probabilities involves a sum over exponentially many possible consideration sets. Is it possible to compute PL+C probabilities in polynomial time, or is it provably hard?

For further discussion of related work, limitations, future directions, and technical details, we refer readers to the full paper [3].

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REFERENCES


