An expectation-maximization method to estimate a rank-based choice model of demand

APPENDIX

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A1 Pseudocodes of the EM method

A1.1 Uncensored demand case

We next summarize the entire EM algorithm for the uncensored demand case using pseudocode.

EM algorithm for estimating the rank-based choice model

[Input data]: Number of compatible customer types N, availability information represented by sets S_t and transaction data $j_t, t = 1, ..., \hat{T}$.

[Preprocessing]: Set initial proportions x_i . Based on the availability information and transaction data, build the sets $\mathcal{M}_t(j_t, S_t) := \{i : \sigma^{(i)}(j_t) < \sigma^{(i)}(k), \forall k \in S_t, k \neq j_t\}.$

Repeat

```
Set m_i := 0, x_{it} := 0, i = 1, \dots, N, t = 1, \dots, \hat{T}.
[E-step]:
For t := 1, \ldots, \hat{T} do
    [Update probabilities of customer types]
   For i \in \mathcal{M}_t(j_t, S_t) do
        Set x_{it} := x_i / (\sum_{h \in \mathcal{M}_t(j_t, S_t)} x_h).
   Endfor
Endfor
[Compute estimates for m_i]
For i := 1 to N do
   For t := 1 to \hat{T} do
      Set m_i := m_i + x_{it}
   Endfor
Endfor
[M-step]:
For i := 1 to N do
  Set x_i := m_i / \sum_{k=1}^N m_k.
Endfor
```

Until Stopping criterion is met.

A few remarks on the implementation are in order. The initialization of x_i , i = 1, ..., N, is arbitrary (as long as the set of types is compatible with the transactions); we merely need starting values different from zero. The stopping criteria can be based on various measures of numerical convergence, e.g., that the Euclidean norm of the difference between two consecutive vectors \hat{x} is less than ϵ . Alternatively, we could set a maximum number of iterations. In all of our experiments we observed very fast convergence, so it would appear that the stopping criterion is not critical.

A1.2 Censored demand case

We next summarize the entire EM algorithm for the censored demand case using pseudocode.

EM algorithm for estimating the rank-based choice model

[Input data]: Number of customer types N, availability information represented by sets S_t and transaction data $j_t, t = 1, ..., T$.

[Initialization]: Set $x_i := 1/N$, and $\lambda = 0.5$. Based on the availability information and transaction data, build the sets $\mathcal{M}_t(j_t, S_t) := \{i : \sigma^{(i)}(j_t) < \sigma^{(i)}(k), \forall k \in S_t, k \neq j_t\}$. Set $a_t := 0, t = 1, \ldots, T$.

Repeat

```
Set m_i := 0, x_{it} := 0, i = 1, \dots, N, t = 1, \dots, T.
[E-step]:
For t := 1, \ldots, T do
    [Update probabilities of customer types]
   For i \in \mathcal{M}_t(j_t, S_t) do
       Set x_{it} := x_i/(\sum_{h \in \mathcal{M}_*(j_*, S_*)} x_h).
   Endfor
   [Update estimates a_t]
   If j_t > 0
       Set a_t := 1,
   Else (i.e., j_t = 0)
       If \mathcal{M}_t(0, S_t) = \emptyset
           Set a_t := 0,
           Set a_t := \lambda \sum_{i \in \mathcal{M}_t(0, S_t)} x_i / (\lambda \sum_{i \in \mathcal{M}_t(0, S_t)} x_i + (1 - \lambda))
       Endif
   Endif
Endfor
[Compute estimates for m_i]
For i := 1 to N do
   For t := 1 to T do
       Set m_i := m_i + a_t x_{it}
   Endfor
Endfor
[M-step]:
For i := 1 to N do
  Set x_i := m_i / \sum_{t=1}^T a_t.
Endfor
```

Set
$$\lambda := \sum_{t=1}^{T} a_t / T$$
.

Until Stopping criterion is met.

We point out that as in the uncensored demand case, the initialization of λ and x_i , i = 1, ..., N, can be set arbitrarily.

A2 Supplement to numerical examples

In the figures below we report the relative errors of Direct Max (left column) and EM (right column) with respect to the true underlying model parameters, for the case where N=10 and the number of periods increases from T=10,000 (top) to T=50,000 and T=100,000 (bottom). Since the results obtained by both versions of Direct Max are (almost) identical, we just report results for Direct Max V2 (the version which runs faster).

Nonsurprisingly, when T increases, the errors of both methods become more target oriented around zero. The distributions of errors for both methods are also very similar. We also verify that the log-likelihoods of the three proportions (based on the generating demand model, estimated via Direct Max, and estimated via EM) are very close (up to three decimal numbers), even when the estimation error is more significant (i.e., when T = 10,000).

A2.1 Uncensored demand case

Figure A1 shows the relative errors for the uncensored demand case when we set $\lambda = 1$ (which is common knowledge).

A2.2 Censored demand case

Figure A2 reports estimation errors for a low volume demand scenario (with $\lambda = 0.2$), and Figure A3 does it for a high volume demand scenario (with $\lambda = 0.8$).

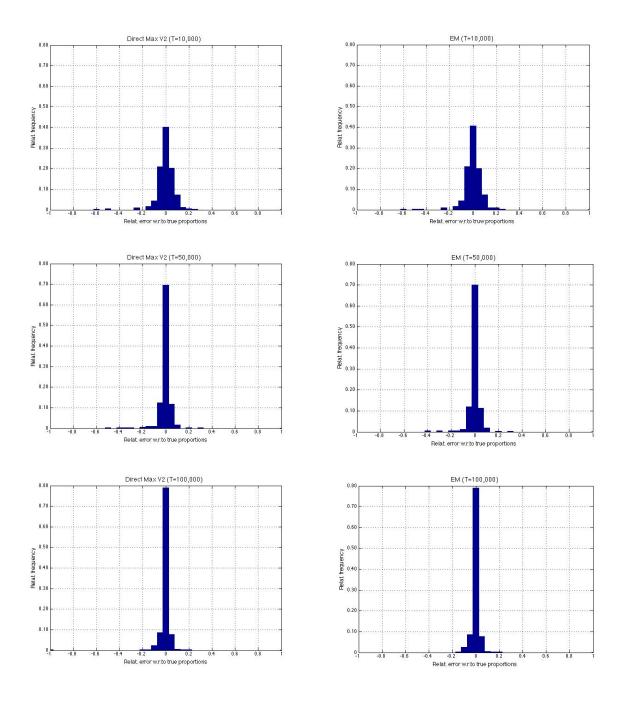


Figure A1: Uncensored demand case. Relative errors of Direct Max V2 (left) and EM (right) with respect to the true underlying proportions \boldsymbol{x} of customer types in the market, for n=15, N=10, and $T\in\{10,000,\,50,000,\,100,000\}$. There are between 2 and 10 products available per period.

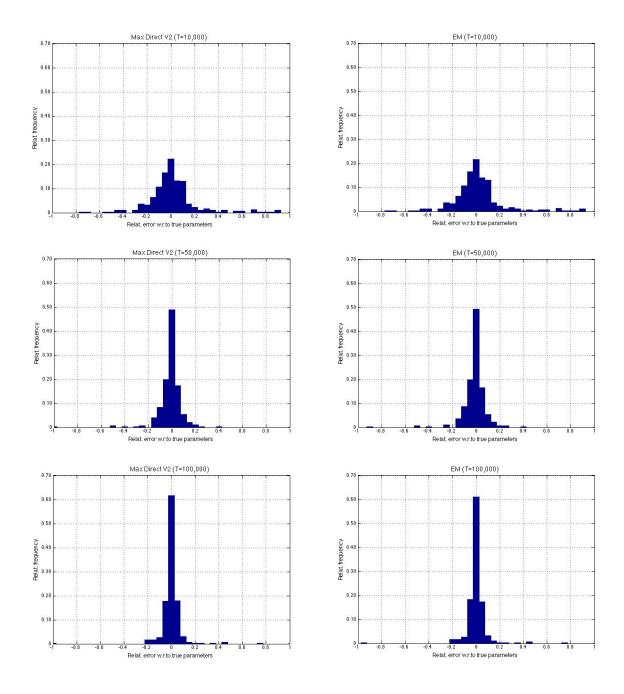


Figure A2: Relative errors of Direct Max V2 (left) and EM (right) with respect to the true underlying proportions x and arrival rate λ of the model, for $\lambda=0.2$, n=15, N=10, and $T\in\{10,000,\,50,000\}$. There are between 2 and 10 products available per period.

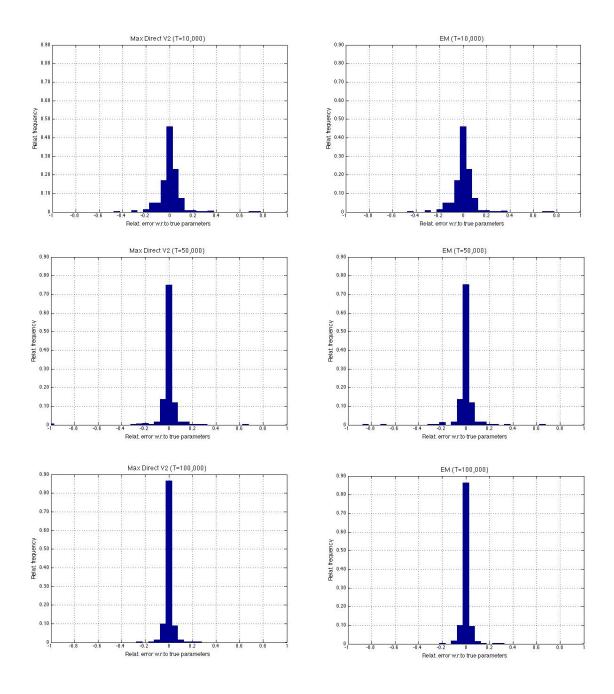


Figure A3: Relative errors of Direct Max V2 (left) and EM (right) with respect to the true underlying proportions \boldsymbol{x} and arrival rate λ of the model, for $\lambda=0.8$, n=15, N=10, and $T\in\{10,000,\,50,000\}$. There are between 2 and 10 products available per period.