# Fast and Stable Maximum Likelihood Estimation for Incomplete Multinomial Models 

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## What is Incomplete Multinomial Model?

- A toy example: Incompelte contingency table

|  | Young | Middle | Senior |
| :---: | :---: | :---: | :---: |
| Female | $p_{1}$ | $p_{2}$ | $p_{3}$ |
| Male | $p_{4}$ | $p_{5}$ | $p_{6}$ |

- Sample 1:
Young Middle Senior
- Sample 2 :

| Female | 21 | 24 | 18 |
| :---: | :---: | :---: | :---: |
| Male | 20 | 25 | 12 |
|  |  |  |  |


|  |  |
| :--- | :--- |
| Female | 18 |
| Male | 22 |

- Sample 3:

| Young | Middle | Senior |
| :---: | :---: | :---: |
| 10 | 20 | 10 |

- Sample 4:

| Female | 53 |
| :---: | :---: |
|  | 47 |
|  |  |

## What is Incomplete Multinomial Model (Cont'd)

Multinomial model: the sample space $\Omega$ is partitioned into $K$ disjoint subspaces. Incomplete cases:
(a) a subset of categories rather than a unique category is reported (partial classification).
(b) the set of possible outcomes contains only part of all categories (truncated outcomes).

$$
L(\boldsymbol{p} \mid \boldsymbol{a}, \boldsymbol{b}, \Delta) \propto \prod_{k=1}^{K} p_{k}^{a_{k}} \prod_{j=1}^{q} \tilde{p}_{j}^{b_{j}}=\prod_{k=1}^{K} p_{k}^{a_{k}} \prod_{j=1}^{q}\left(\delta_{j}^{\top} \boldsymbol{p}\right)^{b_{j}} .
$$

- $\boldsymbol{p}=\left(p_{1}, \ldots, p_{K}\right)^{\top}$ : parameters of the incomplete multinomial model.
- $\boldsymbol{a}=\left(a_{1}, \ldots, a_{K}\right)^{\top}$ : counts of fully classified observations.
- $\boldsymbol{b}=\left(b_{1}, \ldots, b_{q}\right)^{\top}$ : counts of incomplete observations. Positive terms for partial classification, and negative terms for truncated outcomes.
- $\boldsymbol{\Delta}=\left\{\Delta_{k j}\right\}_{K \times q}=\left[\delta_{1}, \ldots, \delta_{q}\right]$ : indicator matrix.


## What is Incomplete Multinomial Model (Cont'd)

$$
\begin{aligned}
& \mathrm{L}(\boldsymbol{p}) \quad \propto \quad p_{1}^{21} p_{2}^{24} p_{3}^{18} p_{4}^{20} p_{5}^{25} p_{6}^{12} \\
& \times\left(p_{1}+p_{2}+p_{3}\right)^{18}\left(p_{4}+p_{5}+p_{6}\right)^{22} \\
& \times\left(p_{1}+p_{4}\right)^{10}\left(p_{2}+p_{5}\right)^{20}\left(p_{3}+p_{6}\right)^{10} \\
& \times\left(\frac{p_{1}}{p_{1}+p_{4}}\right)^{53}\left(\frac{p_{4}}{p_{1}+p_{4}}\right)^{47} \text {. }
\end{aligned}
$$

## Optimality condition

Let $s=\sum_{k=1}^{K} a_{k}+\sum_{j=1}^{q} b_{j}, Q^{+}=\left\{j \mid b_{j}>0, j=1, \ldots, q\right\}$ and $Q^{-}=\left\{j \mid b_{j}<0, j=1, \ldots, q\right\}$ be the sets of indices of positive and negative elements in $\boldsymbol{b}$ respectively.

$$
\ell(\boldsymbol{p} \mid \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{\Delta})=\sum_{k=1}^{K} a_{k} \log p_{k}+\sum_{j=1}^{q} b_{j} \log \delta_{j}^{\top} \boldsymbol{p}-s\left(\sum_{k=1}^{K} p_{k}-1\right) .
$$

Optimality condition: $\nabla \ell(\boldsymbol{p})=0$,

$$
\frac{\partial \ell}{\partial p_{k}}=\frac{a_{k}}{p_{k}}+\sum_{j \in Q^{+}} \frac{\left|b_{j}\right| \Delta_{k j}}{\delta_{j}^{\top} \boldsymbol{p}}-\sum_{j \in Q^{-}} \frac{\left|b_{j}\right| \Delta_{k j}}{\delta_{j}^{\top} \boldsymbol{p}}-s=0
$$

which is equivalent to

$$
a_{k}+\left(\sum_{j \in Q^{+}} \frac{\left|b_{j}\right| \Delta_{k j}}{\delta_{j}^{\top} \boldsymbol{p}}-\sum_{j \in Q^{-}} \frac{\left|b_{j}\right| \Delta_{k j}}{\delta_{j}^{\top} \boldsymbol{p}}-s\right) p_{k}=0
$$

## Stable Weaver Algorithm

## Algorithm 1 Stable Weaver Algorithm

Input: Observations $(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{\Delta})$
Initialize: $\boldsymbol{p}^{(0)}=(1 / K, \ldots, 1 / K)^{\top}, s=\mathbf{1}^{\top} \boldsymbol{a}+\mathbf{1}^{\top} \boldsymbol{b}$
repeat

$$
\begin{aligned}
& \boldsymbol{\tau}=\boldsymbol{b} / \boldsymbol{\Delta}^{\top} \boldsymbol{p}^{(t)}(\text { element-wise division }) \\
& \boldsymbol{\tau}^{+}=\max (\boldsymbol{\tau}, \mathbf{0}), \boldsymbol{\tau}^{-}=\min (\boldsymbol{\tau}, \mathbf{0}) \\
& \boldsymbol{p}^{(t+1)}=\left[\boldsymbol{a}+\left(\boldsymbol{\Delta} \boldsymbol{\tau}^{+}\right) \circ \boldsymbol{p}^{(t)}\right] /\left(s \mathbf{1}-\boldsymbol{\Delta} \boldsymbol{\tau}^{-}\right) \\
& \text {(o represents element-wise product) } \\
& \boldsymbol{p}^{(t+1)}=\boldsymbol{p}^{(t+1)} / \operatorname{sum}\left(\boldsymbol{p}^{(t+1)}\right)
\end{aligned}
$$

until convergence

- The weaver algorithm updates the parameter by $\boldsymbol{p}=\boldsymbol{a} /(s \mathbf{1}-\boldsymbol{\Delta} \tau)$.
- Bayesian weaver is time-consuming due to the inner-outer iteration structure and the selection of the thickening parameter is difficult.


## Application

- Contingency tables with merged and truncated cells.
- Polytomous response data with underlying categories. For example, the phenotype expressions on blood types.
- Interval censored time-to-event data with truncation in survival analysis.
- Include several well-known ranking models as special cases, such as the Bradley-Terry, Plackett-Luce models and their variants.


## Results on Real Datasets

|  |  | NASCAR <br> $(\mathrm{w} / \mathrm{o}$ ties $)$ |  | $(\mathrm{w} /$ ties $)$ | HKJC1416 <br> $(\mathrm{w} / \mathrm{o}$ ties $)$$(\mathrm{w} /$ ties $)$ |
| :---: | :---: | :---: | :---: | :---: | :---: |

* The number of iterations for the trust region constrained algorithm refers to the number of the objective function evaluations.
$\dagger$ We use the approximated Hessian matrix when fitting the trust region constrained algorithm to the HKJC1416 data because its calculation is too time-consuming.
$\ddagger$ For the HKJC1416 data, the self-consistency approach converges to a wrong solution.


## Results on Real Datasets (Cont'd)



Figure 1: Convergence plot of the stable weaver algorithm compared with existing methods on the dataset HKJC9916 against running time (a) $t \in[0,100]$ and (b) $t \in[100,36000]$ (s).

## Thanks for listening.

