Bayesian Nonparametric Clustering and Inference for Inpatient Health Care Utilization

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Background

Inpatient hospital services account for a small share of health care utilization but the majority of total health care spending.

- What are the driving forces of inpatient health care spending? (inference, interpretation)
- How can we account for different patient characteristics (subgroup analysis, clustering)
Background

Mixture distributions are good way to model health care utilization

A mixture distribution \( f_{mix} \) is a weighted sum, \( \sum c_i = 1 \), of a finite set of probability density functions \( p_1(x), \ldots, p_k(x) \)

\[
f_{mix}(x) = \sum_{i=1}^{K} c_i \ p_i(x).
\]

They can account for zero-inflation, over-dispersion, and skewness.
Background

Mixture models can be extended to regression
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The are two ways to specify the number of mixture components (= clusters)

• Specify the number of components before the analysis (*ex-ante*).
• Calculate different models with different clusters and select the "best" (*ex-post*).

Both methods introduce a **decision-bias** and **model selection-bias**.
Methods

Bayesian nonparametric models allow to estimate the number of components $K$ from the data.

- avoids over- and underfitting
- model only as complex as the data require
- in theory, model complexity is unbounded (infinite number of clusters)
Methods

We developed a Dirichlet Process mixture regression model for counts (hospital days), DP-NB

\[ y \mid X \sim \sum_{k=1}^{K} c_k \mid X \cdot \text{NegBin}(\mu_k, \psi_k), \]

with

\[ \mu_k = \exp(X \beta_k). \]

We also extend this model to a zero-inflated version (DP-ZINB).
# Simulation Study

The DP-NB finds the true number of components more accurately than AIC and BIC selection methods.

<table>
<thead>
<tr>
<th>Truth</th>
<th>high overlap</th>
<th>medium overlap</th>
<th>low overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AIC  BIC DP-NB</td>
<td>AIC  BIC DP-NB</td>
<td>AIC  BIC DP-NB</td>
</tr>
<tr>
<td>2</td>
<td>5  1 4</td>
<td>3  3 2</td>
<td>1  1 3</td>
</tr>
<tr>
<td>3</td>
<td>1  1 4</td>
<td>4  4 4</td>
<td>1  1 4</td>
</tr>
<tr>
<td>4</td>
<td>1  1 4</td>
<td>1  1 3</td>
<td>1  1 5</td>
</tr>
<tr>
<td>5</td>
<td>1  1 3</td>
<td>5  1 6</td>
<td>1  1 6</td>
</tr>
</tbody>
</table>
AOK data set

- AOK claims data set with incident lung cancer in 2009 (Schwarzkopf et al., 2015)
- AOK is the largest health insurance company in Germany and covers around a third of the German population
- outcome: total number of inpatient hospital days (1 year period)
- only patients who survived the full year where included (N=7118)
Results

The posterior predictive distribution of replicated outcome $y^{rep}$ is close to the true outcome.
Results

The DP-NB finds three components for the AOK data set
Results

Biggest differences are in treatment coefficients

- age
- sex (female)
- num. metastases
- num. cancer
- Charlson index
- chemotherapy
- radiation therapy
- surgery
- chemo+radio
- chemo+surgery
- radio+surgery
- chemo+radio+surgery
- urban district
- rural district
- thinly popul.

Comp. 1

Comp. 2

Comp. 3

incidence rate ratio
## Results

### Component 1 gets the most chemotherapy and the least surgery

<table>
<thead>
<tr>
<th>Treatment</th>
<th>10%</th>
<th>20%</th>
<th>30%</th>
<th>40%</th>
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</thead>
<tbody>
<tr>
<td>no therapy</td>
<td>23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>chemotherapy</td>
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<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>radiation therapy</td>
<td>23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>surgery</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>chemo+radio</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>chemo+surgery</td>
<td>1</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>radio+surgery</td>
<td>1</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>chemo+radio+surgery</td>
<td>1</td>
<td>32</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Discussion

Component 1 has patients in more advanced stages of lung cancer

- less hospital days ≠ healthy
- less surgery, but more chemotherapy and radiation therapy
Discussion

Component 2 and 3 have more cases with good prospect

- more surgery
- more surgery + chemotherapy + radiation therapy
- Component 3 is very similar to Component 2 but has individuals with more comorbidities and who are older.
Conclusion

- the presented Bayesian clustering and inference method for count data can be used to find subgroups of patients while still being fully interpretable
- because of its non-parametric nature it avoids over- and underfitting of the cluster components.
- on the AOK data set, it can find subgroups with specific properties that correspond well to the different number of hospital days in each component
Thank you
Simulation