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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.

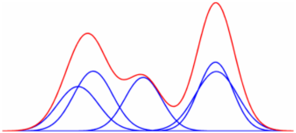
- What are the driving forces of inpatient health care spending? (**inference**, **interpretation**)
- How can we account for different patient characteristics (**subgroup analysis**, **clustering**)

Background

Mixture distributions are good way to model health care utilization

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

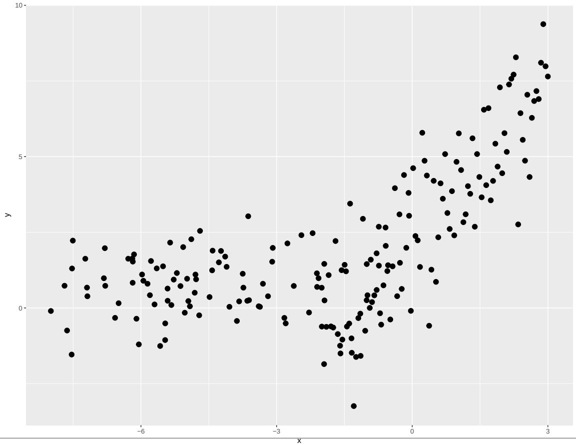
$$f_{mix}(x) = \sum_{i=1}^{K} c_i \, p_i(x).$$



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

Background

Mixture models can be extended to regression



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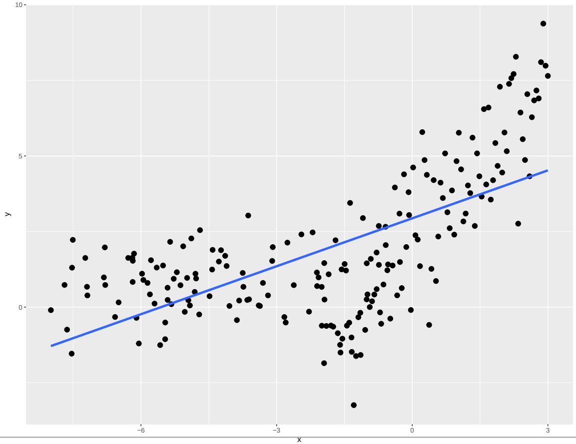

Background

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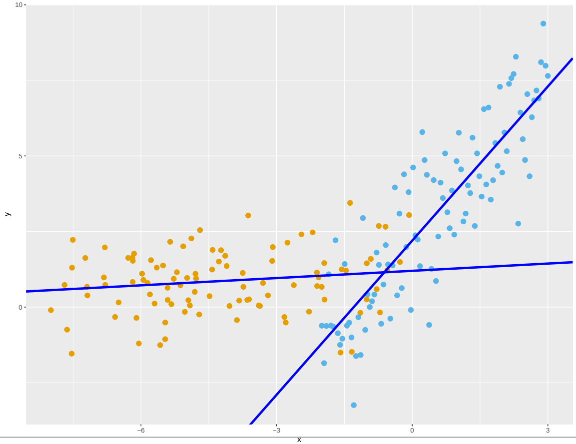


Background

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 **modelselection-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

$$\underbrace{y|X}_{days} \sim \sum_{k=1}^{K} \underbrace{c_k|X}_{weights} \cdot \underbrace{\text{NegBin}(\mu_k, \psi_k)}_{regression\ model},$$

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

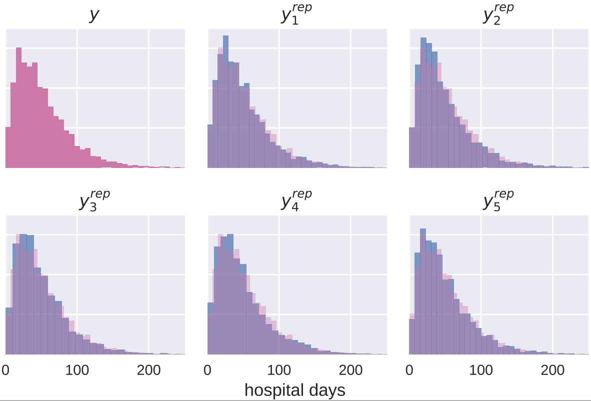
	high overlap			medium overlap			low overlap		
Truth	AIC	BIC	**DP-NB**	AIC	BIC	**DP-NB**	AIC	BIC	**DP-NB**
2	5	1	4	3	3	**2**	1	1	3
3	1	1	4	4	4	4	1	1	4
4	1	1	**4**	1	1	3	1	1	5
5	1	1	3	5	1	6	1	1	6

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)

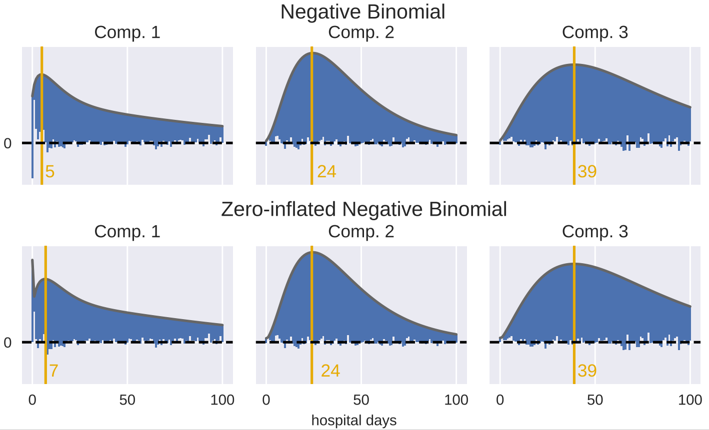
Results

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



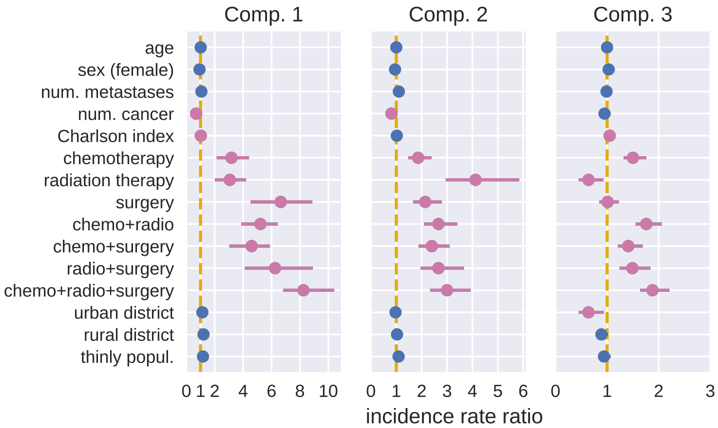
Results

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



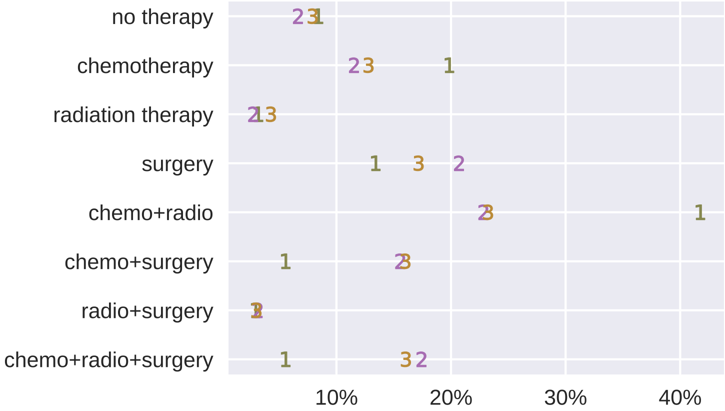
Results

Biggest differences are in treatment coefficients



Results

Component 1 gets the most chemotherapy and the least surgery



Discussion

Component 1 has patients in more advanced stages of lung cancer

- less hospital days $\neq$ healthy
- less surgery, but more chemotherapy and radiation therapy

Discussion

Component 2 and 3 have more cases with good prospect

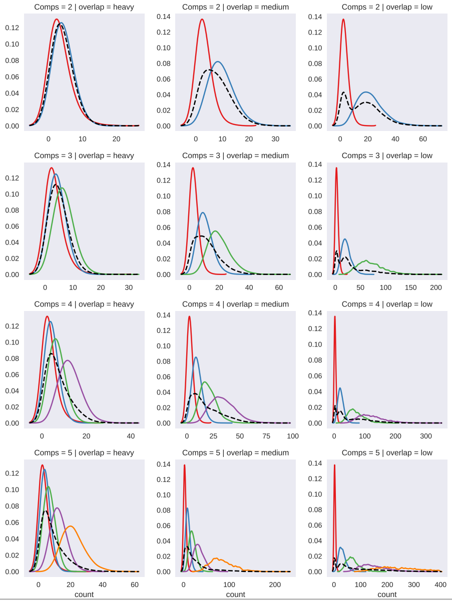
- more surgery
- more surgery + chemotherapy + radiation therapy
- Component 3 is very similar to Component 2 but has individuals with more comorbidities and who are older.

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



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Comps = 2 | overlap = medium
Comps = 2 | overlap = low
Comps = 3 | overlap = heavy
Comps = 3 | overlap = medium
Comps = 3 | overlap = low
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Comps = 4 | overlap = medium
Comps = 4 | overlap = low
Comps = 5 | overlap = heavy
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count
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count