Predicting the life cycle of technologies from patent data

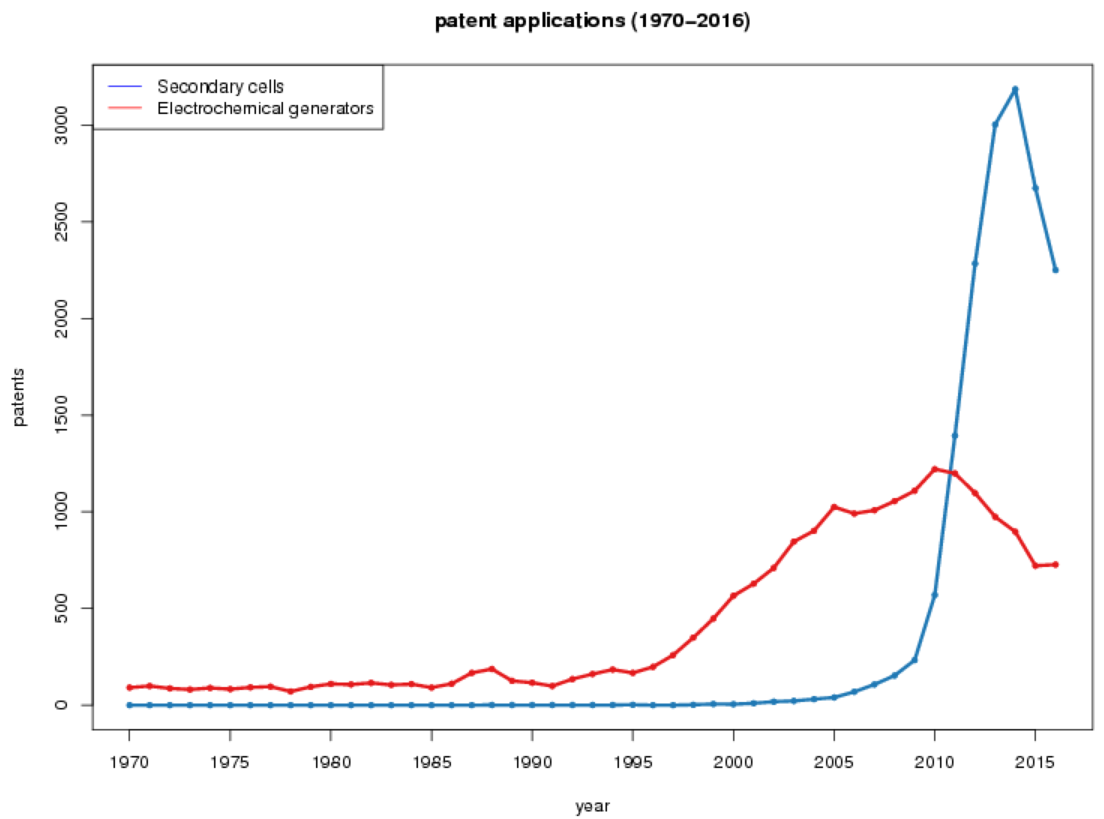
Agenda

- Introduction
- Objective
- Methods
- Results
- Suggestion for future work

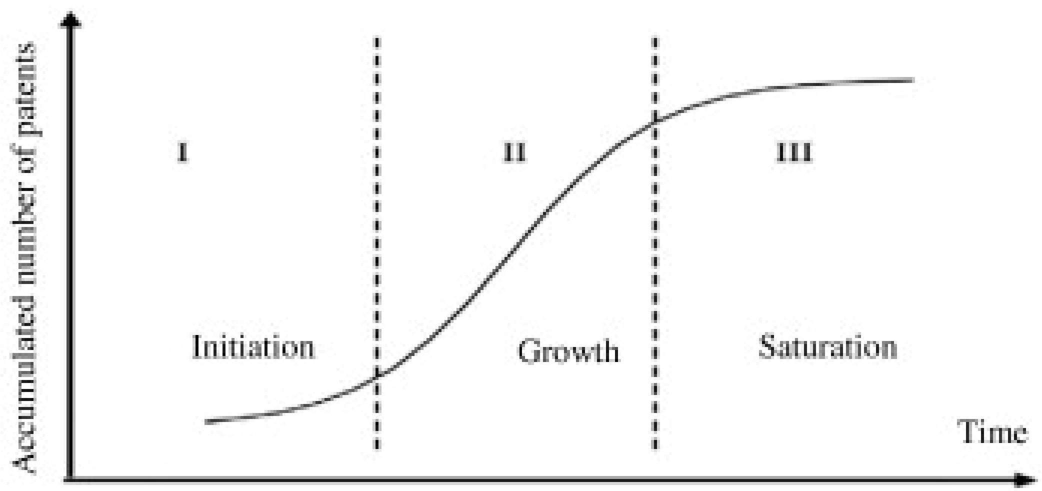
Introduction

- Business competition.
- Monitoring the evolution of technologies.
- Monitoring patent documents.

Patent data over a period of time



Development S-curve in the evolution of technologies



Objective

- The main purpose of this project is to build a data driven model which helps to predict the life cycle of technologies based on patent applications and thereby to determine the stages of the technology in the S-curve.

METHODS

- The life cycle Poisson model.
- The life cycle Poisson model on clustered data.
- Mixture of life cycle Poisson models.
- Prior distributions.
- Model estimations using MLE and Bayesian methods.
- Predictive distribution.

The life cycle Poisson model

$$y_{it} \sim Pois(\lambda_{it})$$

$$\lambda_{it} = C_i \times h_{v_i}(t|\mu_i, \sigma_i^2)$$

Where $h_{v_i}(t|\mu_i, \sigma_i^2)$ density function of a t distribution.
C_i positive constant.

Similar trend patterns of technologies

- Time series clustering.
- Distance measure across all data points.
- Hierarchical Clustering.
- Elbow methods to determine number of clusters.

The life cycle Poisson model on clustered data.

Model:

$$Y_{jt}^{(c)} \sim pois(\lambda_{jt}^{(c)})$$

$$\lambda_{jt}^{(c)} = C_j * h_{v_c}(t|\mu_c, \sigma_c^2)$$

where

$$j = 1, 2, 3, ..., n_c$$

Mixture of life cycle Poisson models

Model:

$$y_{it}|S_i = k \sim pois(\lambda_{it}^{(k)})$$

$$\lambda_{it}^{(k)} = C_i \times h_{v_k}(t|\mu_k, \sigma_k^2)$$

$$Pr(S_i = k) = \pi_k$$

Prior distributions

- $\mu_k \sim N(\mu_{0k}, \tau_{0k}^2)$
  - Battery related technology have 30-35 years of life.
  - Chemical content have 10-20 years of life.
  - Capacitors have 35-40 years of life
- $C_i \sim Gamma(A, B)$, Conjugate prior
- σ_k^2 and v_k uniform prior.

Maximum Likelihood estimation

- Single technology

$$L(\theta_i) = \prod_{t=1}^{T} p(Y_{it}; \lambda_{it}(\theta_i))$$

where $\theta_i = (C_i, \mu_i, \sigma_i^2)$

- Clustered Data

$$L(\theta_c) = \prod_{j=1}^{n_c} \prod_{t=1}^{T} p(Y_{jt}^{(c)}; \lambda_{jt}^{(c)}(\theta_c))$$

where $\theta_c = (C_1, C_2, ...C_{nc}, v_c, \mu_c, \sigma_c^2)$

Markov Chain Monte Carlo

$$p(\theta_c|y_{jt})$$

$$\theta_c = (C_1, C_2, ...C_{nc}, v_c, \mu_c, \sigma_c^2)$$

Gibbs sampling

1. Simulate $C_1, C_2, ...C_{nc}$ given v_c, μ_c, σ_c^2 and data from a Gamma distribution (conjugate prior). $C_j|y_{jt}, v_c, \mu_c, \sigma_c^2 \sim gamma(\sum_{t=1}^T y_{jt} + \alpha_j, \sum_{t=1}^T a_t + \beta)$ where $a_t = h_{v_c}(t|\mu_c, \sigma_c^2)$
2. simulate $v_c|C1, C_2, ..C_j, \mu_c, \sigma_c^2$ from a posterior distribution derivered over a fine grid of values [1,20].
3. Update $\mu_c|C1, C_2, ..C_j, v_c, \sigma_c^2$ by slice sampling.
4. Update $\sigma_c^2|C1, C_2, ..C_j, v_c, \mu_c$ by slice sampling.

Mixture model estimation

The Gibbs sampler outlined above is straightforwardly extended by adding an updating step for the membership indicators and the mixing coefiecient.

The indicators S are modeled as multinationals with parameter π with conjugate prior distribution of
$\pi \sim \mathrm{Dirichlet}(\alpha_1, ..., \alpha_K)$

Predictive Distribution

$$p(y_{i,t+1}, ..., y_{i,t+M} | y_{i,1}, ..., y_{i,t}, \mathcal{Y}) =$$

$$\sum_{k=1}^{K} \int p(S_i = k | y_{i,1}, ..., y_{i,t}, \theta) \times$$

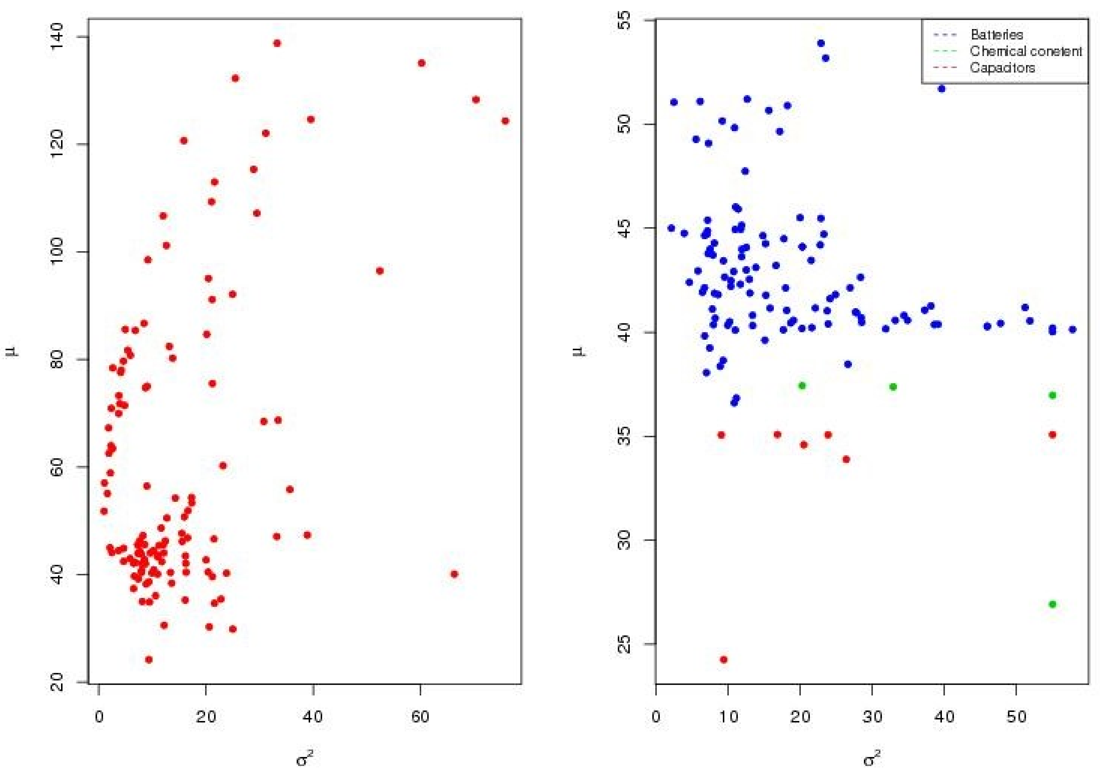
$$p(y_{i,t+1}, ..., y_{i,t+M} | y_{i,1}, ..., y_{i,t}, \theta, S_i = k) \times p(\theta | \mathcal{Y}) d\theta$$

Algorithm to Simulate from $p(y_{i,t+1}, \ldots, y_{i,t+M} | y_{i,1}, \ldots, y_{i,t}, \theta)$.

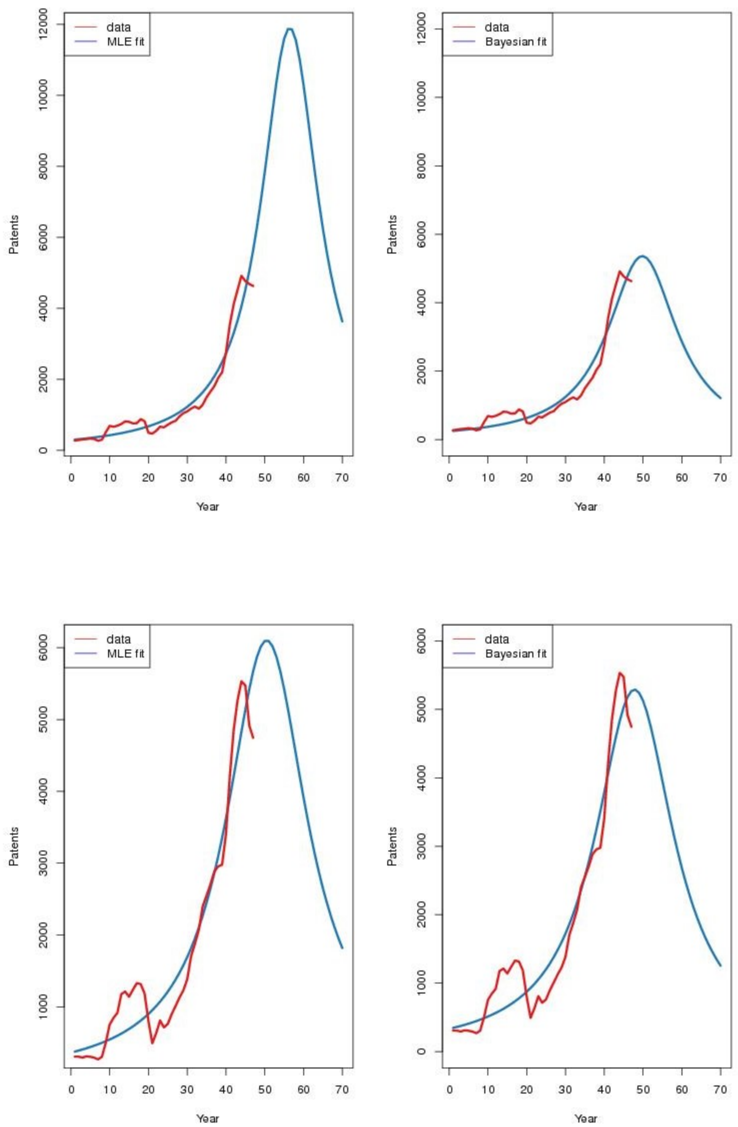
- Draw θ from posterior $p(\theta|\mathcal{Y})$
- Draw $C_i | \{y_{i,1}, \ldots, y_{i,t}\}, \{S_i = k\}, \theta \sim Gamma(A_i + \sum_{j=1}^{t} y_{ij}, B + \sum_{j=1}^{t} h_{v_k}(j|\mu_k, \sigma_k^2))$
- Draw $S_i = k from p(S_i = k | y_{i,1}, \ldots, y_{i,t}, \theta) \propto p(y_{i,1}, \ldots, y_{i,t} | \{S_i = k\}, \theta) \times p(\{S_i = k\}|\theta)$
- Draw $y_{i,t+m} | y_{i,1}, \ldots, y_{i,t}, \theta, S_i = k \sim \text{Pois}(y_{i,t+m} | \lambda_{i,t+m}^{(k)})$

Results

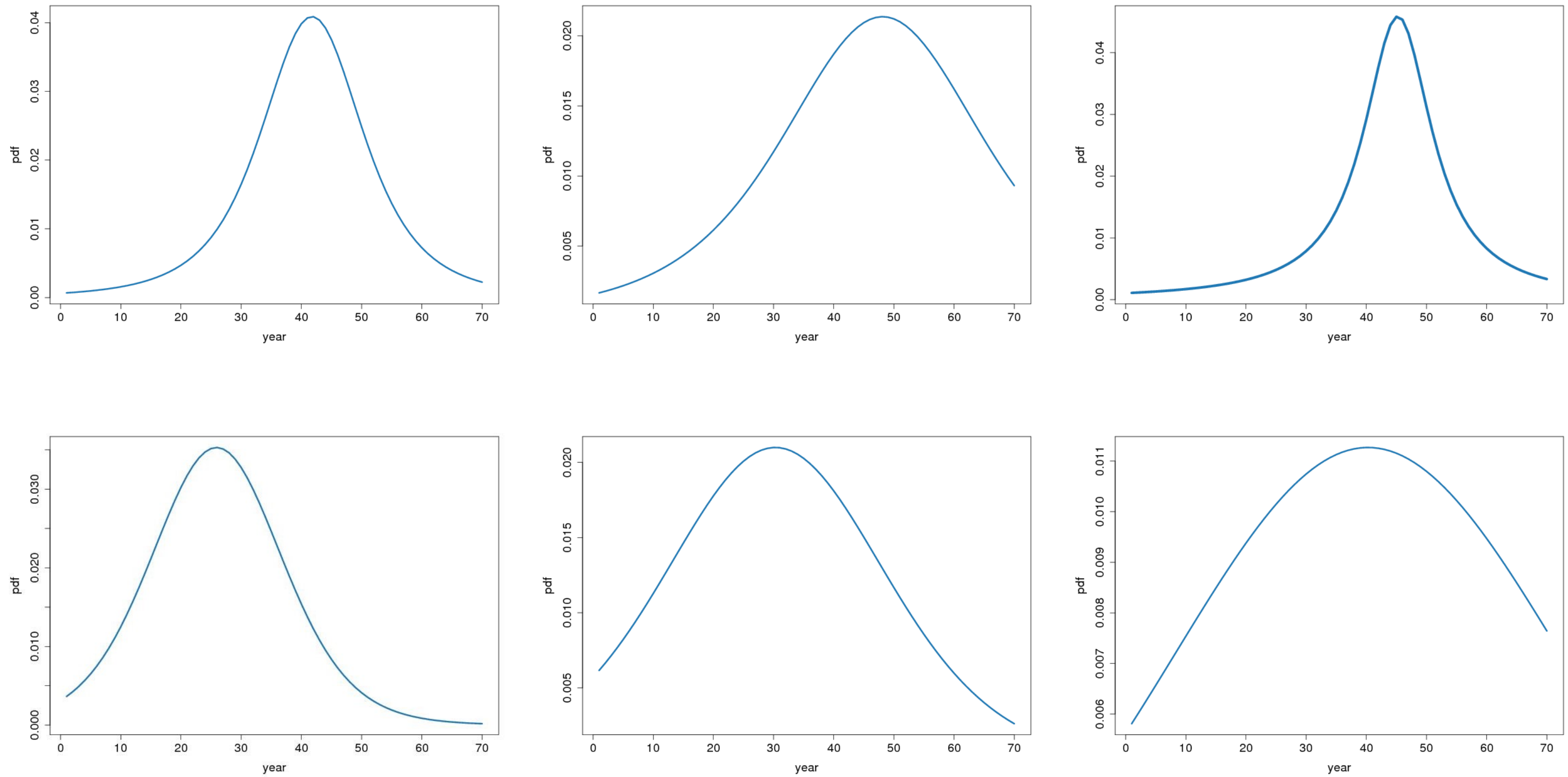
MLE(left) and Bayesian estimates(Right) of mean and variance of all the 123 technologies.



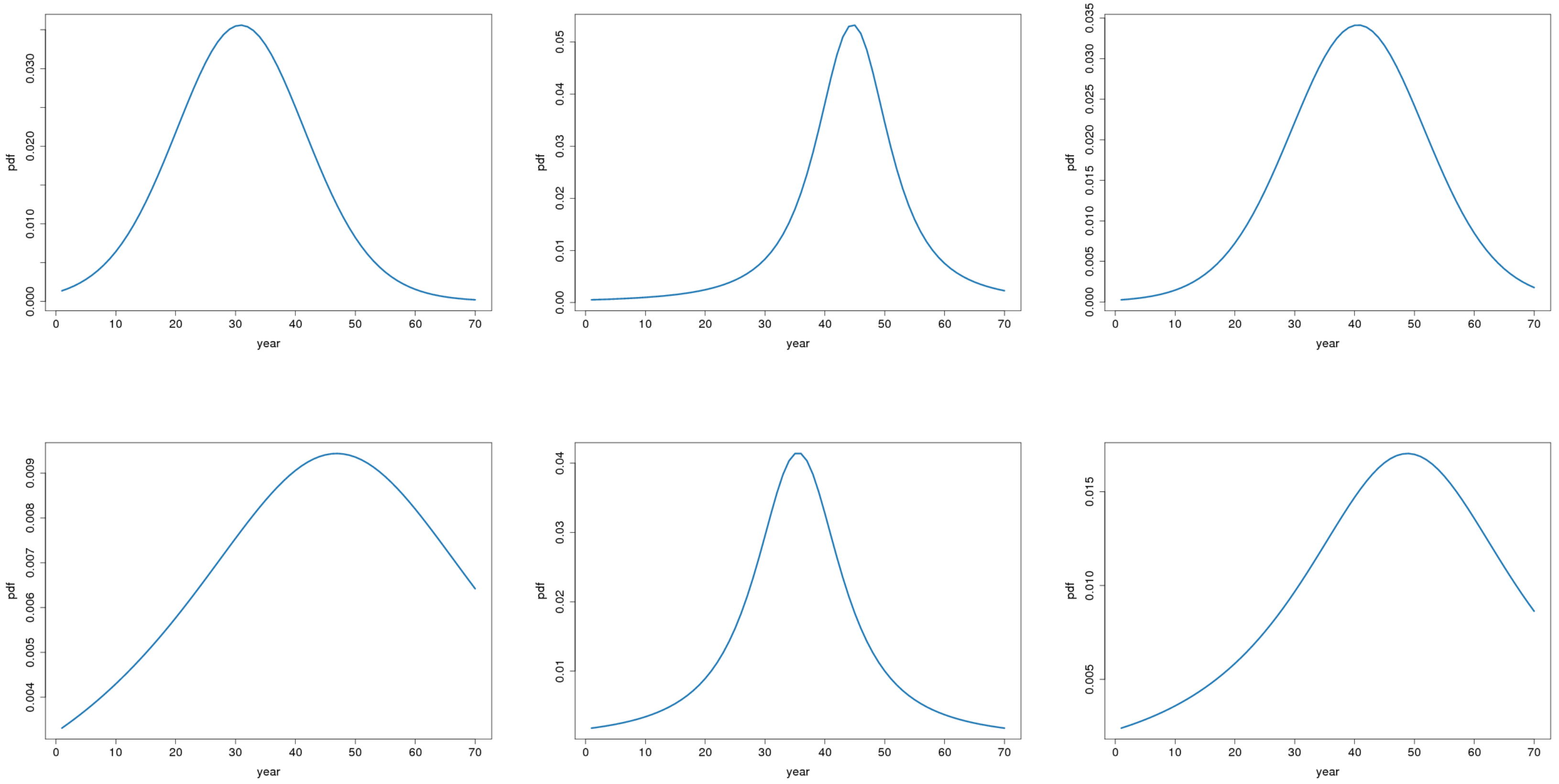
Fitted values of different individual technologies using MLE and Bayesian estimates.



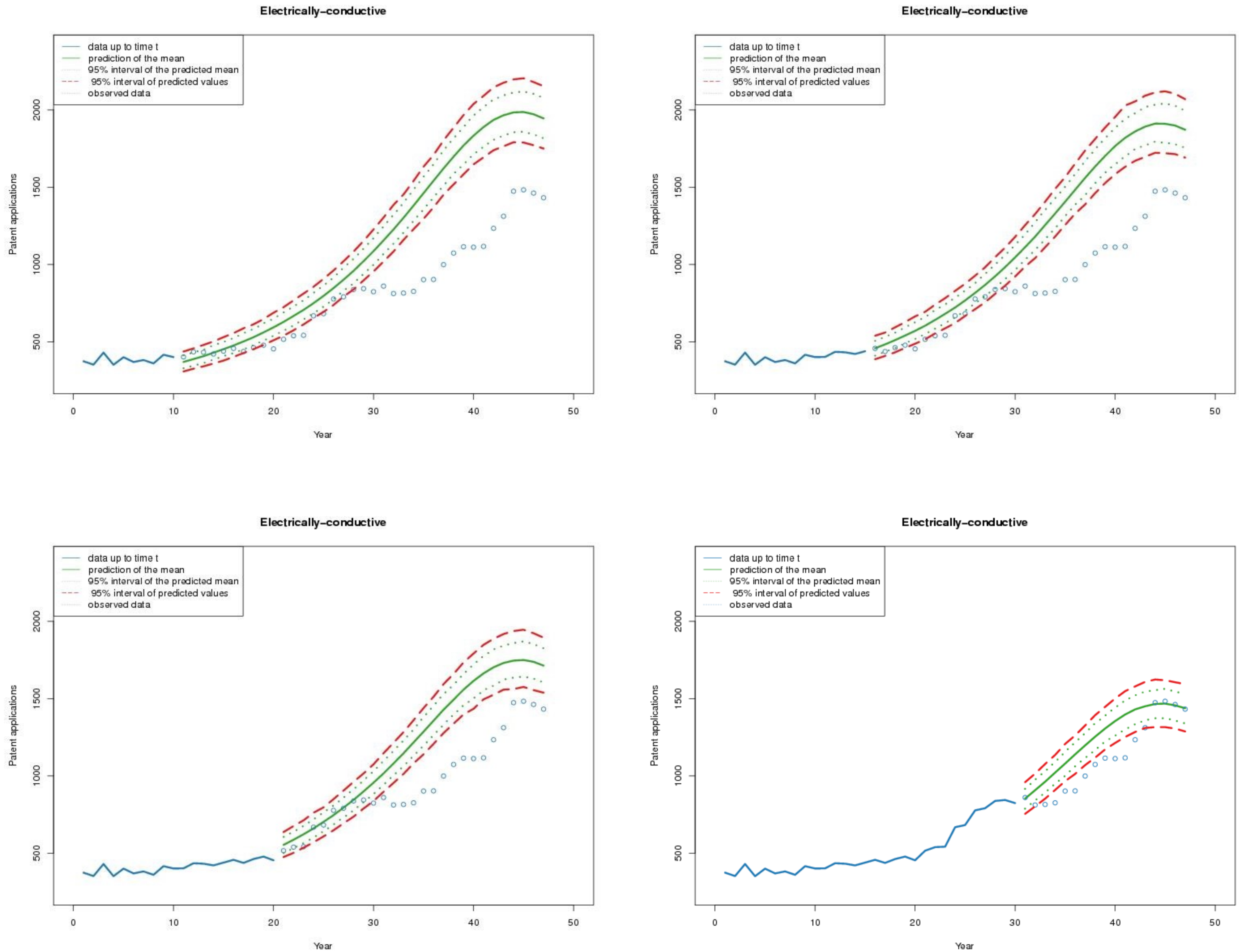
Fitted values using Bayesian estimates of each of the six clusters.



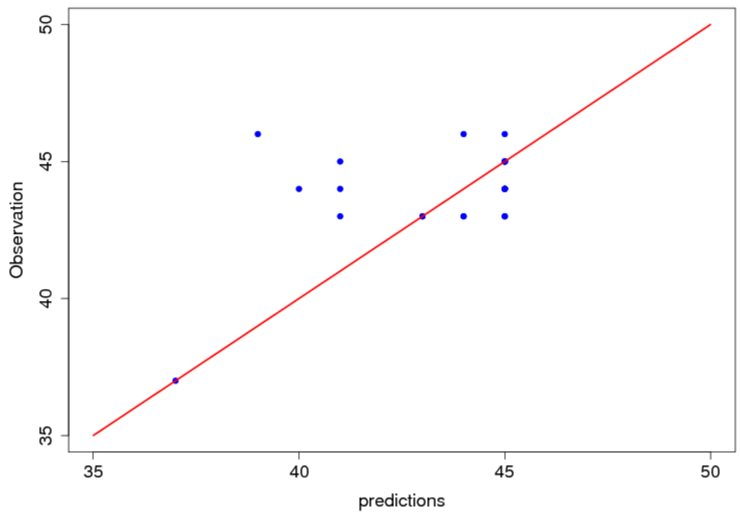
Fitted values of the mixture model with six components.

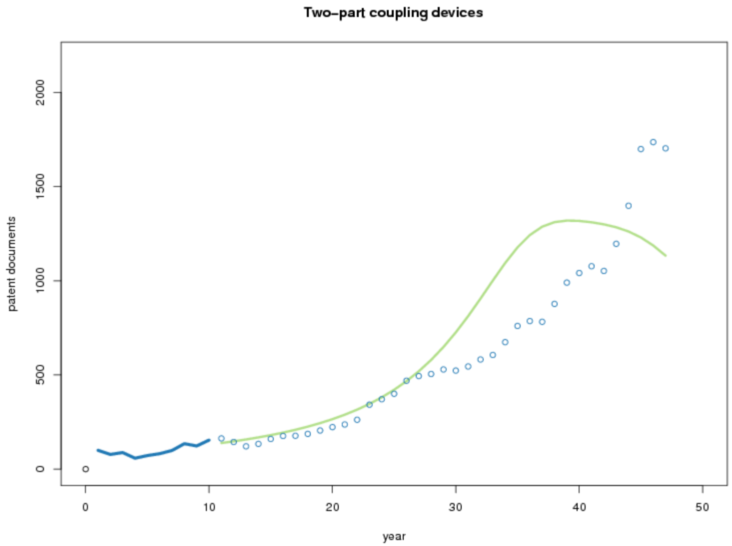


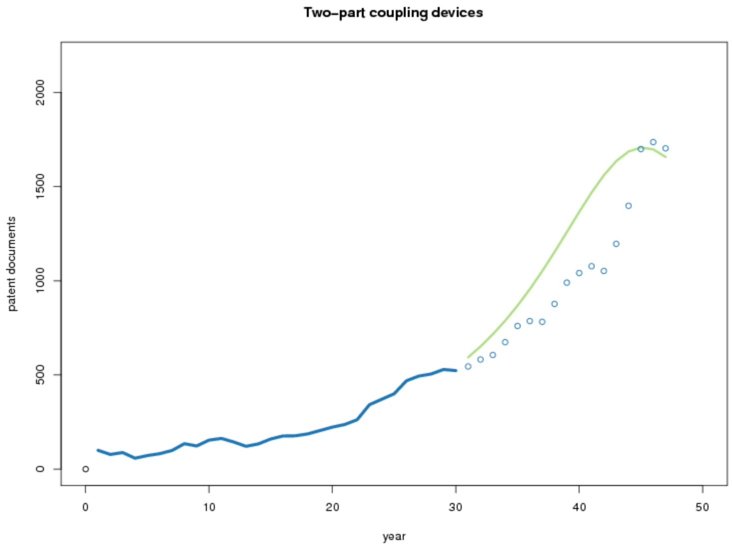
Trend prediction of patent documents of a technology (Electrically-conductive).



Prediction of the peak values







Suggestion for future Work

- Negative binomial Model.