Toward automatic aftershock forecasting in Japan

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@Statsei9
Forecasting aftershocks after the main shock

- Immediate forecast of aftershock is strongly required.
- We need to tailor a forecast model to each aftershock sequence.

<table>
<thead>
<tr>
<th>Year</th>
<th>Event</th>
<th>Magnitude M</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>Chuetsu (M6.8)</td>
<td>6.8</td>
</tr>
<tr>
<td>2004</td>
<td>Niigata-ken Chuetsu (M6.8)</td>
<td>6.8</td>
</tr>
<tr>
<td>1943</td>
<td>Tottori (M7.2)</td>
<td>7.2</td>
</tr>
<tr>
<td>2008</td>
<td>Iwate Miyagi Nairiku (M7.2)</td>
<td>7.2</td>
</tr>
<tr>
<td>2008</td>
<td>Tohoku (M8.9)</td>
<td>8.9</td>
</tr>
<tr>
<td>2005</td>
<td>Fukuoka-ken Seihou-oki (M7.0)</td>
<td>7.0</td>
</tr>
<tr>
<td>2007</td>
<td>Niigata-ken Chuetsu-oki (M6.8)</td>
<td>6.8</td>
</tr>
</tbody>
</table>

Cumulative number of aftershocks over time from the main shock.
Forecasting from an early aftershock data is difficult.

The data in the early period is highly deficient.

1995 Hyogo-Ken-Nambu earthquake of M 7.3

<table>
<thead>
<tr>
<th>Time from the main shock [day]</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>0.01</td>
</tr>
<tr>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>0.1</td>
<td>1.0</td>
</tr>
<tr>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>10.0</td>
<td>3.0</td>
</tr>
<tr>
<td>100.0</td>
<td>5.0</td>
</tr>
</tbody>
</table>

Earthquakes
Seismic Network
missing
Real-time Aftershock forecasting

- Technical Issue: forecasting from “incomplete” and “short” data
  - Considering the incompleteness of early aftershock data
  - Considering the estimation uncertainty of a forecasting model

- Data Issue: forecasting from real-time data
  - Real-time data is more incomplete than fixed data
Real-time Aftershock forecasting

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Detection rate of aftershocks

\[ \Phi(M|\mu(t), \sigma) = \frac{1}{2\pi\sigma^2} \int_{-\infty}^{M} \exp \left[ -\frac{(x - \mu(t))^2}{2\sigma^2} \right] dx \]

- Depending on the time and magnitude (Ogata & Katsura 1993)
- \( \mu(t) \): the time-varying magnitude with 50 \% detection rate
  (Bayesian smoothing, Omi et. al, 2013)

Chuetsu aftershock sequence

![Diagram of Chuetsu aftershock sequence with magnitude versus time plot and detection rate distribution](image)
Detection rate of aftershocks

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Chuetsu aftershock sequence

![Chuetsu aftershock sequence graph](image)
Detection rate of aftershocks

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Chuetsu aftershock sequence

![Graph showing the Chuetsu aftershock sequence with magnitude and time on the x-axis and detection rate on the y-axis. The graph includes a scatter plot of magnitude vs. time, a detection rate curve, and a magnitude distribution curve.](image)
Detection rate of aftershocks

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Chuetsu aftershock sequence

\( \mu \mu \mu \)

Detection Rate

Magnitude Distribution

(G-R law)

(Detection Rate)
Immediate forecast with 2011 Tohoku sequence

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 3 h</td>
<td>0 - 6 h</td>
<td>0 - 12 h</td>
<td>0 - 24 h</td>
<td></td>
</tr>
<tr>
<td>3 - 6 h</td>
<td>6 - 12 h</td>
<td>12 - 24 h</td>
<td>24 - 48 h</td>
<td></td>
</tr>
</tbody>
</table>

Omori-Utsu law

Bar: 95% interval

Omi et al., Scientific Reports (2013)
Real-time Aftershock forecasting

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Plug-in and Bayesian forecasting

**Plug-in Forecasting**

1. **Learning Data**
   - \( P(\theta|Data) \)
   - Maximize

**Bayesian Forecasting**

1. **Sample (MCMC)**
   - \( \theta_1 \)
   - \( \theta_2 \)
   - \( \theta_N \)
   - The “probable” parameters

---

**ETAS model**

- Simulation
- Predictive distribution of the aftershock number

- The “best” parameter

- The “probable” parameters

**Sequence_1**
- **Sequence_2**
- **Sequence_N**

\[ P(n|Data) \]

(Omi et al., JGR 2015)
Plug-in forecasting sometimes misses the observation

(Omi et al., JGR 2015)

Plug-in forecasting: use only the single ETAS-parameter value (MAP estimate).
Bayesian forecasting is better than Plug-in forecasting on average (Omi et al., JGR 2015)

**Plug-in forecasting**: use only the single ETAS-parameter value (MAP estimate).

**Bayesian forecasting**: combine the forecasts from the ETAS model with various probable parameter values: For each simulation, the parameter value is sampled from the posterior distribution (MCMC method).
Real-time Aftershock forecasting

- **Technical Issue:** forecasting from “incomplete” and “short” data
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- **Data Issue:** forecasting from real-time data
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Real-time and Fixed catalog

Seismic Networks
- NIED
- JMA
- Universities

JMA catalog
- Manually determined
- High quality
- Not available in real-time

Hi-net catalog
- Automatically determined
- Incomplete
- Available in real-time
Relative incompleteness of the real-time data to the fixed data (1)

- First day of the main shock

2000 W. Tottori eq. (M7.3)

2014 N. Nagano eq. (M6.7)
Relative incompleteness of the real-time data to the fixed data (2)

(a) 2000 W. Tottori eq. (M7.3)

(b) cumulative number

- 0–3[h]
- 3–6[h]
- 6–12[h]
- 12–24[h]
Forecast test

- Setting

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning period</td>
<td>0-3 [h]</td>
<td>0-6 [h]</td>
<td>6-12 [h]</td>
<td>12-24 [h]</td>
</tr>
<tr>
<td>Forecast period</td>
<td>3-6 [h]</td>
<td>6-12 [h]</td>
<td>12-24 [h]</td>
<td>24-48 [h]</td>
</tr>
</tbody>
</table>

- Use 7 inland aftershock sequences of the M7 class main shocks

- Forecast the number of aftershocks in each magnitude bin in the forecasting period.

- Prepare three forecasts by using the Omori-Utsu law; (1) forecast from the JMA catalog, (2) that from the Hi-net catalog, and (3) that using the generic model.

- Each forecasting is evaluated based on the data in the JMA catalog.
RESULTS

The cumulative number of earthquakes vs magnitude for 3-6 h and 24-48 h, showing different forecast models:

- Forecast from JMA catalog
- Forecast from Hi-net catalog
- Forecast from the generic model

Data points are from JMA and Hi-net catalogs.
RESULTS: Log-Likelihood score

- Relative to the score by the generic model

<table>
<thead>
<tr>
<th>Location</th>
<th>Forecast from Hi-net catalog</th>
<th>Forecast from JMA catalog</th>
</tr>
</thead>
<tbody>
<tr>
<td>W. Tottori (M7.3)</td>
<td>25.8</td>
<td>25.9</td>
</tr>
<tr>
<td>Chuetsu (M6.8)</td>
<td>427.2</td>
<td>419.3</td>
</tr>
<tr>
<td>W-Off Fukuoka (M7.0)</td>
<td>63.4</td>
<td>72.4</td>
</tr>
<tr>
<td>Noto Penin. (M6.9)</td>
<td>237.4</td>
<td>255.3</td>
</tr>
<tr>
<td>Off Chuetsu (M6.8)</td>
<td>-4.2</td>
<td>16</td>
</tr>
<tr>
<td>Iwate-Miyagi (M7.2)</td>
<td>202.4</td>
<td>204.6</td>
</tr>
<tr>
<td>N Nagano (M6.7)</td>
<td>68.4</td>
<td>66.4</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>145.8</strong></td>
<td><strong>151.4</strong></td>
</tr>
</tbody>
</table>

- The two forecasts from the JMA catalog and the Hi-net catalog are similar, but the one from the JMA catalog is slightly better.

- These two forecasts are clearly better than the one from the generic model.
Summary: Real-time Aftershock forecasting

- **Technical Issue**
  - Considering the incompleteness of early aftershock data: Detection rate
  - Considering the estimation uncertainty of a forecasting model: Bayesian forecasting

- **Data Issue**
  - Real-time data can provide useful information for early aftershock forecasting.
References

T. Omi, Y. Ogata, Y. Hirata & K. Aihara,
“Forecasting large aftershocks within one day after the main shock”

T. Omi, Y. Ogata, Y. Hirata & K. Aihara,
“Estimating the ETAS model from an early aftershock sequence”

T. Omi, Y. Ogata, Y. Hirata & K. Aihara,
“Intermediate-term forecasting of aftershocks from an early aftershock sequence: Bayesian and ensemble forecasting approaches”
Thank you !!!