Variational Autoencoder Anomaly-Detection of Avalanche Deposits in Satellite SAR Imagery

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Climate Informatics (2020)
In short

Question:
Avalanche detection from satellite images with limited labels.

Results:
Unsupervised-learning approach outperforms supervised methods.

Impact:
Automatically identify risk zones, stability of snow pack and improve avalanche forecasting.
Motivation

- 4000 avalanches reported in French Alps in winter 2017-2018
- 30 people died in this winter
- Usually reported by local forest offices

Automatic detection of avalanches for remote sensing data:
  - Stability of snow pack
  - Identify avalanche risk zones and time periods
Remote sensing data

- SAR Imagery:
  - Sentinel 1 satellite
  - C-band (4.0 to 8.0 GHz)
  - 6-day repeat cycle
  - 20m resolution
  - Ascending and descending orbit modes
  - Backscatter characteristics over avalanche debris

- topographical feature
Remote sensing data

SAR Imagery:
Preprocessing of data

- Consider only 3000 predefined avalanche paths
- Take difference to snow-free summer images
- Take difference to previous satellite image
- Only small amount of data is labeled
- ~1 % of the data includes avalanches
**Method**

1) Encode new test image
2) Draw $L$ samples from $p(z|x)$ and decode
3) If mean reconstruction error $> \text{optimal threshold}$

Anomaly score:

$$\text{AnomalyScore}(x^i) = -\frac{1}{L} \sum_{j=1}^{L} \left[ \log(p(x^i|z^j; \theta)) \right]$$
Method

1) Training the VAE

<table>
<thead>
<tr>
<th>Unsupervised - VAE</th>
<th>Train VAE on unlabeled training data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-supervised - VAE</td>
<td>Train VAE only on image patches showing no avalanches</td>
</tr>
</tbody>
</table>

2) Tune threshold using labeled validation data set
## Model evaluation

<table>
<thead>
<tr>
<th></th>
<th>All Alps</th>
<th>Haute Maurienne</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Balanced Accuracy</td>
<td>F1-score</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.58</td>
<td>0.05</td>
</tr>
<tr>
<td>Supervised - CNN</td>
<td>0.53</td>
<td>0.10</td>
</tr>
<tr>
<td>Semi-supervised - VAE</td>
<td>0.59</td>
<td>0.11</td>
</tr>
<tr>
<td>Unsupervised - VAE</td>
<td>0.69</td>
<td>0.14</td>
</tr>
</tbody>
</table>

### Recall:

Balanced accuracy: $$BA = \frac{TPR + TNR}{2}$$

F1-score: $$F1 = 2 \cdot \frac{PPV \cdot TPR}{PPV + TPR}$$

- sensitivity: $$TPR = \frac{TP}{TP + FN}$$
- specificity: $$TNR = \frac{TN}{TN + FP}$$
- precision: $$PPV = \frac{TP}{TP + FP}$$
Model evaluation

### Receiver operating characteristic curve (ROC)

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC ROC</th>
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</thead>
<tbody>
<tr>
<td>Supervised - CNN</td>
<td>70.7</td>
</tr>
<tr>
<td>Semi-supervised - VAE</td>
<td>68.3</td>
</tr>
<tr>
<td>Unsupervised - VAE</td>
<td>75</td>
</tr>
</tbody>
</table>
Summary & Discussion

- Propose a semi-supervised approach for anomaly detection with limited amount of labels

- Unsupervised method outperforms semi-supervised VAE,
  - More trainings data
  - Noisier data

- Including one-month-old avalanches improved detection ability
Open Questions

- Is there an upper limit in performance due to anomalies which do not correspond to avalanches?

- Which other variables would improve detection ability?