Automatic Generation of Precisely Delineated Geographic Features from Georeferenced Historical Maps Using Deep Learning
Outline

• Problem Statement
• Background (existing work)
• Challenges of applying the existing work to our problem
• Existing models
• Preliminary Experiment Results
• Future Work
• Summary
Problem

Map Recognition
Use Case: Identify soil pollution sources in the Past from Historical USGS Maps
Convolutional Neural Networks (CNN)

- CNN have shown impressive performance in image recognition
Challenges

• Document images vs. Non-document images
  • image pixels representing a geographic feature of interest in a map document occupy only a small proportion of the entire image (imbalanced data)
  • the graphical representations of cartographic symbols belonging to different map layers can be very similar (the false positives)

• The loss of spatial resolution
Existing Work

• Introduce two state-of-the-art Deep Learning models for document image recognition
• Provide a basic understanding of the performance of Deep Learning models in digital map processing
Fully Convolutional Neural Network (FCN)

- Skip architecture
  - Combine the intermediate and final results
Context Module (CM)

- Dilated Convolutional Layer
  - Enlarge the receptive fields
- Without pooling layers

<table>
<thead>
<tr>
<th>Layer</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolution kernel size</td>
<td>3<em>3</em>32</td>
<td>3<em>3</em>64</td>
<td>3<em>3</em>128</td>
<td>3<em>3</em>256</td>
<td>3<em>3</em>256</td>
<td>3<em>3</em>512</td>
<td>3<em>3</em>512</td>
<td>1<em>1</em>2</td>
</tr>
<tr>
<td>Dilation</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Receptive field</td>
<td>3*3</td>
<td>5*5</td>
<td>9*9</td>
<td>17*17</td>
<td>33*33</td>
<td>65*65</td>
<td>67*67</td>
<td>67*67</td>
</tr>
</tbody>
</table>
Preliminary Experiment Results

• We tested on two geographic features in two maps
• We used correctness and completeness as metrics

<table>
<thead>
<tr>
<th></th>
<th>Bray</th>
<th>Louisville</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Railroads</td>
<td>Waterlines</td>
</tr>
<tr>
<td>Correctness</td>
<td>FCN</td>
<td>Context Module</td>
</tr>
<tr>
<td></td>
<td>84.74%</td>
<td>92.59%</td>
</tr>
<tr>
<td>Completeness</td>
<td>97.46%</td>
<td>98.01%</td>
</tr>
<tr>
<td></td>
<td>92.59%</td>
<td>88.81%</td>
</tr>
<tr>
<td></td>
<td>98.01%</td>
<td>98.26%</td>
</tr>
<tr>
<td></td>
<td>68.60%</td>
<td>78.83%</td>
</tr>
<tr>
<td></td>
<td>96.64%</td>
<td>96.73%</td>
</tr>
</tbody>
</table>

- Extracted centerline results
- Reference
• Overall, both models extracted railroad and waterline features reliably (i.e., high completeness)

• The receptive fields
  • Larger receptive fields (CM) are good for railroads
  • But not for water lines
Future Work

• Explore different architectures of models and loss functions for the map recognition (the imbalanced data)
• Design the architecture and loss functions for the map recognition
• Incorporate the topological and geometric characteristics of the features (e.g., railroads should be straight in some distance) to improve the recognition results
Summary

• Goal: convert information in maps into a machine-readable format
• The existing Convolutional Neural Networks show promising recognition results.
• In the future, we plan to design the CNN for map recognition.
Thank you!

Weiwei Duan  weiweidu@usc.edu

Spatial Sciences Institute
University of Southern California