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

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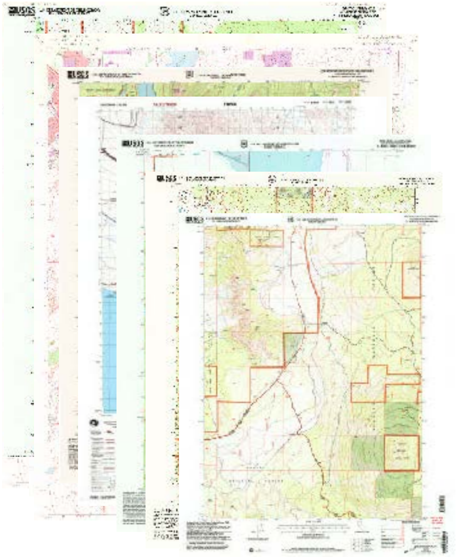
spatial computing INNOVATION
COMPUTER SCIENCE × SPATIAL SCIENCE

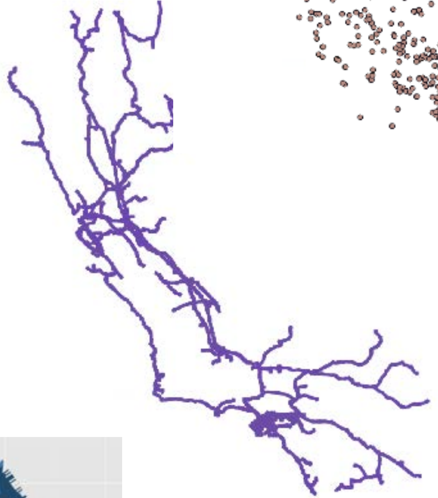
Outline

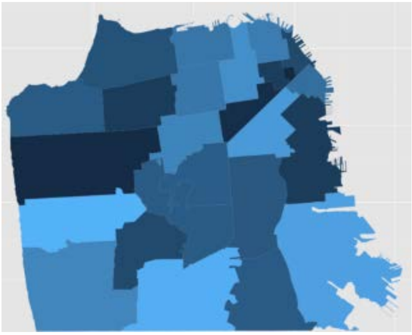
- Problem Statement
- Background (existing work)
- Challenges of applying the existing work to our problem
- Existing models
- Preliminary Experiment Results
- Future Work
- Summary

Problem



Map Recognition

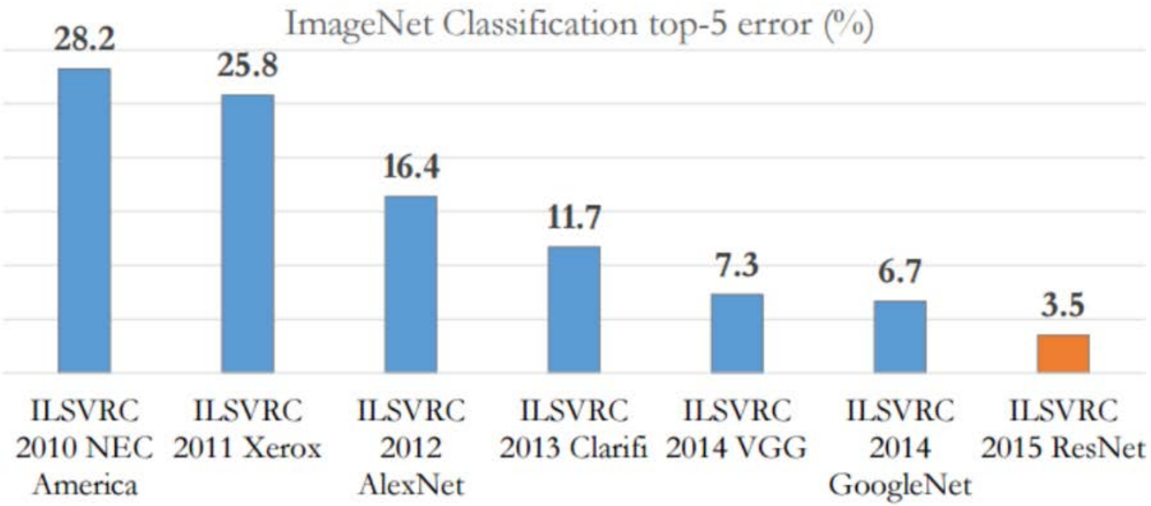


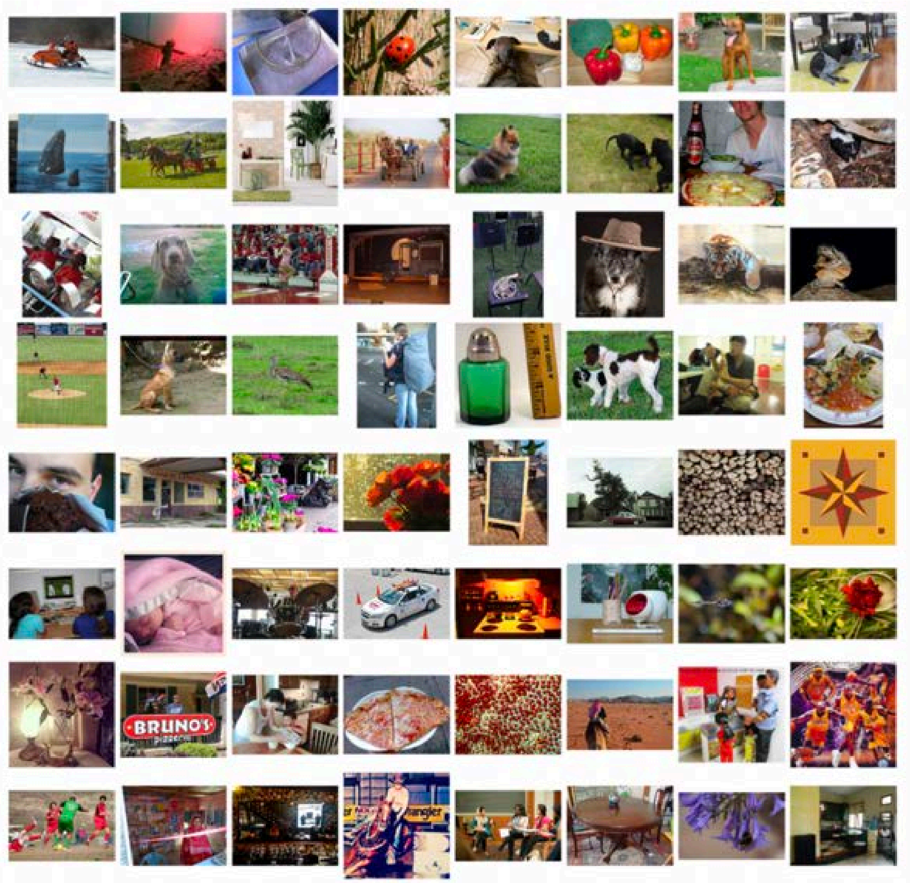


Use Case: Identify soil pollution sources in the Past from Historical USGS Maps

Convolutional Neural Networks (CNN)

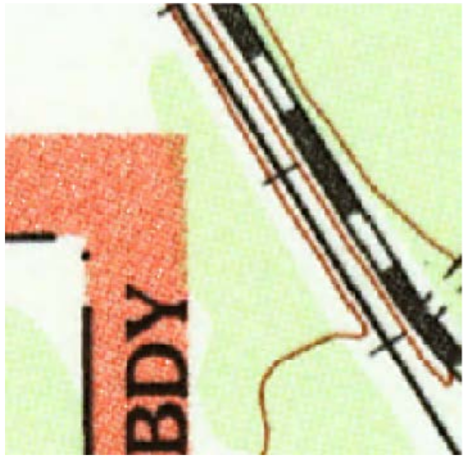
- CNN have shown impressive performance in image recognition

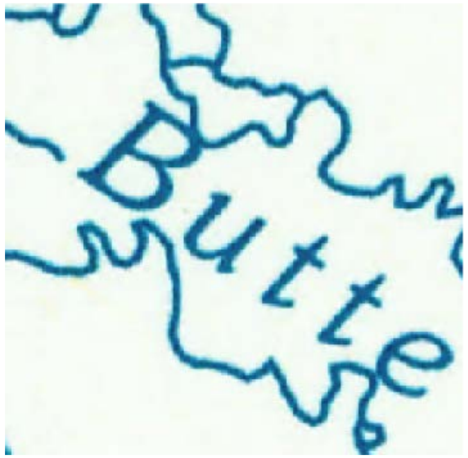




Challenges

- 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



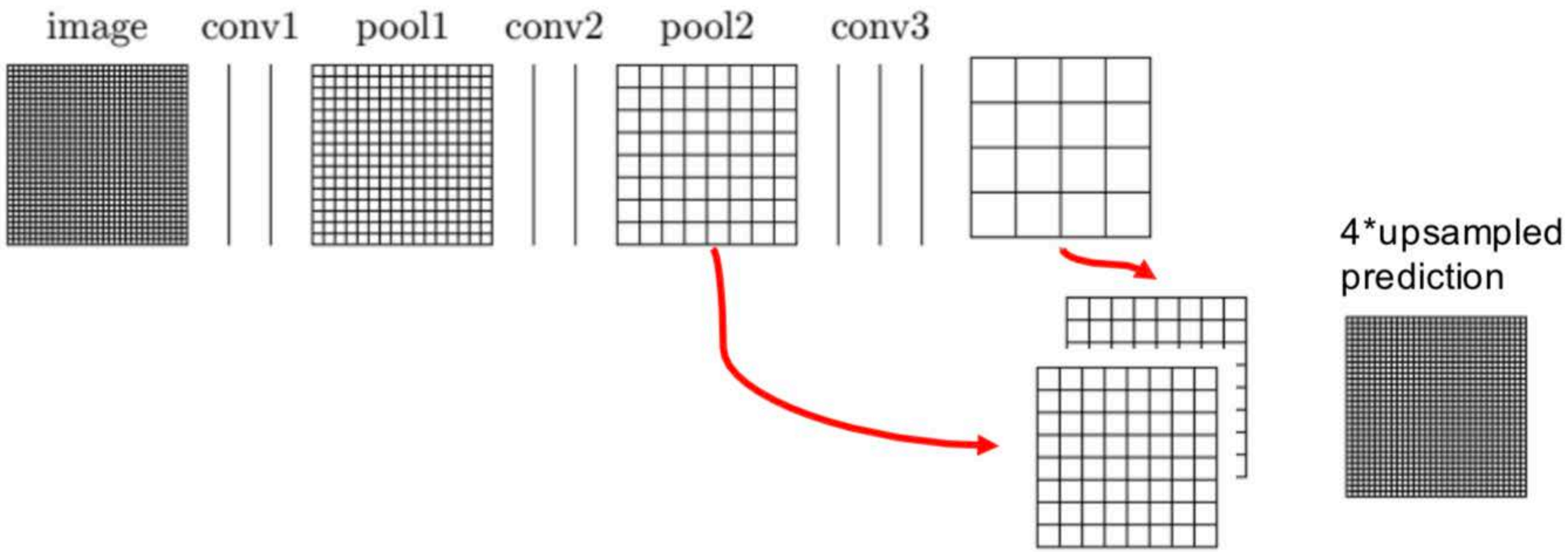


Existing Work

- 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

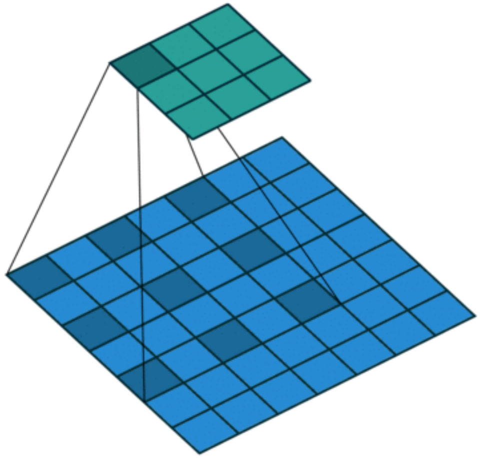
Fully Convolutional Neural Network (FCN)

- Skip architecture
  - Combine the intermediate and final results



Context Module (CM)

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

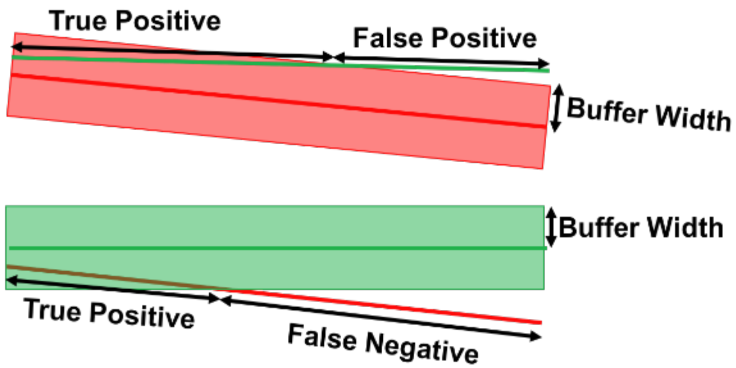


Layer	1	2	3	4	5	6	7	8
Convolution kernel size	3*3*32	3*3*64	3*3*128	3*3*256	3*3*256	3*3*512	3*3*512	1*1*2
Dilation	1	1	2	4	8	16	1	1
Receptive field	3*3	5*5	9*9	17*17	33*33	65*65	67*67	67*67

Preliminary Experiment Results

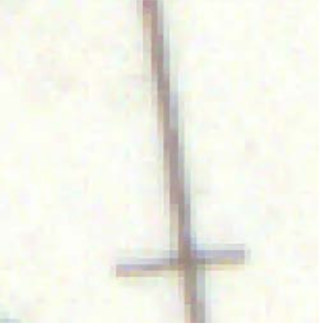
- We tested on two geographic features in two maps
- We used correctness and completeness as metrics

	Bray				Louisville	
	Railroads		Waterlines		Railroads	
	Correctness	Completeness	Correctness	Completeness	Correctness	Completeness
FCN	84.74%	97.46%	92.59%	98.01%	68.60%	96.64%
Context Module	82.90%	97.86%	88.81%	98.26%	78.83%	96.73%



Extracted centerline results

Reference



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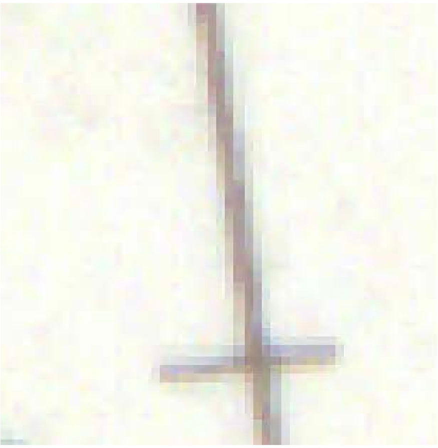
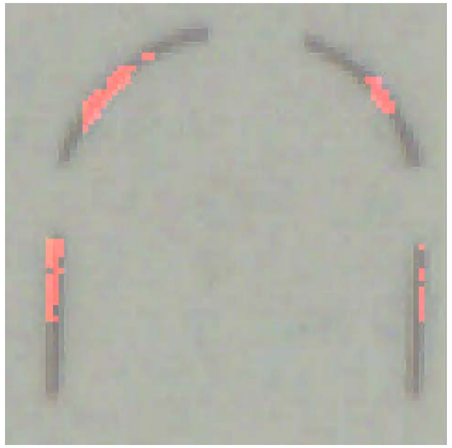
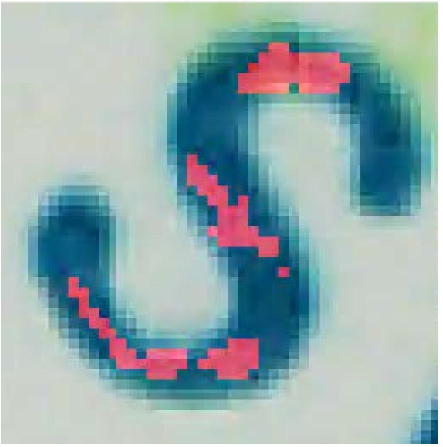
- Overall, both models extracted railroad and waterline features reliably (i.e., high completeness)
- The receptive fields
  - Larger receptive fields (CM) are good for railroads
  - But not for water lines

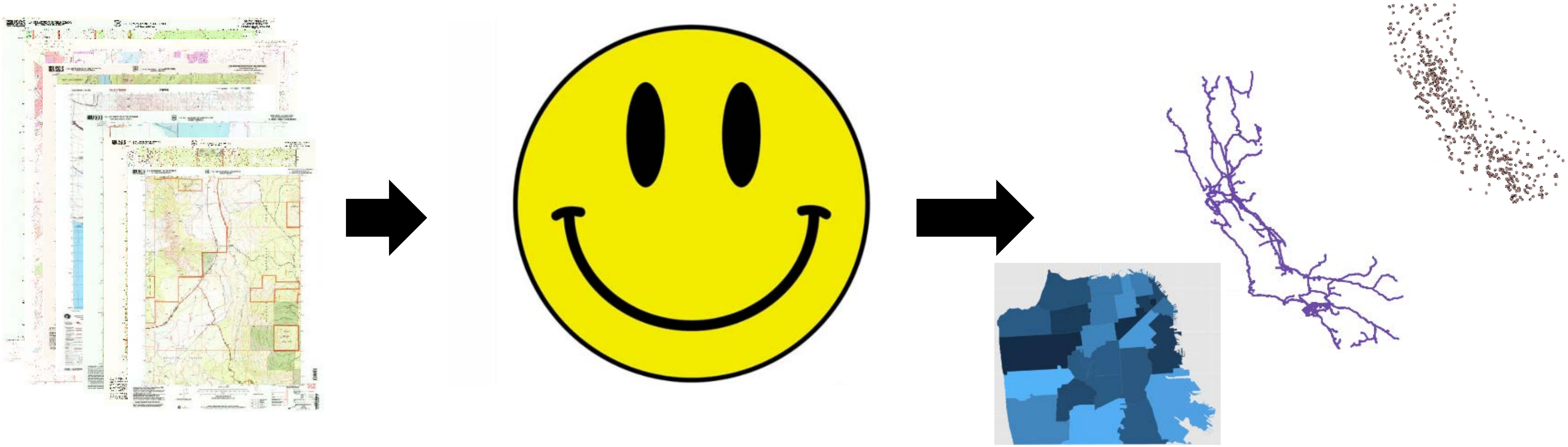
   

Future Work

- 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!

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