Scale Challenges in Explainable GeoAI

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*Given an audience, an **explainable** Artificial Intelligence [XAI] is one that produces details or reasons to make its functioning clear or easy to understand*

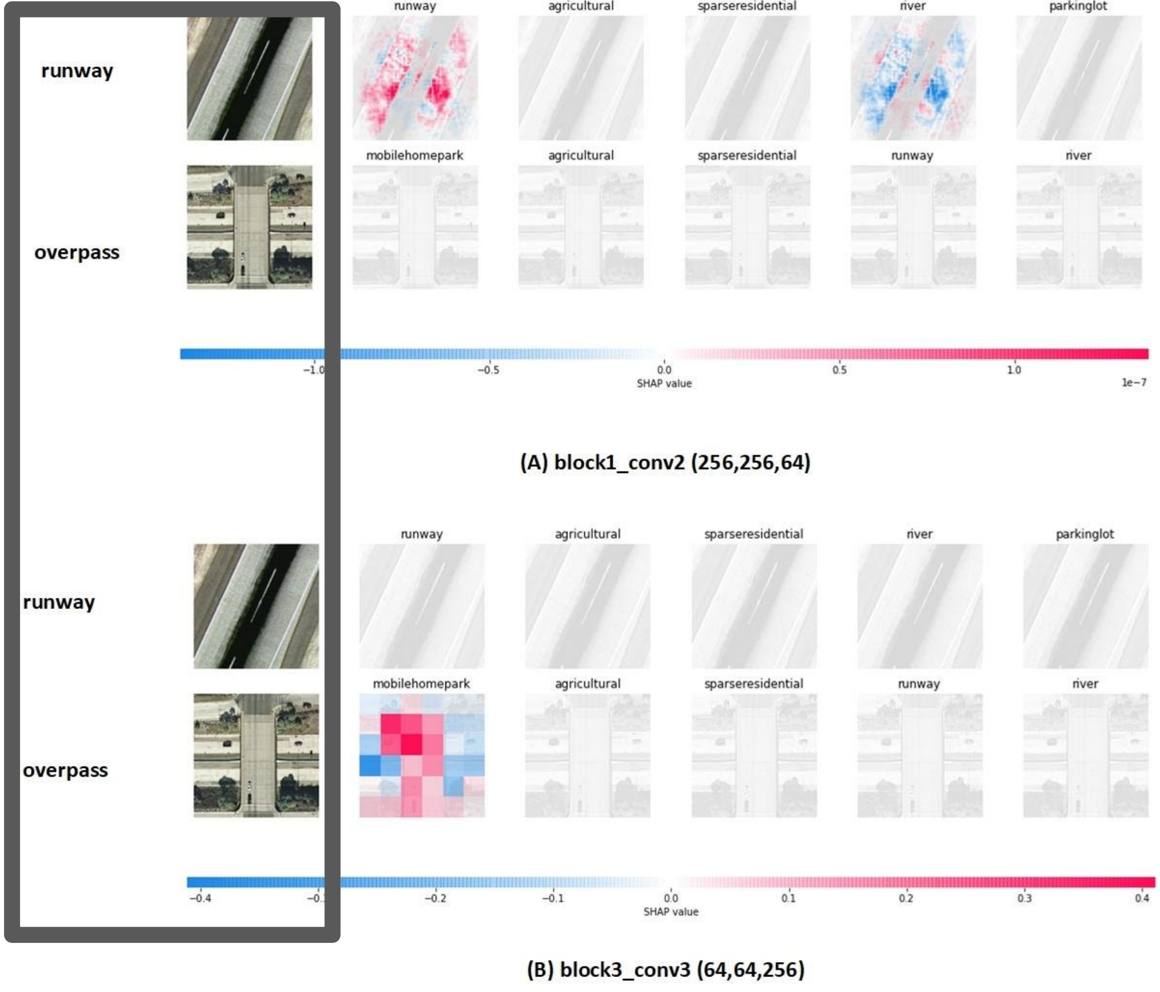
Arrieta et al. 2020, p. 85

XAI usually refers to a set of algorithms or metrics (occasionally visualizations) to evaluate performance ("explainability", "interpretability")

- Scale is an innate component of Geography and GIScience
- Scale is treated as spatial resolution in Deep Learning but scale, resolution means something differently
- GeoAI usually requires data decomposition which distorts the original spatial extents
- GeoXAI also means we need to consider the semantic meaning and audience

Our Case Study:

Land use classifications



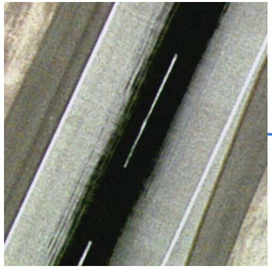
Xing and Sieber, 2021

XAI is resolution-dependent

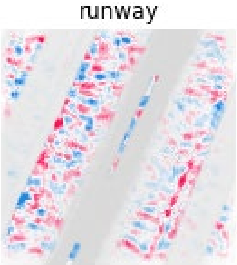
XAI outputs at different resolutions might not be equal in explaining classification results

We should choose the optimal scale for XAI or use Scaling operations (e.g, aggregation) ?

Spatial Resolutions within XAI

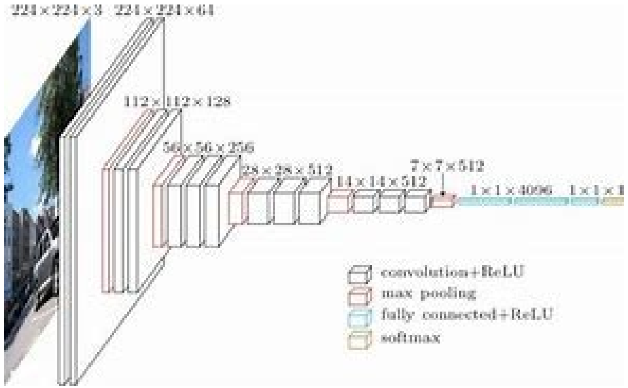


(256,256, 64)

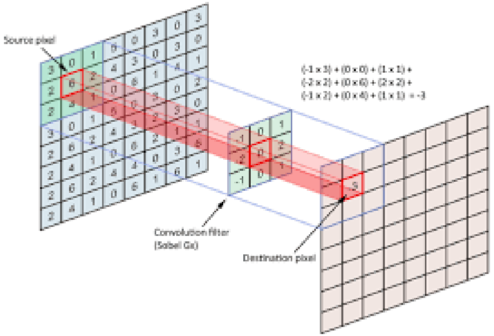


(128,128,128)

(64,64,256)



https://neurohive.io/en/popular-networks/vgg16/



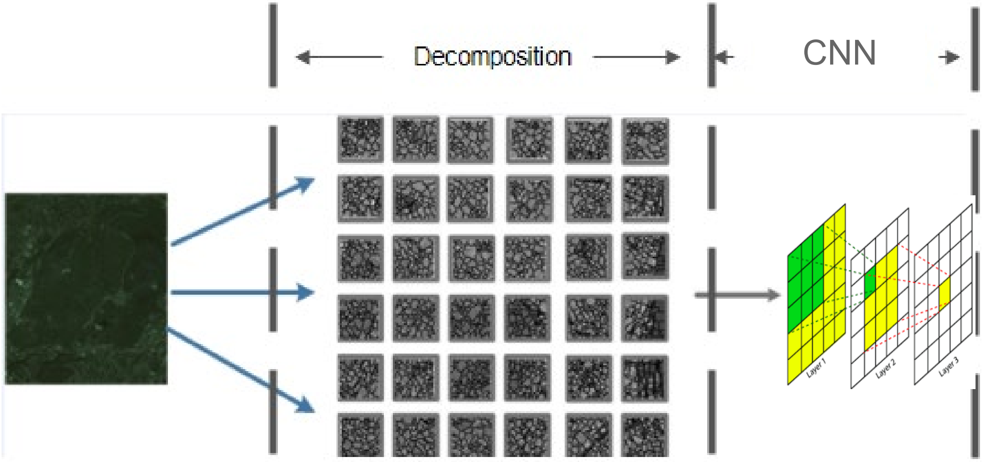
https://medium.com/ai-salon/understanding-deep-self-attention-mechanism-in-convolution-neural-networks-e8f9c01cb251

Spatial Extent for Overpass Classification

Do we have the right spatial extents?

https://www.ideastatica.com/case-studies/394-foot-120-meter-st-jacques-street-overpass-montreal-canada

Challenges of Spatial Extent Distortion



Adapted from Xing, Sieber, and Kalacska, 2014

Semantic Scales

Example: the partonomy of a freeway.

Why it is so similar in a AI to an arterial road or service road?

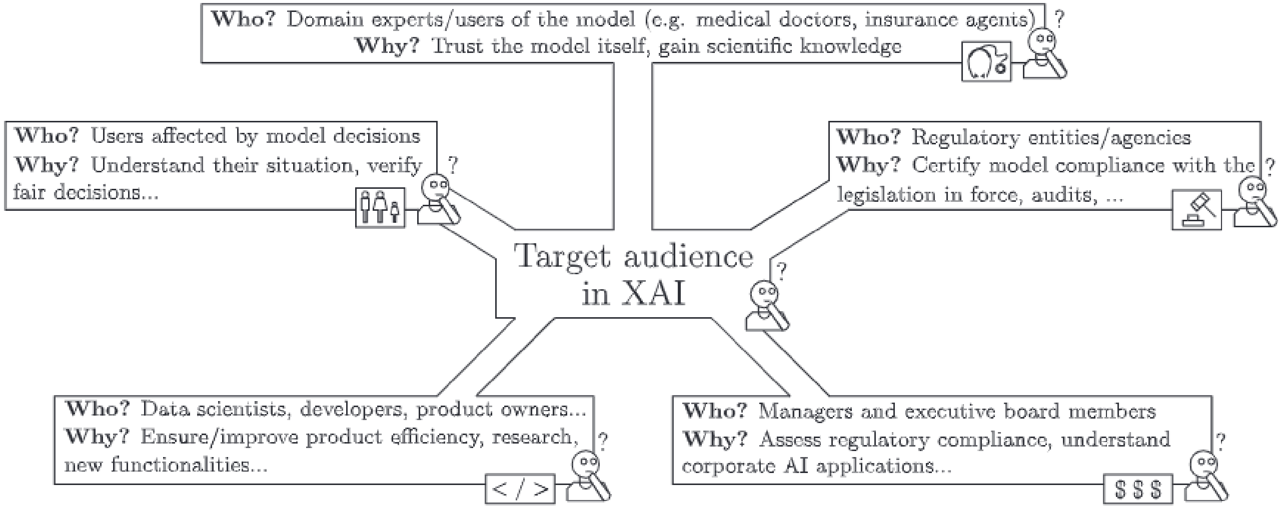
Yang and Newsam (2010)

The Scale of XAI Audiences

In XAI, different types of audiences require different explanations

But that focuses on intergroup differences; in scale it’s **intragroup** differences: Each group in an audience may have different requirements

What should be the right audience size for GeoXAI?



Arietta et al., 2011

Ethical Issues of Scale in GeoXAI

- MAUP and its inference
  - Different geometries (points to areas)
  - Same geometries: Aggregation, zones (e.g., of areas or points to centroids)
  - Similar effect with NLP--Zheng & Sieber (2022)

- Not solved by XAI, with its current focus on classification accuracy & performance

- Use of XAI to reify the ecological fallacy & amplify inequity. All too easy to explain what happens to you based on what spatial aggregation in which you live and not who you are.

- Challenges of explainability by design

Conclusion

Scale is the key to link XAI and GeoAI as GeoXAI

From feature-based explanation to location-based explanation we have to address scale transformation

Semantic scales and audience scales present new challenges to GIScience

Thank you!

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References

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