

# Geospatial Data for Small Area Estimation

## Machine learning for SAE

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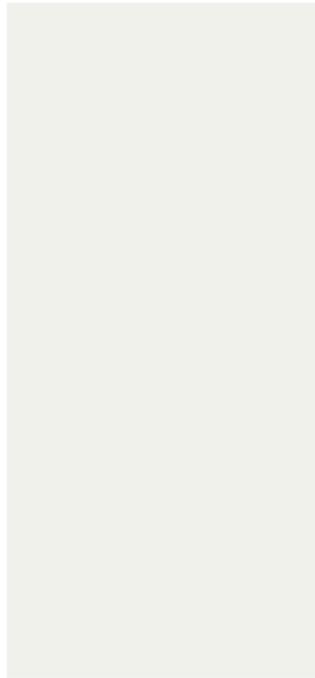
# Introduction

- This presentation: machine learning for small area estimation (SAE)
  - Focus of SAE will be geographic
- Will focus on convolutional neural networks (CNNs)
  - Application to satellite imagery
  - Small discussion of vision transformers

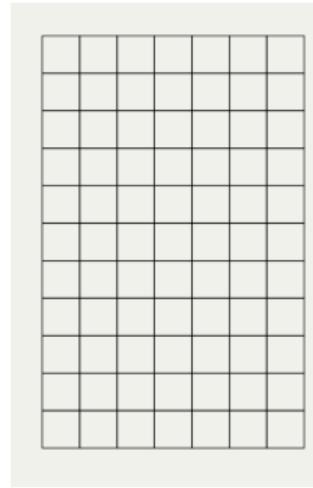
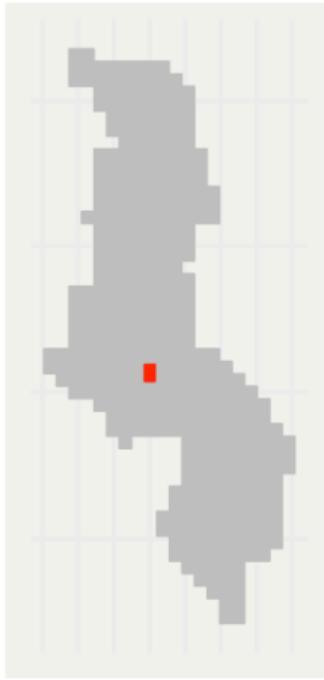
# Malawi



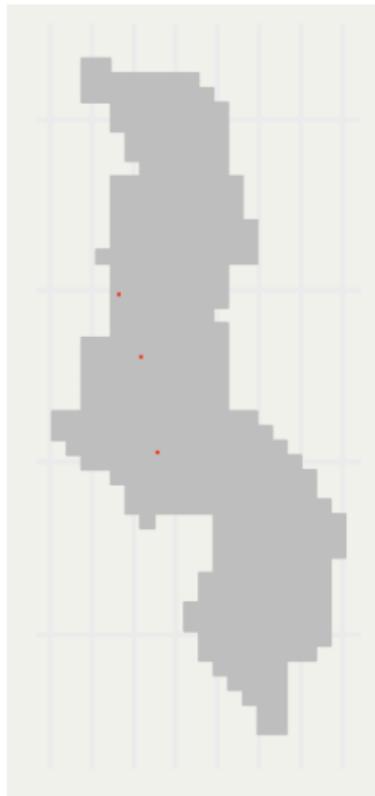
# Malawi - as grids



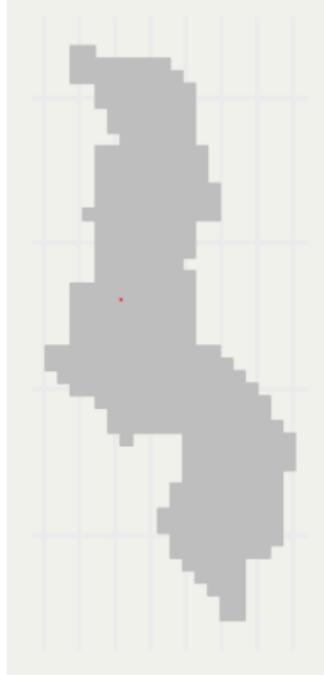
# Malawi - as grids



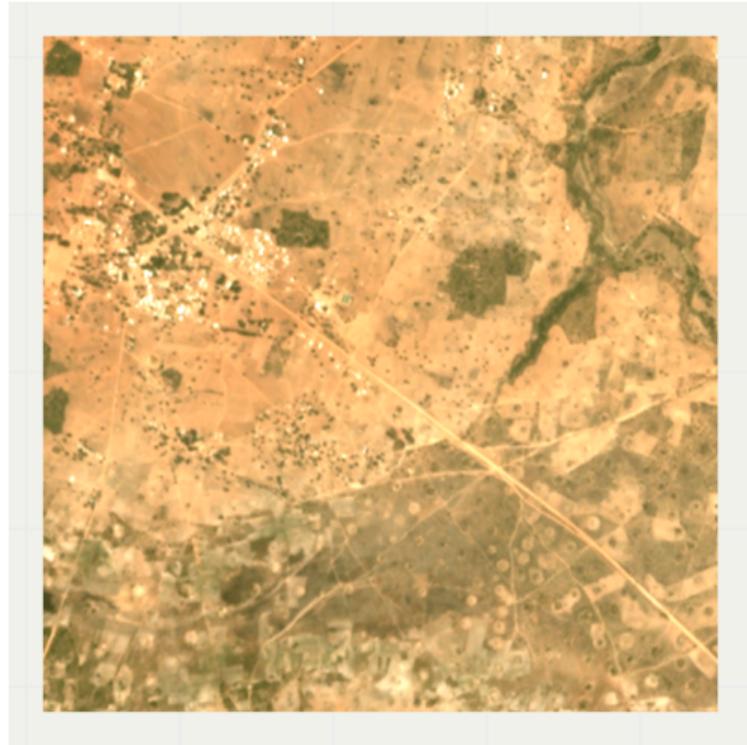
## Malawi - three grid cells



# Example grid image 1



## Example grid image 2



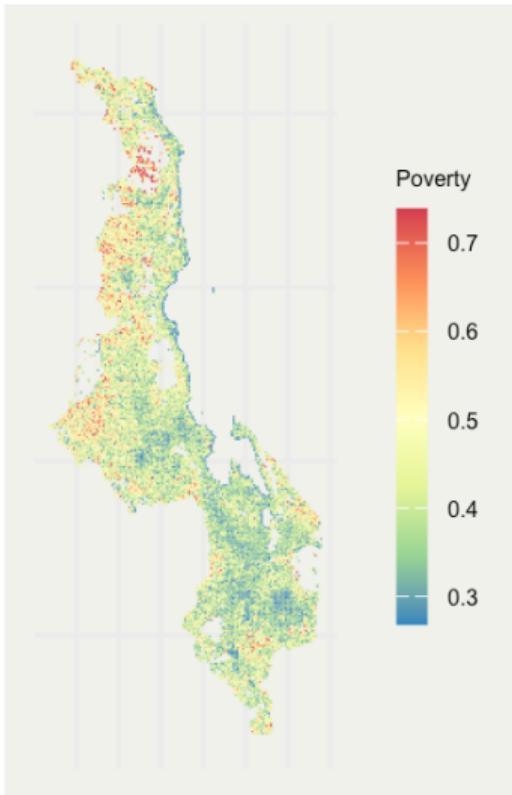
## Example grid image 3



# Images to predictions

- We have our images
- We will build some model
- We then predict the outcome (e.g. welfare) based on each image

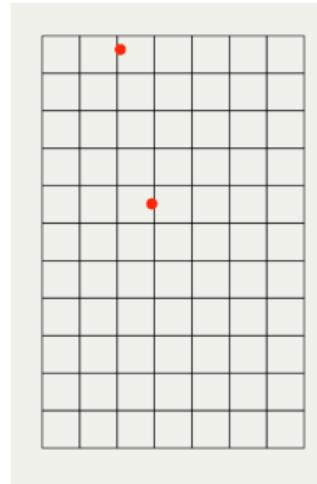
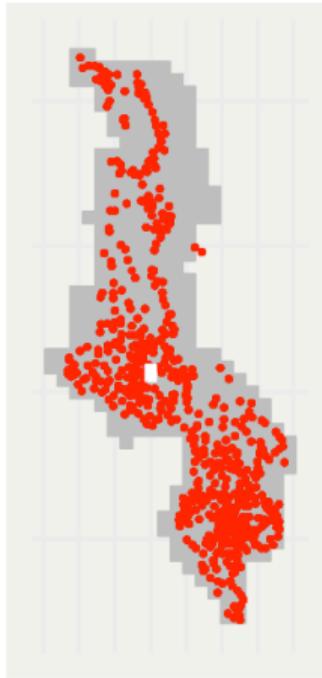
# Images to predictions



# Convolutional Neural Networks (CNNs)

- CNNs have been a common tool in image analysis and prediction
  - “Supervised” machine learning
- Requires labeled data
  - In our example, each grid cell needs a poverty “label”
  - Common to get it from surveys with latitude/longitude

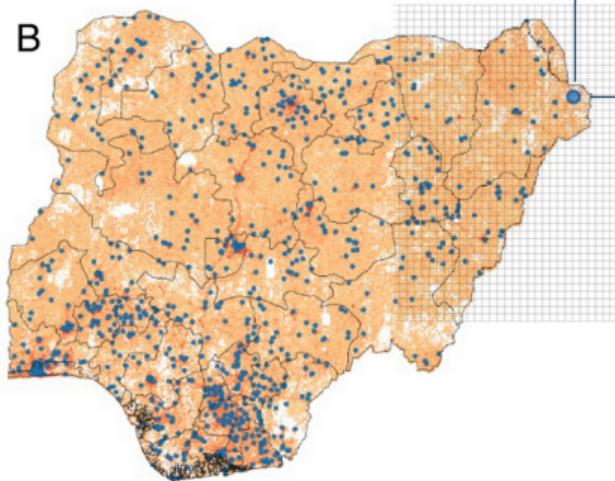
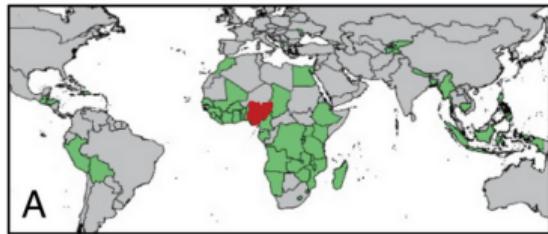
# Poverty labels



# Common to combine methods

- Chi et al. (2021)
  - CNNs to extract “features” (more later)
  - Gradient-boosted regression trees to predict welfare
- Note that the use of gradient-boosted trees has been proposed for SAE before!
  - Merfeld et al. (2024)
  - Key issue is variance estimation

# Chi et al. (2022) Figure 2



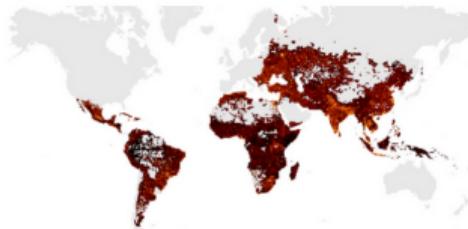
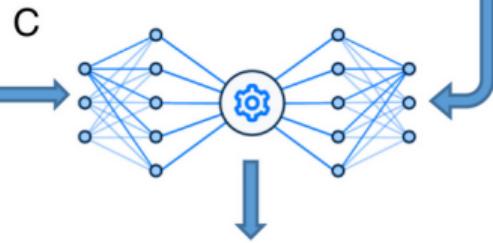
## GROUND TRUTH DATA

- Villages with surveys
- 📄 20-50 surveys per village
- ⌚ 2-4 hours per survey

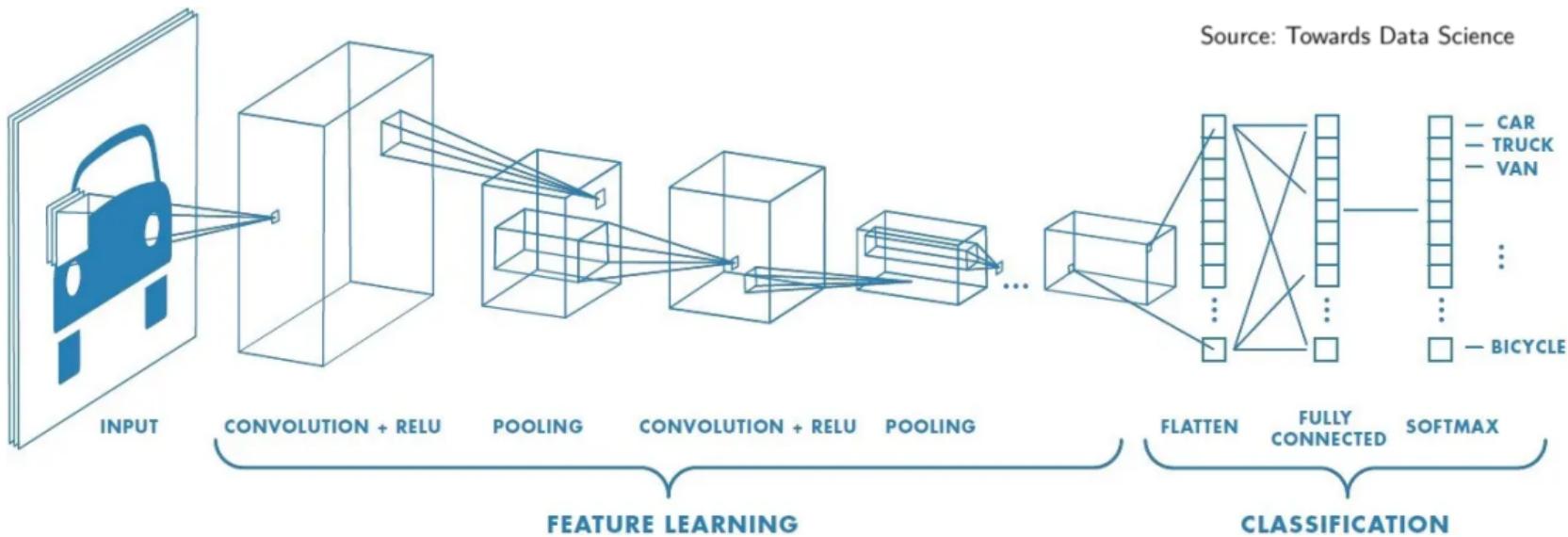
## GEOSPATIAL “BIG” DATA

- 📍 Satellites  
High-res imagery, night lights
- 📶 Connectivity  
Cell towers, devices
- ⌚ Demography  
Population
- 🌐 Geography  
Road density, elevation

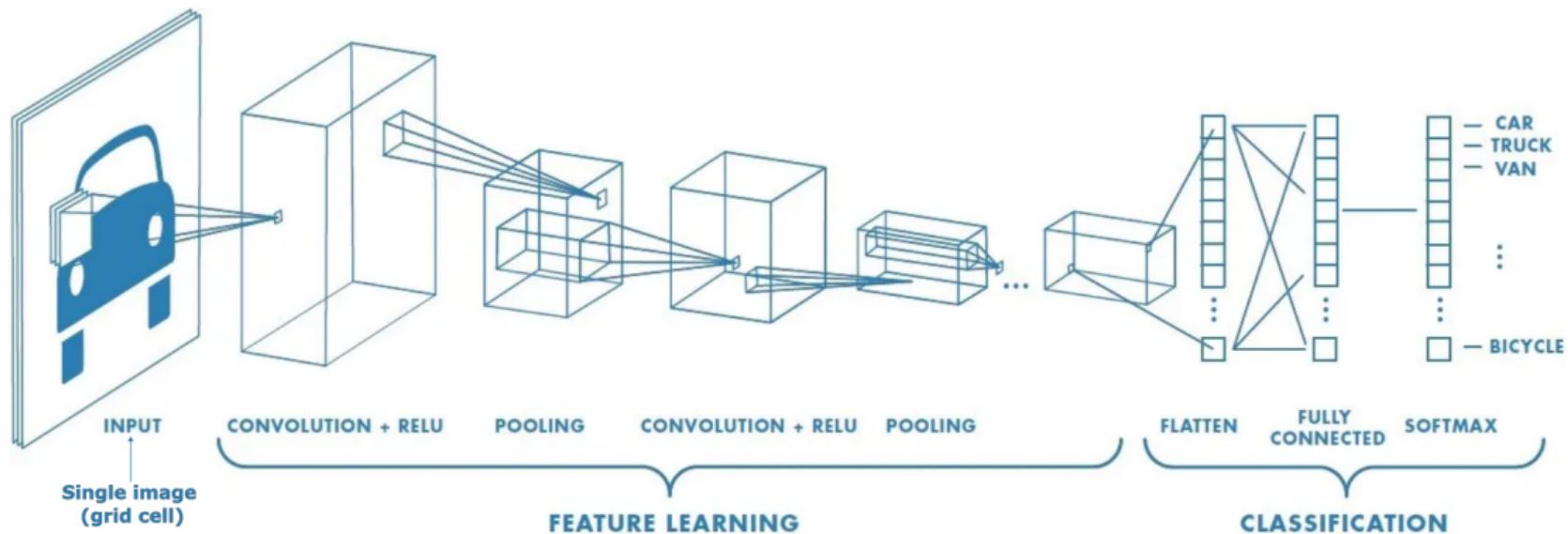
## MACHINE LEARNING



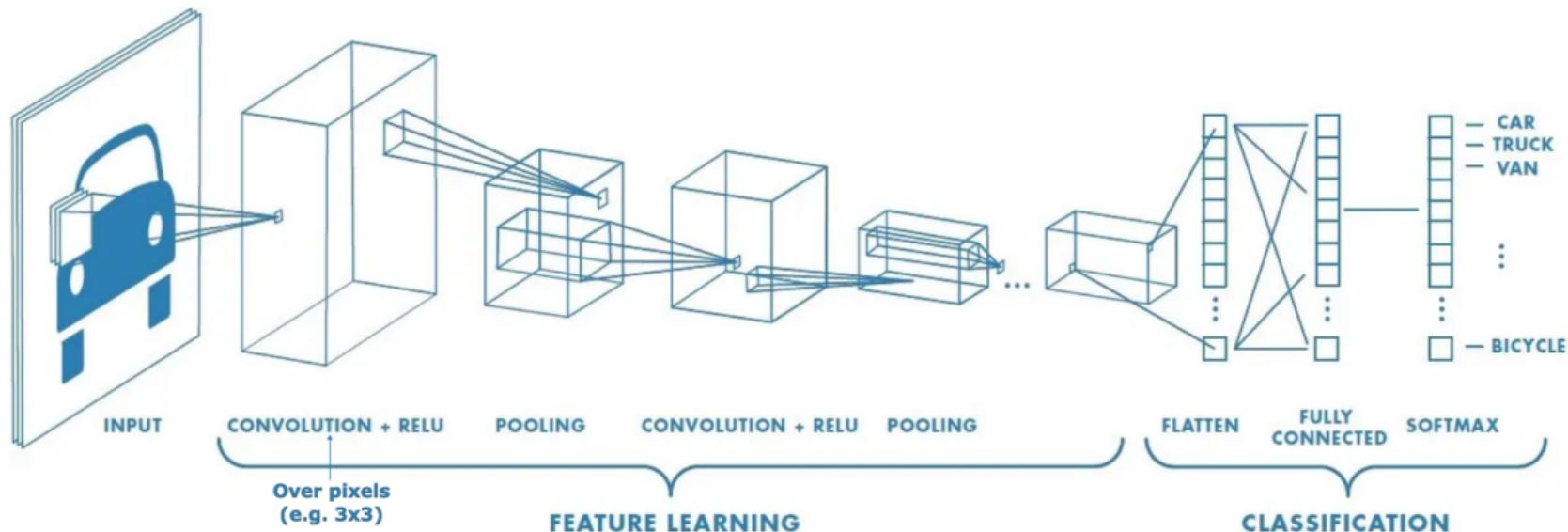
# CNNs



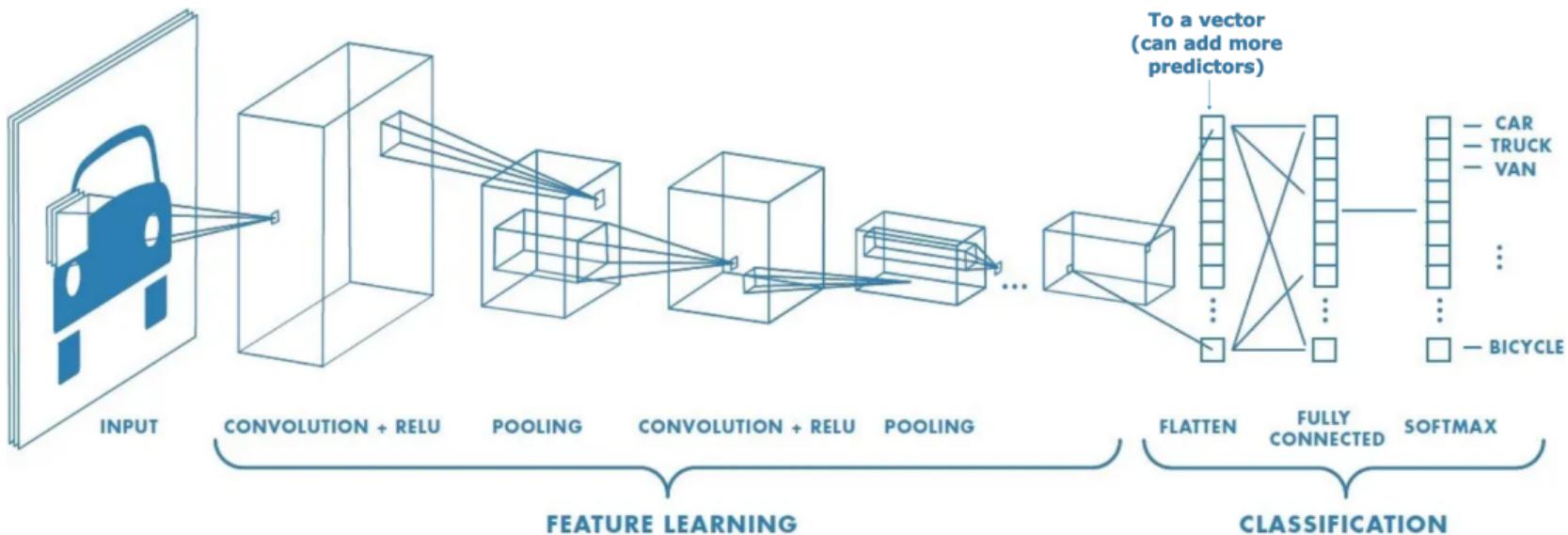
# CNNs



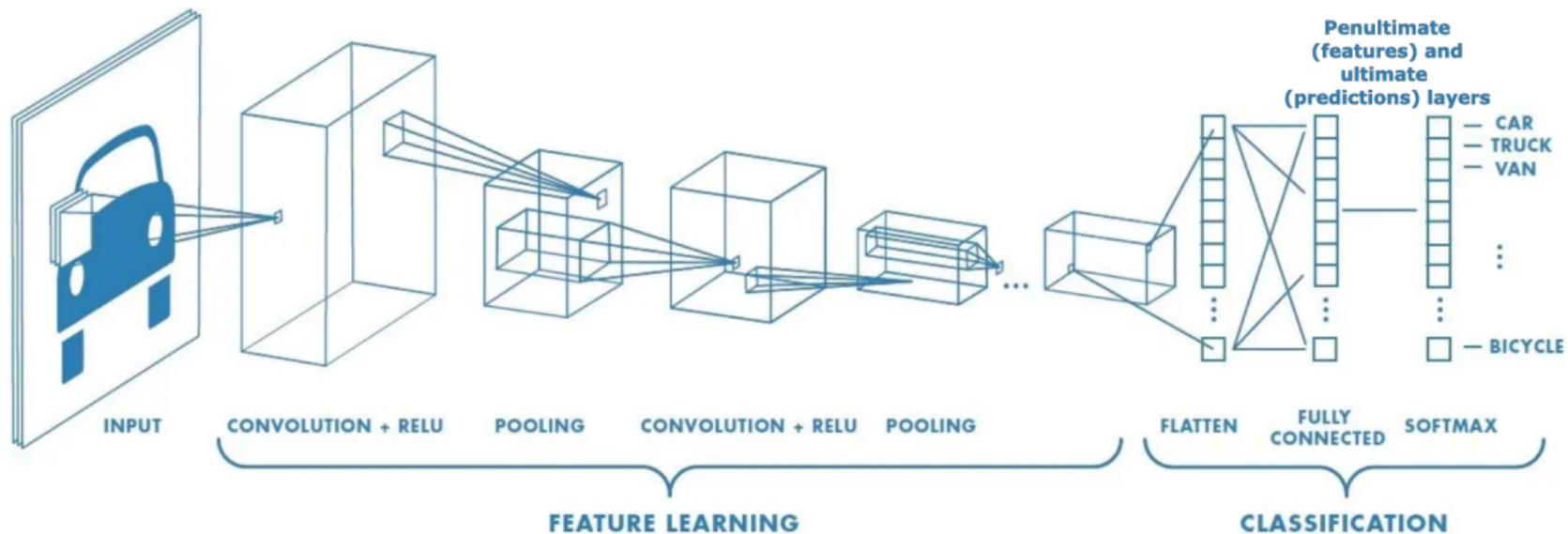
# CNNs



# CNNs



# CNNs



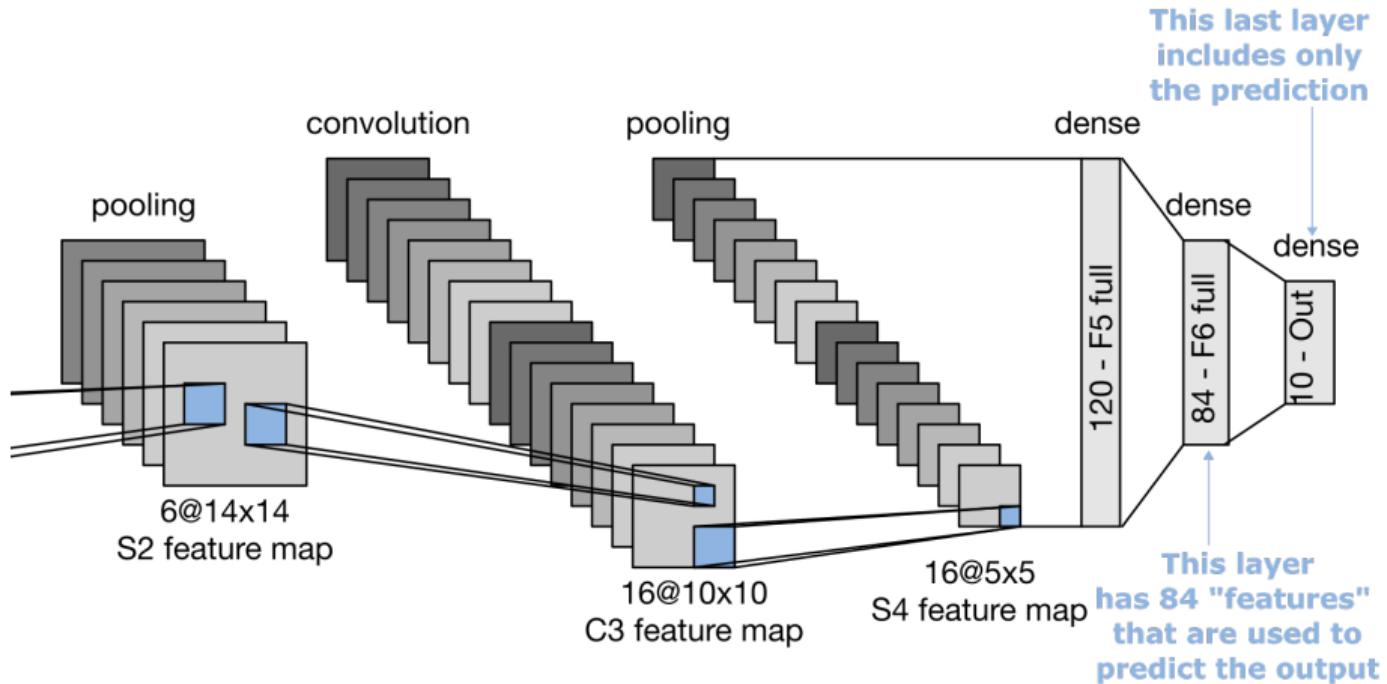
# CNN architecture

- CNN “architecture” is completely flexible
  - Number of layers
  - Number of nodes in each layer
  - Number of convolutions
  - Activation functions
  - Type of output (e.g. classification? prediction?)
  - etc.
- Common to use a “pre-trained” model
  - E.g. ResNet, AlexNet, etc.
  - Transfer learning
  - “Fine-tuning”

# Two ways to use CNNs for SAE

1. Just use pure predictions from the CNN itself
  - Issue: no variance estimates
2. Use some CNN output as a feature in a traditional SAE model
  - Can use prediction itself
  - Can use *features* from e.g. penultimate layer

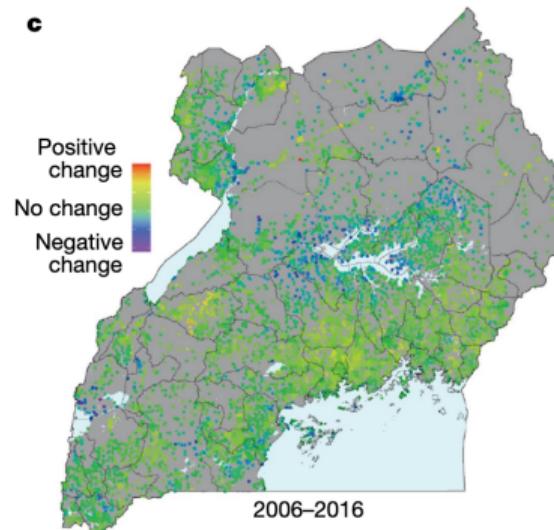
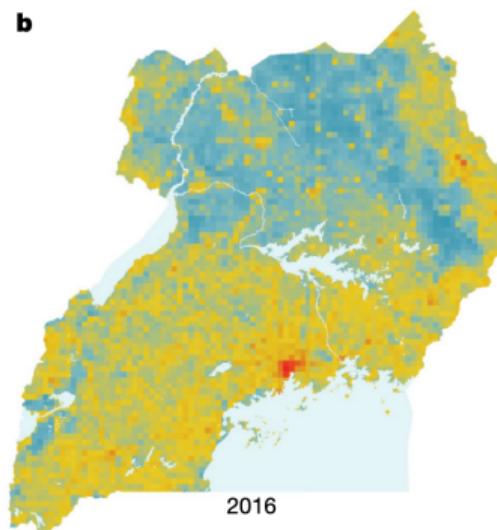
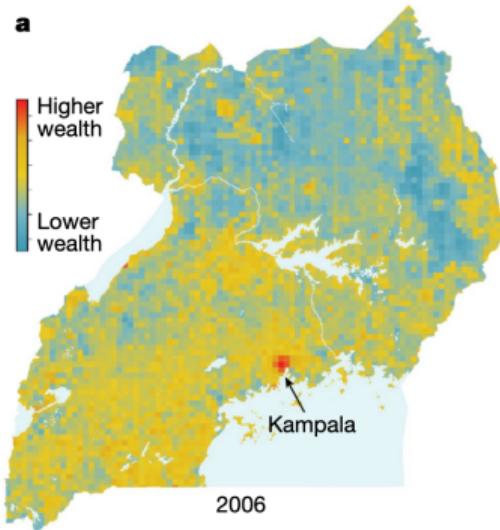
# Outputs of LeNet (Source: D2L.ai)



## Example 1: Ratledge et al. (2022)

- CNN to predict wealth
- Variance estimates (for treatment effects) from bootstrapping

# Example 1: Ratledge et al. (2022)



## Example 2: Newhouse et al. (2024)

- CNN to predict poverty, land classification
- Use these predictions as features in traditional SAE model
- Performs well!

## Example 2: Newhouse et al. (2024)

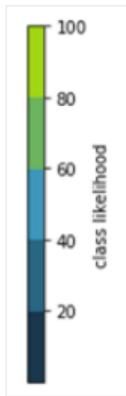
Planet Image



Roads



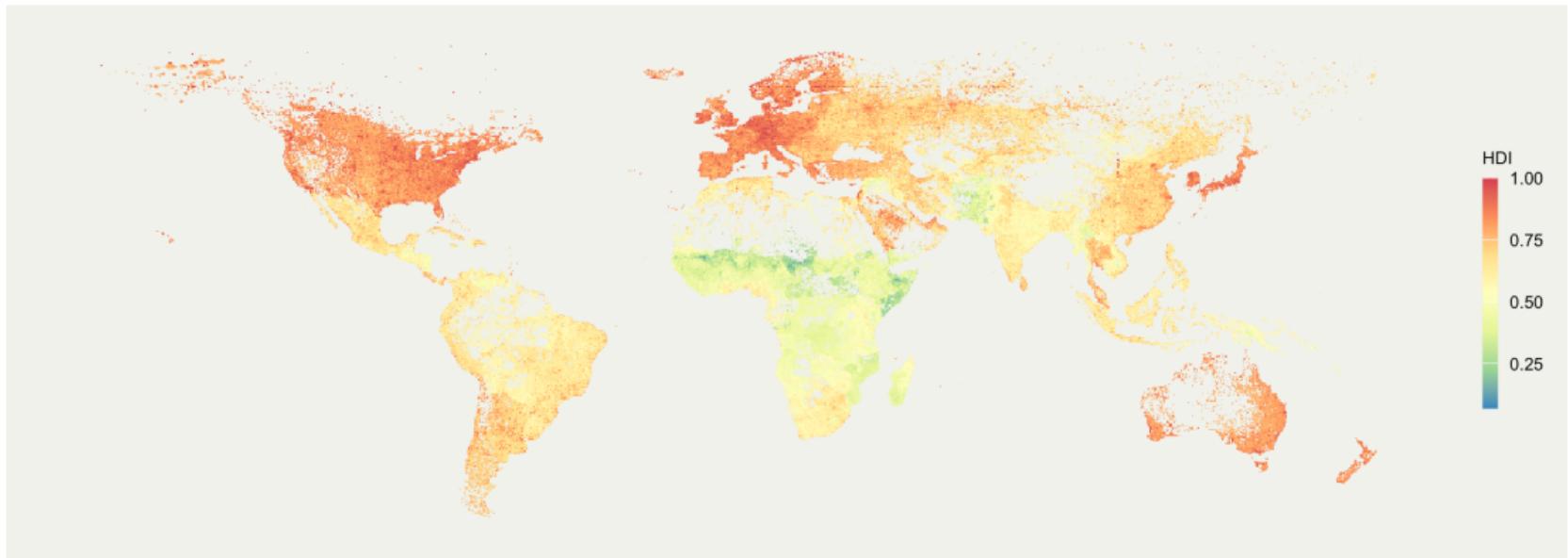
Buildings



## Example 3: Merfeld et al. (2024)

- Vision transformers (ViT), not CNNs
  - Some features in common with LLMs (e.g. ChatGPT), like “attention” mechanisms
  - Pure ViTs may perform better than CNNs (e.g. Dosovitskiy et al., 2021)
- Use features from penultimate layer as features in traditional SAE model
- Work in progress!
- Very little work of this kind

# Mosaiks - Rolf et al. (2021)



# Mosaiks features in SAE

- They make available all of the “features” from the penultimate layer of a CNN
  - Around 5,000 of them
- We have used these as candidate features before!
  - E.g. in Kim et al. (2024) for human capital

# Thank you!

<https://joshmerfeld.github.io>

<https://github.com/JoshMerfeld>