MapReader Workshop

Spatial Humanities

September 25, 2024
Bamberg, Germany

Our Partners

The Alan Turing Institute

British Library

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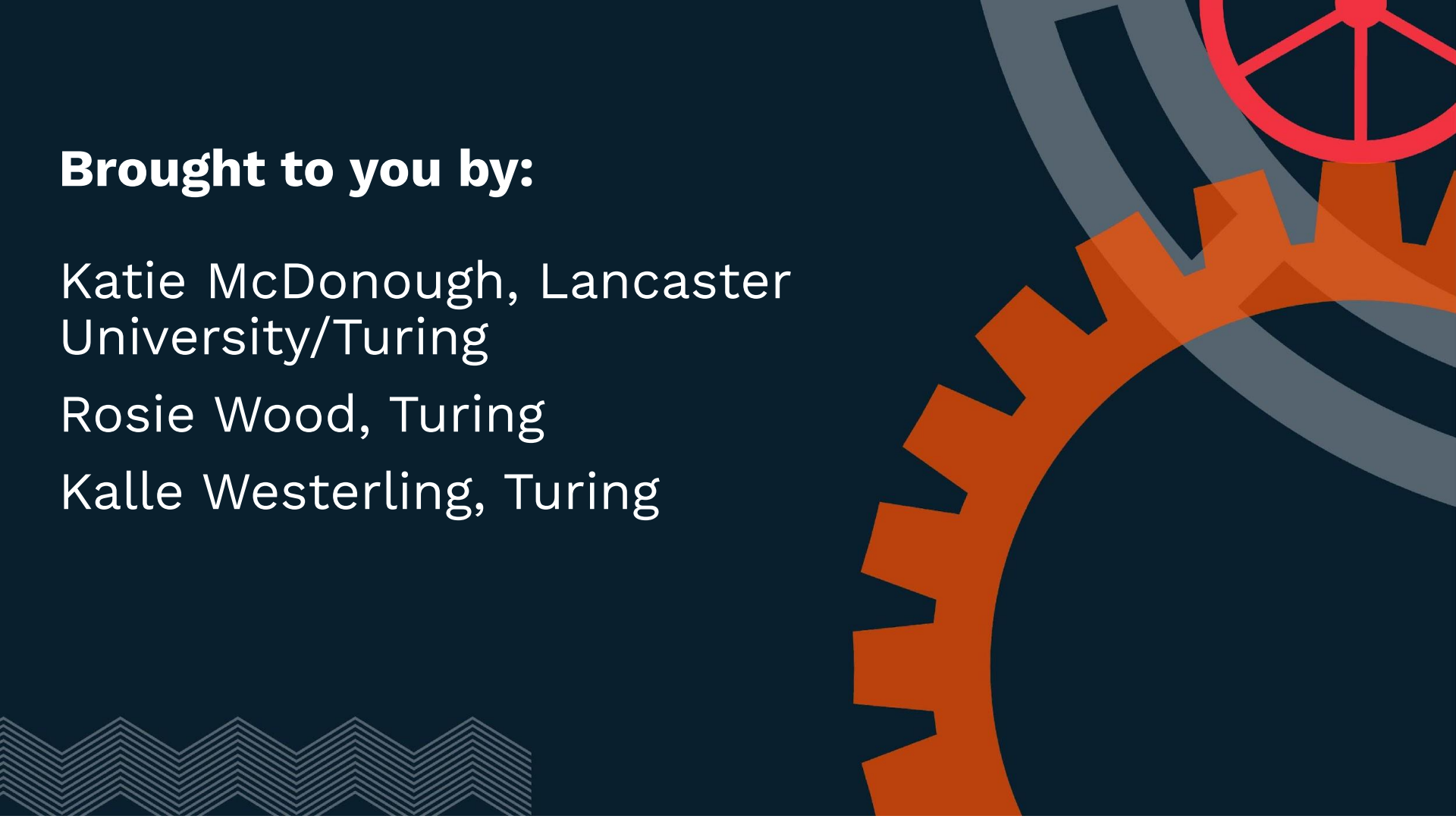
Brought to you by:

Katie McDonough, Lancaster University/Turing

Rosie Wood, Turing

Kalle Westerling, Turing



Workshop material and research applications co-developed with:

Daniel Wilson, Turing

Kaspar Beelen, SAS, University of London

Tim Hobson, Turing

Kasra Hosseini, Zalando (formerly Turing)

Josh Rhodes, Durham

Jon Lawrence, Exeter

Andy Smith, Turing

Practical matters

Wifi network: Eduroam/BayernWLAN

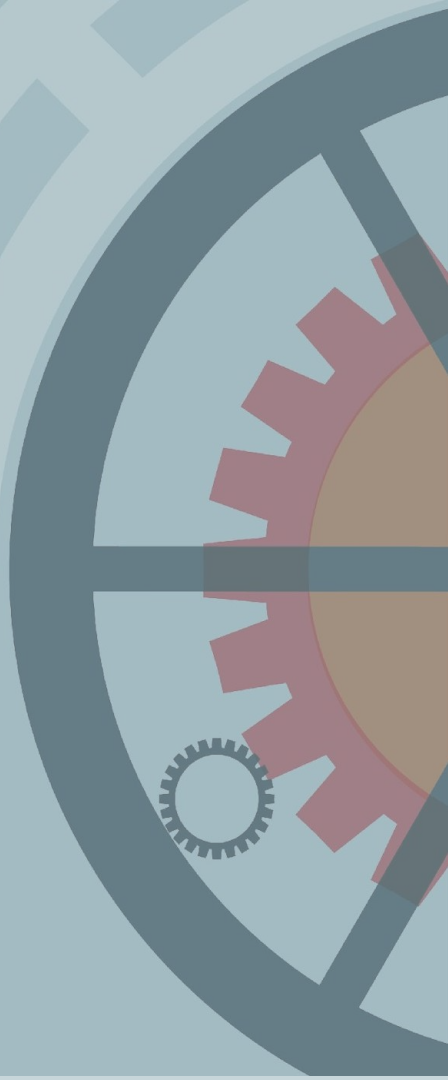
Event repo:
https://github.com/maps-as-data/spatial-humanities-mapreader-workshop

Schedule

9:00-9:20	Introductions
9:20-10:00	About MapReader
10:00-10:15	Break
10:15-11:30	Using Mapreader
11:30-12:00	Discussion

Meet your neighbour

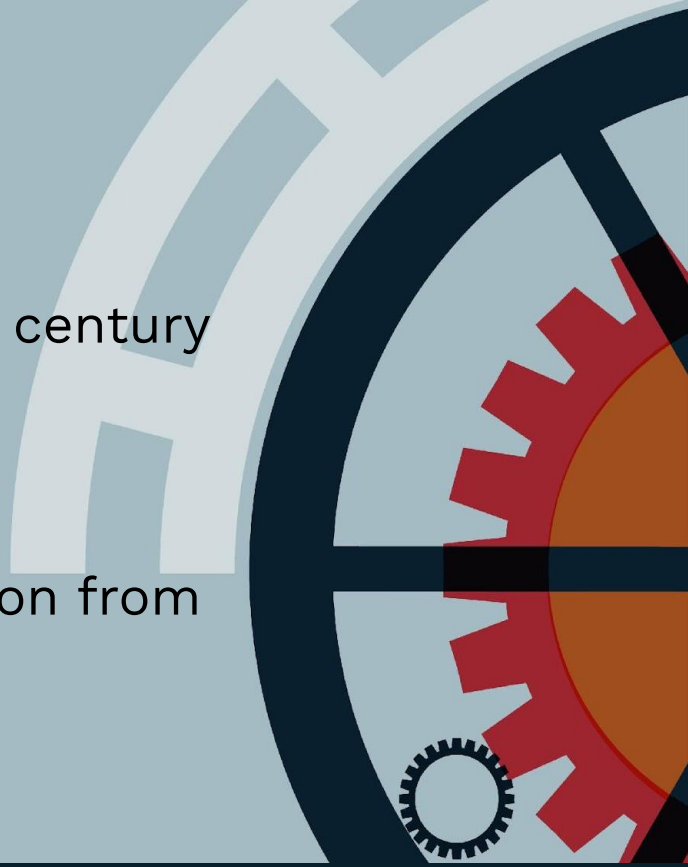
1. **Introduce yourself to a neighbour in 2 minutes:**
    a. Name
    b. Role/Institution/Place
    c. Why are you interested in historical maps?
2. **Switch**
3. **Introduce your neighbour to the group in less than 1 minute**



Why MapReader?

Living with Machines

- Digitised collections from the long 19th century
- Computational methods
- Multidisciplinary approach
- Digitised Ordnance Survey map collection from the National Library of Scotland



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The Living with Machines Team

Principal and Co-Investigators

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Mia Ridge
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From Living with Machines to Data/Culture

Living with Machines ended July 2023!
Data/Culture began October 2023

Data/Culture is a sandbox for the re-use of data and tools in the humanities and arts, in ways that develop high-quality research and strong collaborative communities.

In its pilot year (2023-24), the team is focused on:

- Building communities of historians around 1) the **Seshat: Global History Databank** and 2) the **Living with Machines** project, whose outcomes include the MapReader software library, as well as data and tools related to historical British newspapers.
- Establishing a stronger network of Research Software Engineers for the Arts and Humanities, driving collaborative innovation and embedding skills. Delivering a roadmap for a national capability tailored to Arts and Humanities needs.

Data/Culture Team

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Theme Lead for Arts, Humanities and Cultural Heritage, and Associate Professor in Cultural…

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Turing Fellow

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André Piza
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Rosie Wood
Research Data Scientist

Credit: National Library of Scotland for map image,
https://maps.nls.uk/geo/explore/#zoom=15.849043282320103&lat=51.47748&lon=-3.16875&layers=6&b=1

1888

How do researchers work with maps?

Digitized maps can be more than sheets to browse in a virtual reading room. *But how?*

Ordnance Survey maps of England, Wales, and Scotland

6 inches to 1 mile
1888-1913
(2nd edition)

~15K sheets

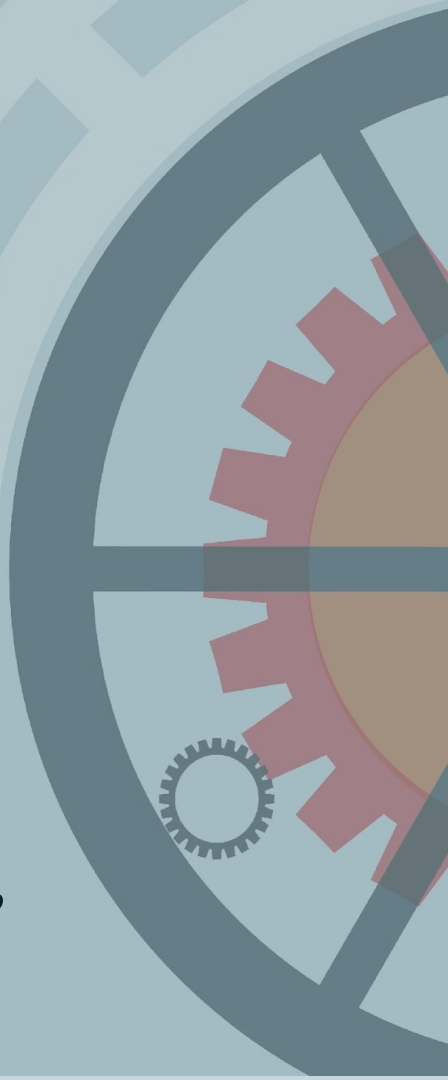
Credit: Olivia Vane for visualisation, National Library of Scotland for map images & metadata

Make trustworthy claims based on *thousands* of maps

case studies → ‘high resolution’ local archival research or anecdotes from printed materials

aggregated statistics → ‘low resolution’ regional/national

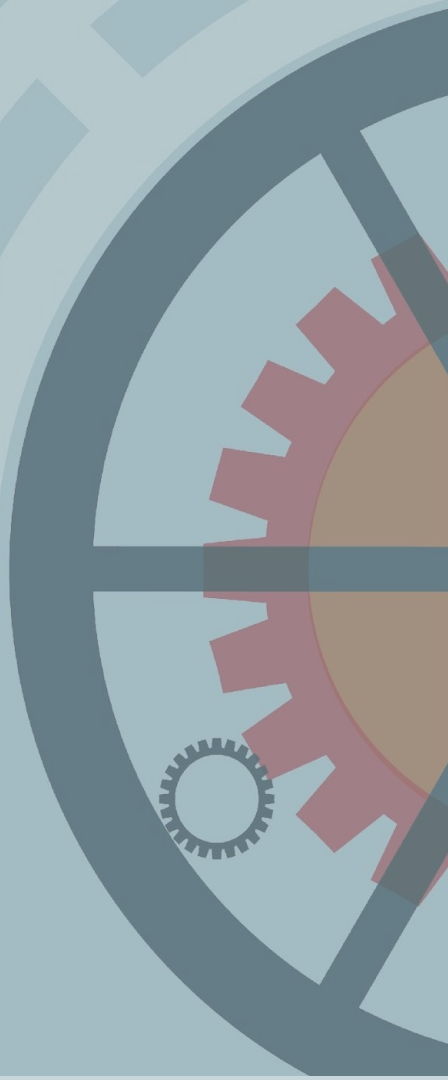
Ordnance Survey (series) maps as non-aggregated, high-resolution, national-coverage sources



You Cannot Ground Truth the Past

Historical OS maps tell us how Victorians represented the British landscape, and how that landscape was changing, but they are not a ‘ground truth’.

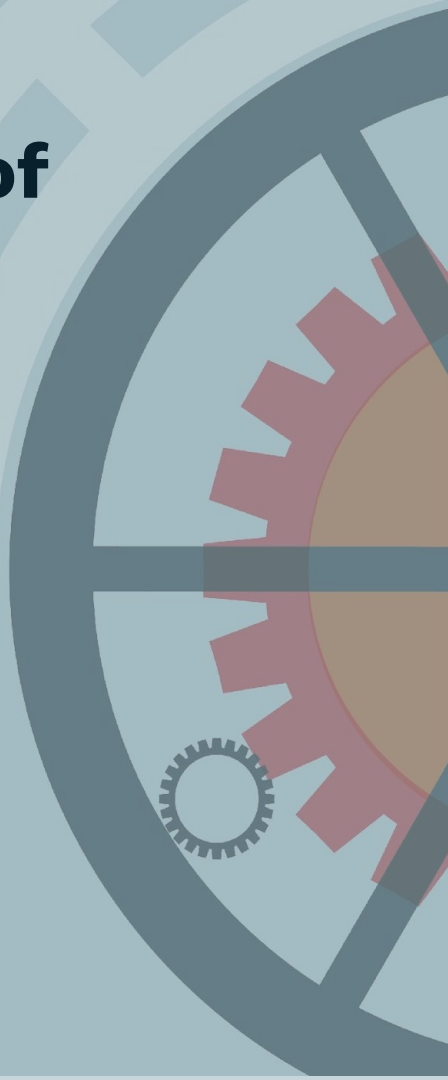
We want to ***use CV to advance interpretation, not define truth.***



Step away from the GIS paradigm of vectorizing everything on a map

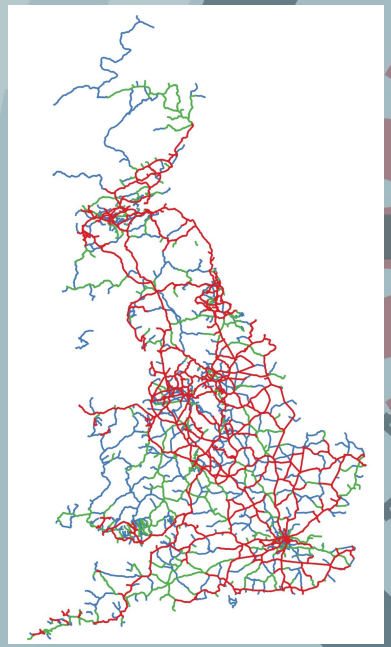
Stop historical **data “mining”/“extraction”** and insisting on overly-precise data

Start developing methods that permit **critical distance between scholars and sources** & question-appropriate data collection and exploration



Traditional GIS Data → Cultural Spatial Data Creation

Can we identify and search for new shapes as **intentionally imprecise visual signs** forming new **patterns** rather than just trying to automate manual GIS tasks?



Solution: ‘Patches’ as a new shape for historical research

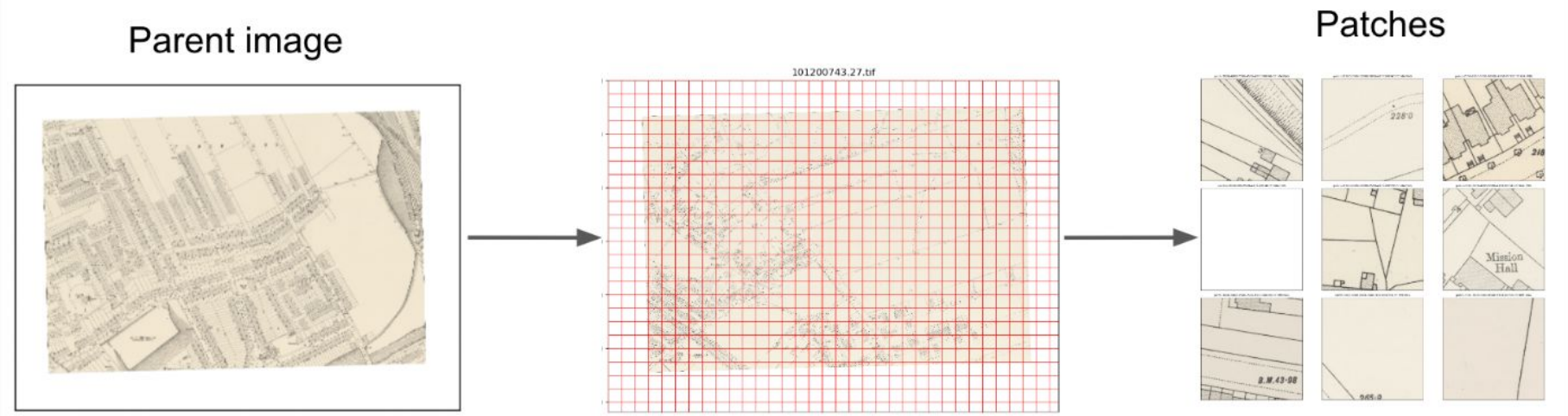


Image Classification for Map Patches

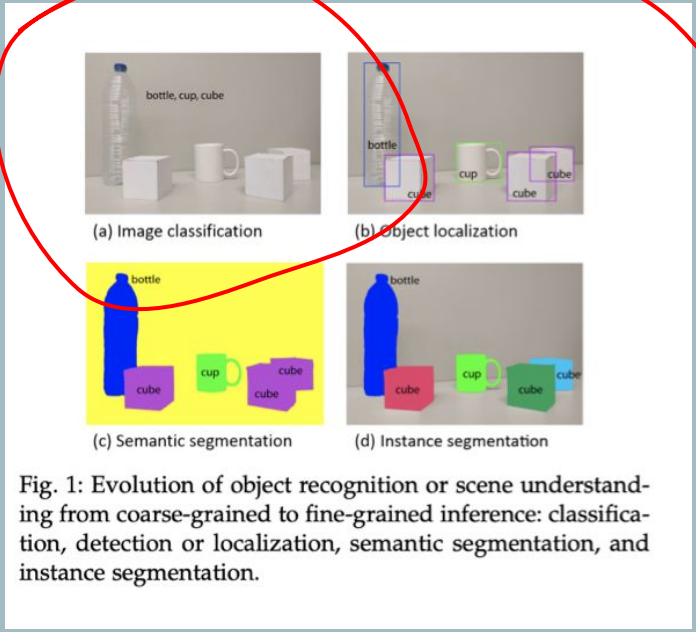
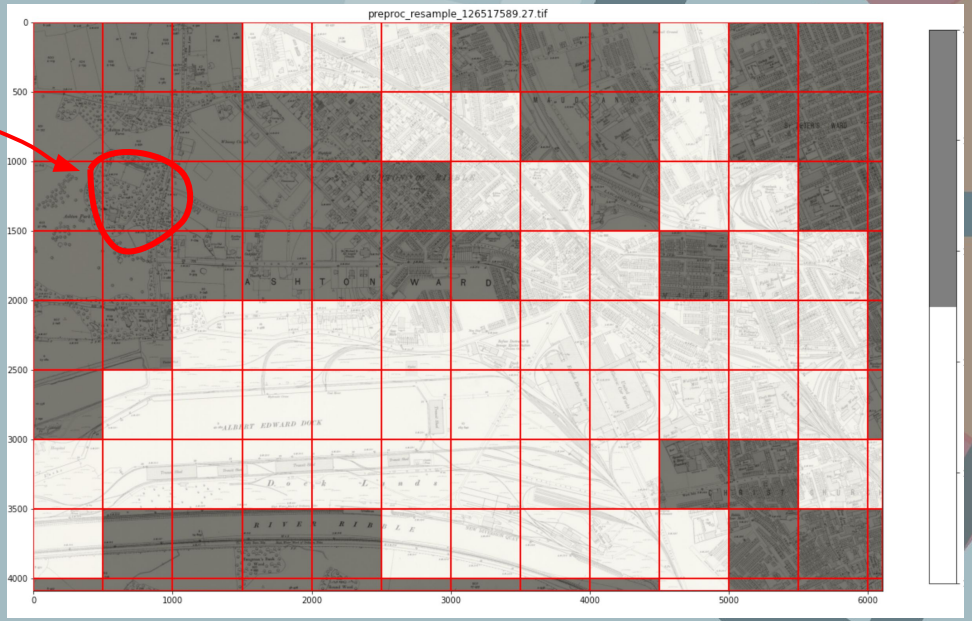


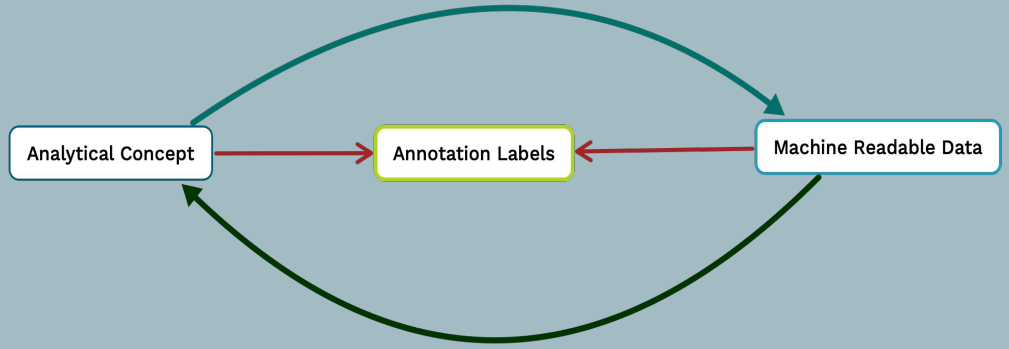
Fig. 1: Evolution of object recognition or scene understanding from coarse-grained to fine-grained inference: classification, detection or localization, semantic segmentation, and instance segmentation.

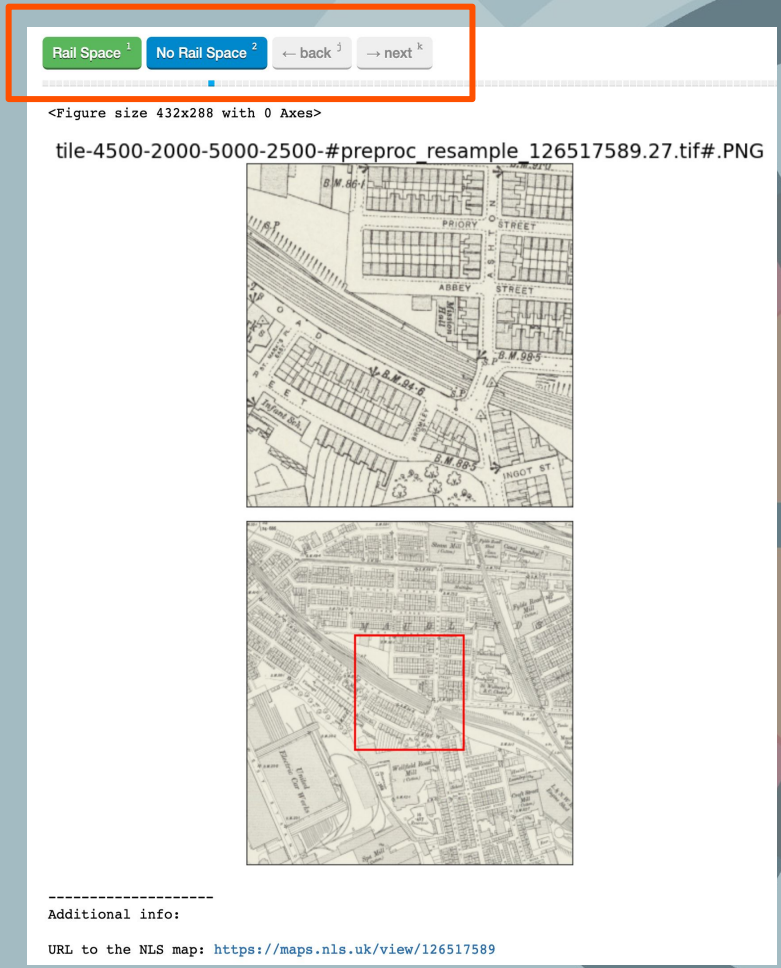
https://arxiv.org/pdf/1704.06857.pdf



Map patches annotated as training data

Annotating patches: What is a good label?





Beyond the Tracks:

Connecting People, Places and Stations to Re-assess the Impact of Rail in Victorian Britain

Kaspar Beelen, Jon Lawrence, Katie McDonough, Joshua Rhodes, Daniel Wilson

Living with Machines

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What was it like to live *with* railways?

Railspace as the total footprint of rail infrastructure

- Railspace label inferred on ~15K late nineteenth-century 6” OS maps (NLS)
- ~30.5 million 100x100m patches
- ~62k expert-annotated patch dataset now available on Zenodo/Hugging Face

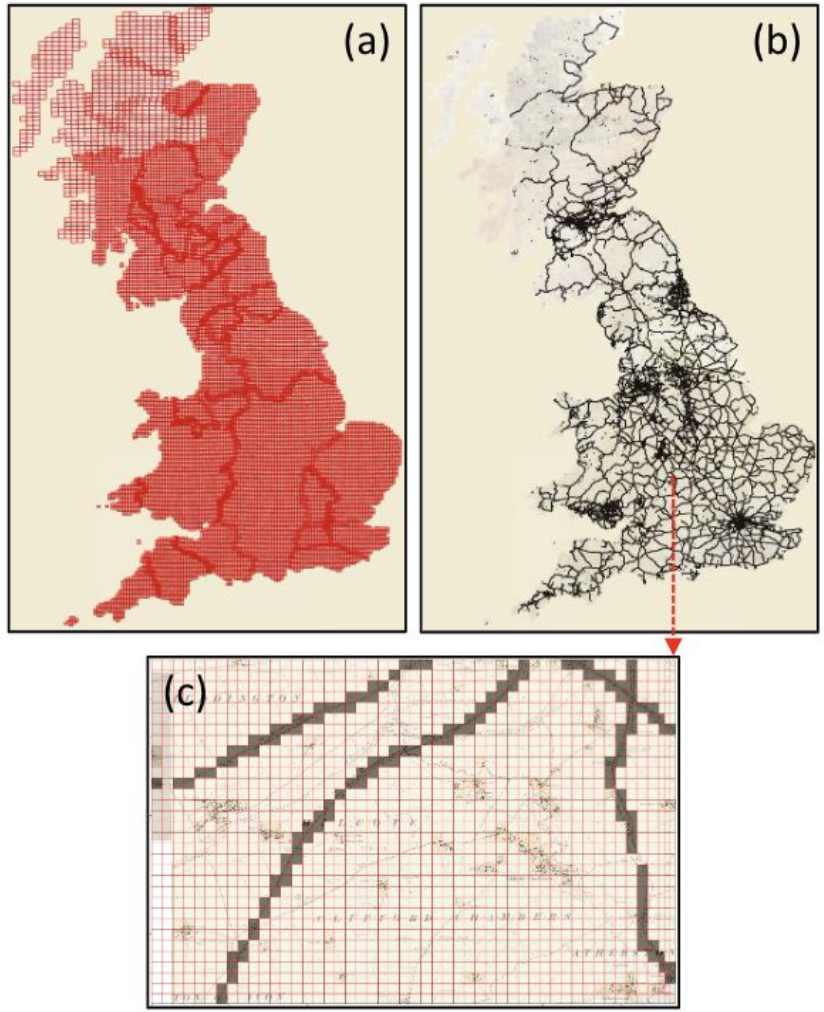
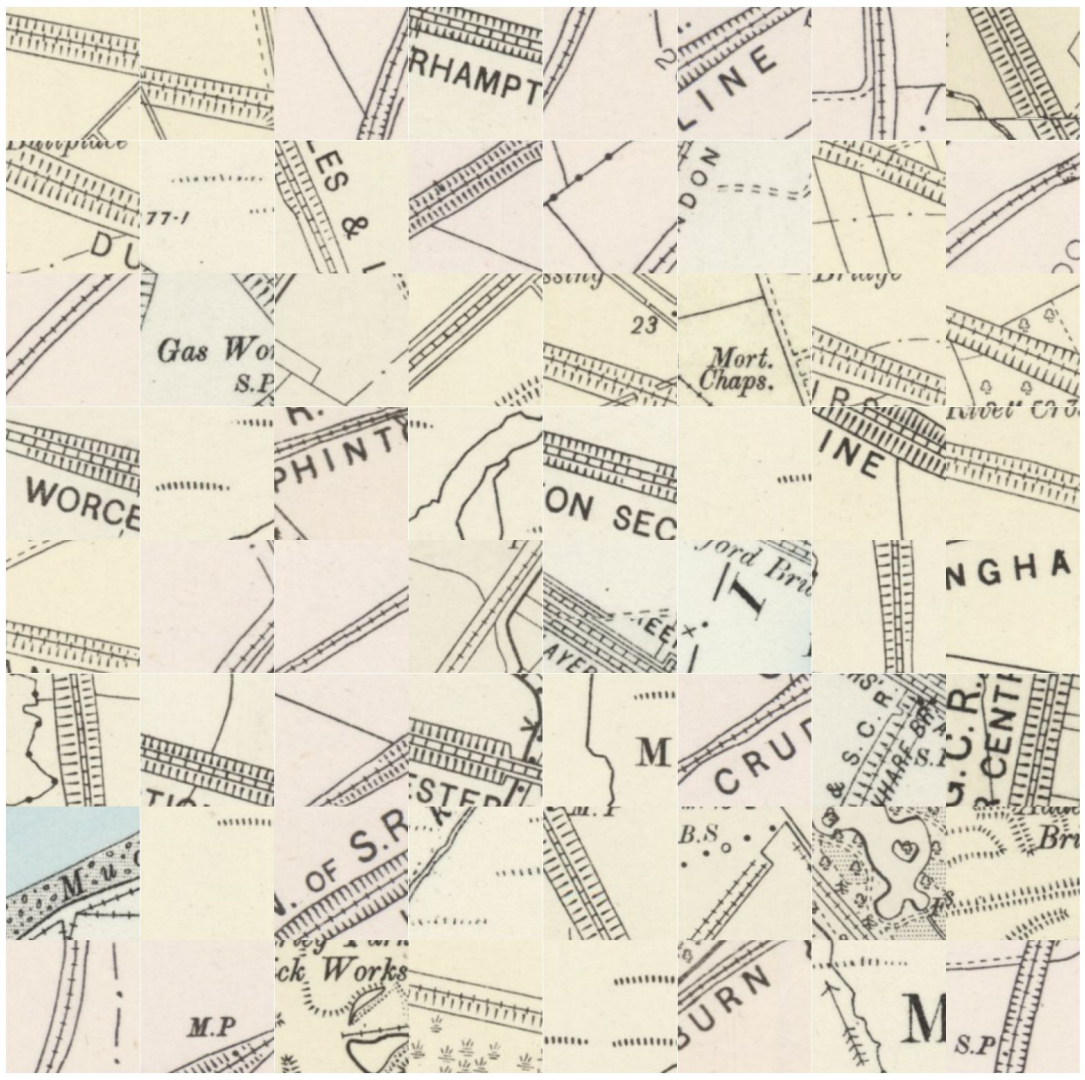


Image credit: Kasra Hosseini

Railspace (rural)



Railspace (urban)

Buildings


MAWSON
LAKE ROAD
203·7
29·6
L.B
Pavilion
STREET
LAR ST.
UNION STREET
WOOTTON
GLADSTONE

Who benefited from the arrival of rail?

What we know: residential (class) segregation increased in a number of cities

What we don't know:

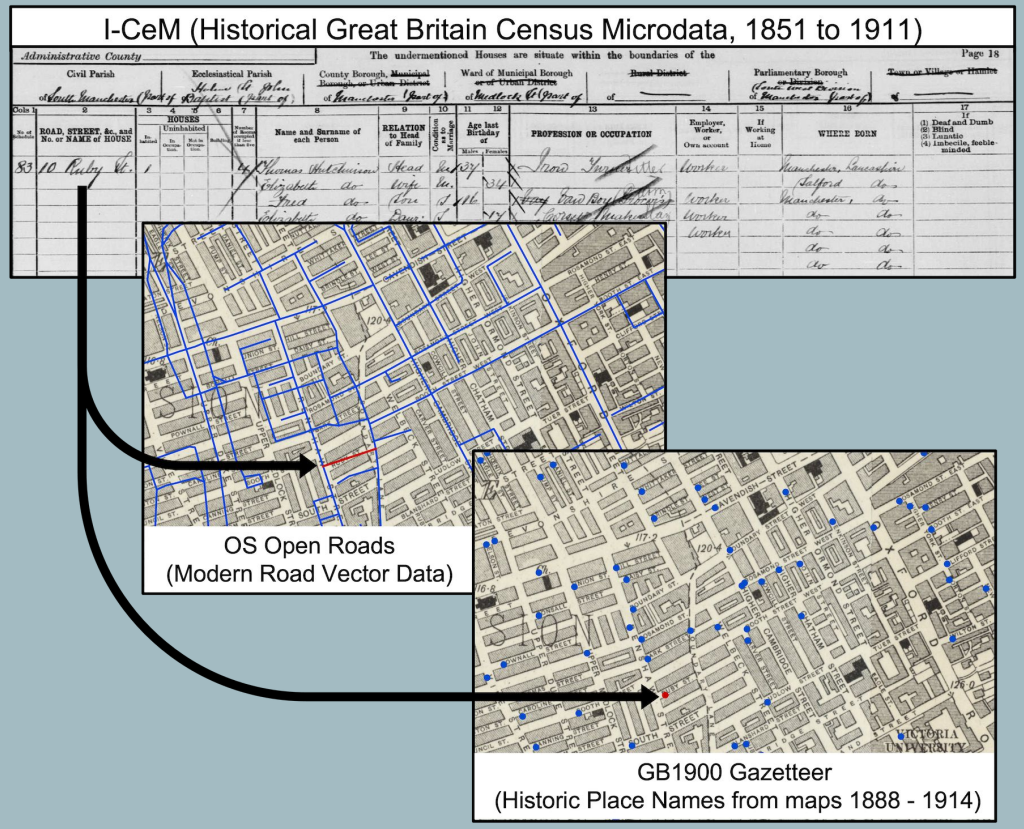
What happened at the national scale?

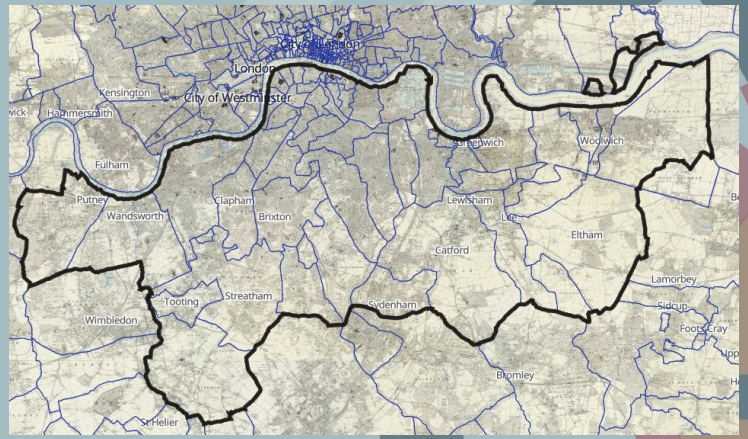
Does the density of rail infrastructure matter?

To ask this question, we **combine three datasets for the first time**:

1. Census (geolocated residential streets)
2. Railway stations
3. Railspace patches

Geo-coded individual historic census data



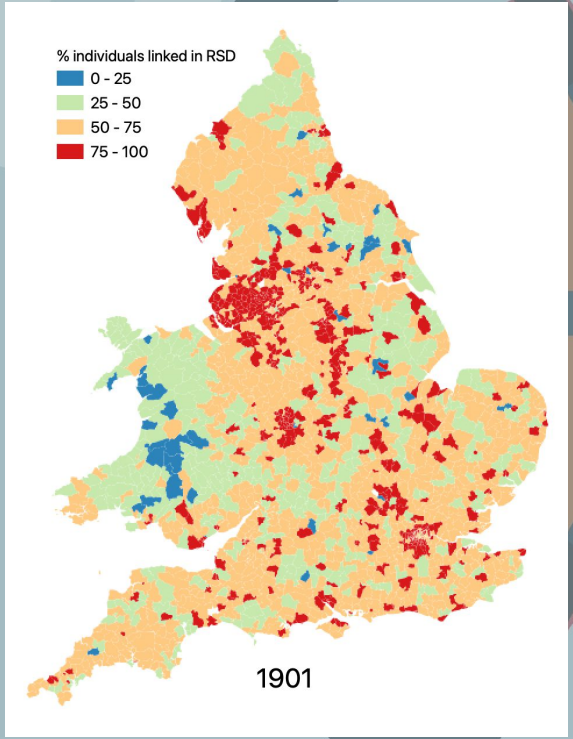


Census street linking results

Strongest for urban areas, weakest in Wales and some rural parishes

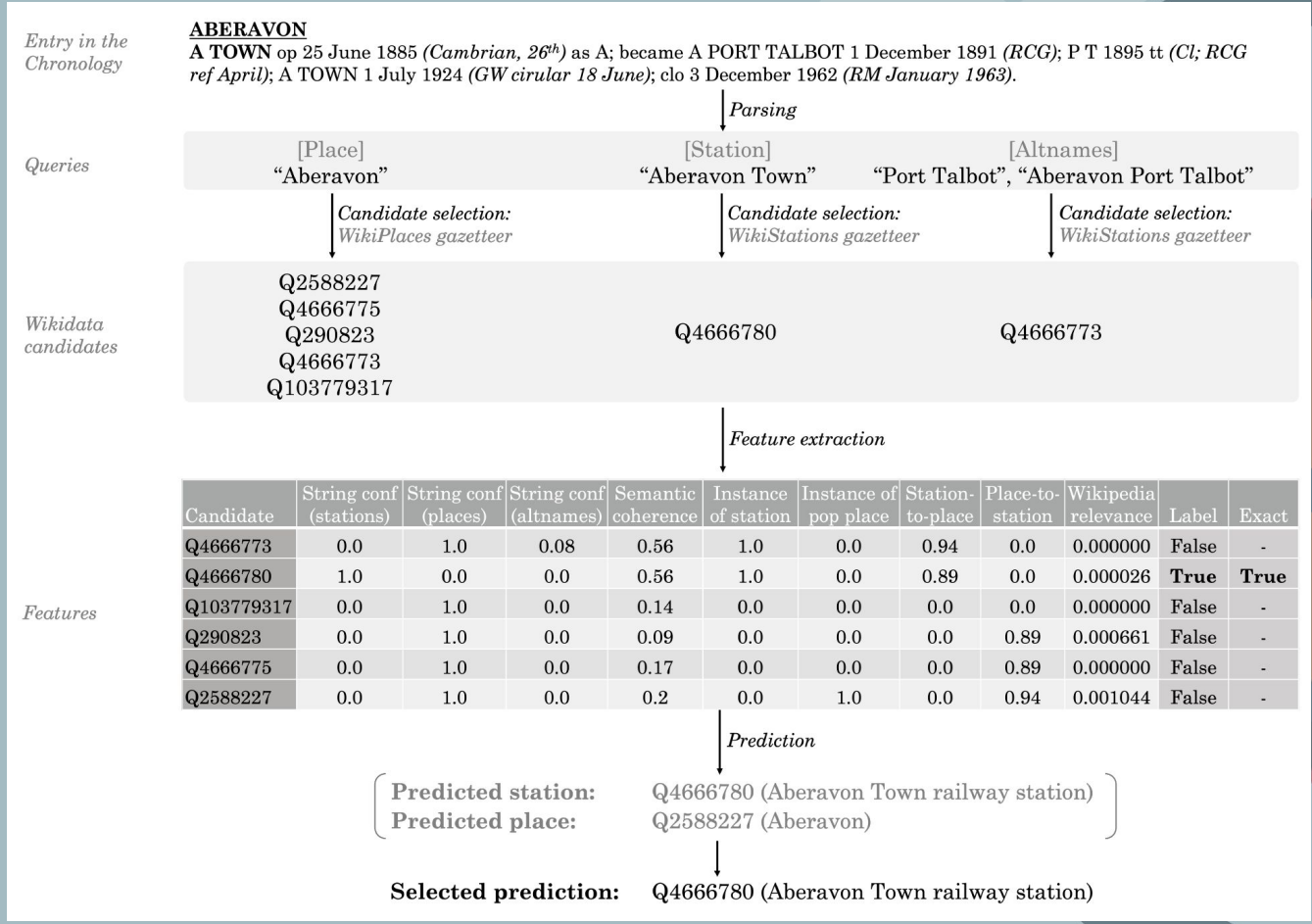
Target Geometry Dataset	Individuals linked (n)	Individuals linked (%)
GB1900 Only	4,795,403	14.8
OS Open Roads Only	6,148,360	18.9
OS Open Roads and GB1900	12,129,467	37.3
Not Linked	9,420,088	29.0

71%



StopsGB

- Identified and parsed 12,676 railway stations (from 420p Word document)
- Fuzzy string matching (*DeezyMatch*) to select Wikidata candidates
- Resolution step to predict best candidates for station and nearest non-station place
- Dataset structured to capture details of opening, closing, company, etc.



Candidate	String conf (stations)	String conf (places)	String conf (altnames)	Semantic coherence	Instance of station	Instance of pop place	Station-to-place	Place-to-station	Wikipedia relevance	Label	Exact
Q4666773	0.0	1.0	0.08	0.56	1.0	0.0	0.94	0.0	0.000000	False	-
Q4666780	1.0	0.0	0.0	0.56	1.0	0.0	0.89	0.0	0.000026	**True**	**True**
Q103779317	0.0	1.0	0.0	0.14	0.0	0.0	0.0	0.0	0.000000	False	-
Q290823	0.0	1.0	0.0	0.09	0.0	0.0	0.0	0.89	0.000661	False	-
Q4666775	0.0	1.0	0.0	0.17	0.0	0.0	0.0	0.89	0.000000	False	-
Q2588227	0.0	1.0	0.0	0.2	0.0	1.0	0.0	0.94	0.001044	False	-

Image credit: Mariona Coll-Ardanuy

Convergence: Three Open Historical Datasets

People by Street [Census +OS Streets/GB1900]

- 32 million people in England and Wales (1901 only) → **23 million** people
- 806k OS Streets (post slicing) 2.5 million GB1900 labels → **222k** streets (unsliced)

Railway infrastructure x2 [Railspace & StopsGB]

- 15k OS 6” maps → 30.5 million predicted patch labels → **487k** railspace patches
- 12k automatically geolocated passenger stations → **5,374** opened <1901 & with confidence score of >=0.5

Streets x railspace

Railspace patches

Streets as a proportion of railspace patches within 200m:
blue is low density
yellow/orange mid density
red high density

Beyond the Tracks: re-connecting people, places and stations in the history of late-Victorian railways

Joshua Rhodes, Jon Lawrence, Kaspar Beelen, Katherine McDonough, Daniel C.S. Wilson

https://read.uolpress.co.uk/projects/living-with-machines

Living with Machines

Computational Histories of the Age of Industry

by Ruth Ahnert, Emma Griffin, Jon Lawrence, The Living with Machines Team

Living With Machines is a data-driven history of the coming of the machine age in Britain in the long nineteenth century. Featuring an innovative open access edition enhanced with interactive maps, datasets and visualisations, digital notebooks, video, audio and images, this book harnesses the combined power of massive digitised historical collections and computational analytical tools to examine the ways in which technology altered the very fabric of human existence on a hitherto unprecedented scale.

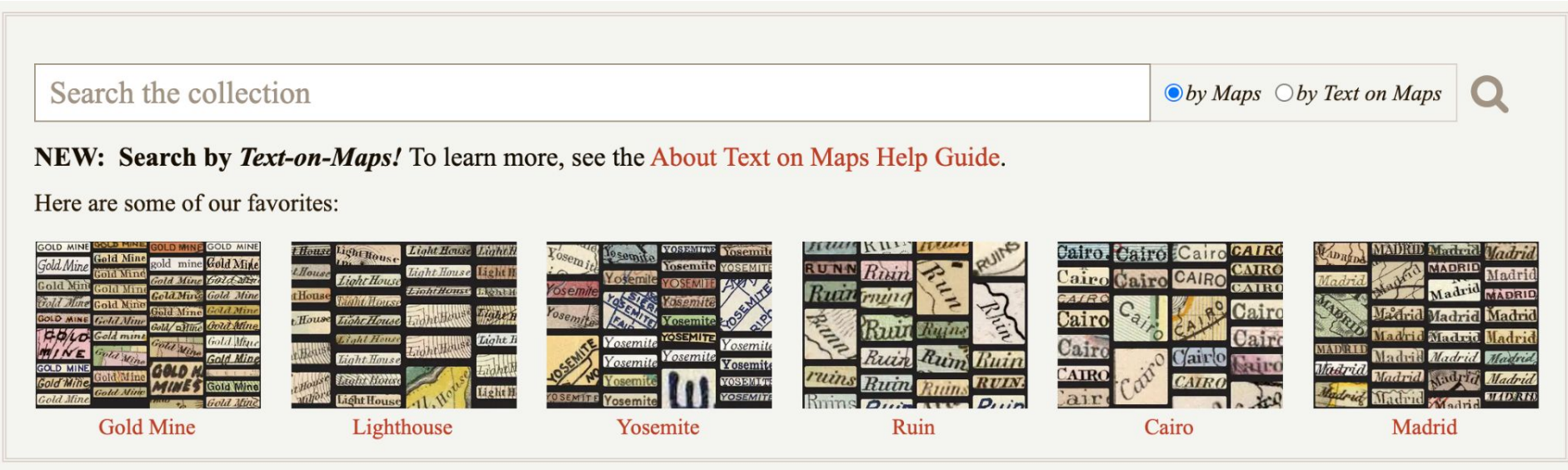
Machines Reading Maps: From patches to text

Can we read *map text* (not "as text")?

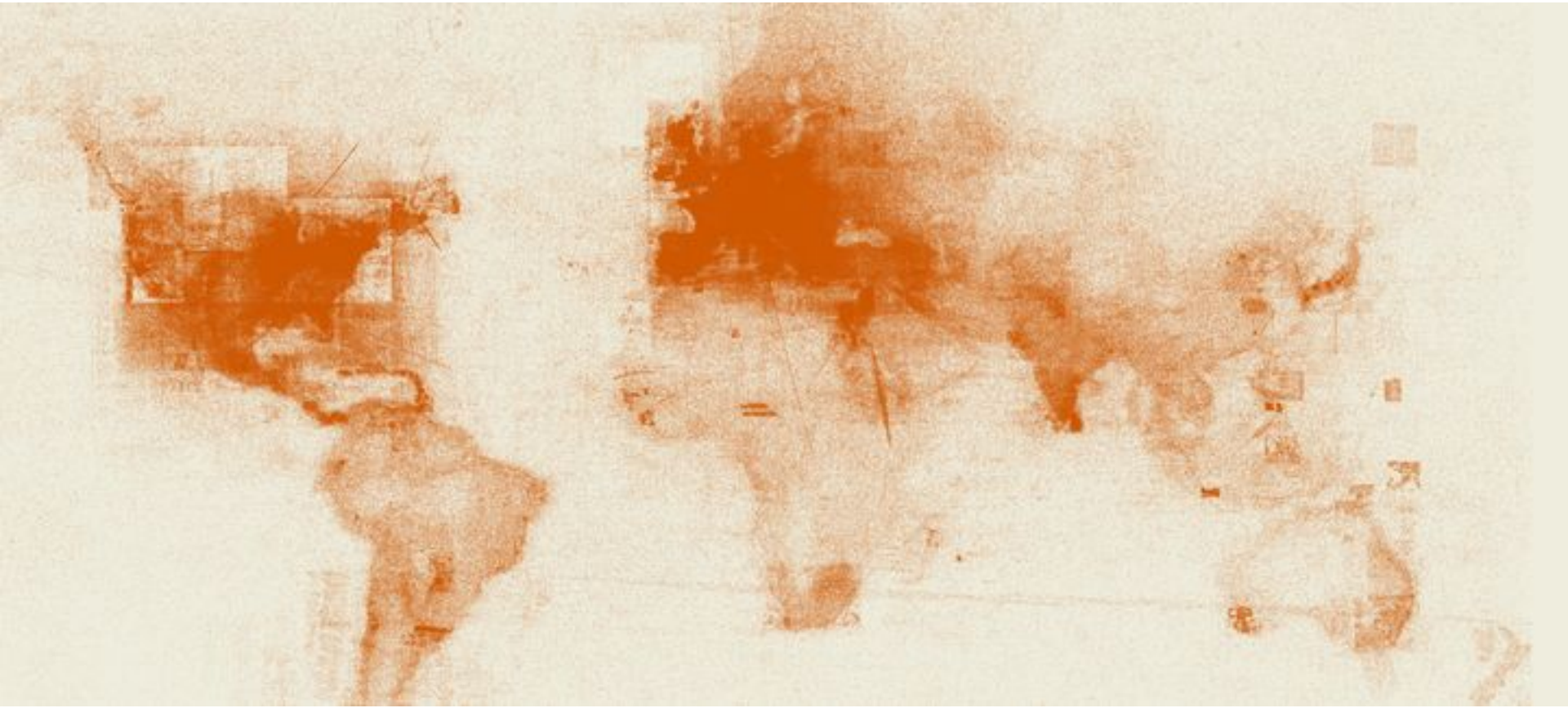
"[These] two systems, maps and language, are essentially incompatible."

Barbara Petchenik, *The nature of maps: Essays toward understanding maps and mapping* (1976)

Search (& validate!) 110 million tokens on 57k maps



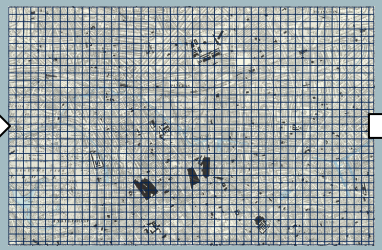
davidrumsey.com



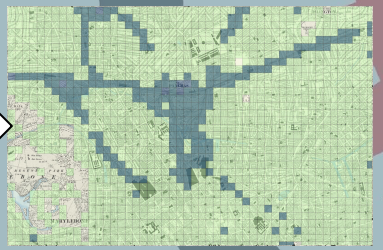
MapReader as an Open-Source Software Library

Classification pipeline

Download	Load	Annotate	Classify
Optional: - Download maps	- Load image files - Load metadata - Patchify	- Annotate patches based on visual features	- Train classifier - Predict labels

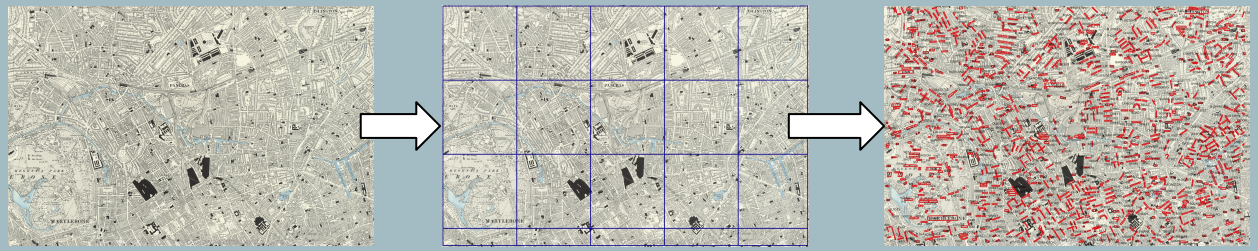


railspace



Text spotting pipeline

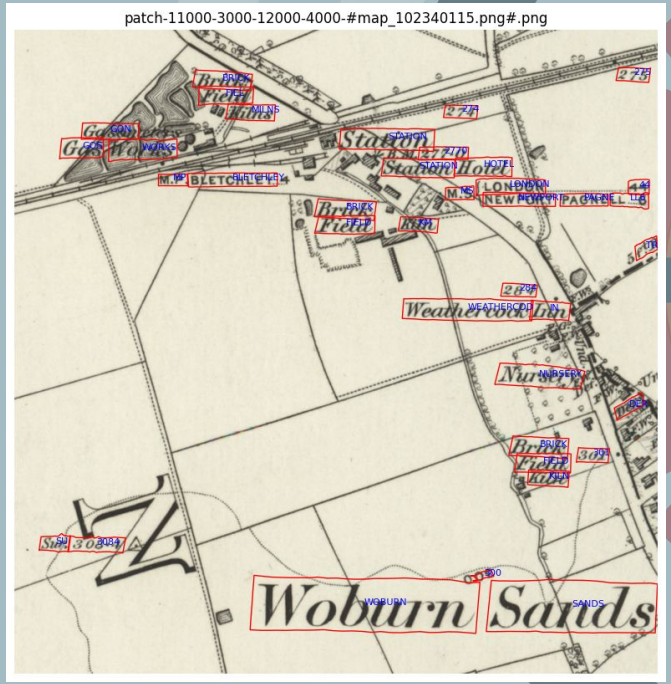
Download	Load	Spot text
Optional: - Download maps	- Load image files - Load metadata - Patchify	- Detect and recognise text



Text spotting frameworks

Three different options in MapReader:

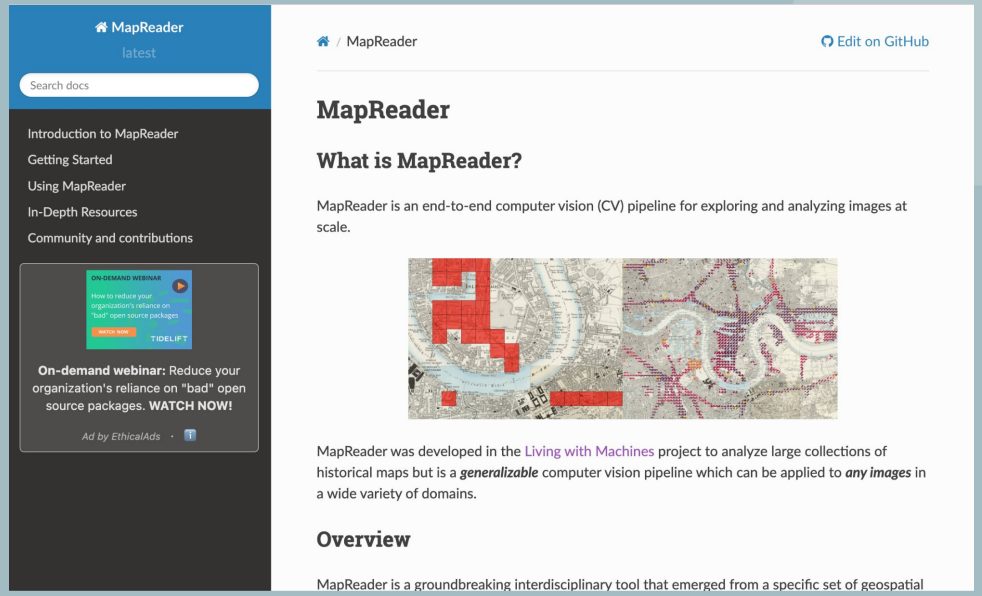
1. **DPText-DETR** (detection only)
2. **DeepSolo** (detection + recognition)
3. **MapTextPipeline** (detection + recognition)



Before we begin...

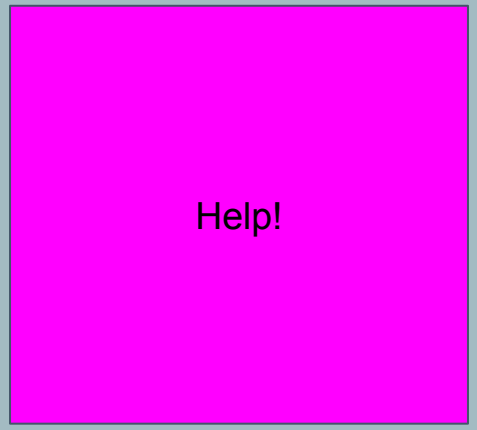
MapReader documentation

https://mapreader.readthedocs.io/en/latest/



Reporting issues/bugs

In the workshop: Sticky notes



Notebook basics

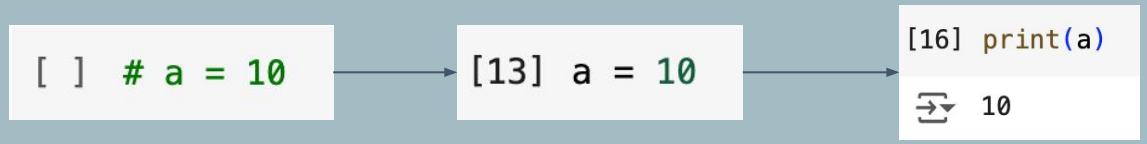
- Two different cell types - Code or Text
- Running cells - Press "▶" or "⌘/Ctrl/Shift+Enter"
- If you are writing new code, "Shift+Tab" activates suggestions/help

WARNING: Google Colab will time out after a while so make sure you save your work!

Python basics

- “#” indicates a comment in Python. Remove the “#” to make the code executable.

- Variables used to assign values to strings.



Pause: Open Notebook

https://github.com/maps-as-data/spatial-humanities-mapreader-workshop

README

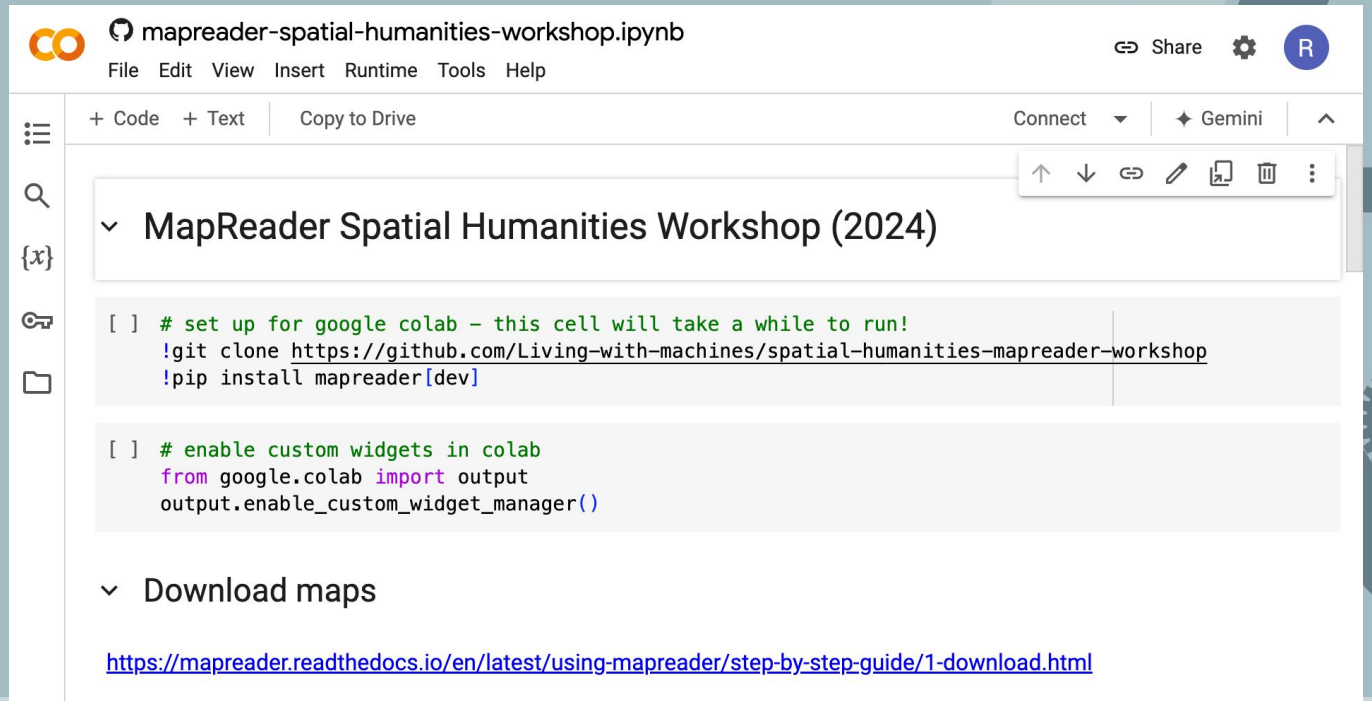
Spatial Humanities Mapreader Workshop 2024

This repo contains a worked example of running MapReader, designed for the Spatial Humanities conference 2024.

Follow the instructions below to set up the notebook on Google Colab (recommended), in Docker or locally.

Table of contents

Open notebook & run first code cell

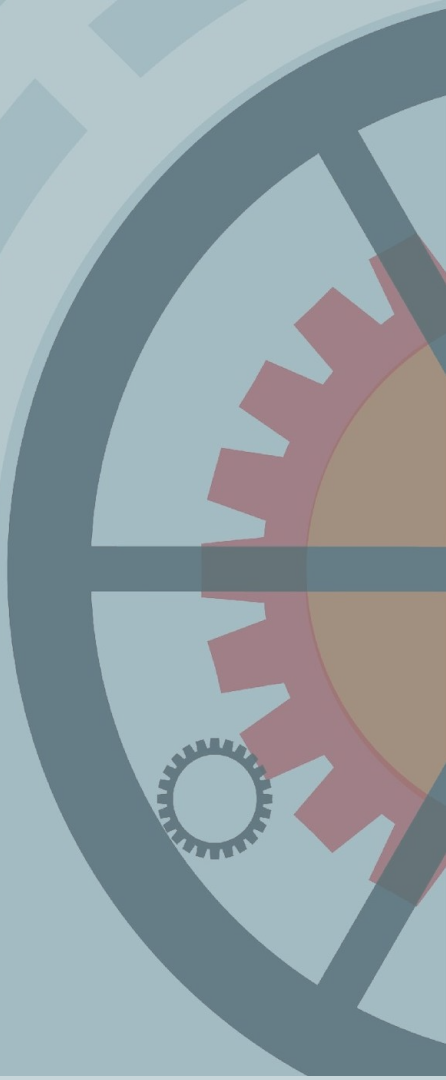


Introduction to Computer Vision & Machine Learning

What is computer vision (CV)?

- AI methods that are used to extract information from visual data (e.g. images or videos)

- Various tasks



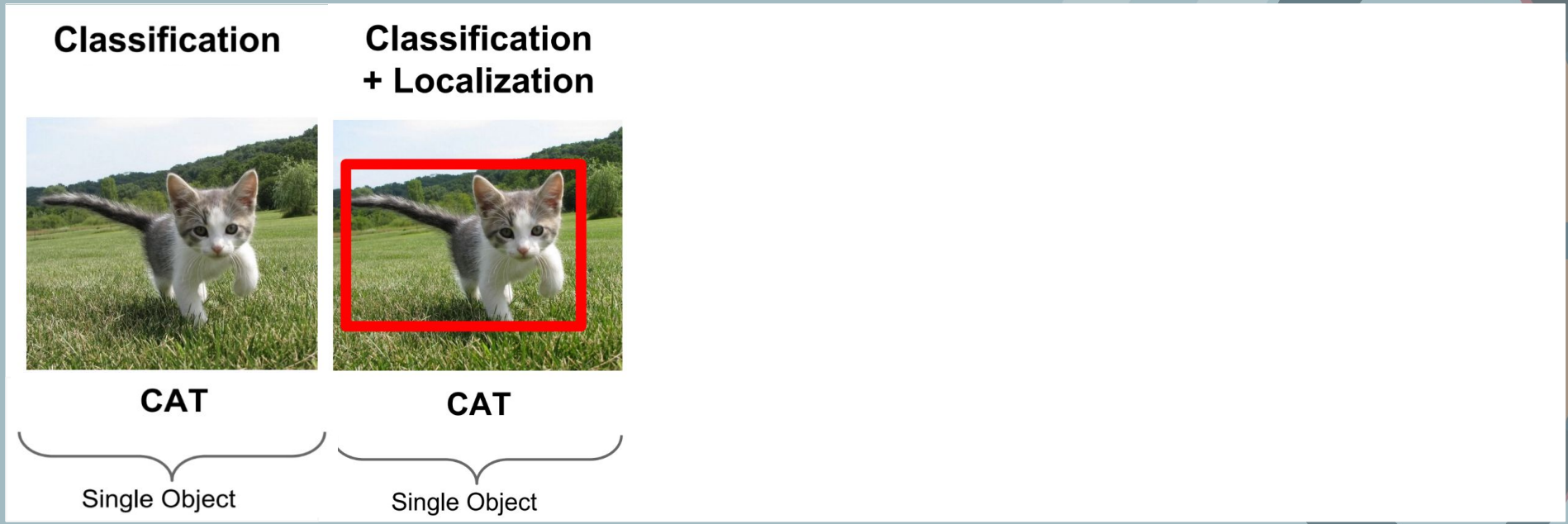
CV tasks

Classification

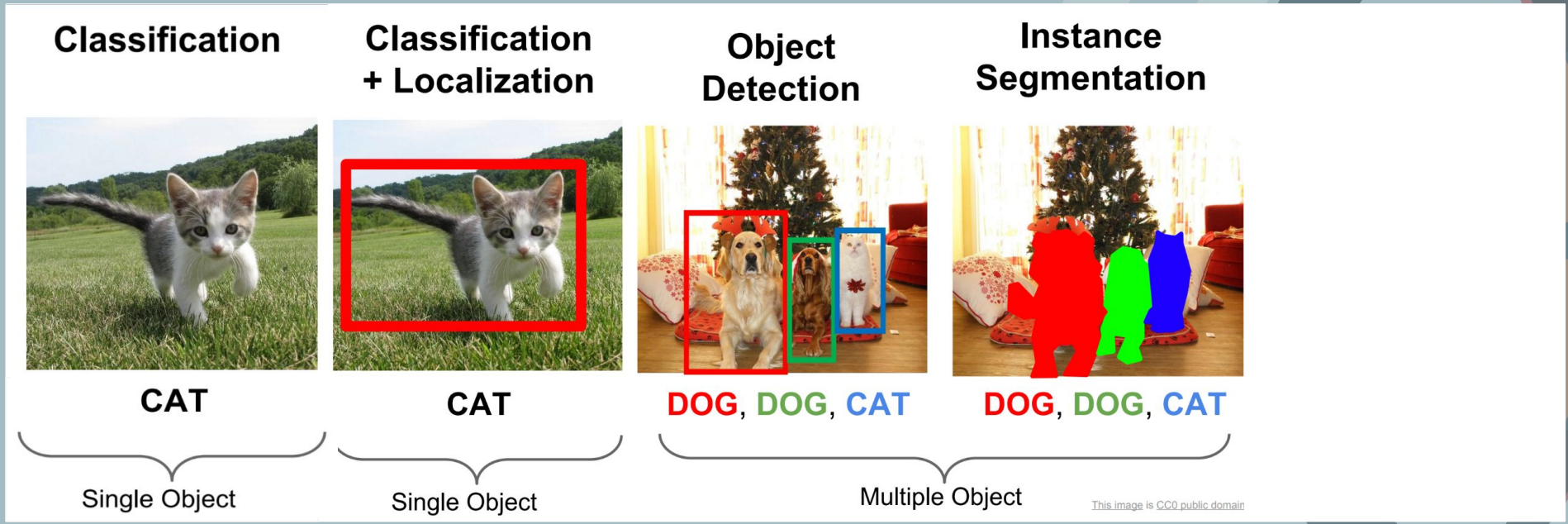
CAT

Single Object

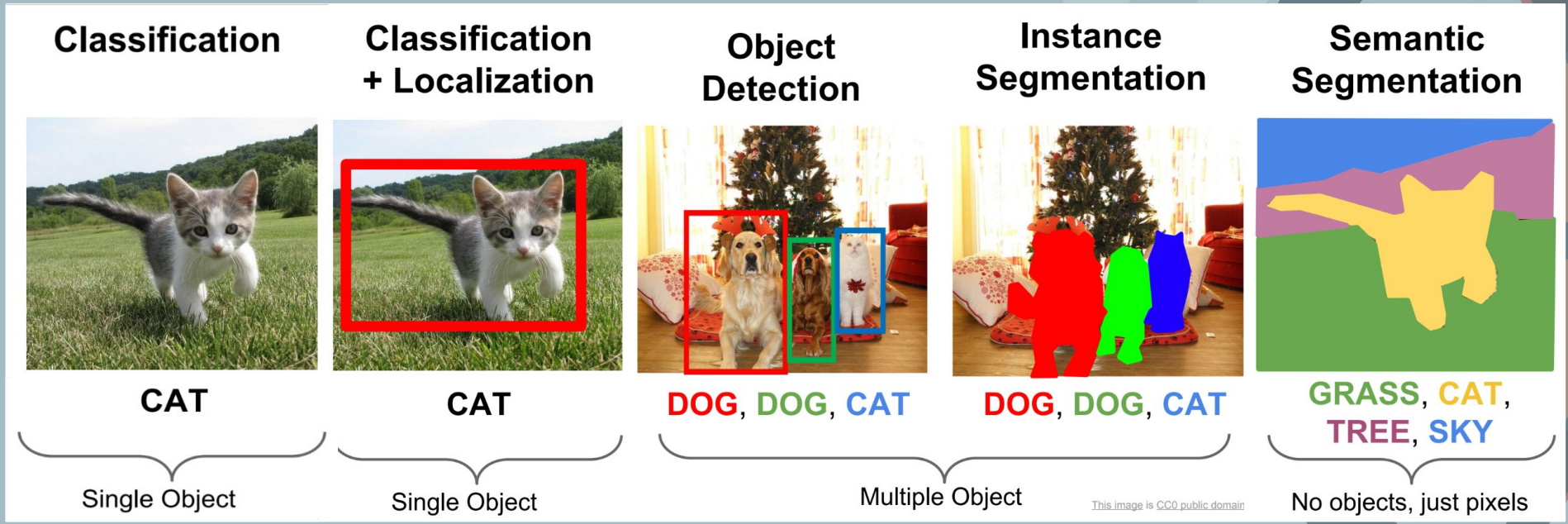
CV tasks


Classification
Classification
+ Localization
CAT
CAT
Single Object
Single Object

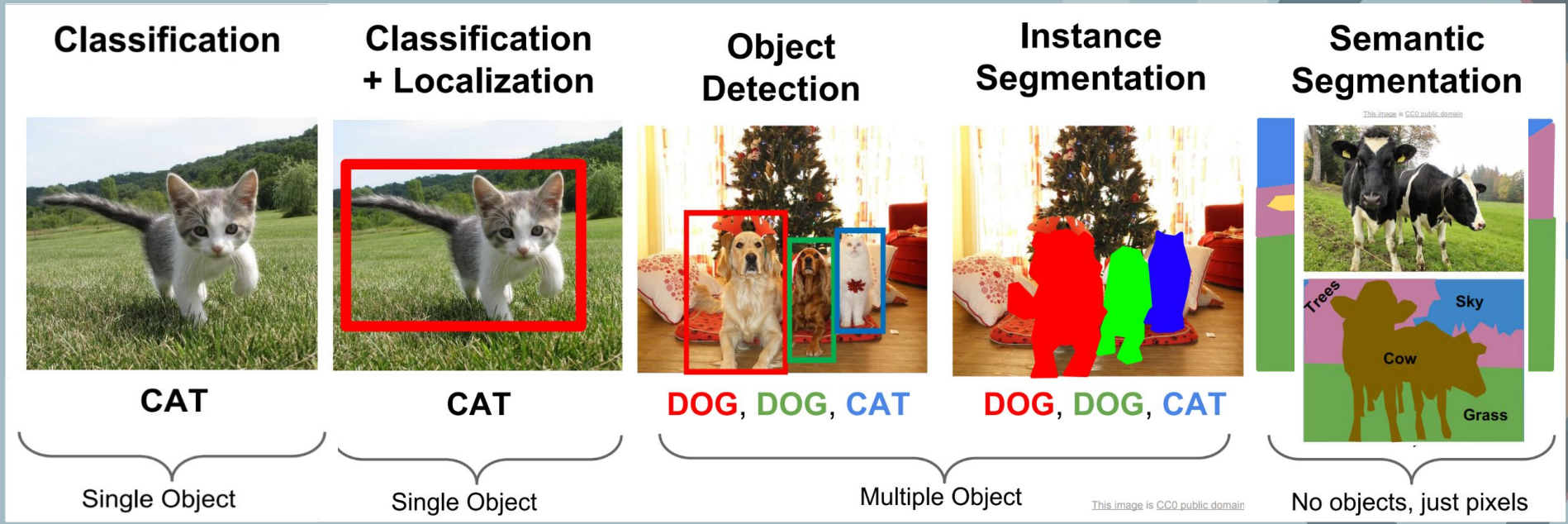
CV tasks


Classification
Classification + Localization
Object Detection
Instance Segmentation
CAT
CAT
DOG, DOG, CAT
DOG, DOG, CAT
Single Object
Single Object
Multiple Object
This image is CC0 public domain

CV tasks


Classification
Classification + Localization
Object Detection
Instance Segmentation
Semantic Segmentation
CAT
CAT
DOG, DOG, CAT
DOG, DOG, CAT
GRASS, CAT, TREE, SKY
Single Object
Single Object
Multiple Object
No objects, just pixels
This image is CC0 public domain

CV tasks


Classification
Classification + Localization
Object Detection
Instance Segmentation
Semantic Segmentation
CAT
CAT
DOG, DOG, CAT
DOG, DOG, CAT
Trees
Sky
Cow
Grass
Single Object
Single Object
Multiple Object
No objects, just pixels

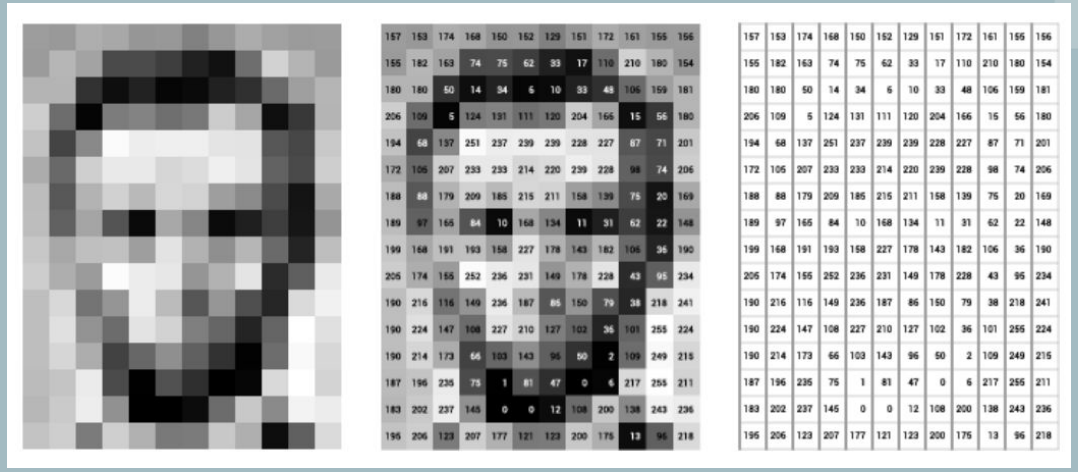
How does a computer ‘see’ an image?

- Images are made up of a grid of pixel values
- Each pixel has a value (or multiple values) to indicate the intensity of the colour in that pixel

254	107
255	165

How does a computer ‘see’ an image?

A grayscale image consists of pixels with values representing the intensity of that pixel.

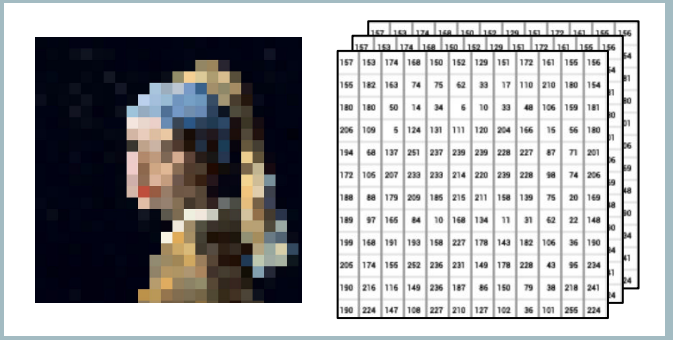


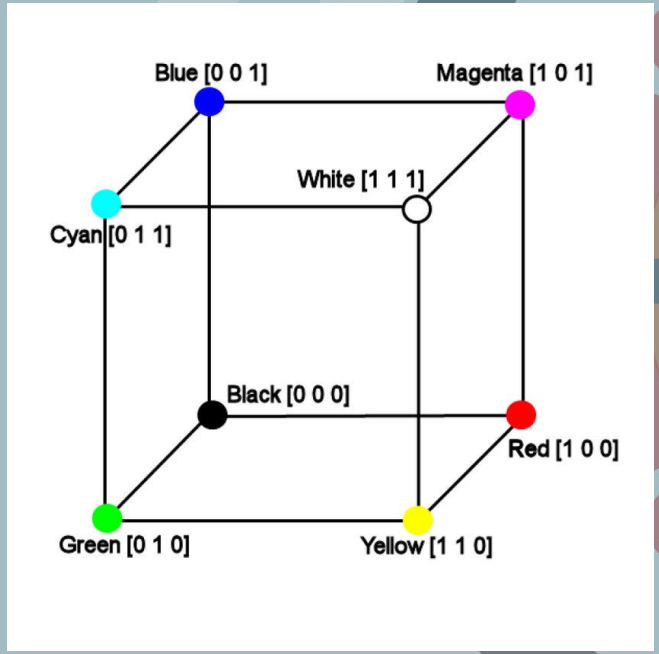
157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

How does a computer ‘see’ an image?

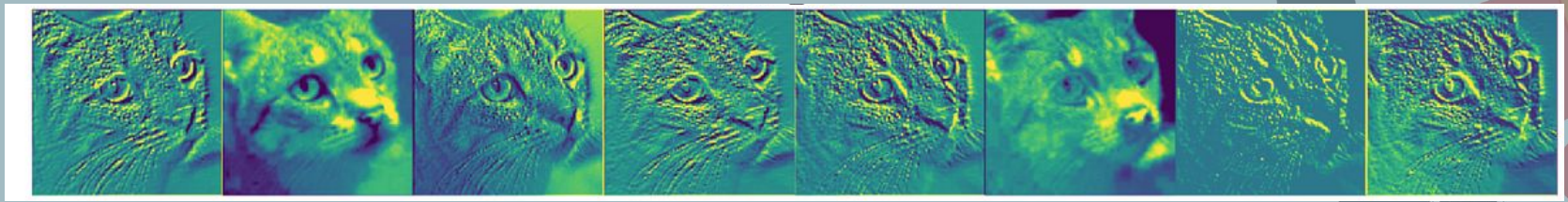
In an RGB image, each pixel has a Red, Green and Blue value/intensity.





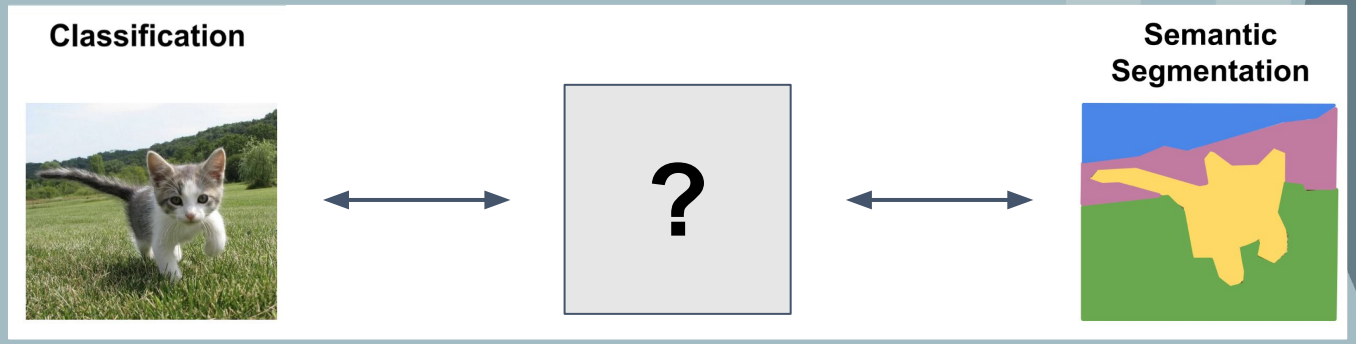
How are images processed in CV?

- Image pixel values used as input
- Computer identifies important features



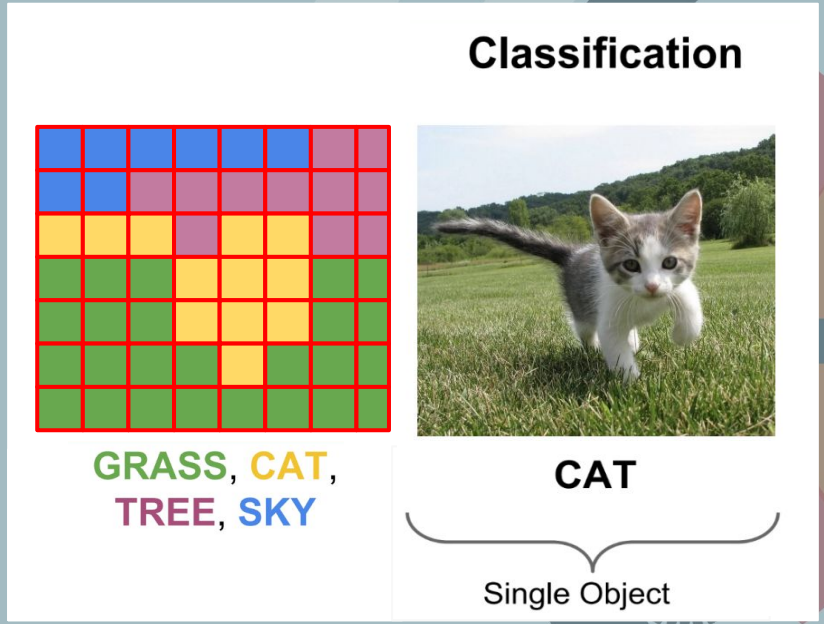
Our method

- Middle ground between image classification and image segmentation



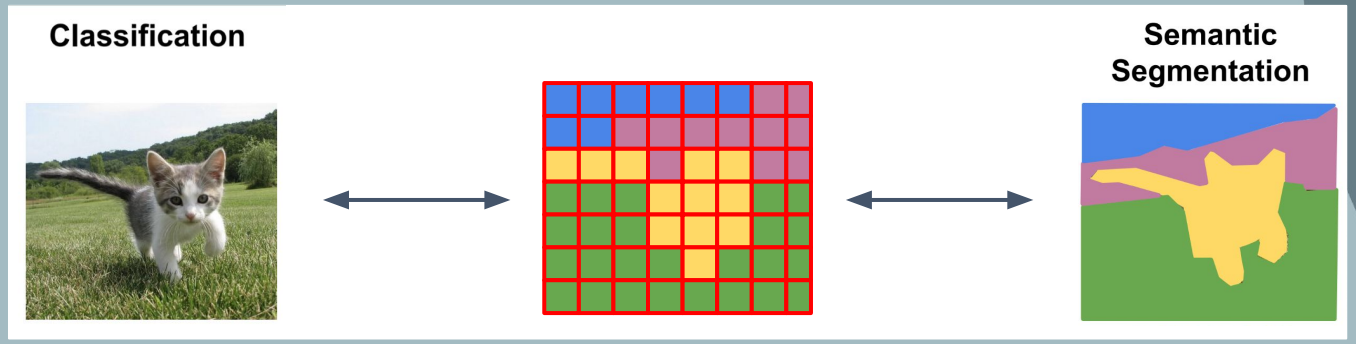
Patch classification

- Extract higher resolution information vs single object classification but not overly specific (pixel)
- More efficient computation
- Capture local information features or patterns



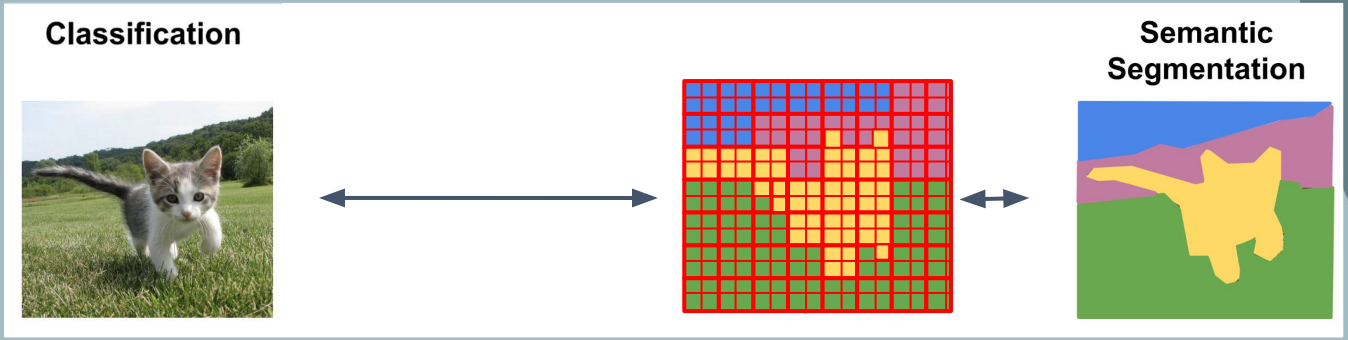
Patch classification

- Sensitive to patch size
- Choosing patches that are representative and informative for a particular task is crucial.



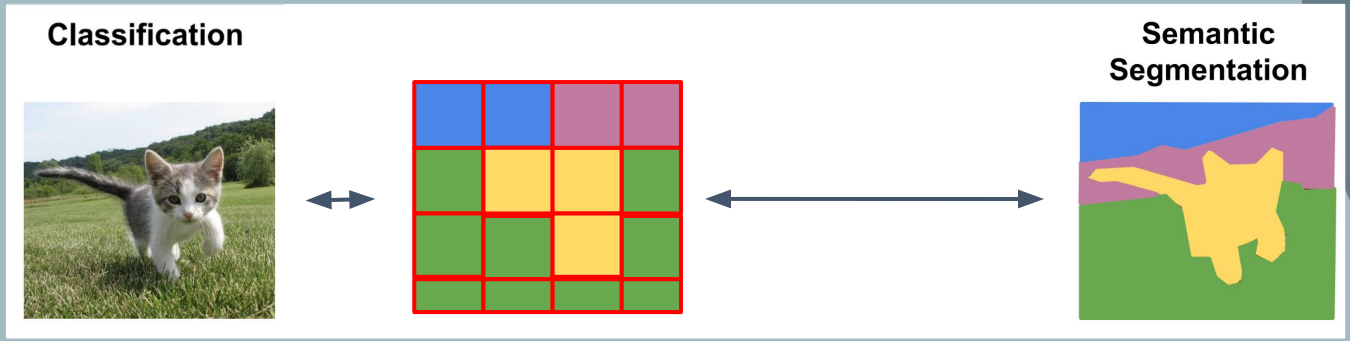
Patch sizes

- Small patch size: losing important visual information and patterns.



Patch sizes

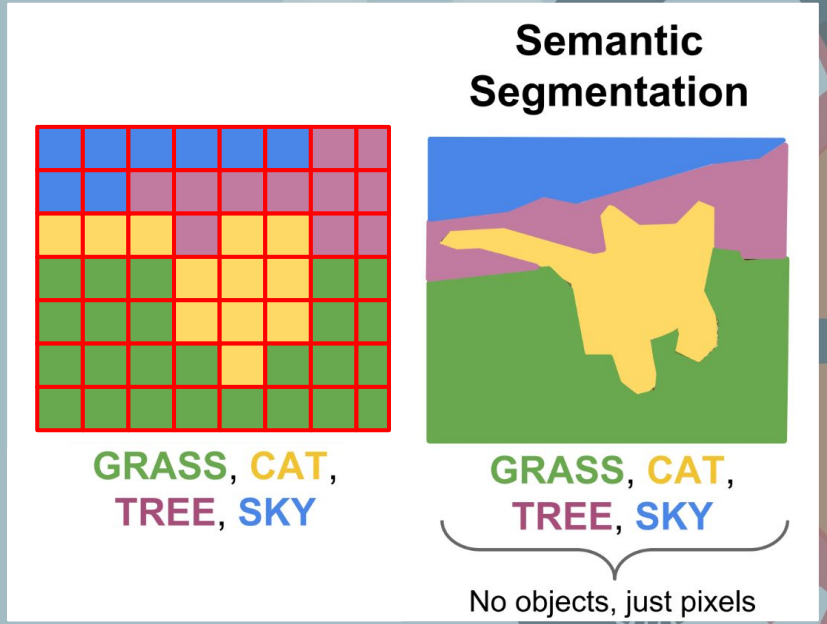
- Small patch size: losing important visual information and patterns.
- Large patch size: low resolution.



Patch classification

Patch classification in MapReader:

- Baseline for more advanced methods
- Simple end-to-end pipeline
- Quick experimentation
- In our use cases (e.g., railspace), patch-level information was sufficient
- Easy to scale up



Check your notebook & run next cells

Walk through of each cell

Pause at “Train your model”

Classify - Fine-tuning models

Choosing starter model

- Models that have been pre-trained on:
  - similar tasks
  - large and diverse datasets

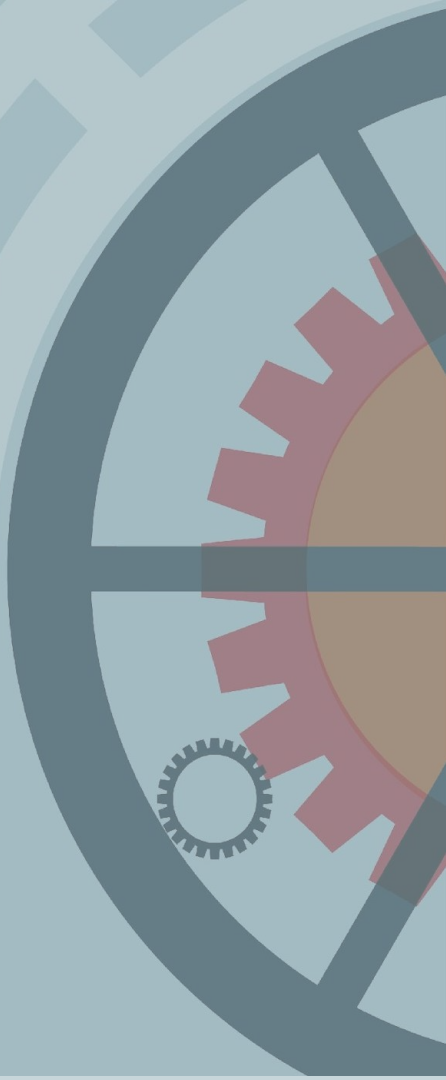
- Easily available:
  - hugging face
  - torchvision.models

Can I reuse a model?

Considerations:

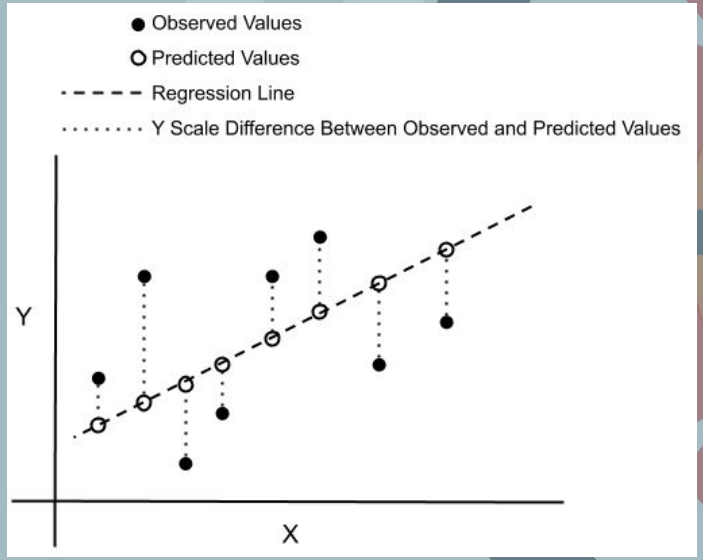
- How similar are the visual representations?
- Patch sizes?

Best answer is to have a go.



Loss function, optimiser and scheduler

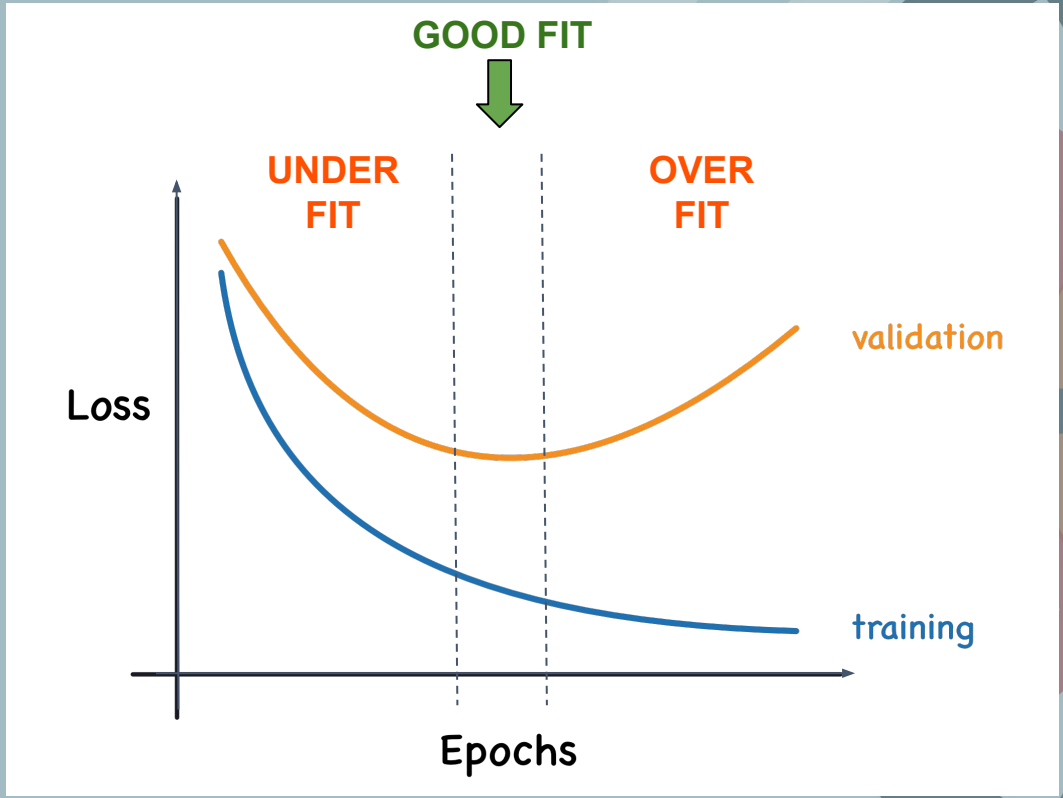
- Loss function calculates error
  - e.g. mean squared error (MSE)
- Optimiser works out how to adjust the neural network to reduce the error
- Scheduler controls how much the neural network changes throughout training



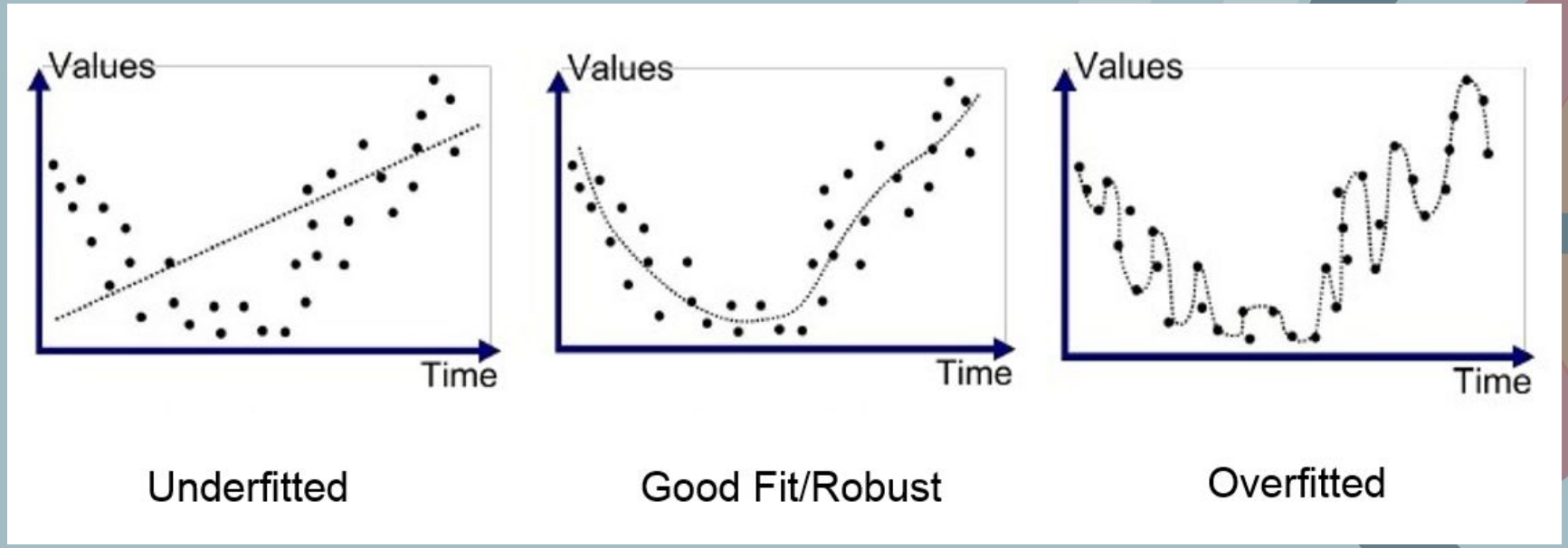
Training

Annotations split into train, validation and test datasets

Goal is to minimise **both** training and validation losses

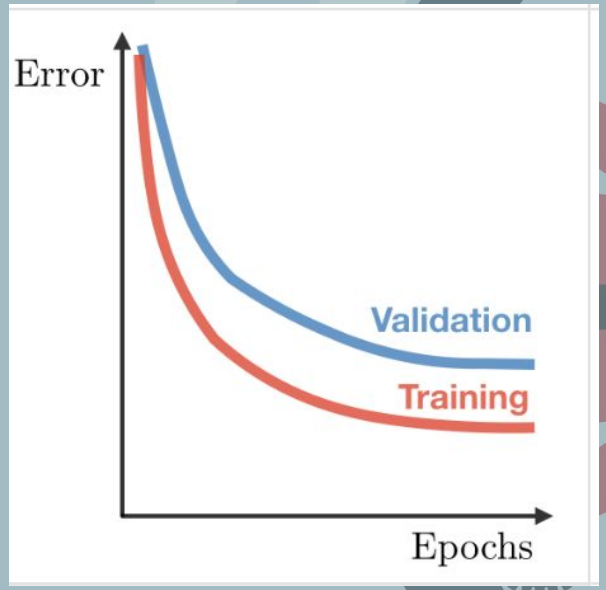


Training


Values
Time
Underfitted
Values
Time
Good Fit/Robust
Values
Time
Overfitted

Metrics

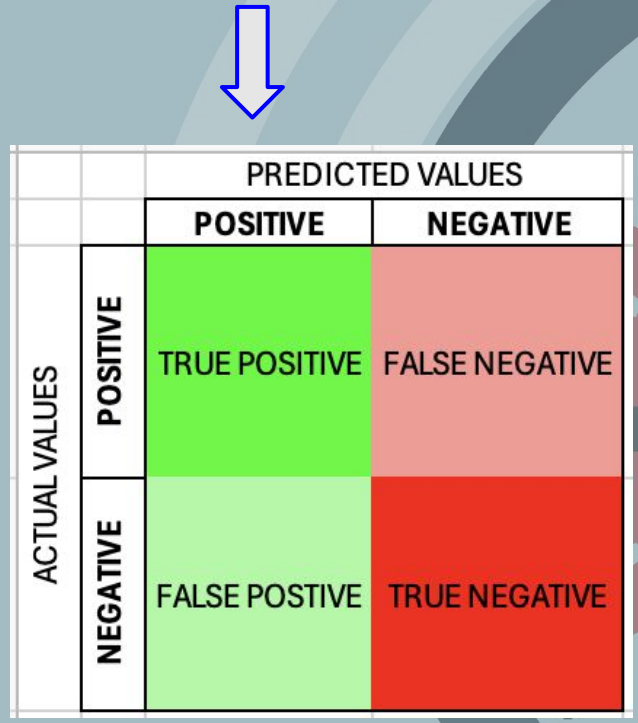
- Loss - **defined by loss function**



Metrics

- Loss - defined by loss function
- Precision - **proportion of positive predictions that are correct**

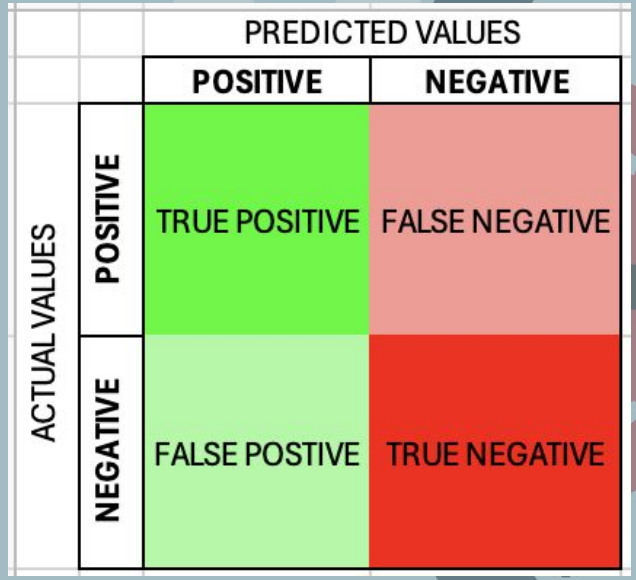
$$\text{Precision} = \frac{TP}{TP + FP}$$



Metrics

- Loss - defined by loss function
- Precision - proportion of positive predictions that are correct
- Recall - **proportion of actual positives correctly identified**

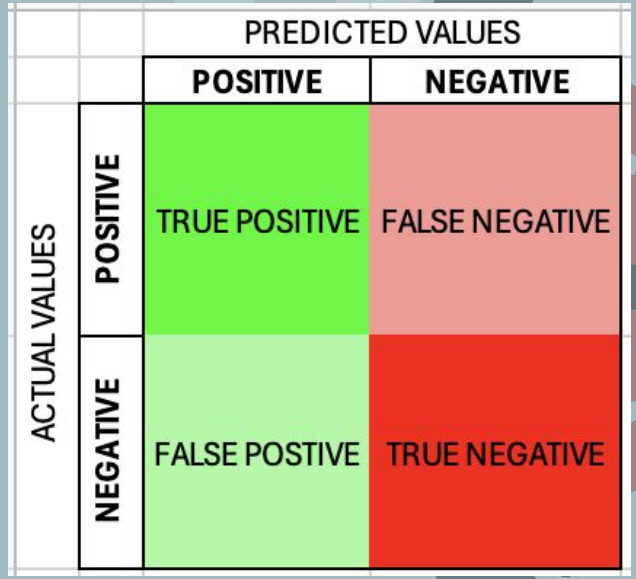
$$\text{Recall} = \frac{TP}{TP + FN}$$



Metrics

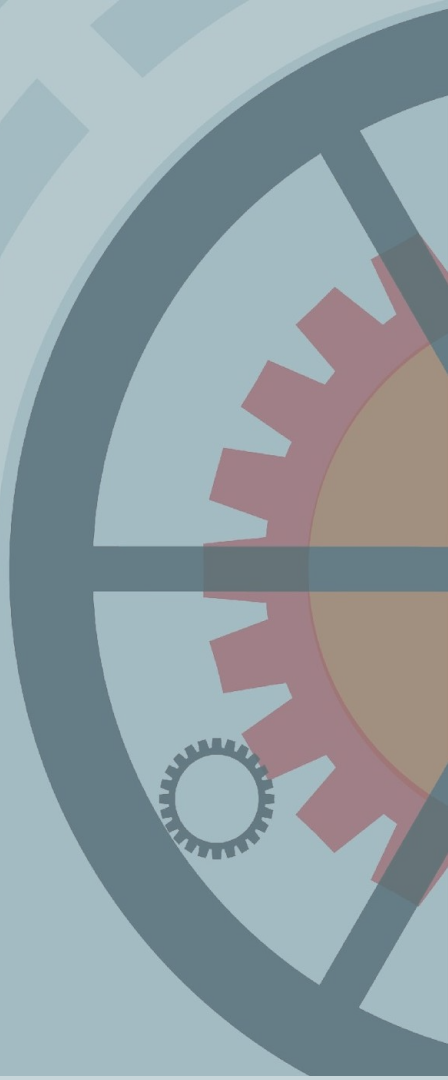
- Loss - defined by loss function
- Precision - proportion of positive predictions that are true
- Recall - proportion of actual positives correctly identified
- F-scores - **combination of precision and recall**

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$



So now what?

Once you have your fine-tuned model, you can start using it to infer (predict) the labels of new patches!

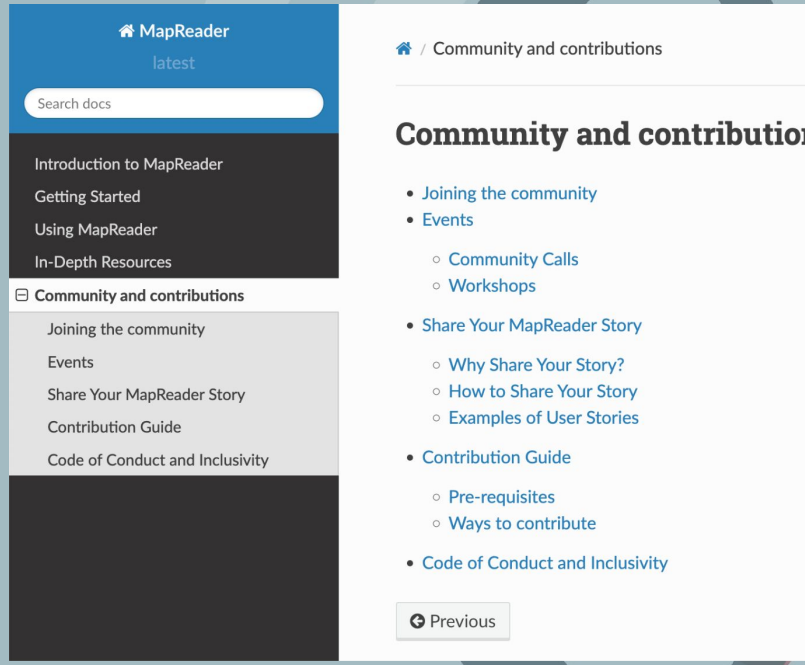


Finish the notebook!

Stay in touch: Community Calls

https://mapreader.readthedocs.io/en/latest/community-and-contributions/index.html

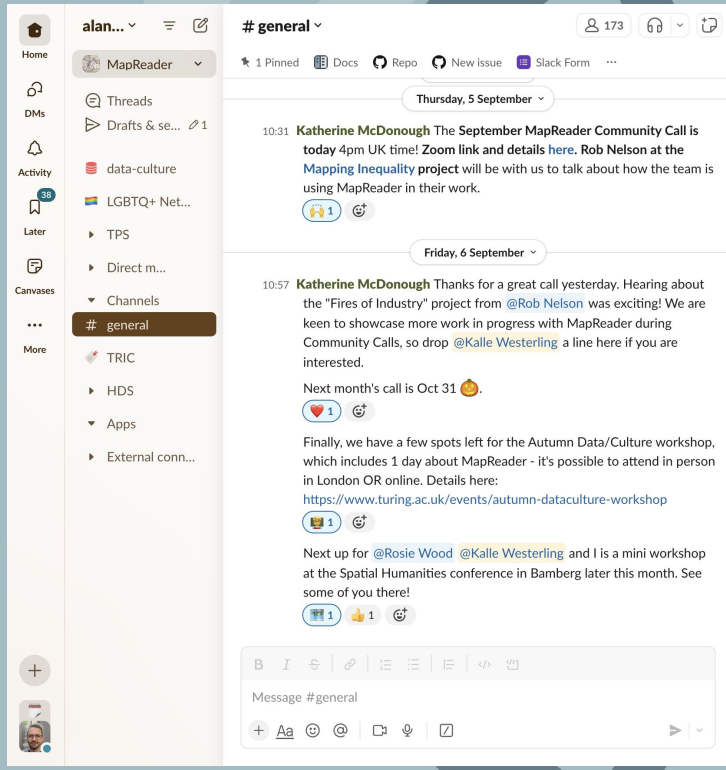
- **Connect with the Team:** Ask questions and get real-time updates from MapReader developers.
- **Learn Best Practices:** Pick up tips and workflows from experts and users alike.
- **Hear Success Stories:** Discover how others are using MapReader in their research.
- **Influence Development:** Share your ideas to help shape future features.
- **Build Community:** Network with fellow researchers and developers.



Stay in touch: Slack

[MapReader slack sign up form]

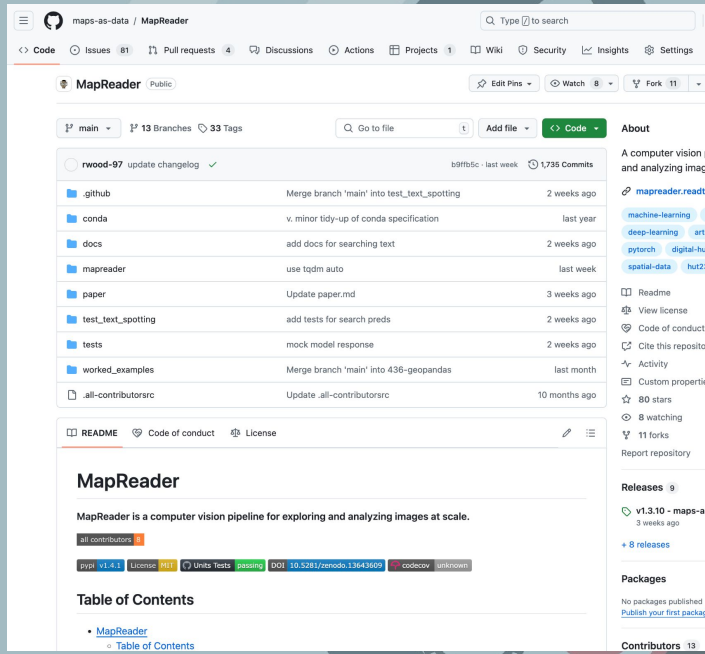
- **Get Help Fast:** Ask questions and get immediate support from the team and community.
- **Stay Informed:** Hear about new releases, features, and events first.
- **Share Ideas:** Discuss, learn, and exchange real-world use cases with others.
- **Shape the Future:** Contribute feedback, suggestions, or code to improve MapReader.
- **Connect with Experts:** Network with researchers and developers using MapReader.



Stay in touch: Github

https://github.com/maps-as-data/MapReader

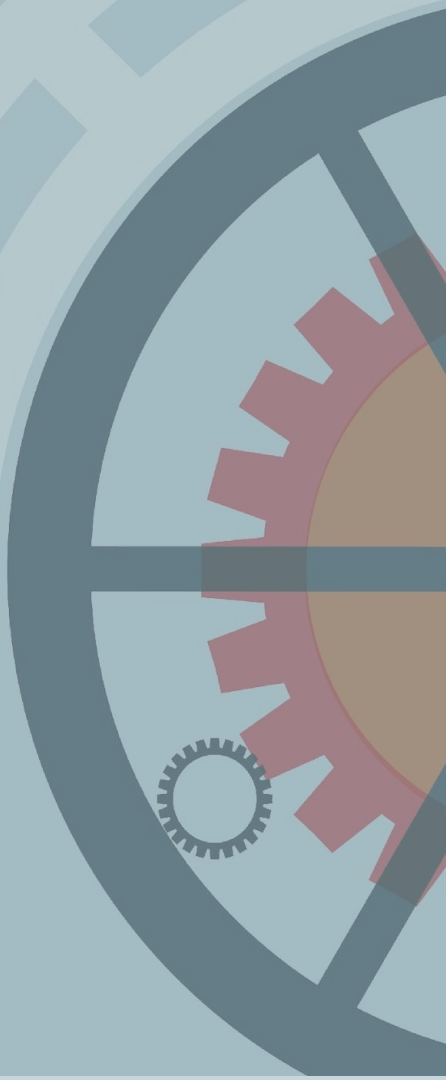
- **Share Feedback:** Report bugs, suggest features, or give general input.
- **Improve Docs:** Help make guides and tutorials clearer by raising issues.
- **Track Progress:** Follow development updates in GitHub discussions.
- **Contribute Code:** Submit pull requests to add features or fix bugs. (For those who are more code-inclined!)
- **Collaborate:** Join discussions to shape the future of MapReader.



Feedback Form

https://forms.office.com/e/BcAX53CuxB

& please sign the consent form :)



Final Discussion

With your table, discuss:

- **What was motivating/not motivating today?**
- **What was too hard?**

What was too easy?

What might you use from what we have learned today?

Acknowledgements

Living with Machines MapReader Team: Kasra, Daniel, Rosie, Andy, Kalle, Kaspar - and Ruth

Beyond the Tracks authors: Josh, Kaspar, Daniel, Katie, Jon, Griff

Data/Culture Team: Rosie, Ed, Tim, Nilo, Kalle, Laura, Issy, André, Fede, Dave, Cyara, Daniel - and Ruth and Pieter