



Week 6

Visual AI in Practice

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11.S951

Senseable City: Data and Analytics

Mar. 11

Review

- Treepedia



- AI Perception Map



- Infinite Corridor



- Smart Curbs



- [In]Distinct Cities



Outline

- City
 - Helsingborg, Trieste, Paris, & Stockholm
- Data
 - Passive Image Collection - GSV
 - Active Image collection – Mobile Cameras
- Method
 - Machine Learning & CNN
 - Hands-on Demonstration
 - Image Classification
 - Image Object Detection
 - Image Segmentation

City

Helsingborg, Trieste, Paris, Stockholm

Study Sites



Study Sites



Helsingborg, Sweden

98,693 panorama



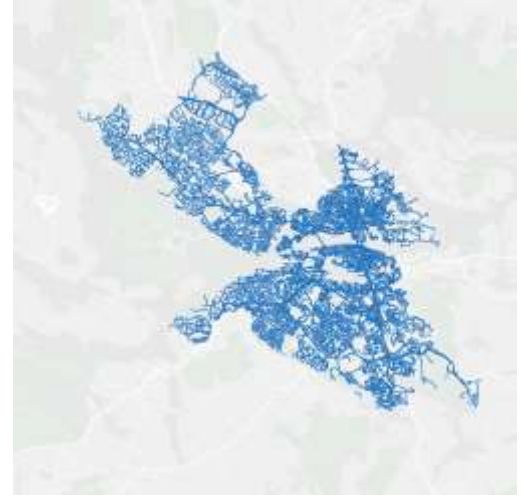
Trieste, Italy

21,201 panorama



Paris, France

354,400 panorama



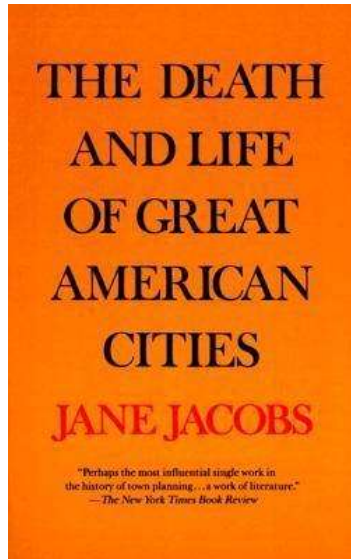
Stockholm, Sweden

252,024 panorama

City – Helsingborg

SAFETY, TIPPING POINT

Motivation



Defensible Space Oscar Newman
CRIME PREVENTION THROUGH URBAN DESIGN

AN ALTERNATIVE TO THE
FORTRESS-APARTMENT

AN INVESTIGATION OF
HOW ARCHITECTURE CAN
AFFECT THE ATTITUDES AND
ACTIONS OF TENANTS

A PROPOSAL TO DESIGN
CRIME-FREE URBAN HOUSING



The International
**Crime Prevention Through
Environmental Design**
Association

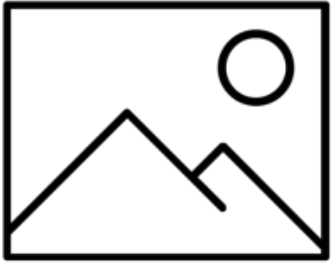
Crime and built environment

Hypothesis

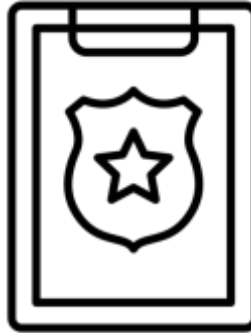
Tipping Point Theory

Neighborhoods in bad physical condition will get progressively worse, whereas nicer areas will get better?

Data



Street view image

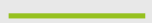


Police Record

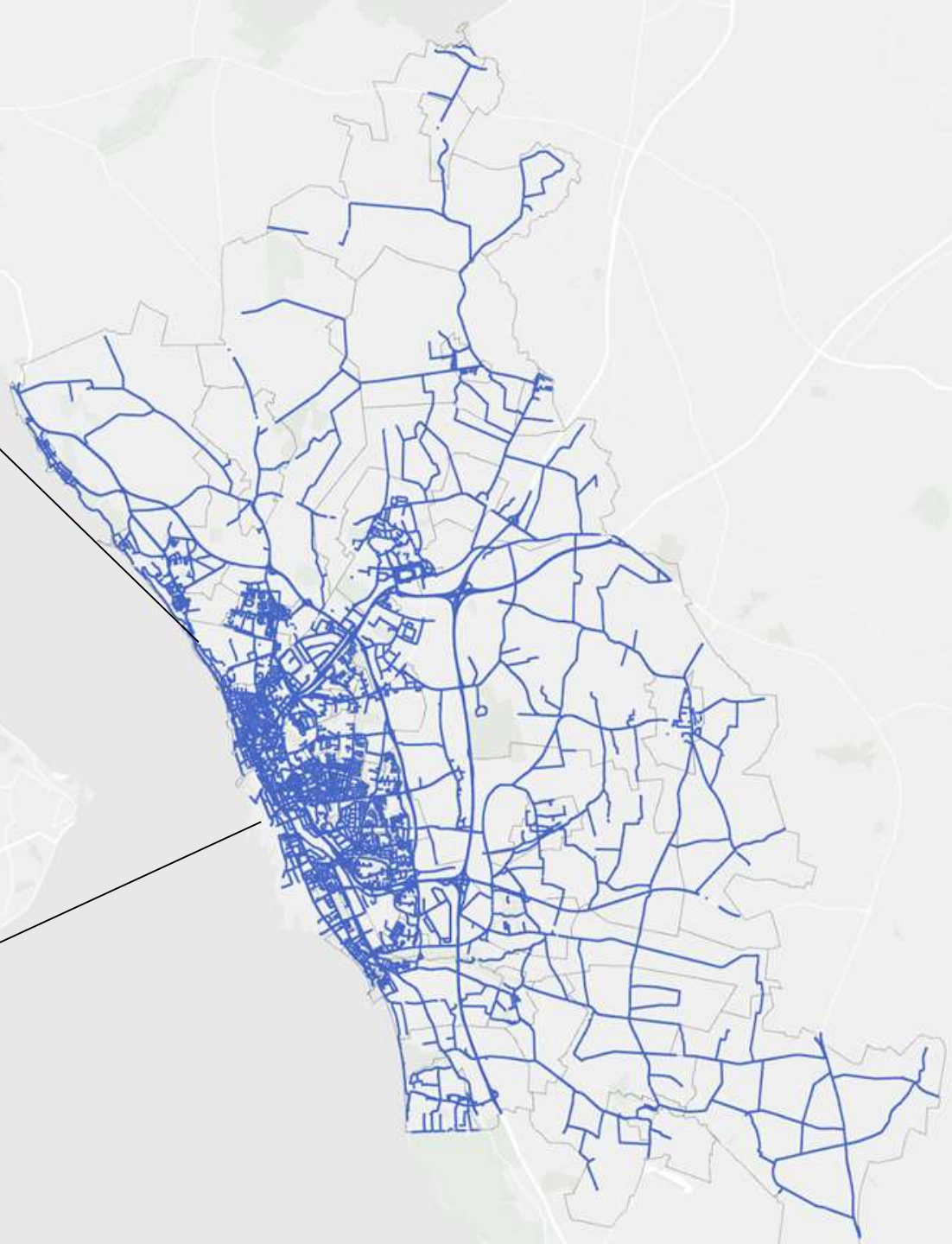


Census data

Data - GSV



Overview of GSV data



Data - GSV

Perceived safe



Perceived unsafe



Data - GSV



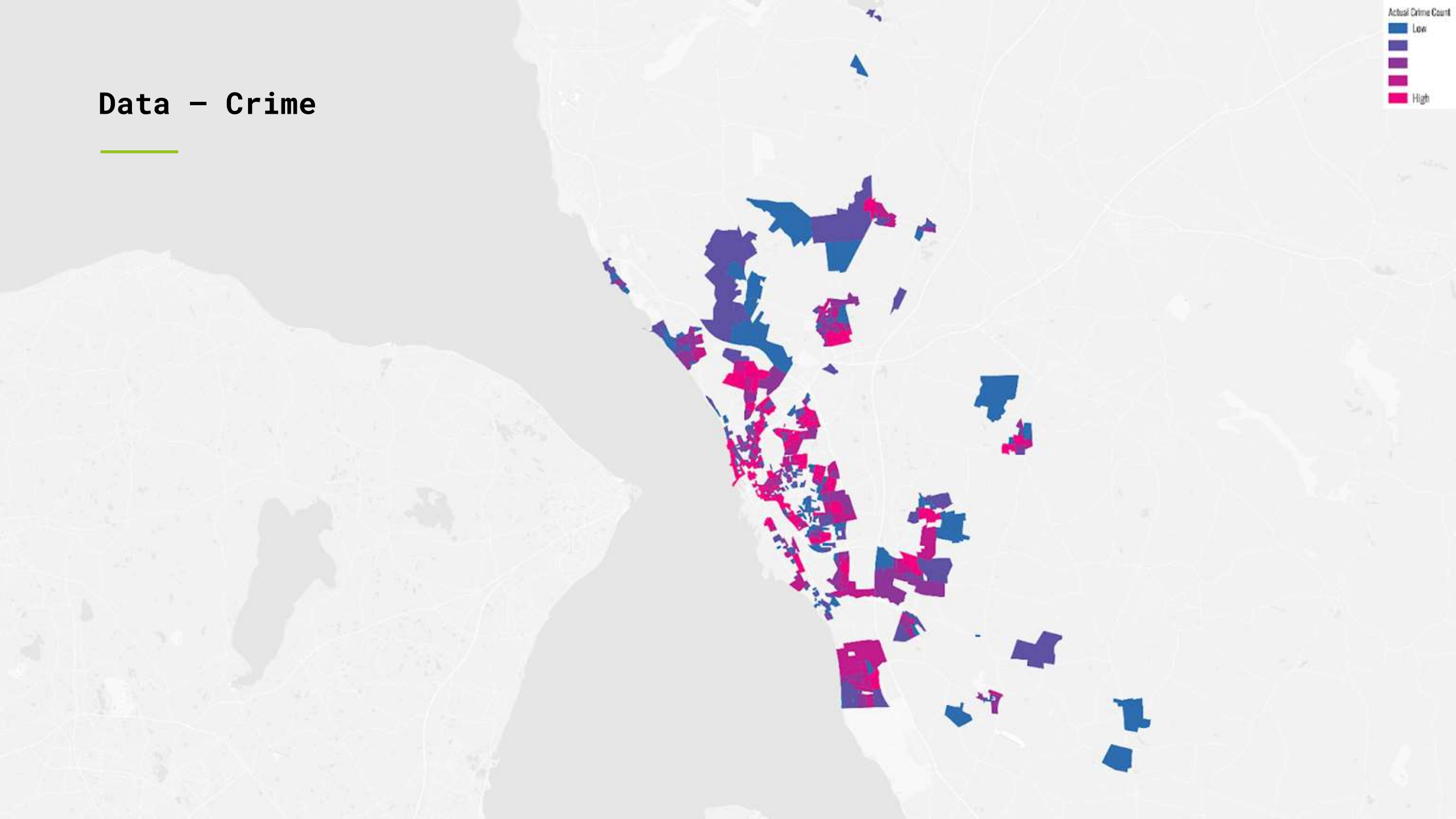
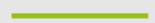
Filter GSV data

Data – Police Record

	BROTTSKOD	BROTSTEXT	BROTTSTID_START	BROTTS DAG_START	BROTTSTID_SLUT	BROTTS DAG_SLUT	C_CODE	E_CODE	Quarter
0	414	Ofredande mot grupp	01:15	torsdag	01:30	torsdag	0213	21300	2015 Q1
1	1203	Skadegörelse, annan skadegörelse (ej klotter)	NaN	torsdag	NaN	lördag	0561	56110	2015 Q1
2	429	Ofredande mot pojke under 18 år	NaN	torsdag	NaN	fredag	1931	193141	2015 Q1
3	428	Ofredande mot flicka under 18 år	NaN	torsdag	NaN	fredag	1931	193141	2015 Q1
4	1203	Skadegörelse, annan skadegörelse (ej klotter)	00:35	torsdag	00:35	torsdag	0834	83410	2015 Q1

Data source: Helsingborg Police Department

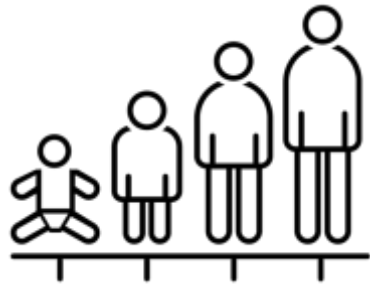
Data - Crime



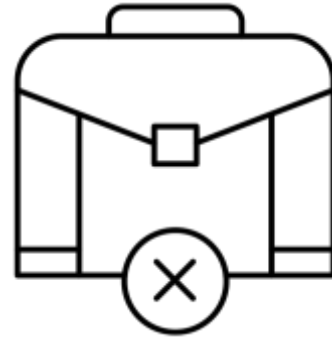
Data – Demographics



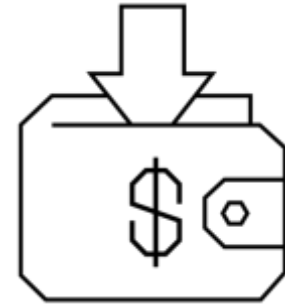
Daytime population



Age

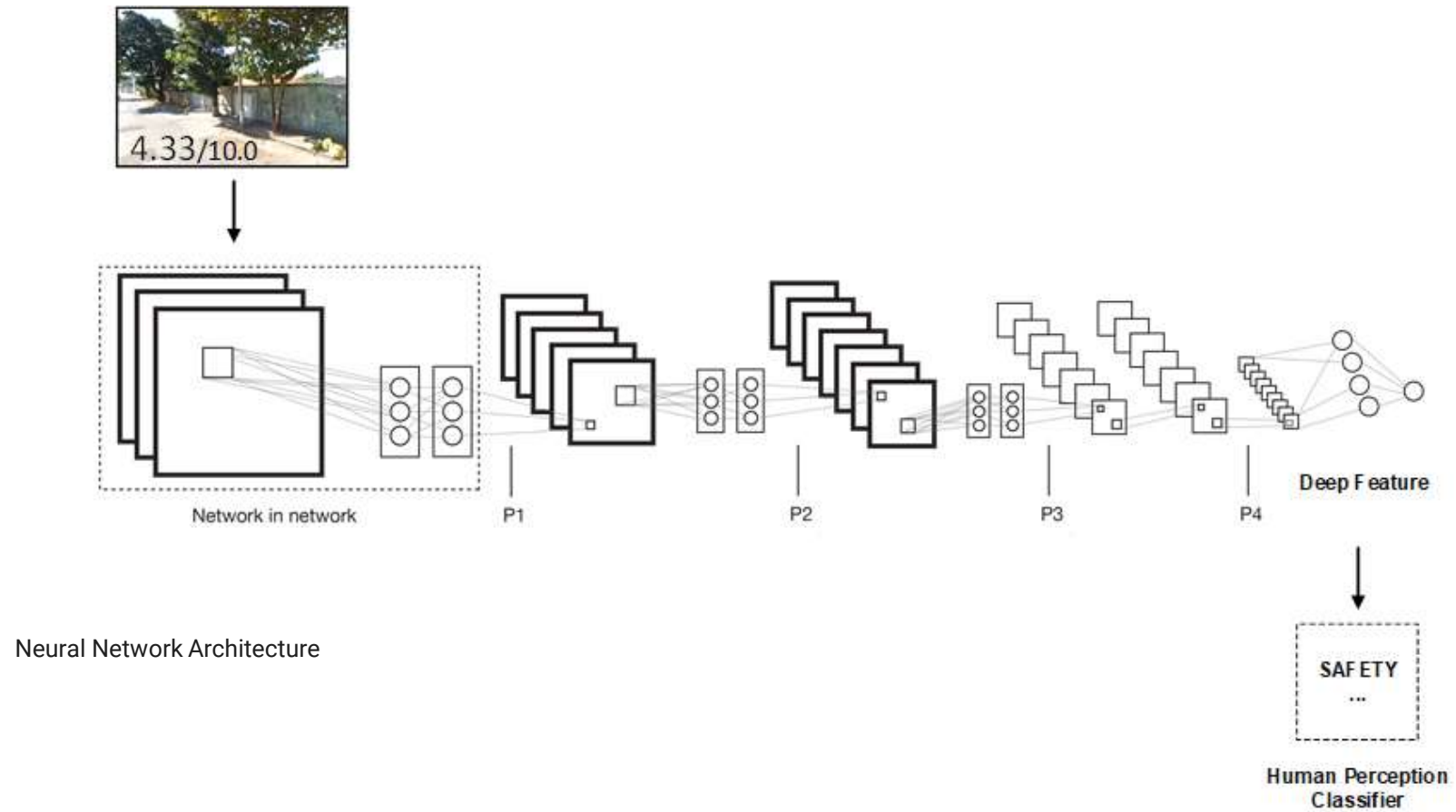


Unemployment rate

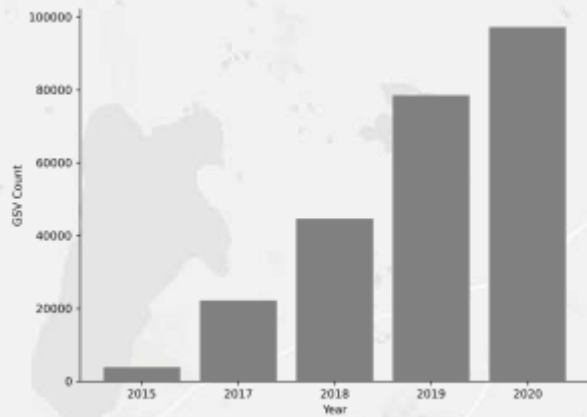


Average income

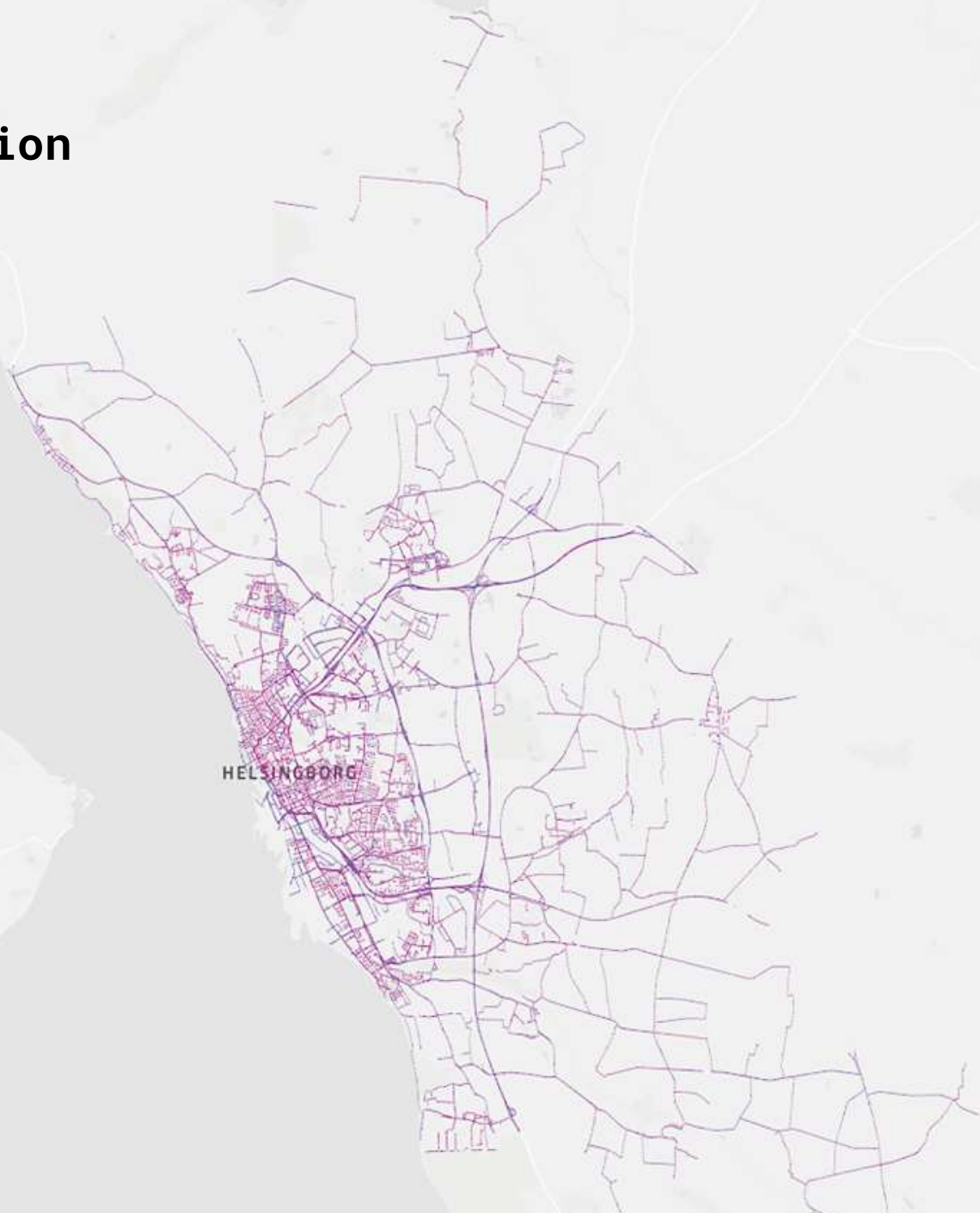
Methodology – Perception



Methodology – Perception



GSV numbers by year



Layer Legend

POINT SAFETY SCORE
by safety

- 2.37 to 4.45
- 4.45 to 4.62
- 4.62 to 4.93
- 4.93 to 5.12
- 5.12 to 5.29
- 5.29 to 6.93

Map navigation controls including a home button, a language button labeled 'EN', and other standard map interface elements.

Result – Tipping Point Theory

$$CrimeChange = \beta * GSVSafetyScore + \theta * BuiltEnvironment + \lambda * Demographics$$

*Crime*₂₀₁₉ – *Crime*₂₀₁₅

DistancetoCityCenter

DaytimePopulation

AverageIncome

UnemploymentRate

Result – Tipping Point Theory

$$\text{CrimeChange} = \beta * \text{GSV SafetyScore} + \theta * \text{BuiltEnvironment} + \lambda * \text{Demographics}$$

OLS Regression Results

```
=====
Dep. Variable:      crime_change_standardize    R-squared:          0.092
Model:              OLS                      Adj. R-squared:     0.069
Method:             Least Squares            F-statistic:        3.994
Date:               Mon, 21 Feb 2022         Prob (F-statistic): 0.00179
Time:               20:24:06                 Log-Likelihood:     -279.16
No. Observations:  204                      AIC:                570.3
Df Residuals:      198                      BIC:                590.2
Df Model:           5
Covariance Type:   nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-1.388e-17	0.068	-2.05e-16	1.000	-0.133	0.133
GSV_safety_standardize	-0.1872	0.076	-2.450	0.015	-0.338	-0.037
daytime_population	0.2134	0.068	3.135	0.002	0.079	0.348
aver_income_standardize	0.0517	0.082	0.633	0.527	-0.109	0.213
unemployment_rate	0.1213	0.081	1.489	0.138	-0.039	0.282
dist_to_center_standardize	-0.0290	0.076	-0.382	0.703	-0.179	0.121

```
=====
Omnibus:           168.764    Durbin-Watson:      2.202
Prob(Omnibus):     0.000    Jarque-Bera (JB):   6170.823
Skew:              -2.700    Prob(JB):           0.00
Kurtosis:          29.397    Cond. No.           1.91
=====
```

Data – Passive Collection

GOOGLE STREET VIEW

Street View Images



Image credit: Google



How Google collects data

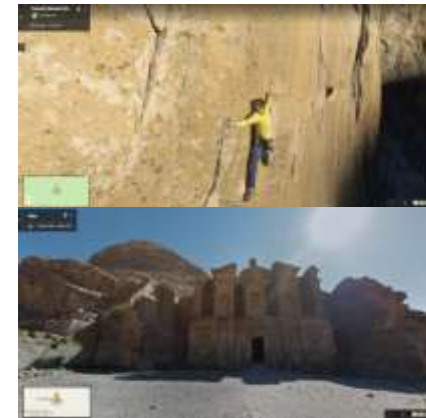
❑ Street View Car



❑ Street View Trolley



❑ Street View Trekker



Street View Service



Image credit: wikipedia

Google Street View

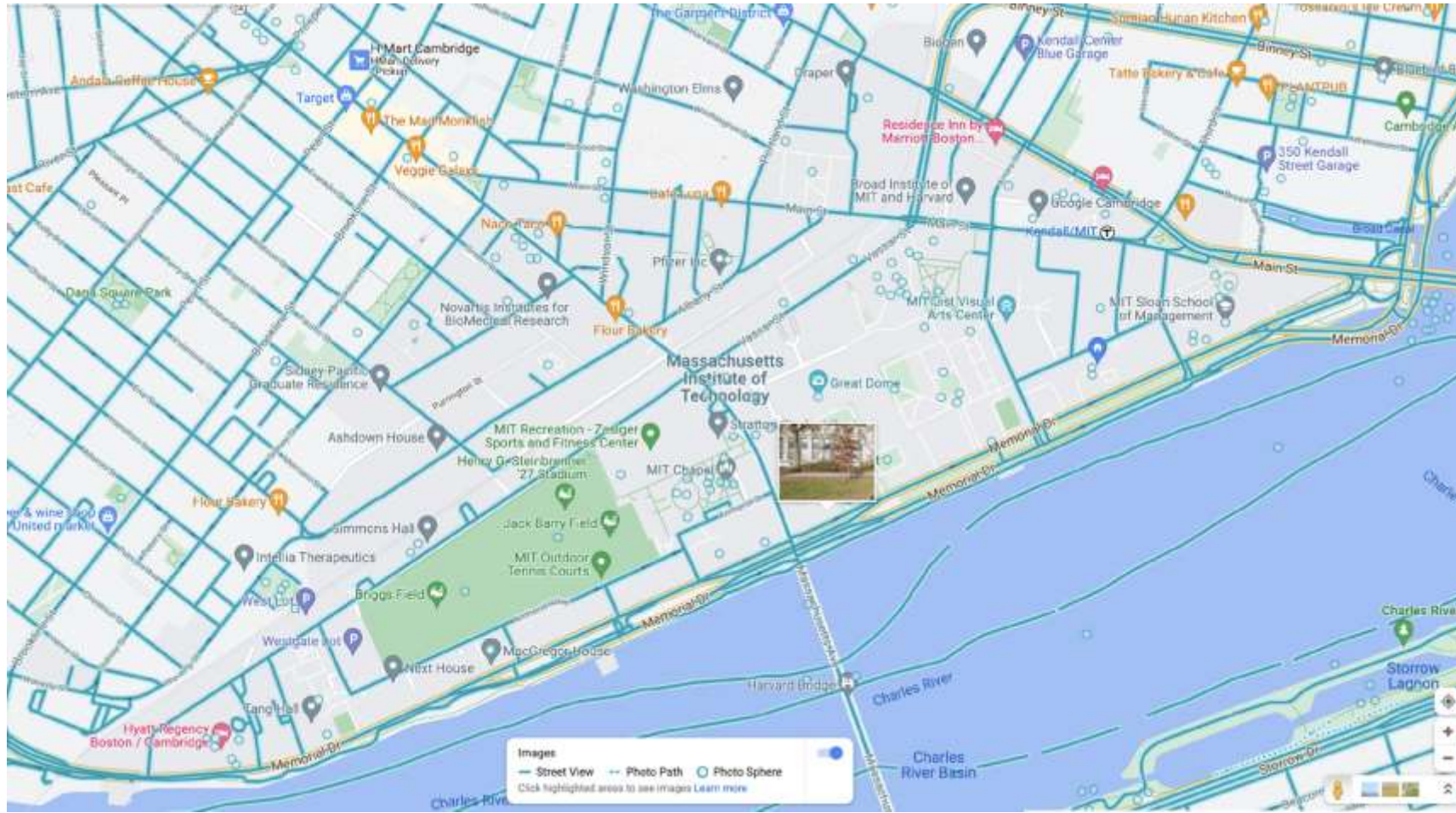


Image credit: Google

GSV Perspectives

Natural view



(a)

Panoramic view



(b)

GSV API

`https://maps.googleapis.com/maps/api/streetview/metadata?location={}&key={}`

Location

lat,lng

Key

Do not share with others!

[Example 1](#)

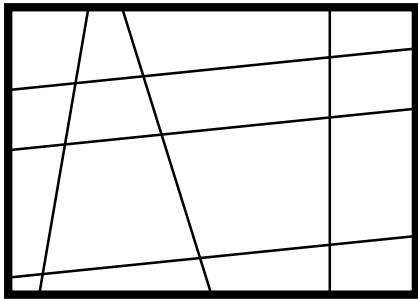
GSV API

`https://maps.googleapis.com/maps/api/streetview?size={width}x{height}&pano={}&heading={}&pitch={}&fov={}&key={}`

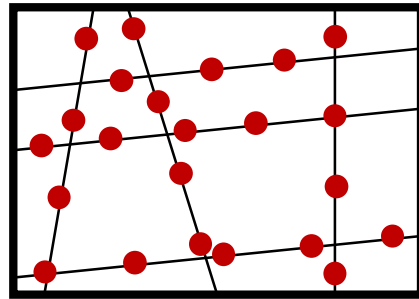
Size	Pano	Heading	Pitch	FOV	Key
Max size: 640 * 640	Unique panoID	0 - 360 degree	-90 - 90 degree	Max value: 120	Do not share with others!
	location	North: 0	Straight up: 90	Default: 90	
	Unique panoID	East: 90	Stright down: -90		
		South: 180			
		West: 270			

[Example 2](#)

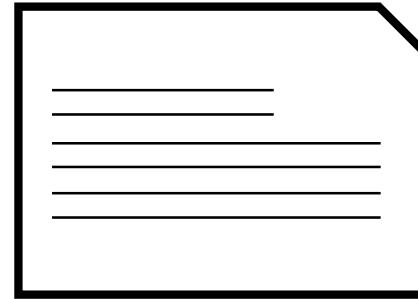
Large-scale GSV Download Process



Download street network



Generate request point



Get image meta data



Download image

Large-scale GSV Download Example



Download street network



Generate request point

Tutorial for GSV collection

<https://colab.research.google.com/drive/1o2cB5WuvF4vmsukeZsxTCx4ePr7jECpA?usp=sharing>

Data – Active Collection

MOBILE SENSEING, CAMERA

Self-collection

❑ Wearable Camera









GoPro



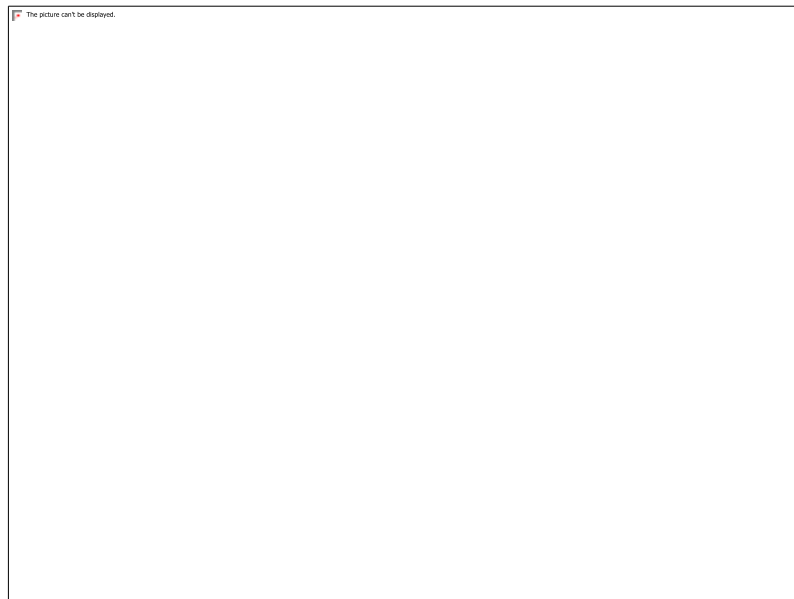
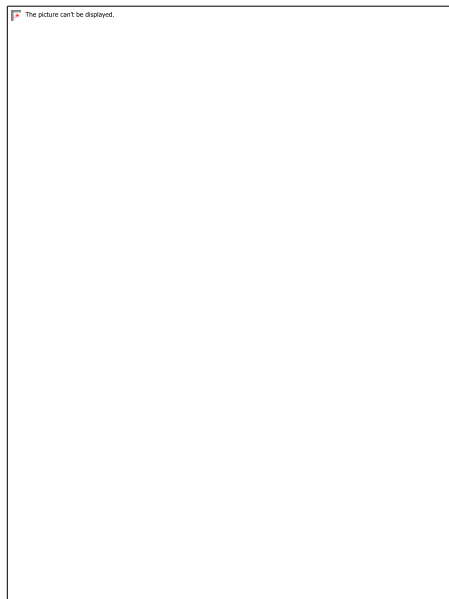
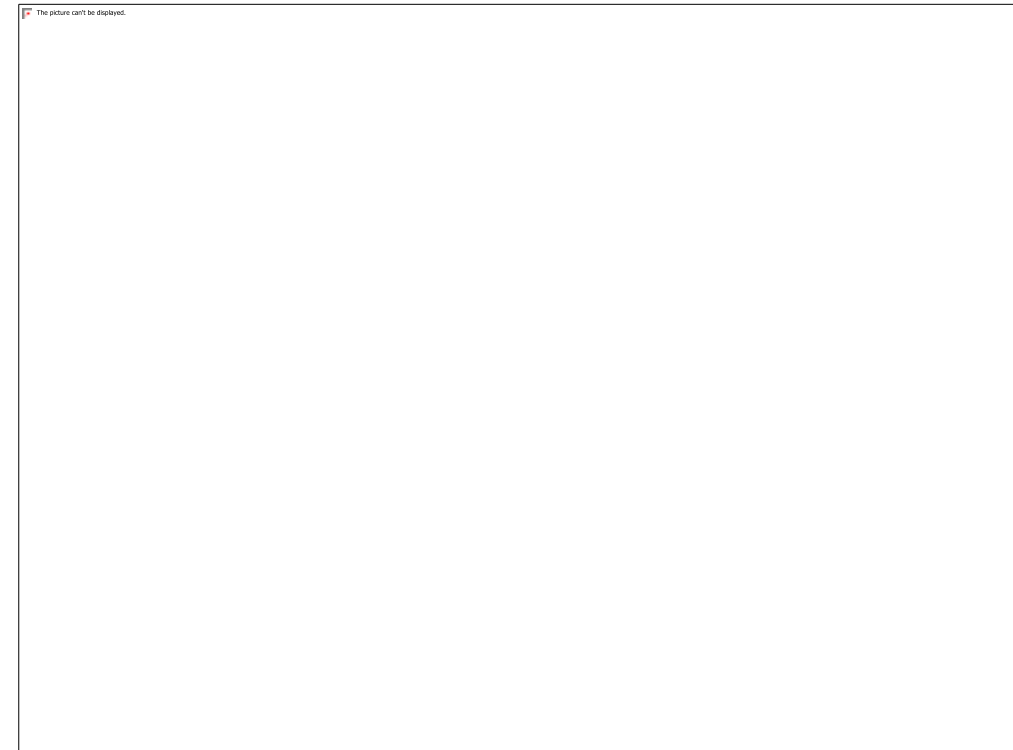
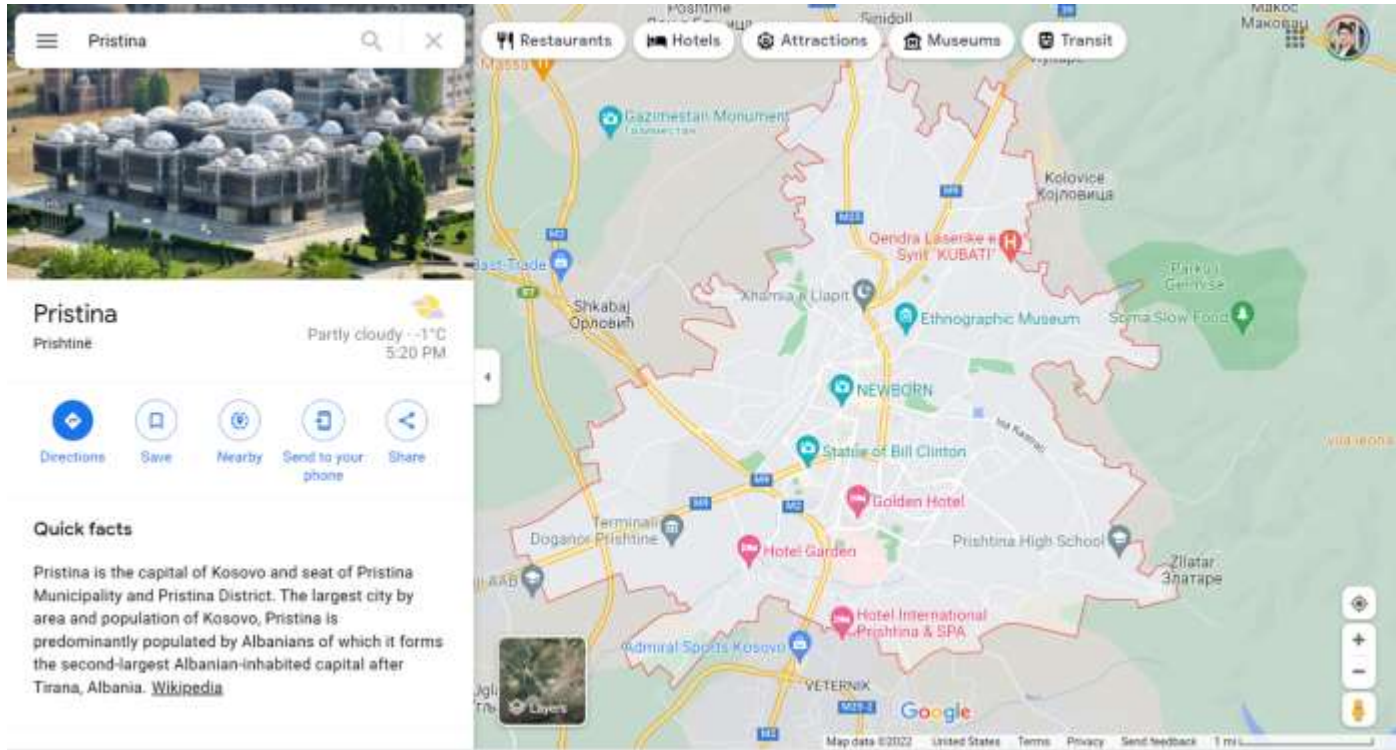
❑ Vehicle Mounted



❑ Device

 <p>Pilot Era 360*</p> <ul style="list-style-type: none">• Realtime stitching at 7FPS, no post production• Publish directly to Google from the camera• Easy Touch screen operation, suitable for untrained personnel	 <p>INSTA360 PRO2</p> <ul style="list-style-type: none">• Integrated GPS Module• FlowState - Cinematic Stabilization• Paraglide - Long Range Live Monitoring	 <p>INSTA360 PRO</p> <ul style="list-style-type: none">• 8K at 5 Frames per second• 180° vertical FOV reveals all• Real-time image stabilization
 <p>RICOH THETA Z1</p> <ul style="list-style-type: none">• 1.0-inch back-illuminated CMOS image sensor• 6.7K at 5 frame per second• Street View Android app (beta)	 <p>RICOH THETA V</p> <ul style="list-style-type: none">• 5.4K at 30 Frames per second• Street View Android app (beta)	 <p>GoPro Fusion</p> <ul style="list-style-type: none">• 5.8K at 24 Frames per second• Publish using the 360cam from Panasonic

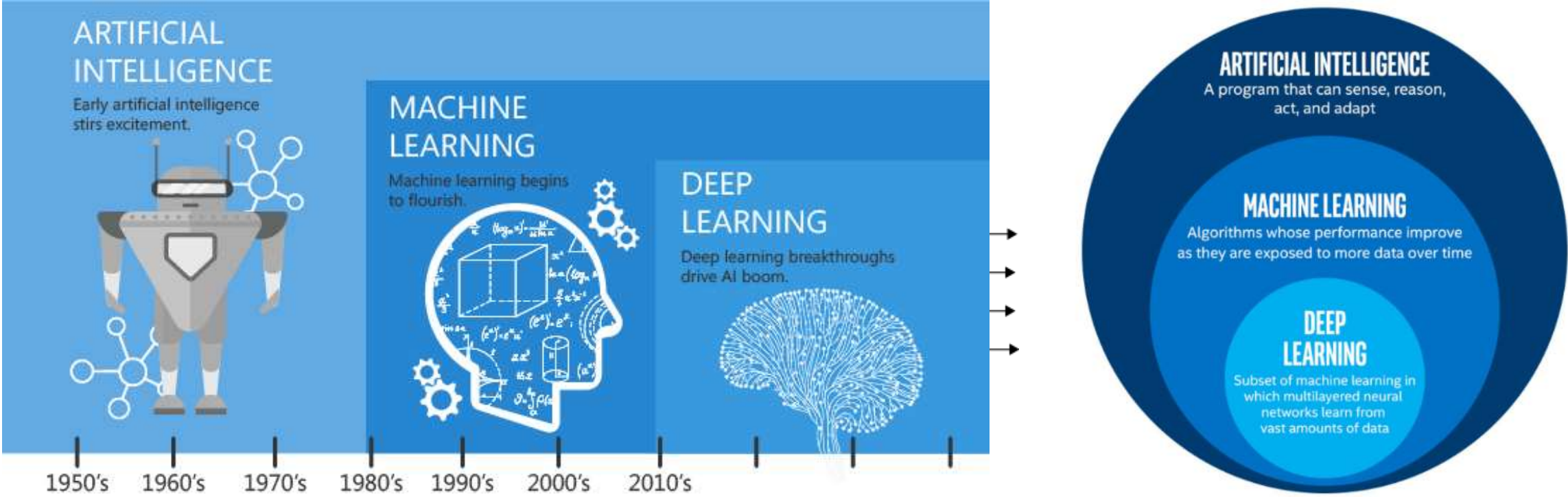
<https://www.google.com/streetview/contacts-tools/>



Method – Deep Learning

MACHINE LEARNING, NEURAL NETWORK

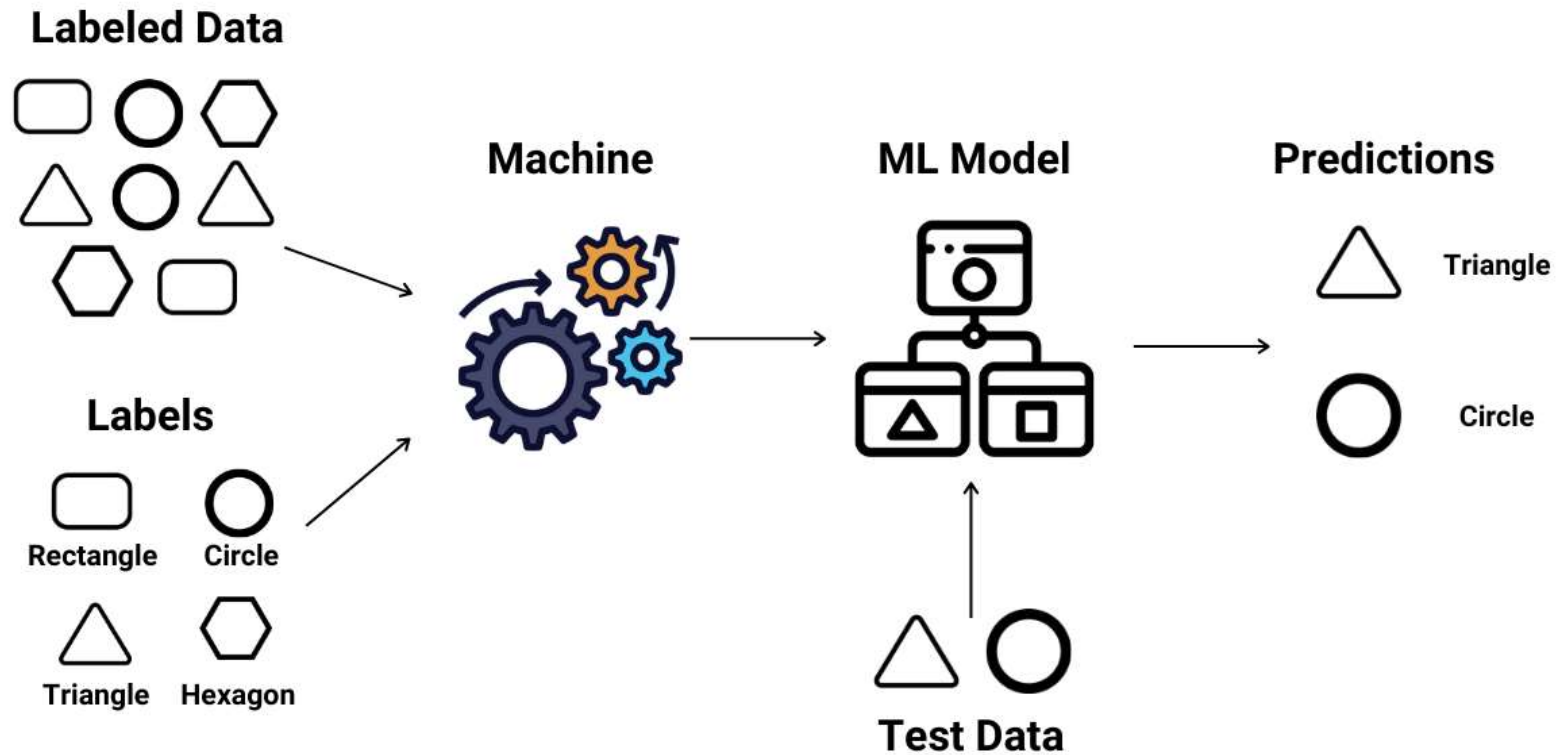
AI vs. ML vs DL



Machine Learning



Supervised Learning

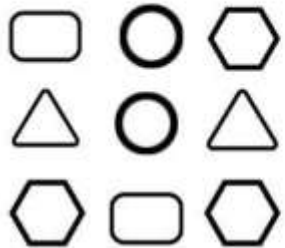


Machine Learning

Unsupervised Learning



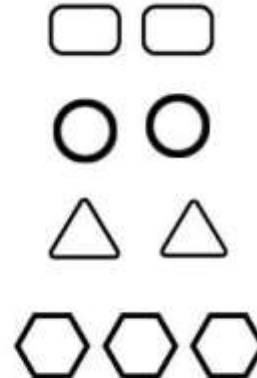
Unlabelled Data



Machine



Results

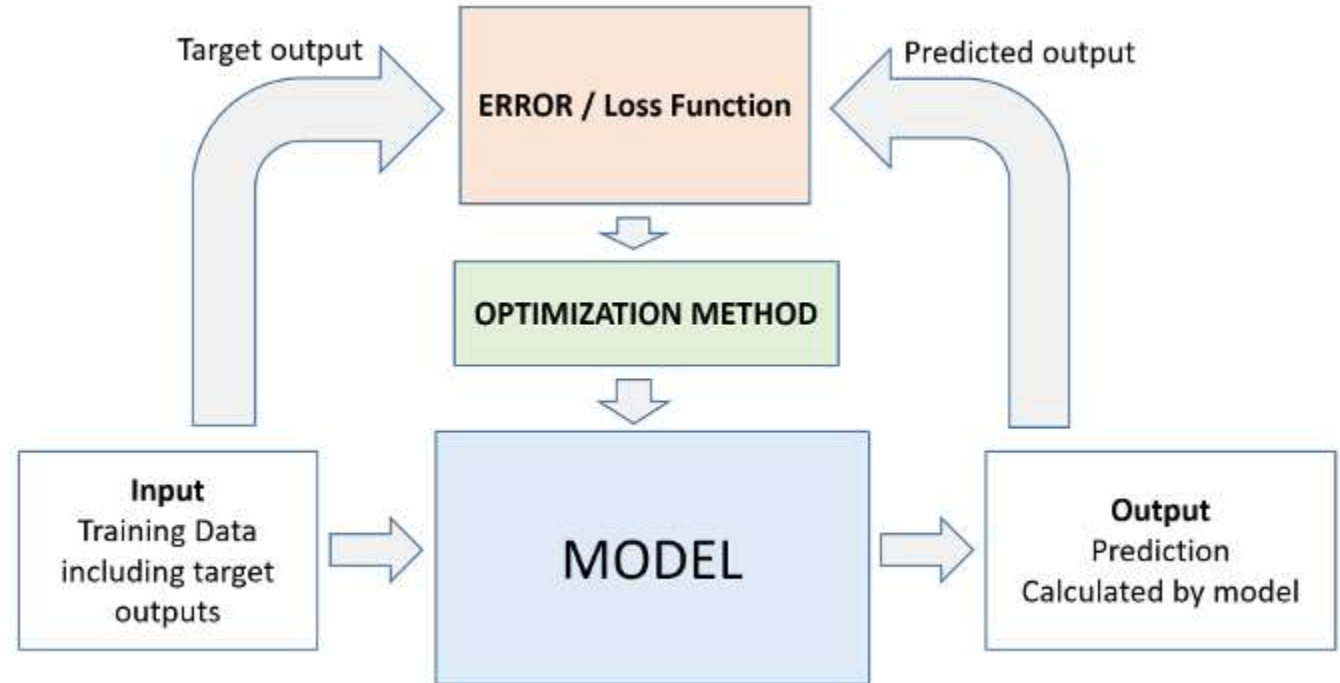


Machine Learning

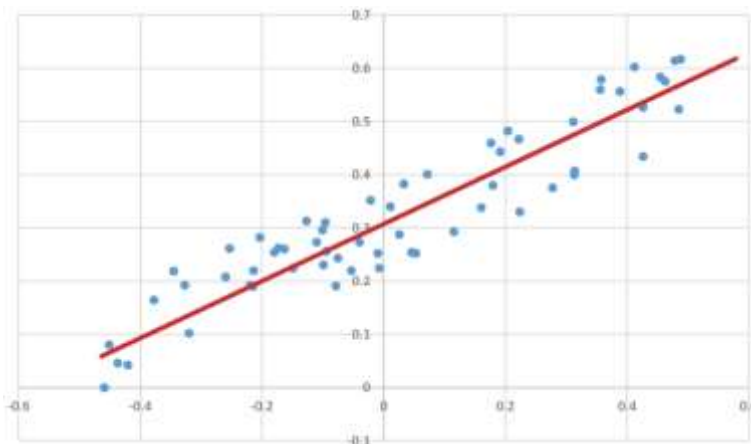
Three Key Components of ML:

1. Model
2. Loss Function
3. Optimization Method

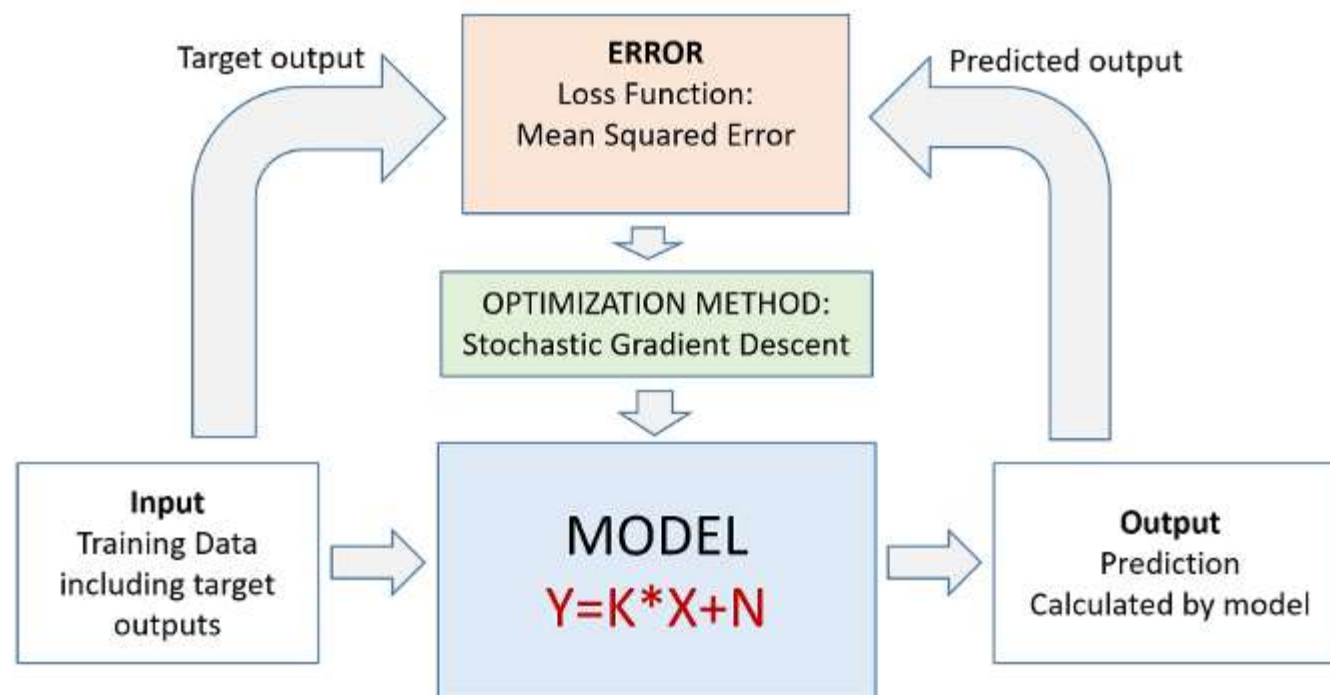
- Learning as loss minimization



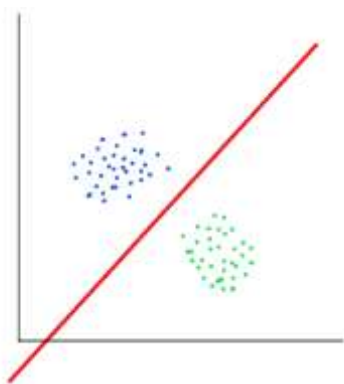
Machine Learning



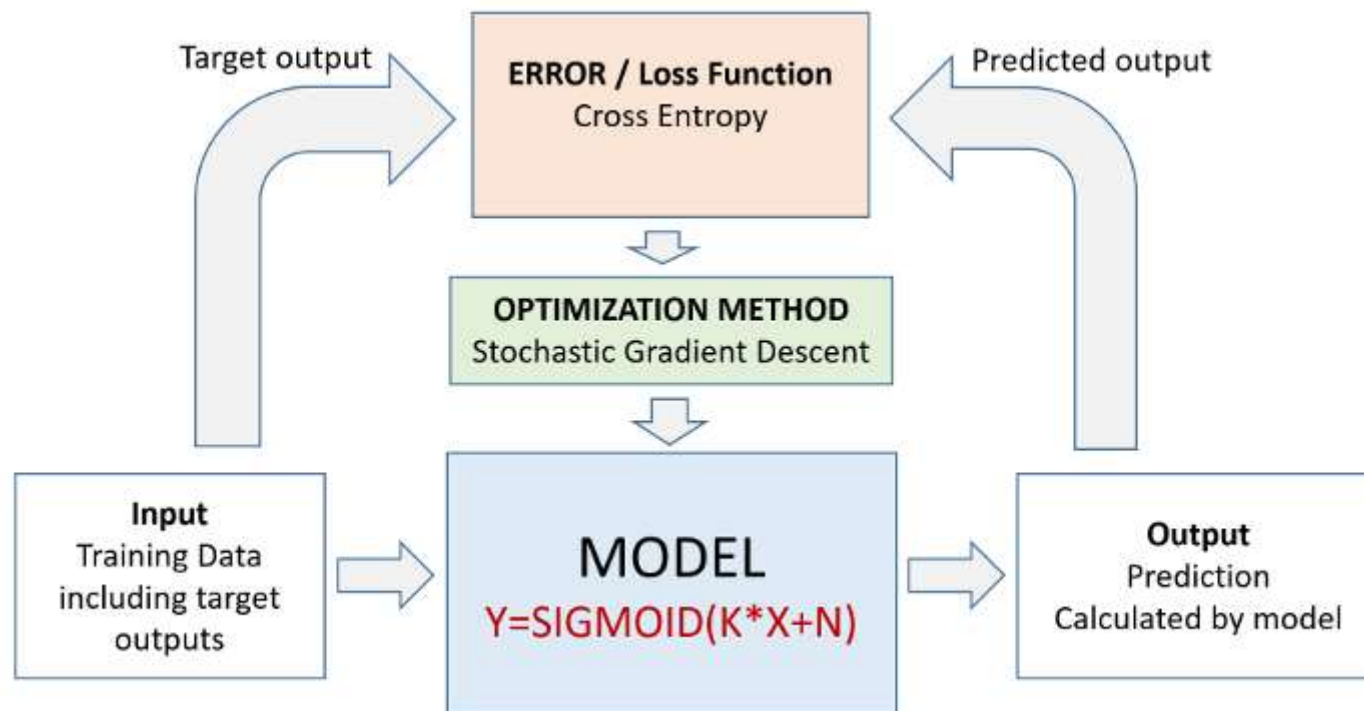
Linear Regression



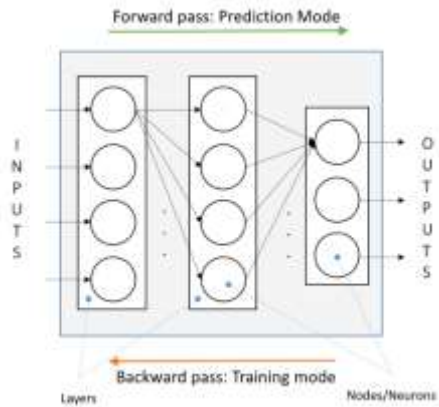
Machine Learning



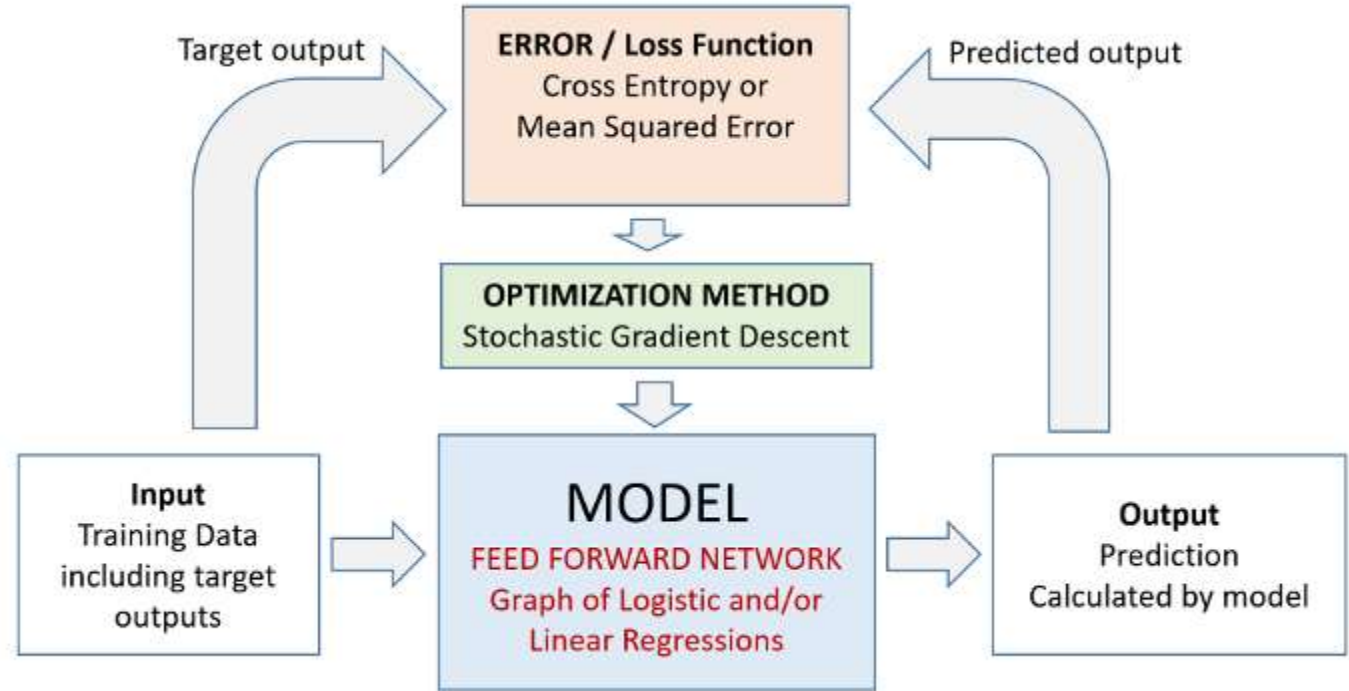
Logistic Regression



Machine Learning



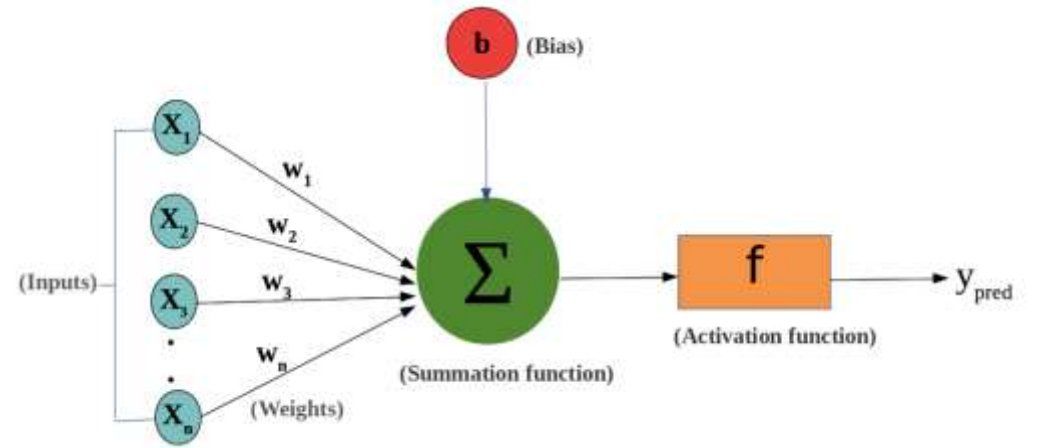
Neural Network



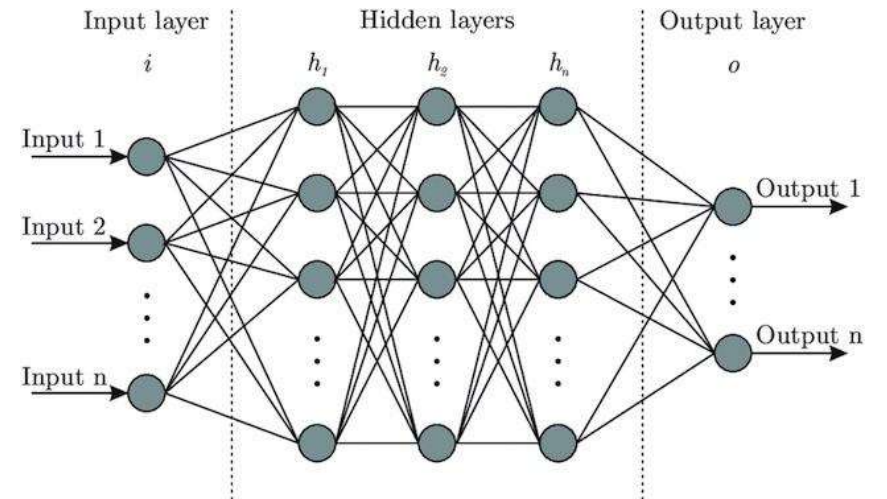
Training a neural network

For a fixed architecture, a neural network is a function parameterized by its weights

- Given
 - A network architecture (layout of neurons, their connectivity and activations)
 - A dataset of labeled examples
- The goal: Learn the weights of the neural network



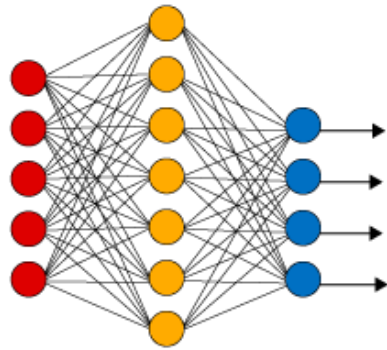
Perceptron - a single layer neural network



Neural Network - multilayer perceptron

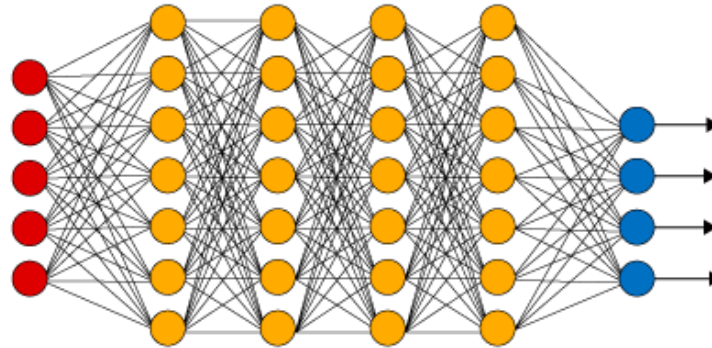
NN vs. DNN vs. DCNN

Simple Neural Network



● Input Layer

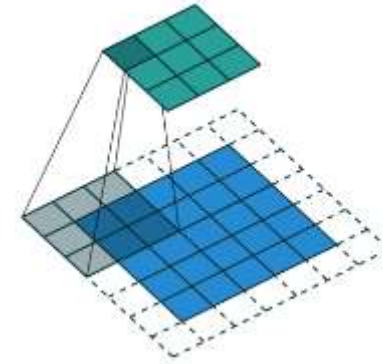
Deep Learning Neural Network



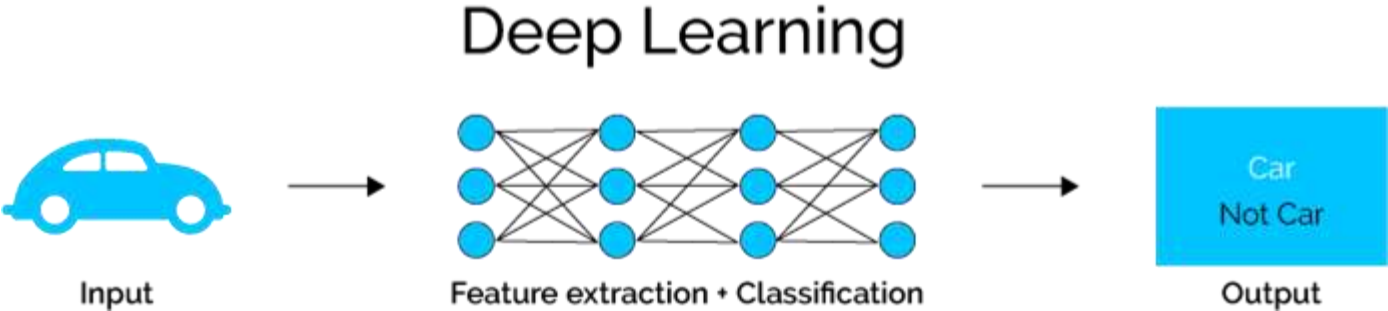
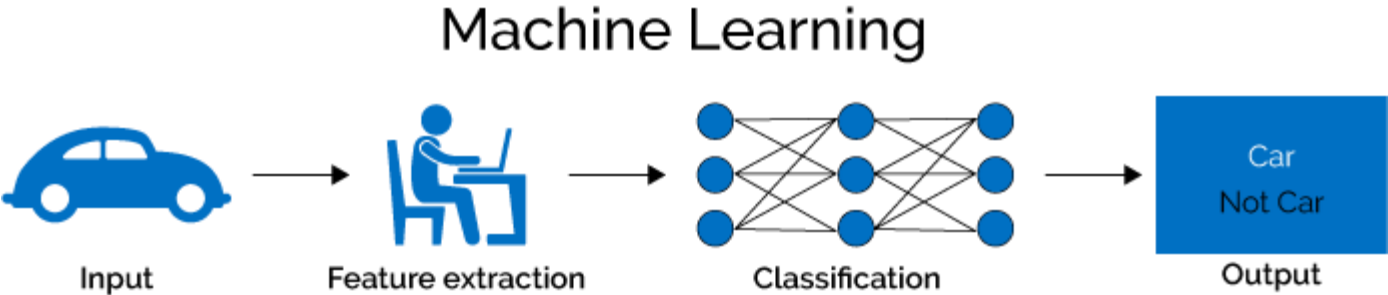
● Hidden Layer

● Output Layer

Convolution



Why Deep Learning?



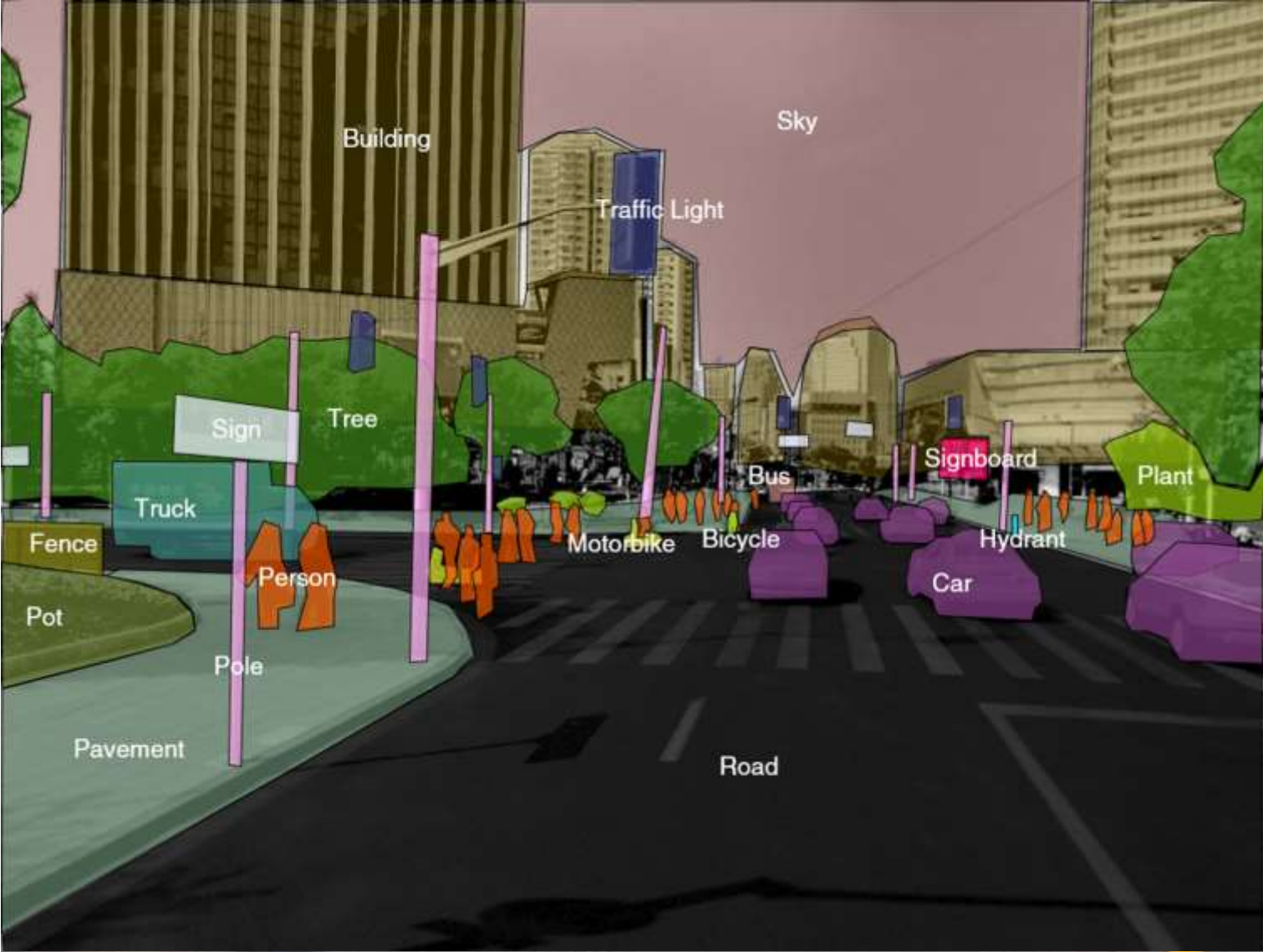
Computer Vision Applications

Image Object Detection



Computer Vision Applications

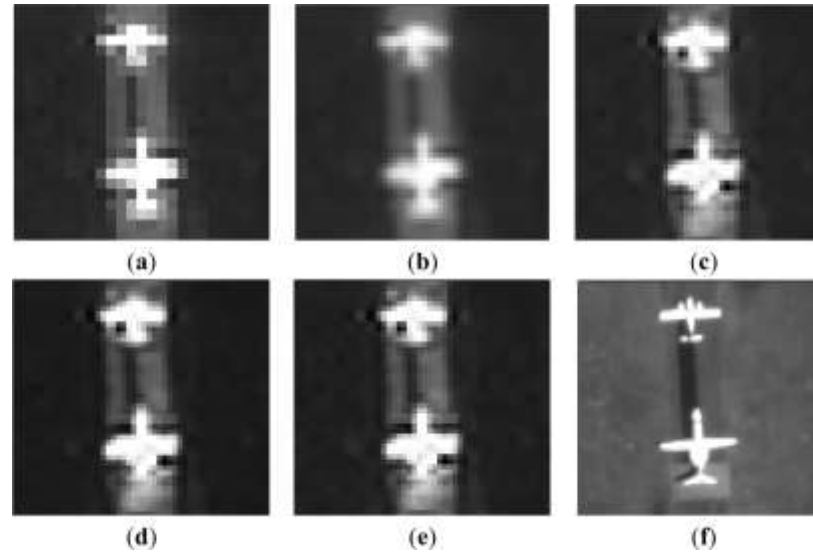
- Image Segmentation



Computer Vision Applications

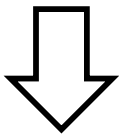
□ Image Super Resolution

- Reconstruction of the high resolution imagery from the observed low resolution image
- Applications: surveillance video, medical imaging, satellite imagery

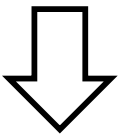


Computer Vision Applications

- Style Transferring



Style Extraction



Content Extraction



Style-content synthesis



Computer Vision Applications

- Style Transferring for Image Generation



Computer Vision Applications

- Image Captioning
- Text-to-image Generation



A computer screen with a Windows message about Microsoft license terms.



A can of green beans is sitting on a counter in a kitchen.



A photo taken from a residential street in front of some homes with a stormy sky above.



A blue sky with fluffy clouds, taken from a car while driving on the highway.



A hand holds up a can of Coors Light in front of an outdoor scene with a dog on a porch.



A digital thermometer resting on a wooden table, showing 38.5 degrees Celsius.



A Winnie The Pooh character high chair with a can of Yoohoo sitting on it in front of a white wall.



A cup holder in a car holding loose change from Canada.

Learn more about ML/DL/CV?

- 6.036 Introduction to Machine Learning
- 6.S191 Deep Learning
- 6.801 Machine Vision
- 6.819 Advances in Computer Vision

Hands-on session

IMAGE CLASSIFICATION

OBJECT DETECTION

IMAGE SEGMENTATION

Google Colab



My Drive > scl-class

Name	Owner
scene classification	me
YOLO	me
deeplabv3_xception65_ade20k-h5	me
Demo 1: Scene Classification.ipynb	me
Demo 2: Object Detection.ipynb	me
Demo 3: Image Segmentation.ipynb	me



```
+ Code + Text

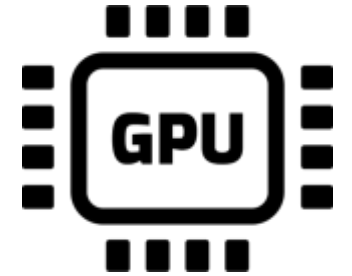
- Scene Classification

Current tutorial from: https://ovisn.ai/shakihussain2020/intel-scene-classification-pytorch-cnn

[1] 1 from google.colab import drive
    2 drive.mount('/content/drive')
    3 import os
    4 os.chdir('/content/drive/My Drive/scl-class/')

Mounted at /content/drive

[2] 1 import os
    2 DATA_DIR = 'scene_classification/dataset'
    3 print(os.listdir(DATA_DIR))
    4 print(os.listdir(DATA_DIR+'seg_train/seg_train')[1:10])
```



Demo 1: Image Classification



steel-frame



concrete



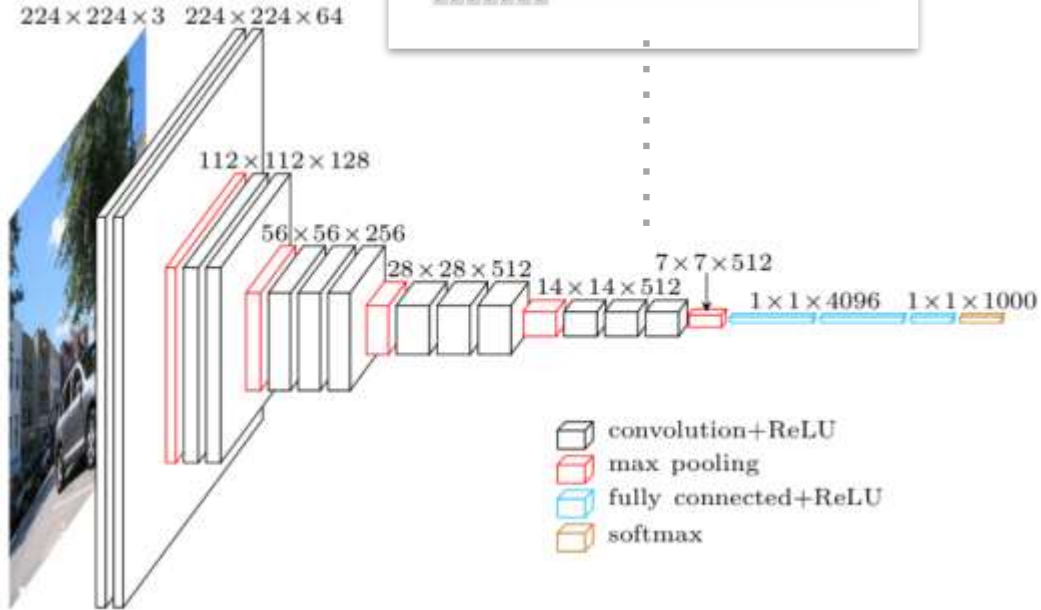
masonry



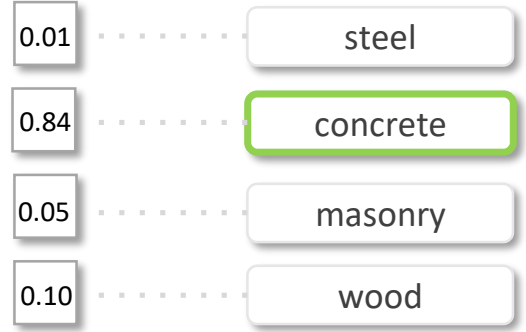
wood



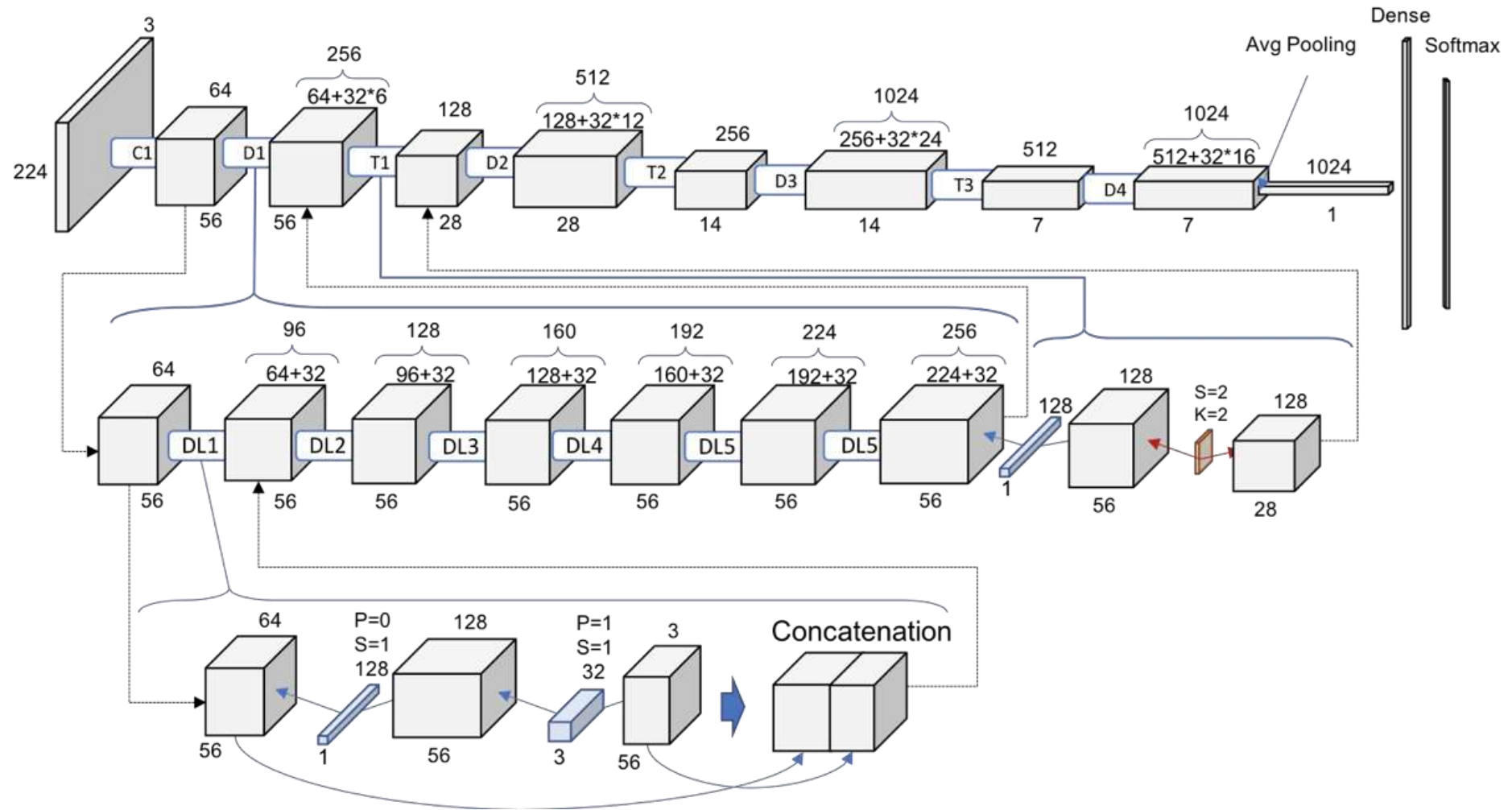
concrete?



- Input: 224x224 images
- Output: 5x1 label vector

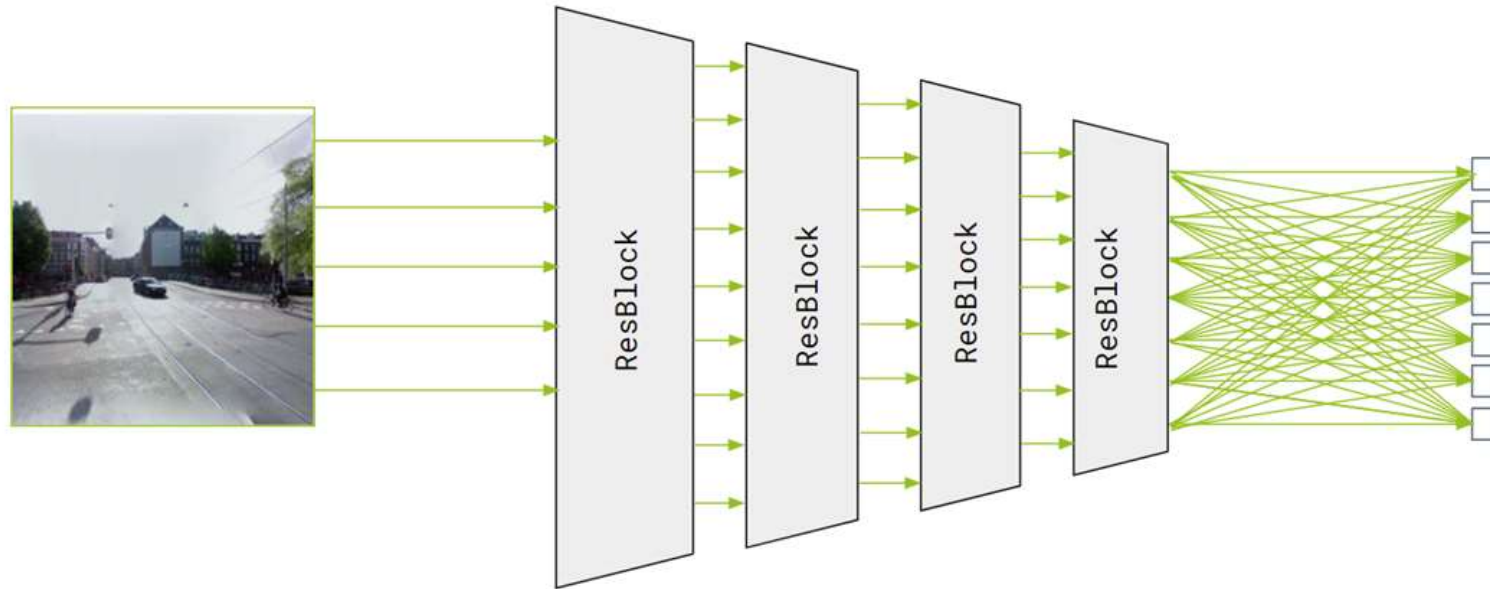


ResNet



ResNet 121 architecture

ResNet



Training Framework



Data Loader



Load images and labels from file and split them into batches

Model



Neural Network with weights ready to be trained

Train Loop

```
for epoch in range(NUM_EPOCHS): # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        inputs, labels = data # get a batch from the dataloader
        optimizer.zero_grad()
        outputs = model(inputs) # compute labels
        loss = criterion(outputs, labels) # compute loss
        loss.backward() # update weights
        optimizer.step() # adjust learning rate

    running_loss += loss.item()
```

Loss Function

$$J = \frac{1}{2m} \sum_{i=1}^m (\hat{y} - y)^2$$

Difference between predicted and target value

Optimizer

Slow down or speed up learning rate

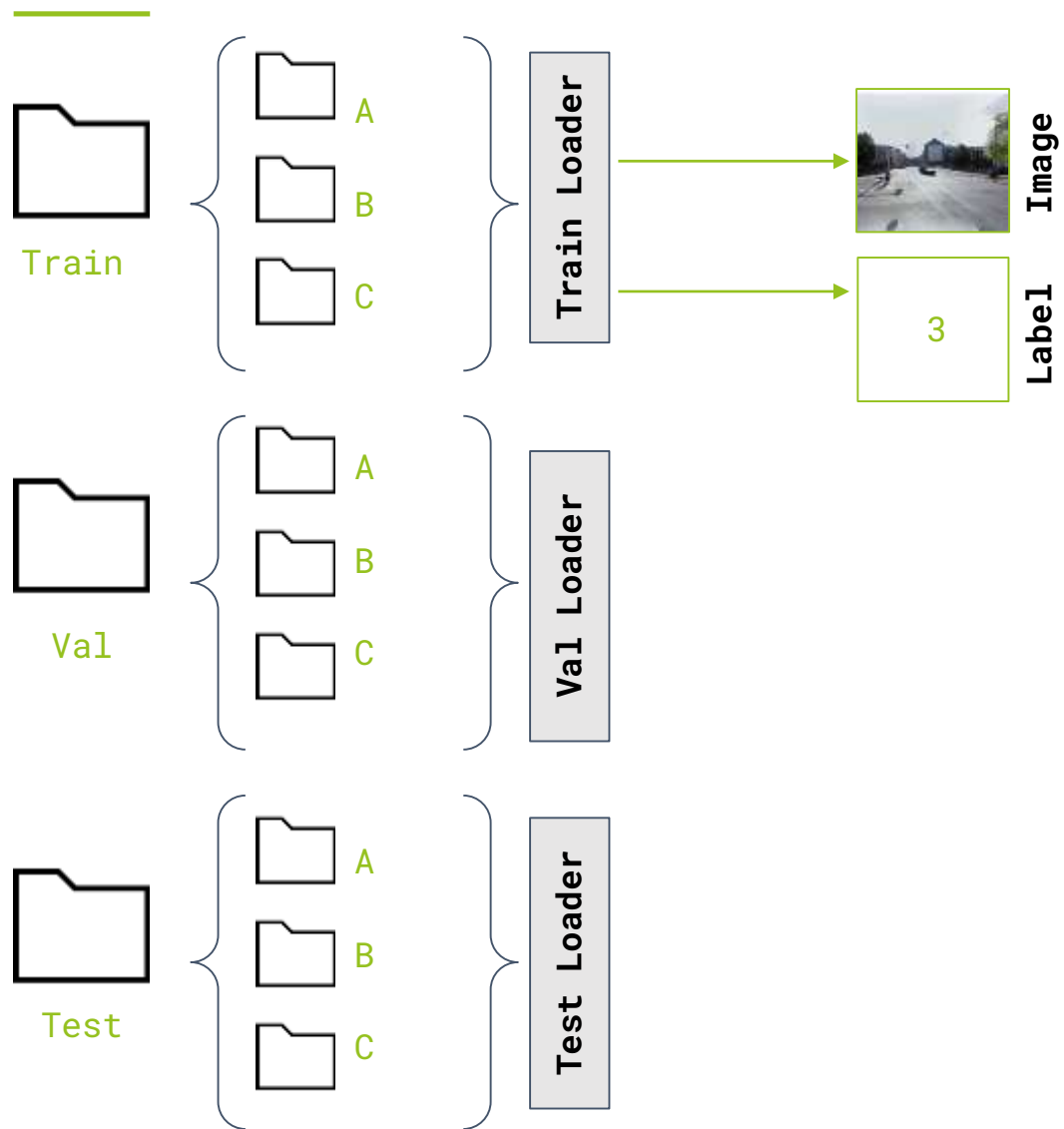
Backpropagation

Find weights in the model and update them

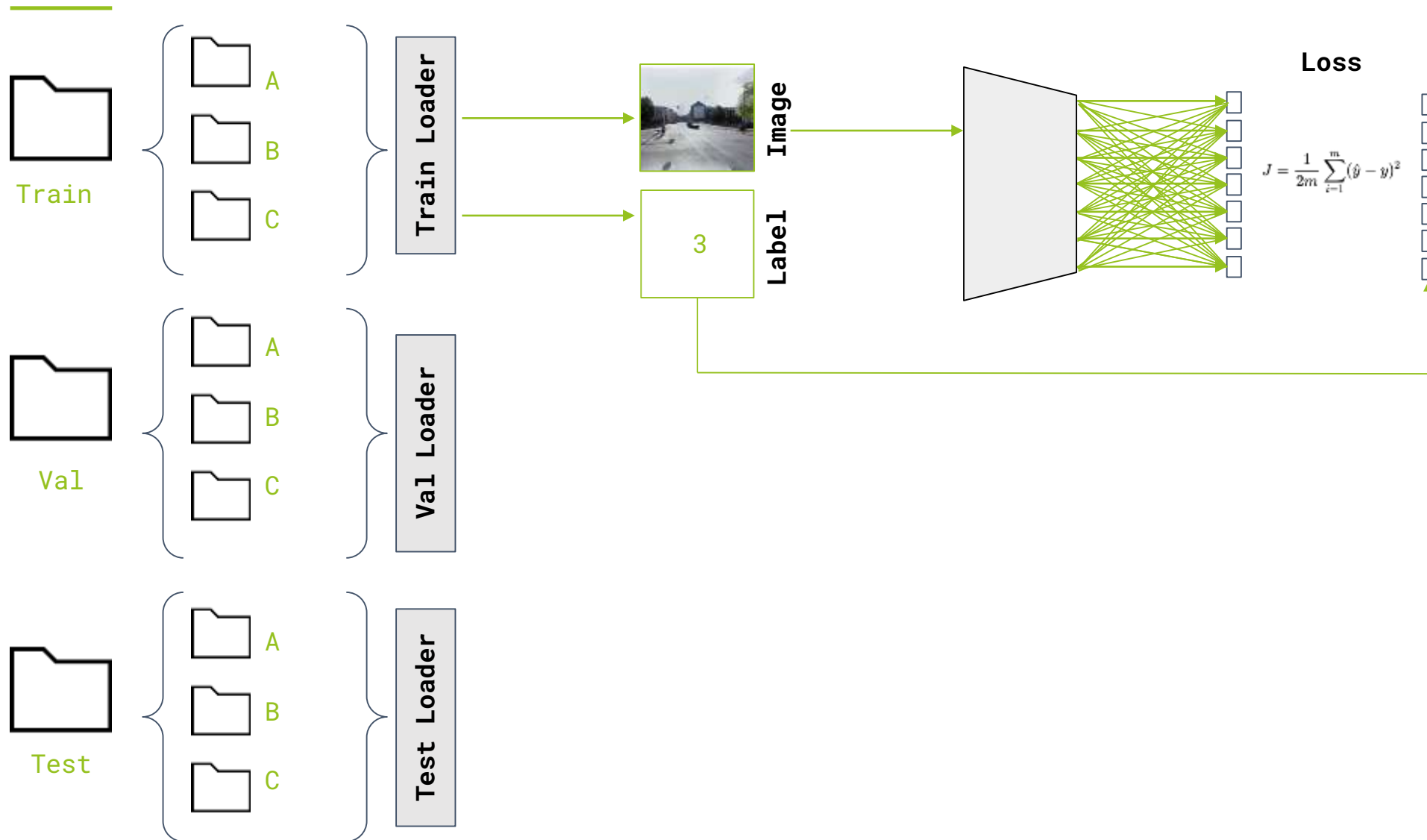
Manage GPU Usage

```
device = torch.device('cuda')
model = model.to(device)
```

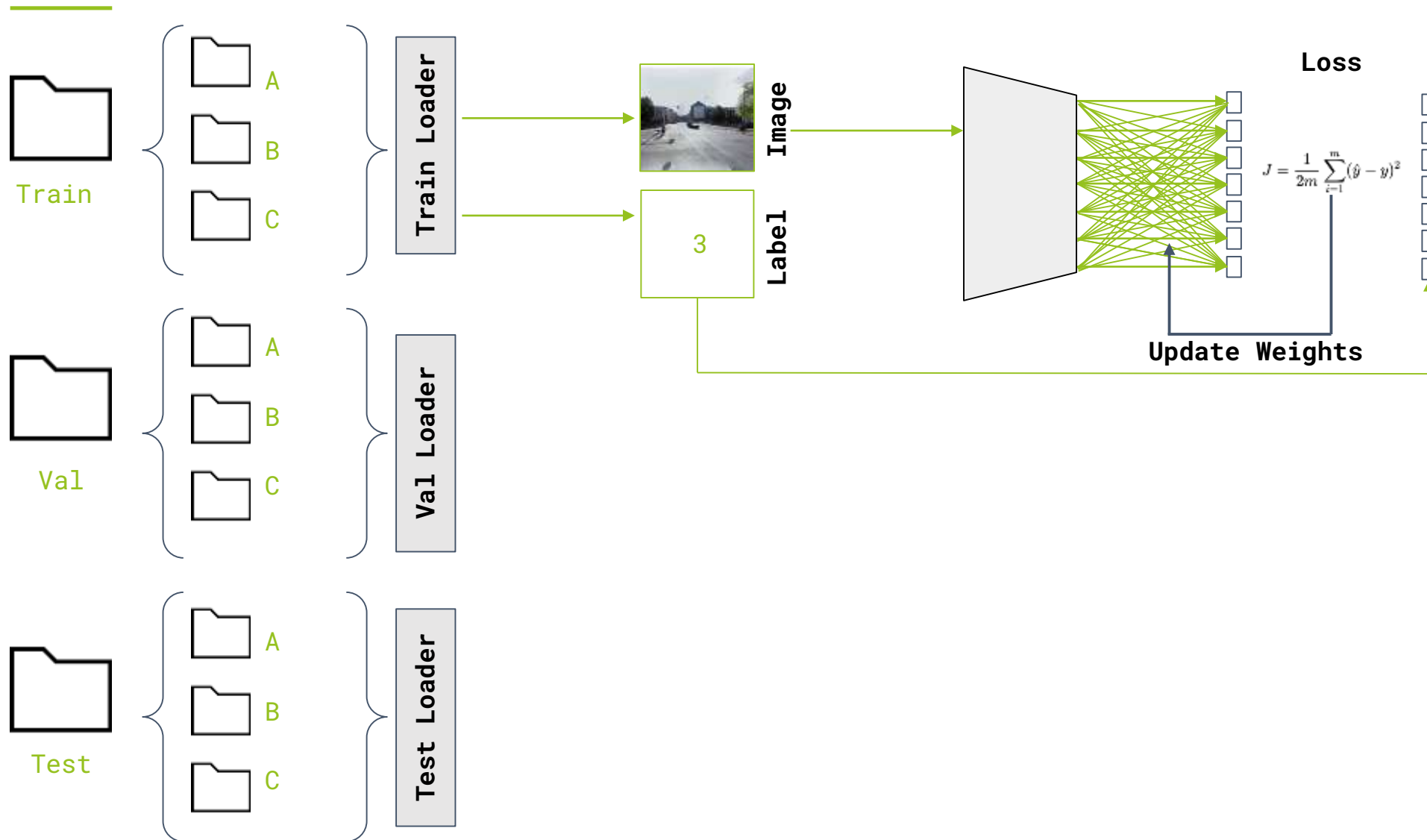
Training Workflow



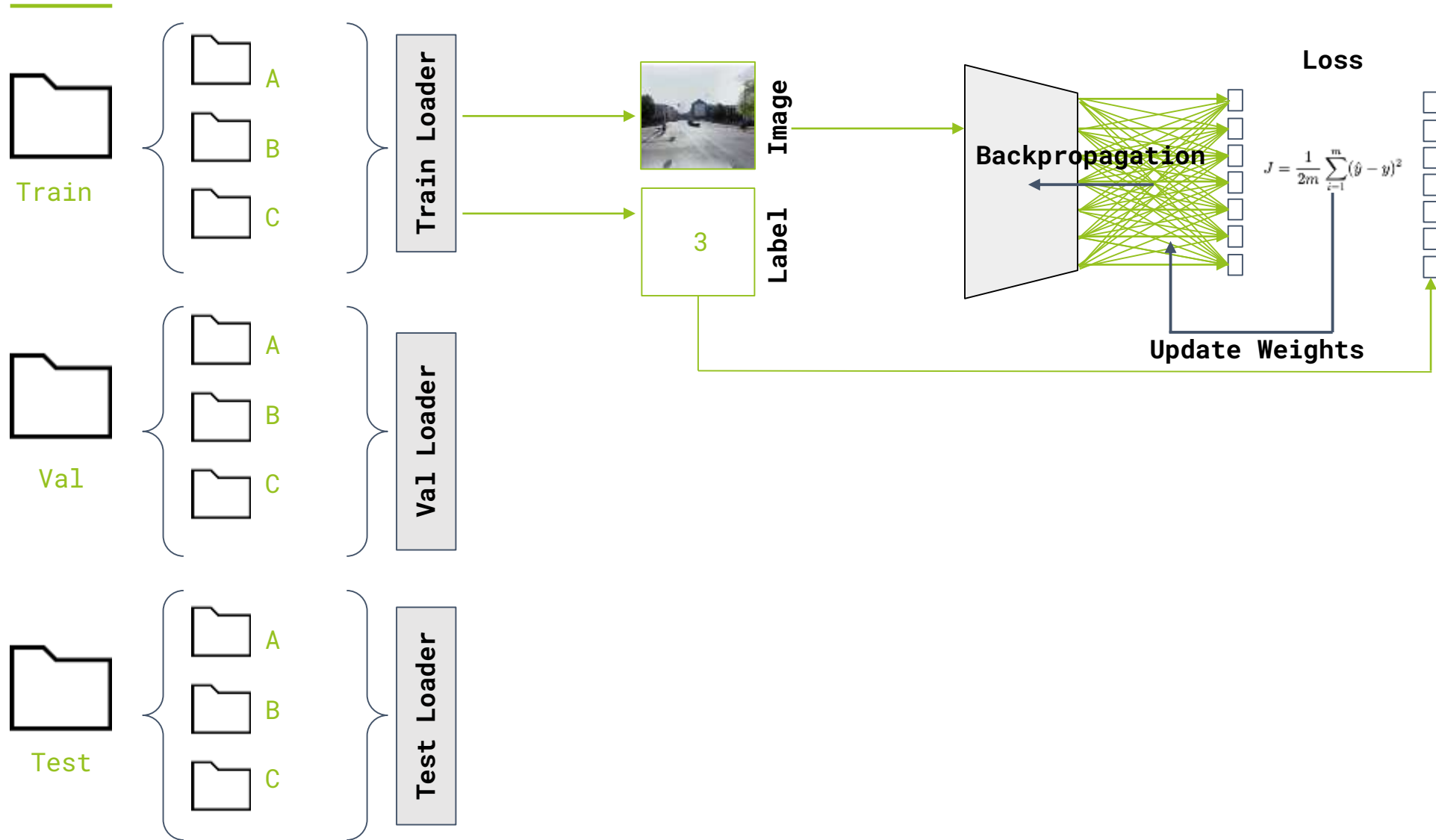
Training Workflow



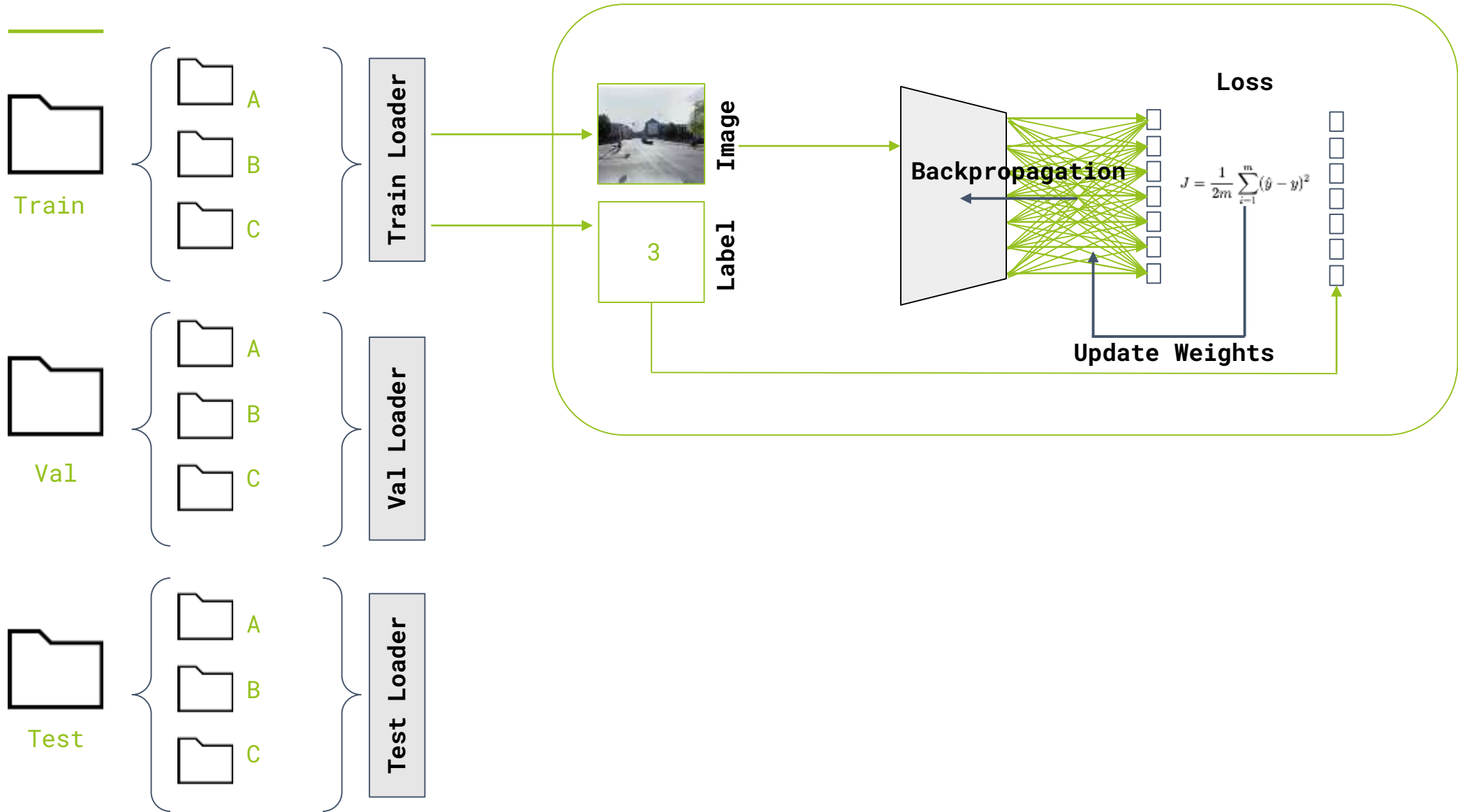
Training Workflow



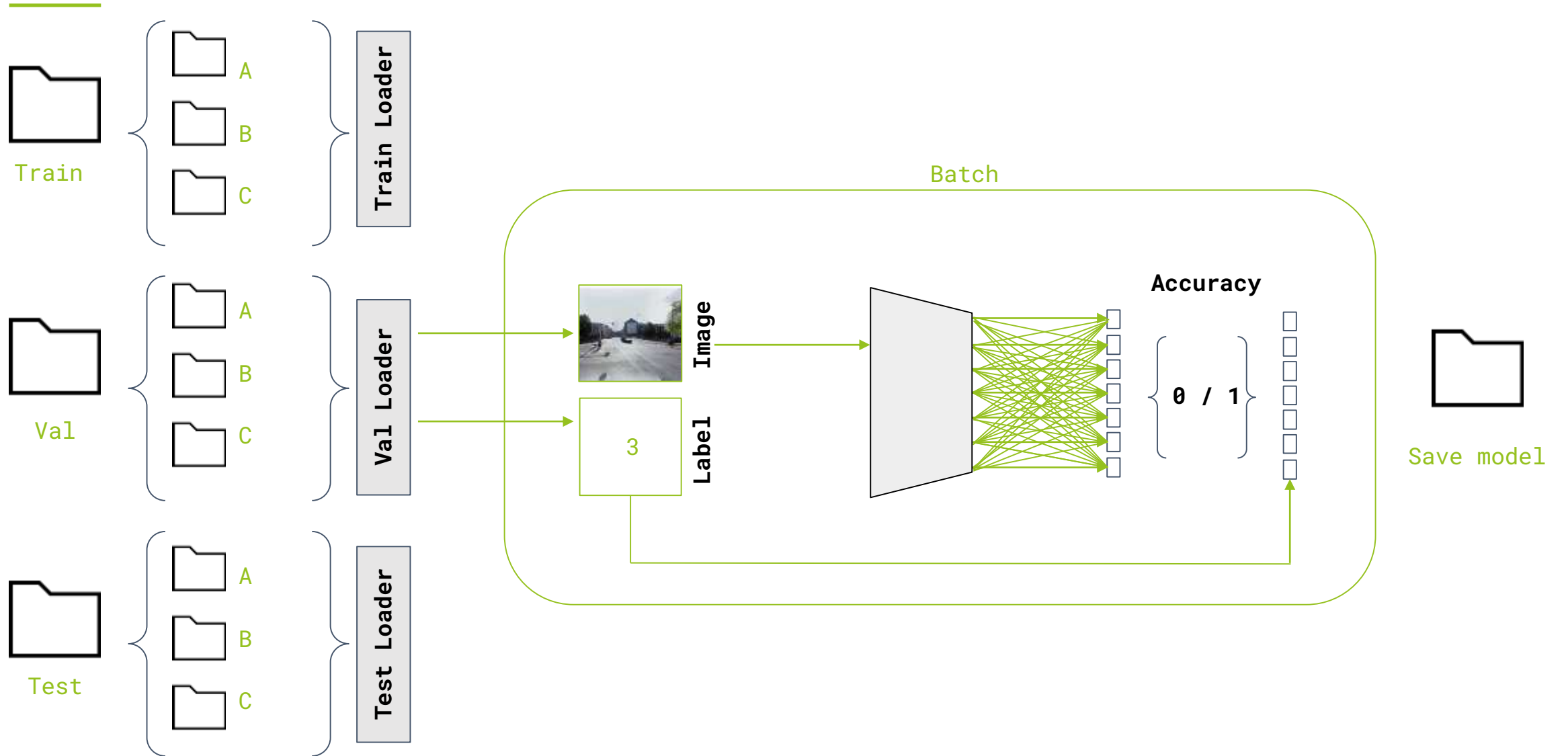
Training Workflow



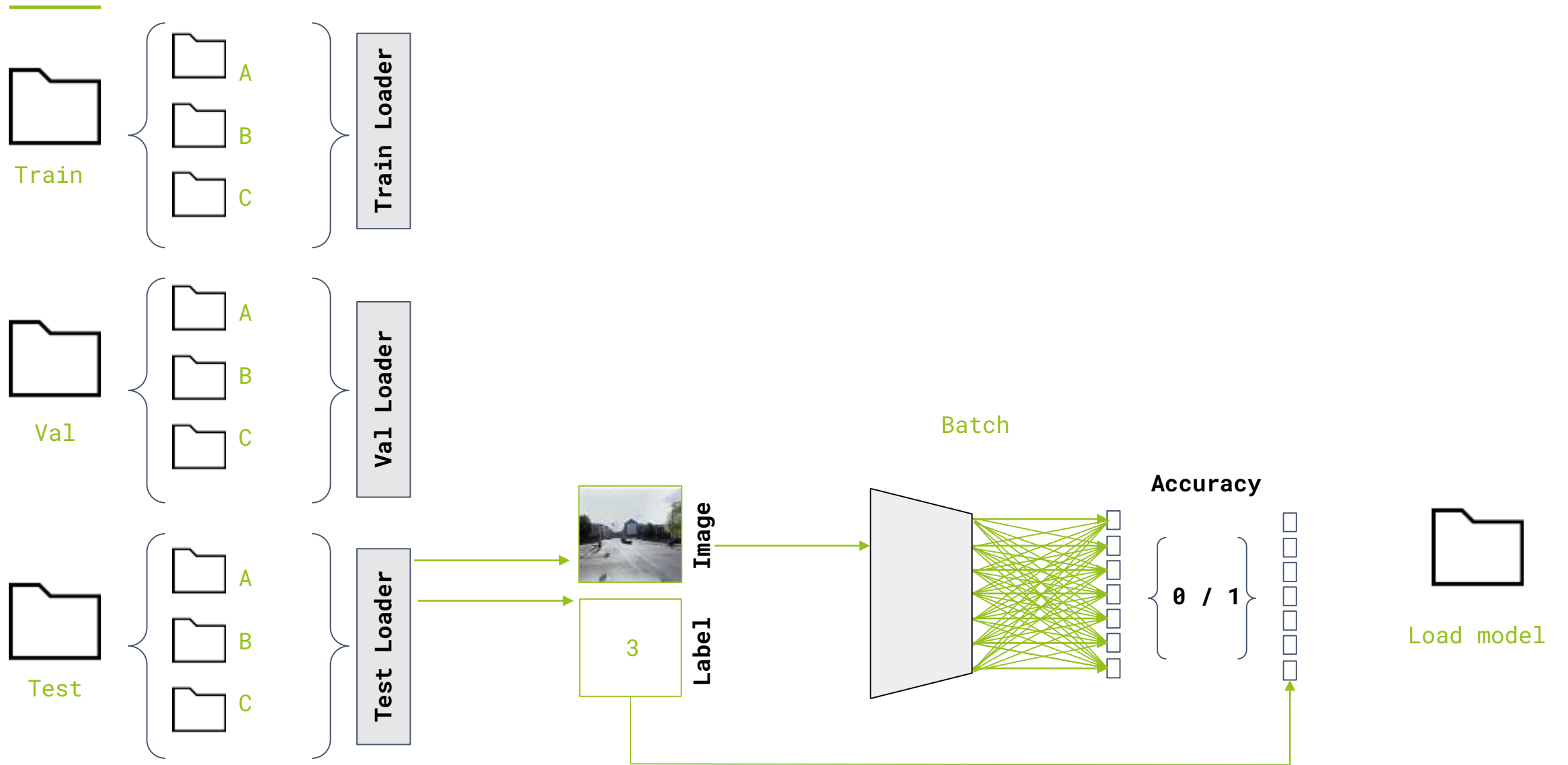
Training Workflow



Training Workflow



Training Workflow



Demo 1:Classifier

Go to [Google Drive](#) and Open `Demo 1.ipynb`

Demo 2: Image-to-Image Networks

- Architecture**

- Input and output are both images
- Produced image compared to target image pixel-by-pixel
- Has a narrow 'bottleneck' layer to encourage extraction of most important features

- Applications**

- Style transfer
- Denoising
- Image abstraction
- Produce segmentations, masks

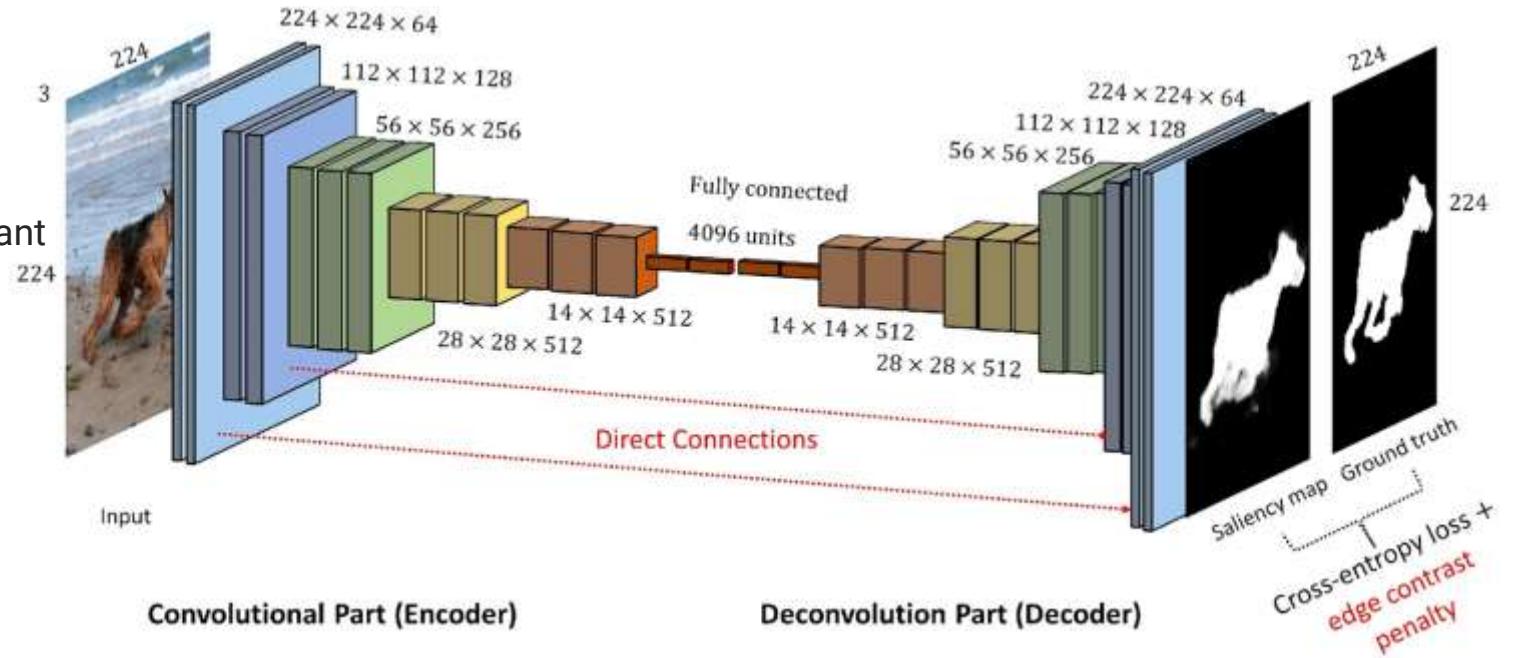
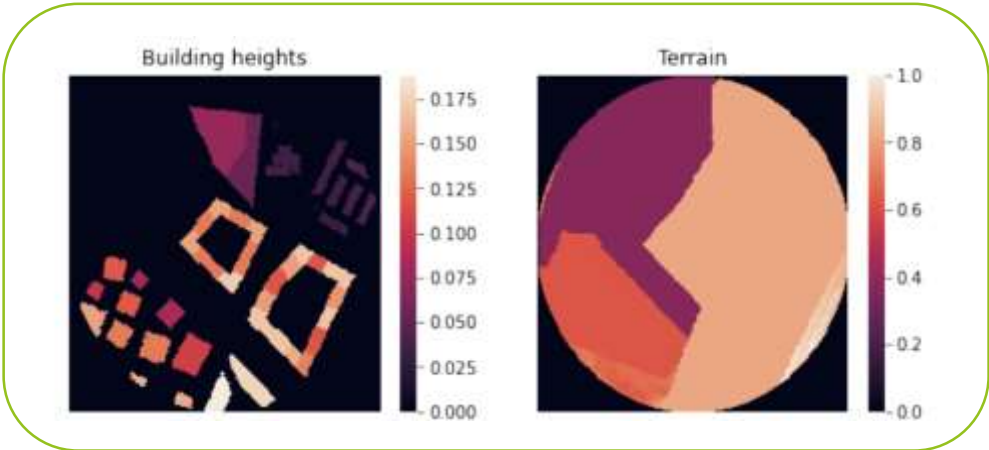
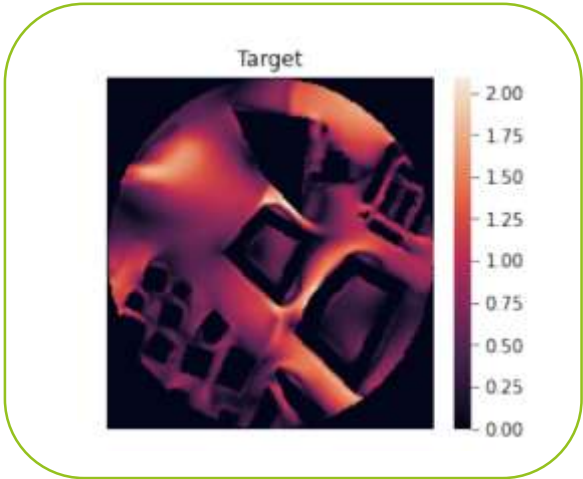


Image-to-Image Networks: Wind Heatmaps

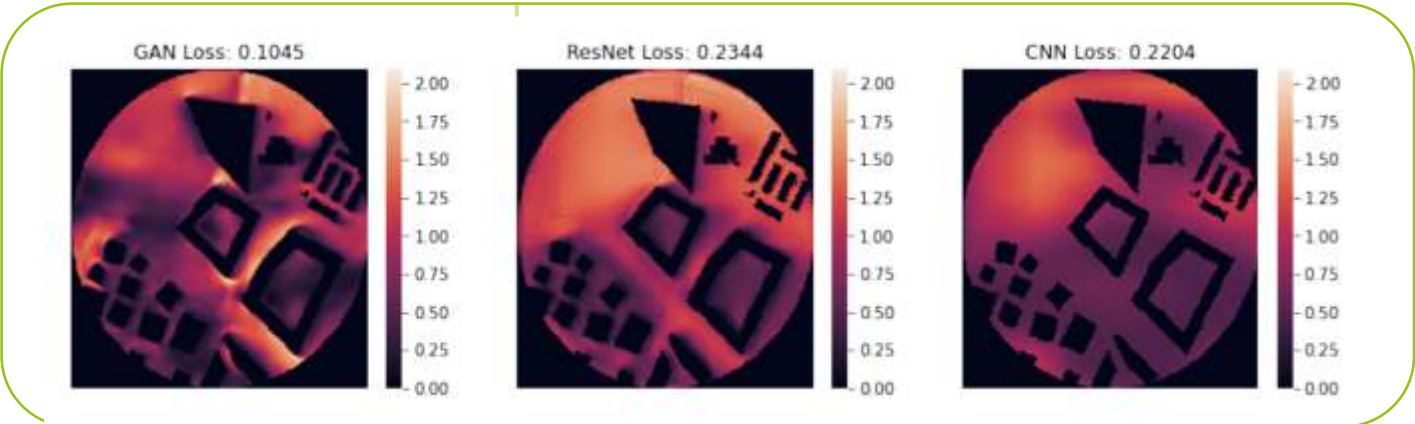
Input



Target



Network Outputs



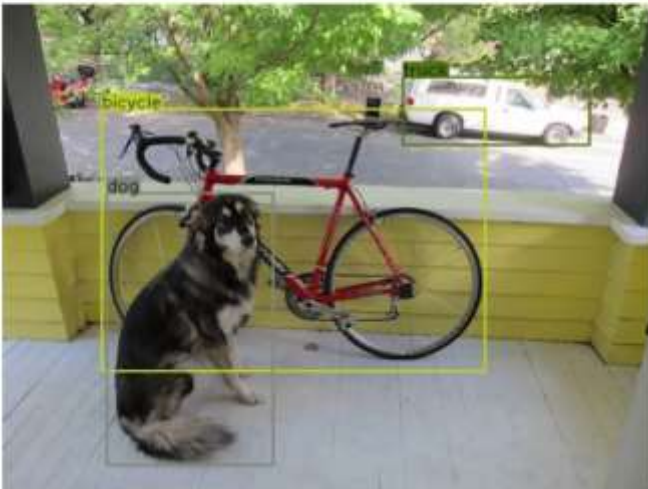
Demo 2:Image->Image

Go to [Google Drive](#) and Open `Demo 2.ipynb`

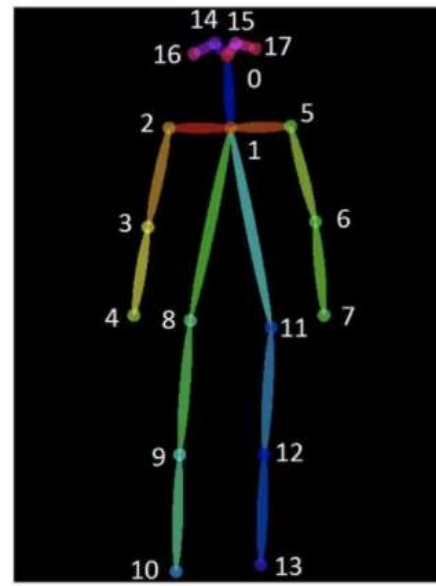
Demo 3: Object Detection

- **COCO Dataset**
 - 330 000 images
 - 91 object categories
 - 250 000 people

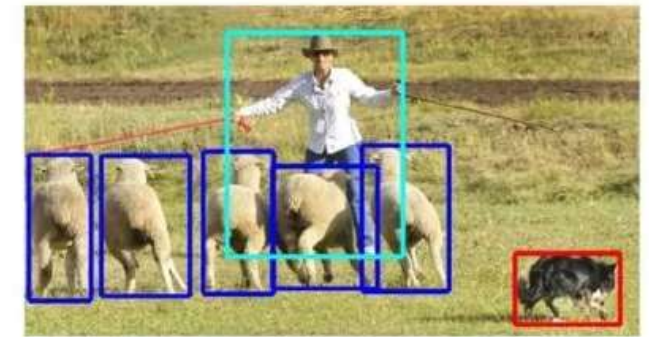
```
'person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train', 'truck',  
'boat', 'traffic light', 'fire hydrant', 'stop sign', 'parking meter', 'bench',  
'bird', 'cat', 'dog', 'horse', 'sheep', 'cow', 'elephant', 'bear', 'zebra',  
'giraffe', 'backpack', 'umbrella', 'handbag', 'tie', 'suitcase', 'frisbee',  
'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat', 'baseball glove',  
'skateboard', 'surfboard', 'tennis racket', 'bottle', 'wine glass', 'cup', 'fork',  
'knife', 'spoon', 'bowl', 'banana', 'apple', 'sandwich', 'orange', 'broccoli',  
'carrot', 'hot dog', 'pizza', 'donut', 'cake', 'chair', 'couch', 'potted plant',  
'bed', 'dining table', 'toilet', 'tv', 'laptop', 'mouse', 'remote', 'keyboard',  
'cell phone', 'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'book',  
'clock', 'vase', 'television', 'teddy bear', 'hair drier', 'toothbrush'
```



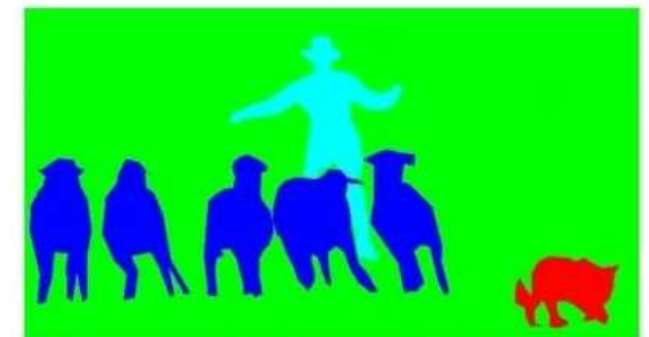
```
"nose", "left_eye", "right_eye", "left_ear", "right_ear", "left_shoulder",  
"right_shoulder", "left_elbow", "right_elbow", "left_wrist", "right_wrist",  
"left_hip", "right_hip", "left_knee", "right_knee", "left_ankle", "right_ankle"
```



1) Image Classification



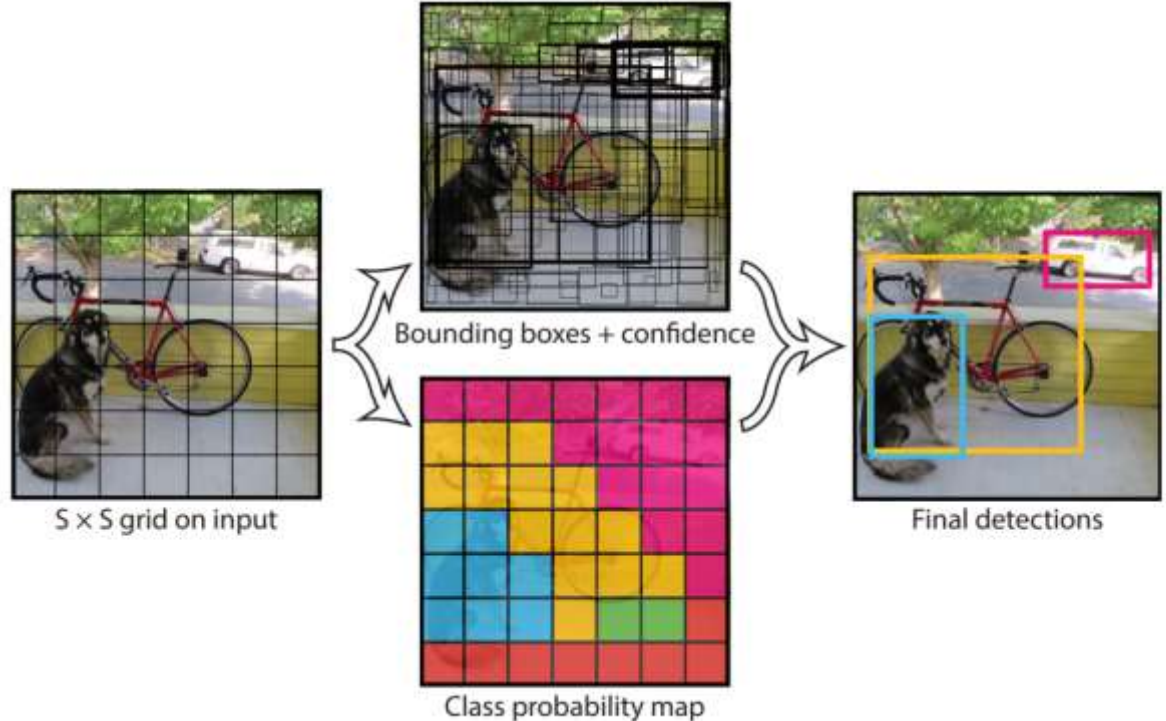
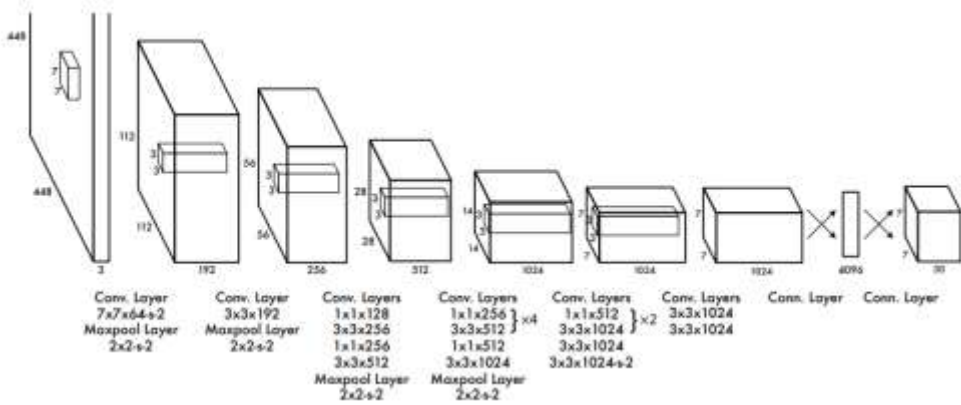
2) Object Localization



3) Semantic Segmentation

Demo 3: Object Detection

- YOLO – ‘You Only Look Once’**
 Convolutional Neural Network
 Input: 224x224 image
 Output: 7x7x30 tensor

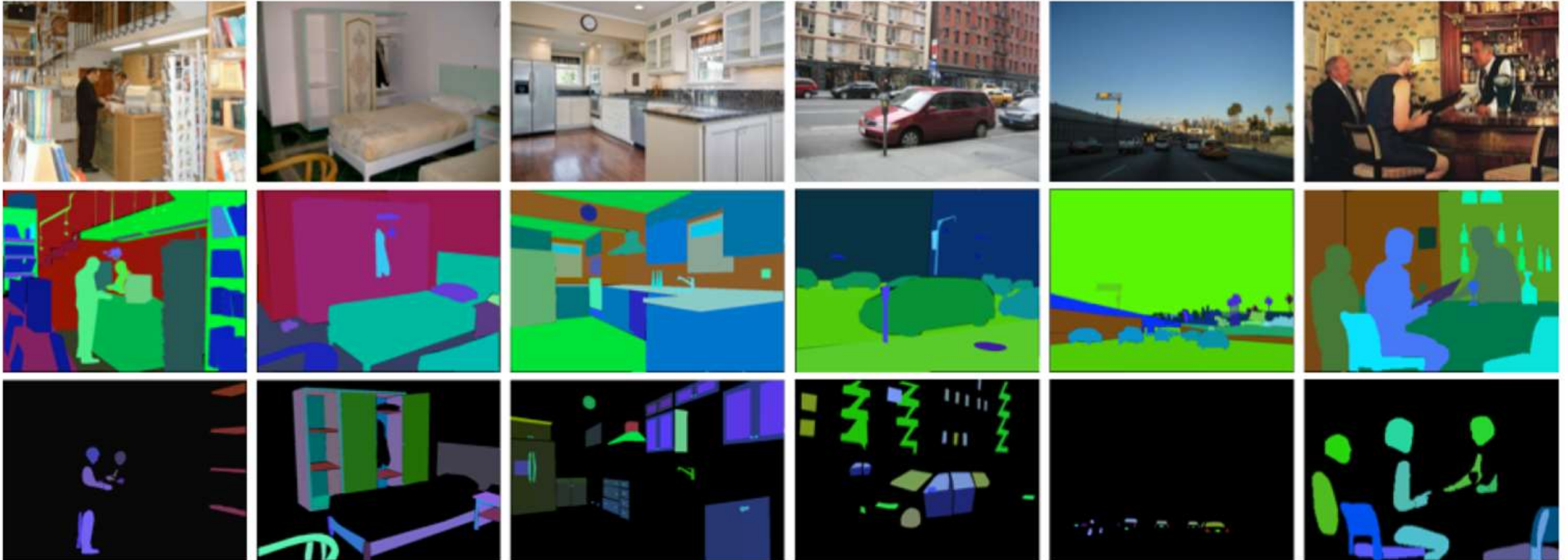


Demo 3: Detection

Go to [Google Drive](#) and Open `Demo 3.ipynb`

Demo 4: Image Segmentation

- **ADE20k Dataset**
 - 27 000 Images, 3000 Object Categories, 150 Semantic categories, 193,238 annotated objects, polygon annotations
 - By MIT CSAIL



Demo 4: Segmentation

Go to [Google Drive](#) and Open `Demo 4.ipynb`

In-Class assignment

`GSV Downloading and Image Segmentation`

In-class Practice

(In Google CoLab)

1. **Download GSV** of a small area (or use images from the last GSV downloading assignment);
2. Using **image segmentation** to process these images, show the data structure of the mask of one image sample;
3. Calculate the ratios of some objects (tree, cars, etc.), and **aggregate the results from all images** together. The final results could be, for example, the greenery ratio of all images of Mass. Ave., Cambridge.