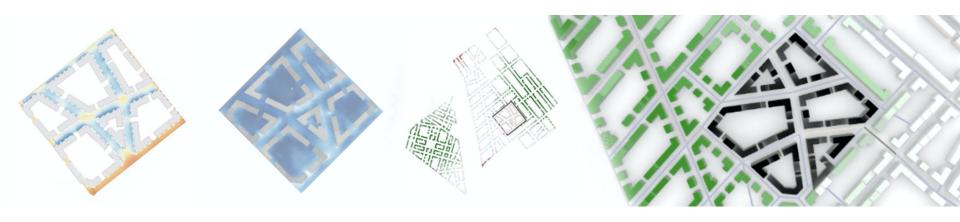
#### Artificial Intelligence for resilient urban planning





#### Day 2 (Mon 29th)

<u>Aa</u> Name	Room	Time (GMT)	■ Description
Talk: Intro	Webinar	10:00 - 10:05	Recap + today's schedule
Talk: Intro to Computer Vision	Webinar	10:05 - 10:20	How do computers make sense out of images using convolutional neural networks?
Demo: Semantic Segmentation	Webinar	10:20 - 10:35	Introduction to semantic segmentation in Colab and how to use it on your own images
Demo: Style Transfer	Webinar	10:35 - 10:50	Introduction to style transfer in Colab and how to use it on your own images
Demo: pix2pix in GH	Webinar	10;50 - 11:20	Introduction of the pix2pix model and demo on how to integrate it into GH workflow
Demo: DQL in GH	Webinar	11:20 - 11:50	Introduction of the DQL model and demo on how to integrate it into GH workflow
Talk: Summary	Webinar	11:50 - 12:00	Overview and summary of models
Break	break	12:00 - 12:15	
Exercise: Project Work	Meeting	12:15 - 13:30	In breakout rooms with advisory supervision
Presentation: Refined Pitches	Webinar	13:30 - 14:00	Update presentation from groups



Convolutional Neural Networks and how computers see images



#### Convolutional Neural Networks and how computers see images

Generative Adversarial Networks (GAN)
Pix2pix

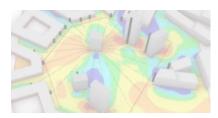
Generates new images based on an input image



Reinforcement learning (RL)

Deep-Q-learning

Trains a decision making and strategy developing agent



Convolutional Neural Networks (CNN)

Mask R-CNN model

Finds and labels objects in images



Generative Adversarial Networks (GAN)

#### Style Transfer

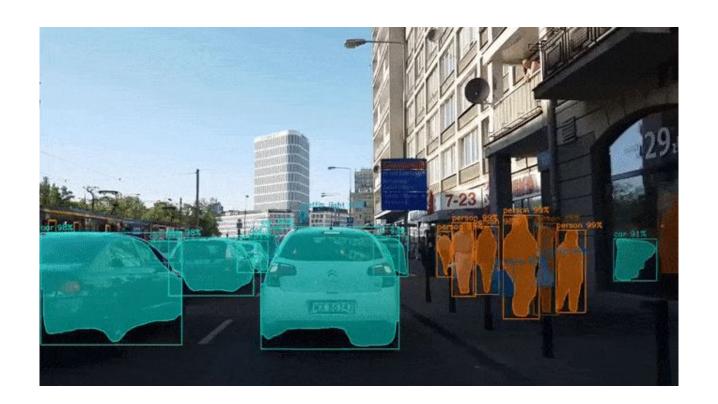
Changes the look of images based on a reference image







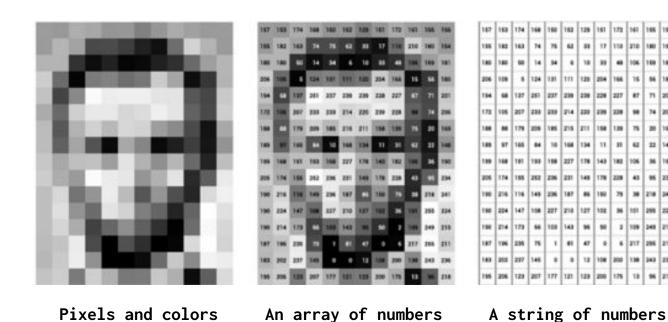
#### Convolutional Neural Networks and how computers see images



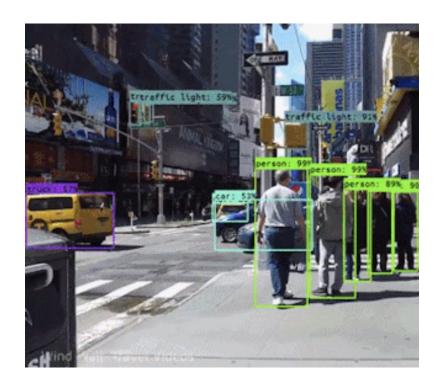


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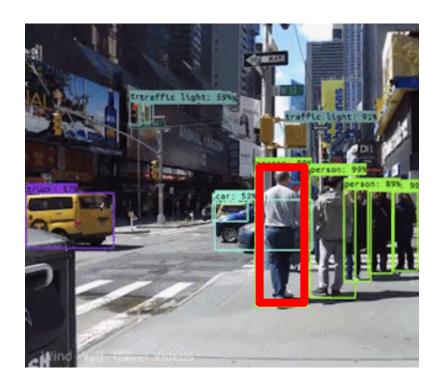




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172	106	207	213	299	214	220	239	228	*	74	204
188	**	179	219	185	215	211	158	139	75	20	169
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199	168	191	198	158	227	176	143	182	106	36	190
204	174	195	545	236	211	148	178	228	43	96	234
190	216	116	149	296	187	*	190	29	38	218	241
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196	206	129	207	177	125	129	200	125	18	96	218

A string of numbers





147	153	174	168	158	162	129	161	122	141	196	196
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199	168	181	198	198	227	176	143	182	106	36	190
206	174	195	545	236	211	148	178	228	43	96	234
190	216	116	149	296	187	*	190	29	38	218	241
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A string of numbers

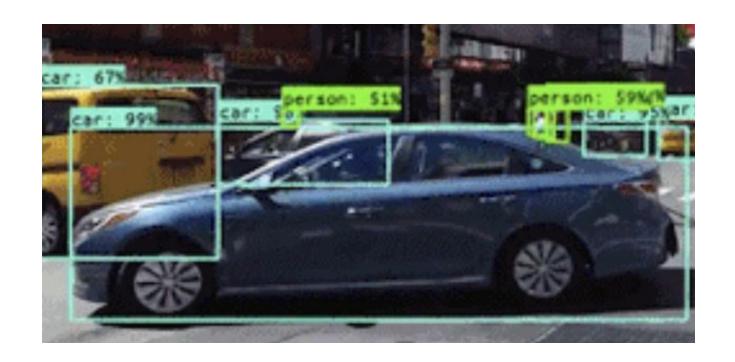




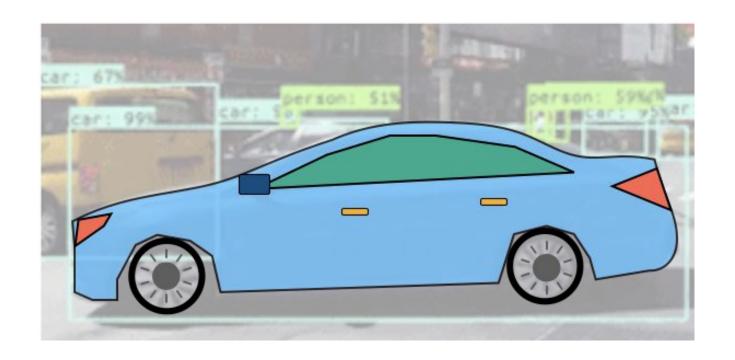
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172	106	207	213	299	214	229	239	238	*	74	204
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A string of numbers

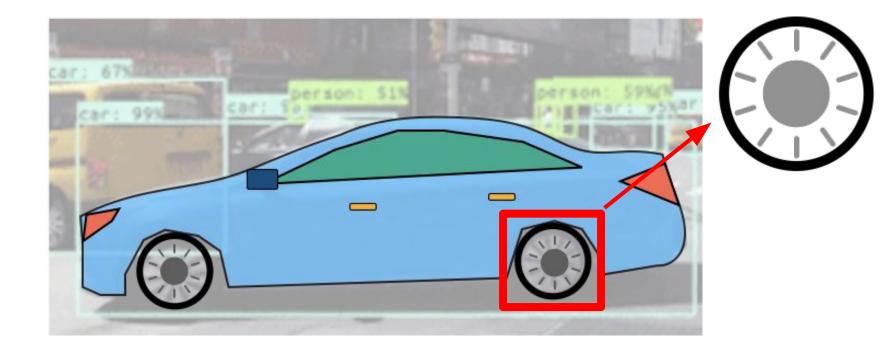




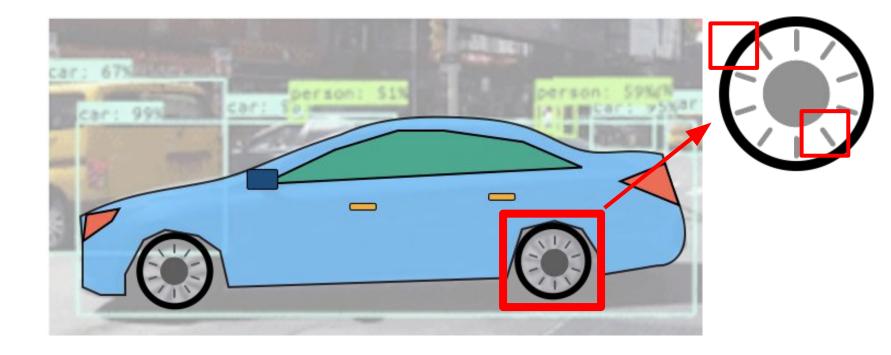




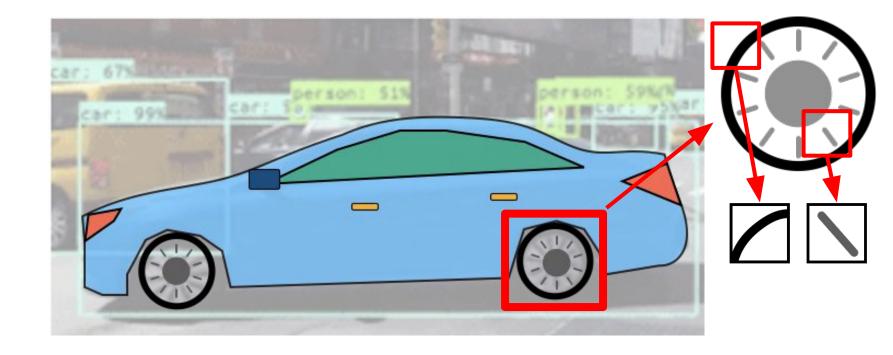




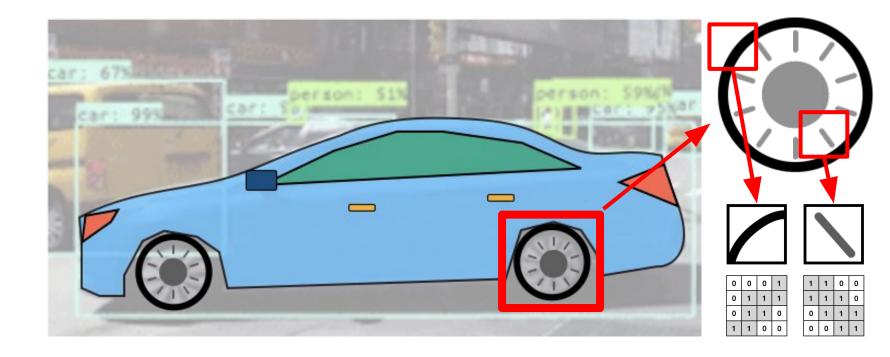




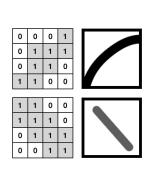


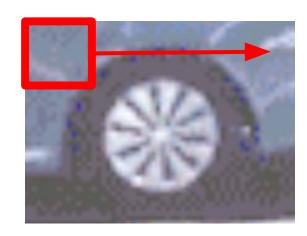




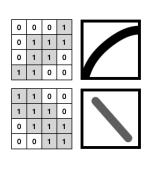


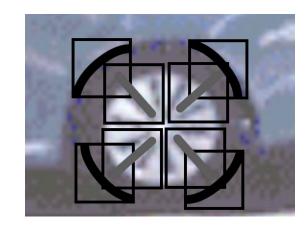




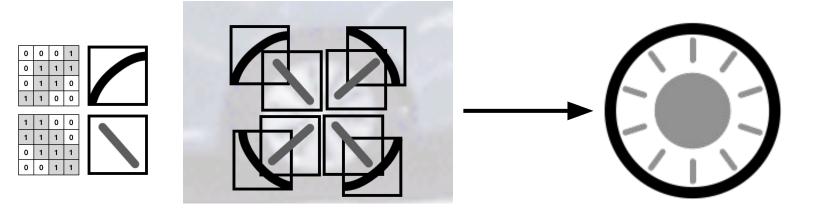






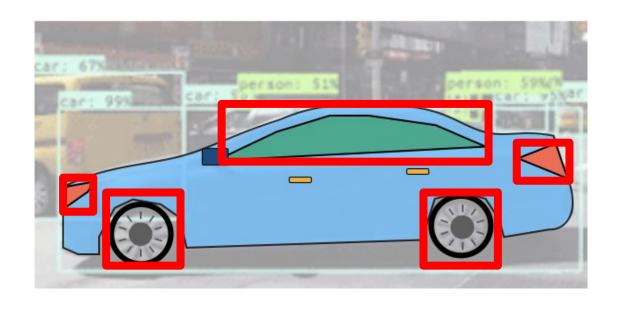






This is probably a wheel

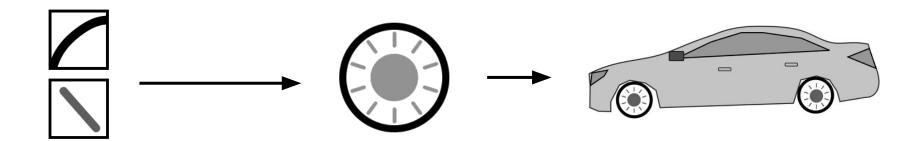




Two wheels, door handles, carrosserie, windows, lights

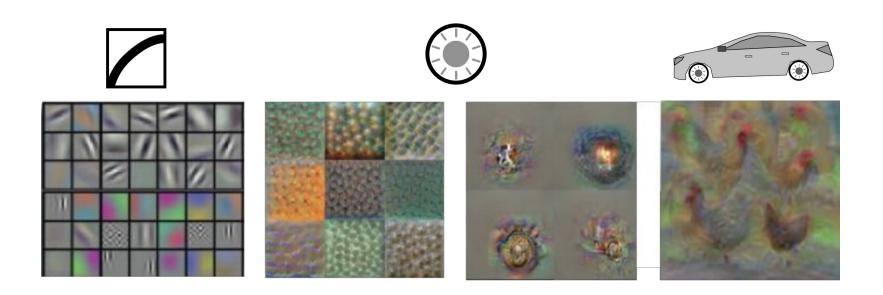






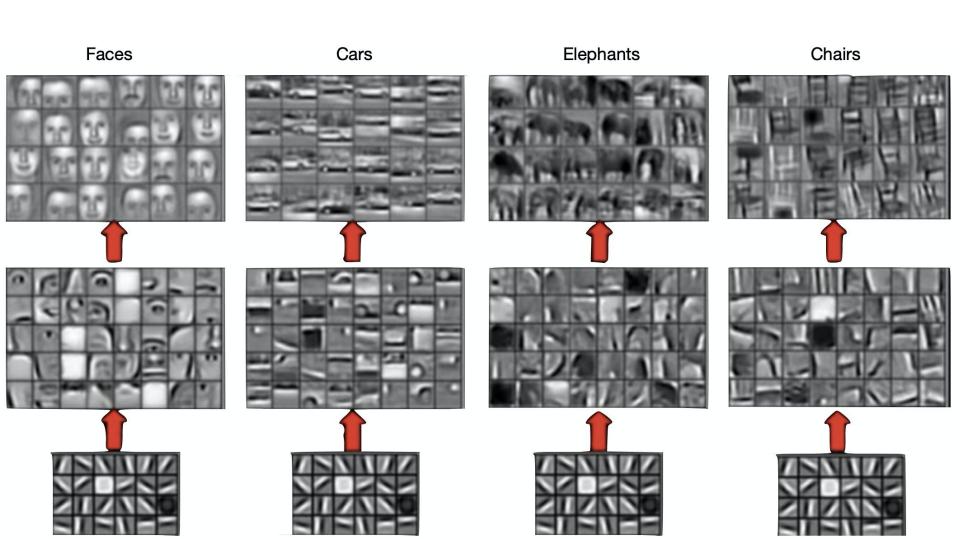
Simple elements \_\_\_\_\_ Complex objects

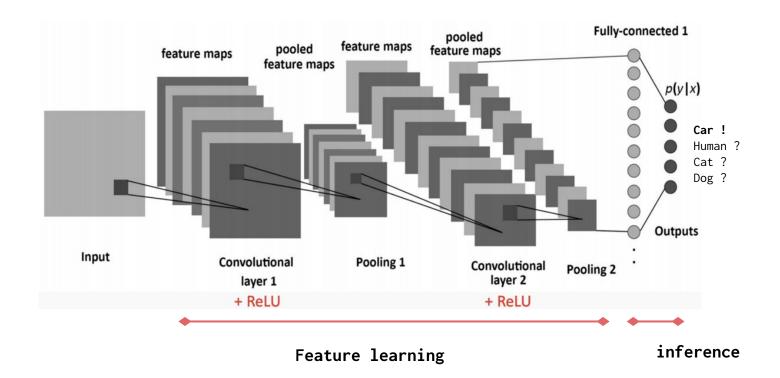




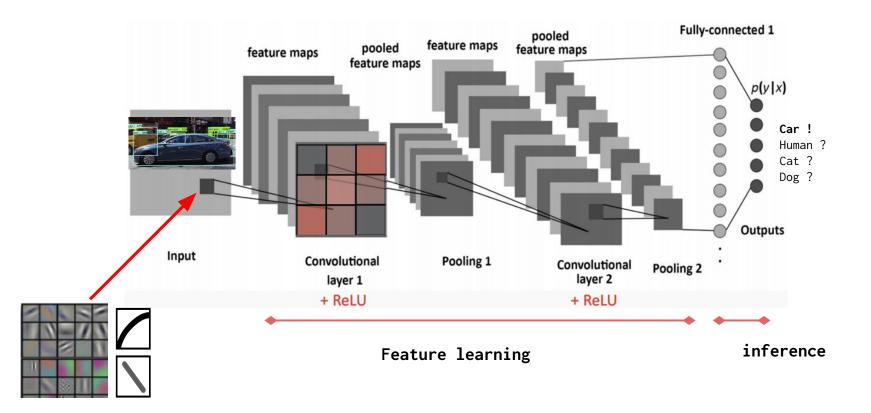
Simple elements \_\_\_\_\_ Complex objects



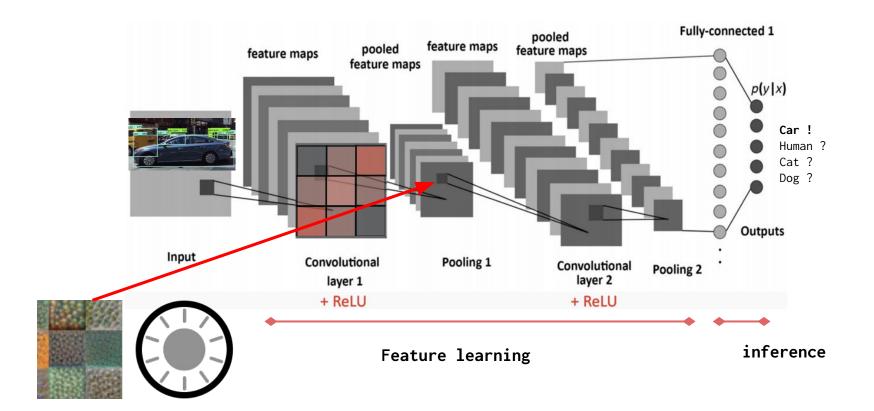




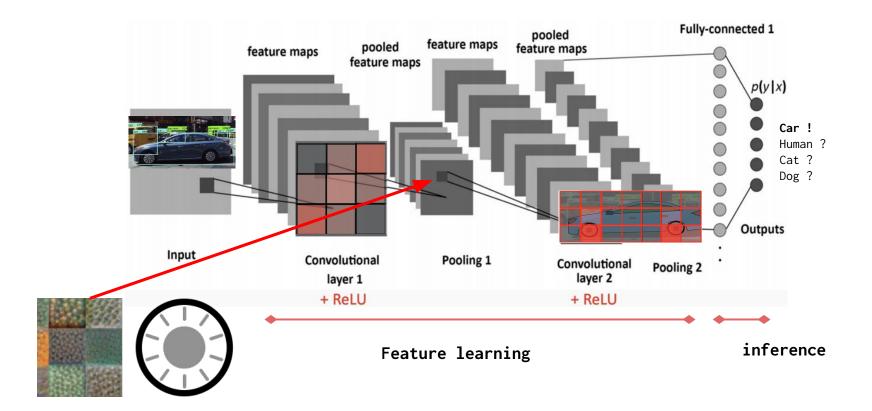














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0	1

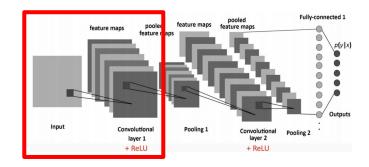
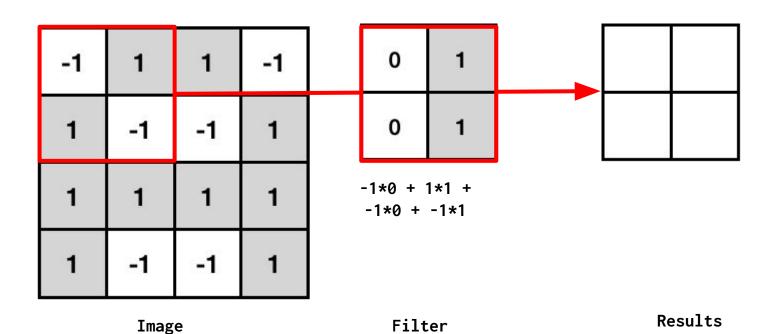
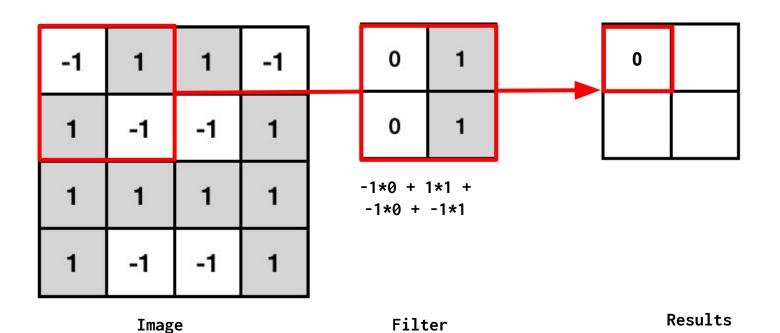


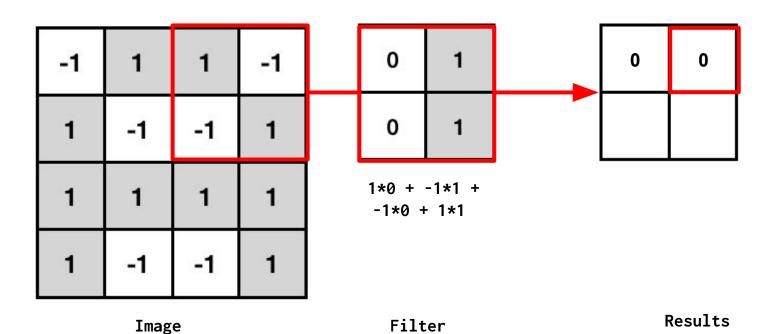
Image Filter



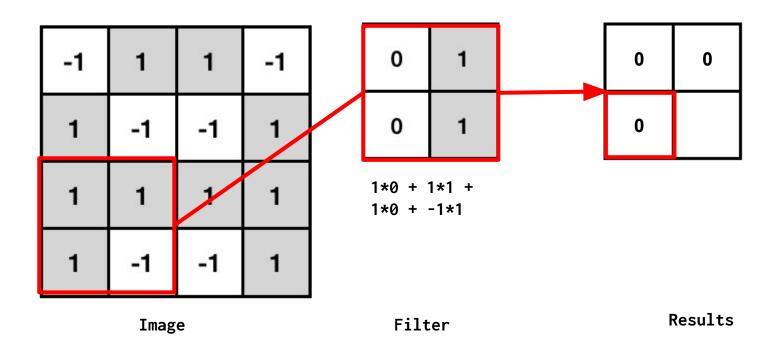


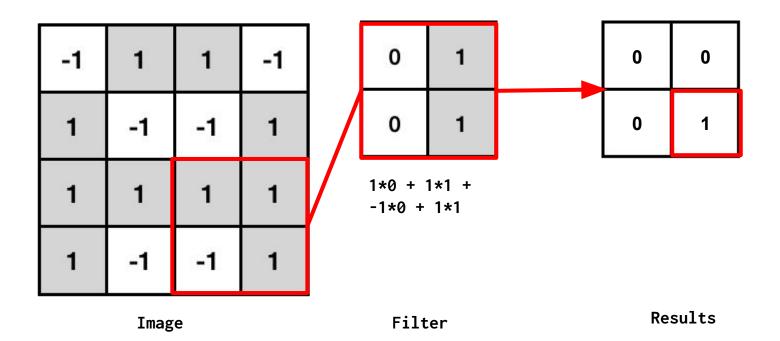
CILITY

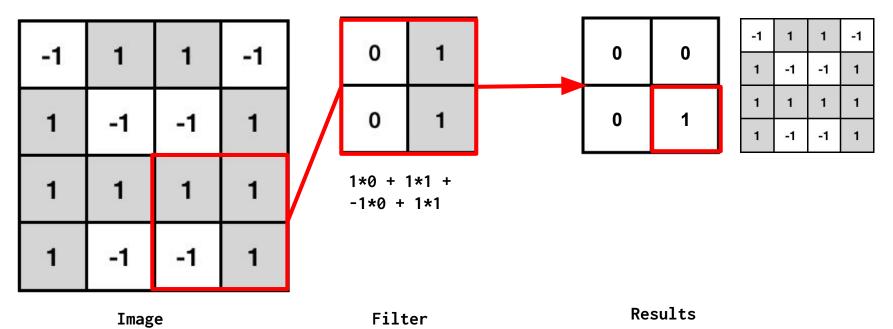




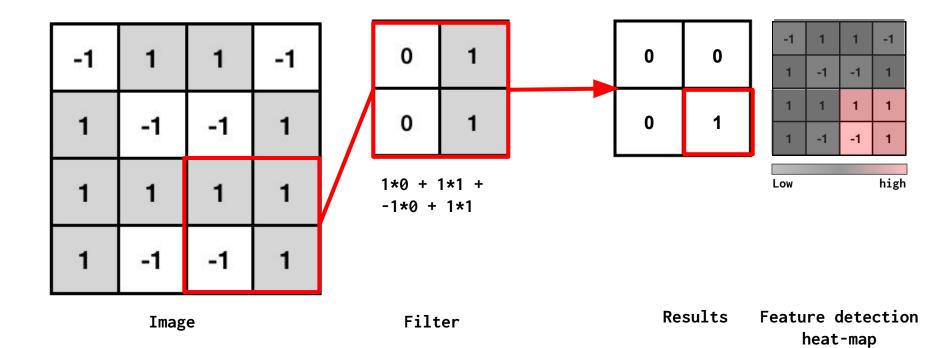
CILITY

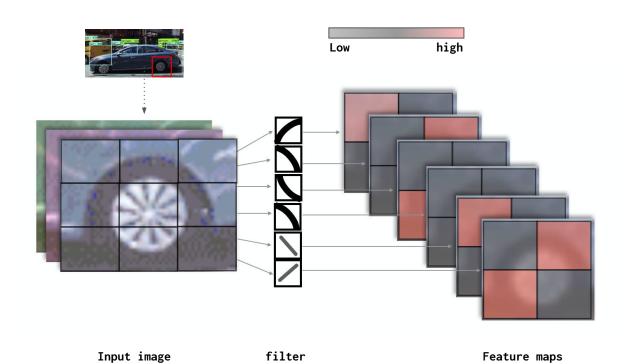




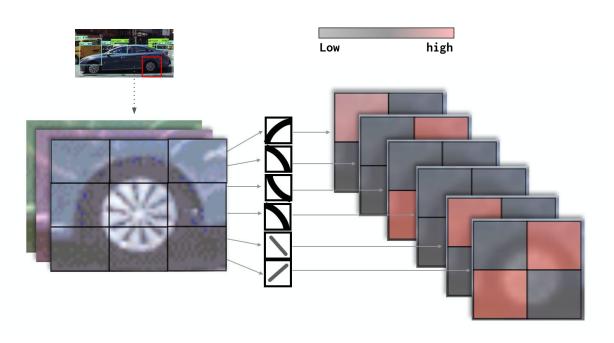














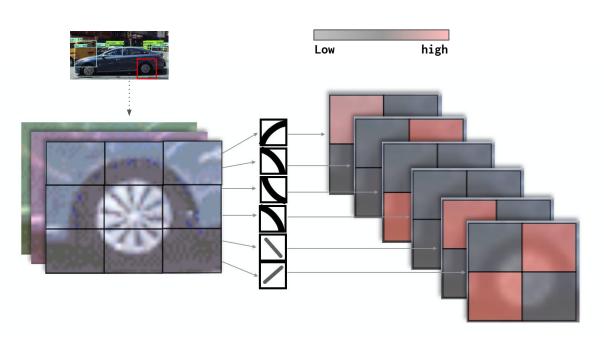
Input image

filter

Feature maps

Feature map activations visualized

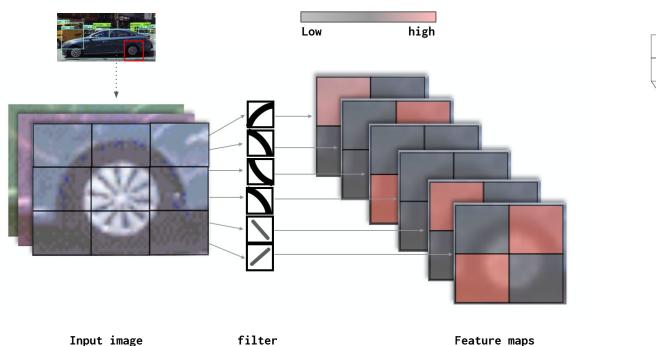


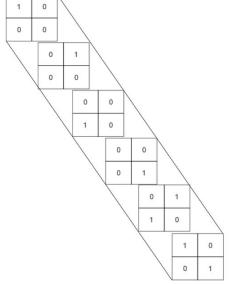




Input image filter Feature maps Looks like a wheel!

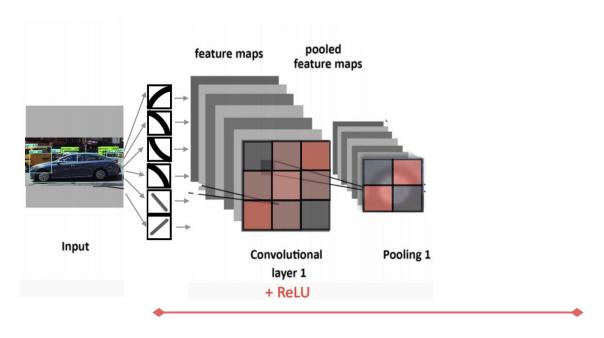






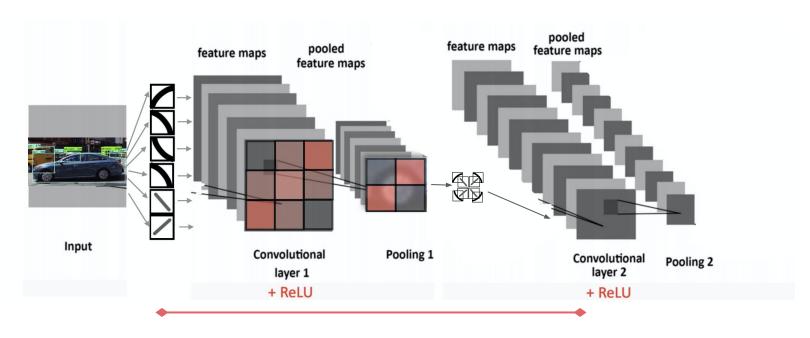
New filter

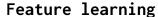
Feature maps



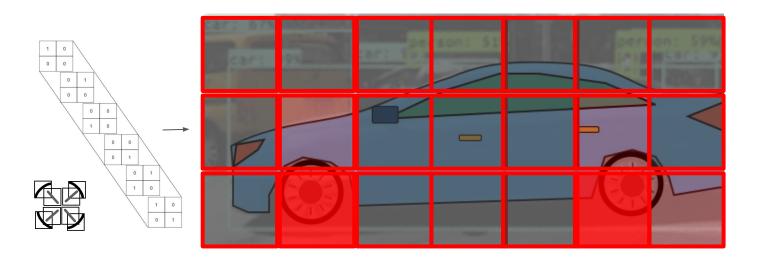
Feature learning





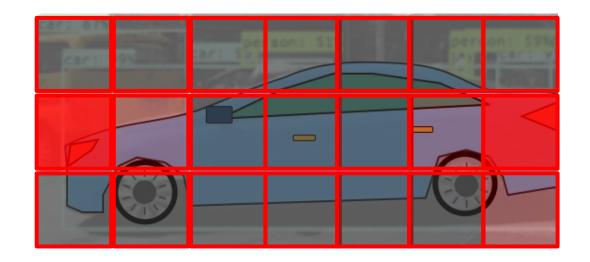






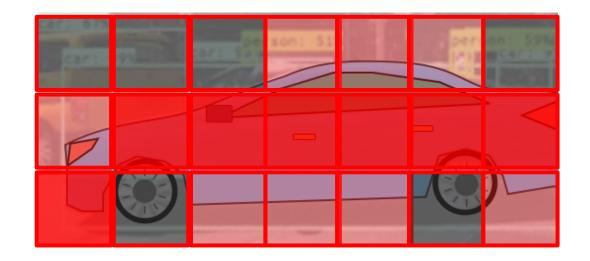
Feature map: Wheels





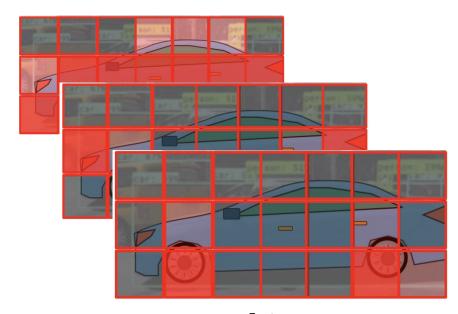
Feature map: lights





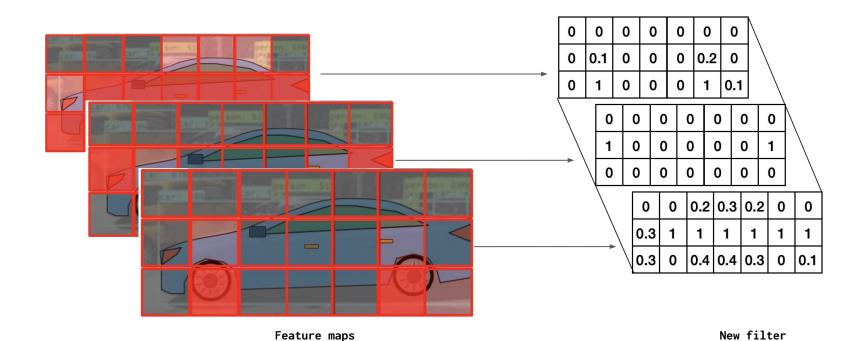
Feature map: body





Feature maps







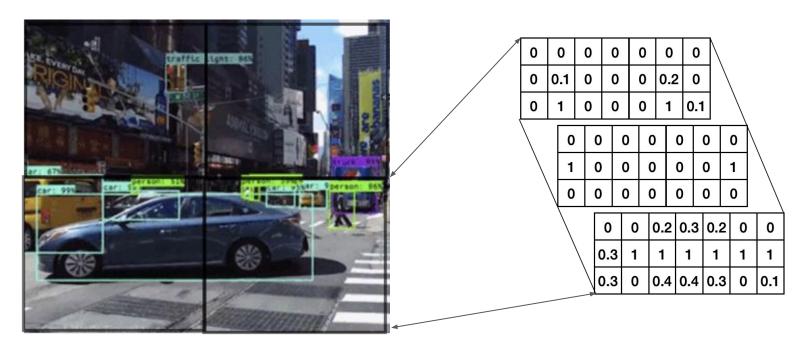
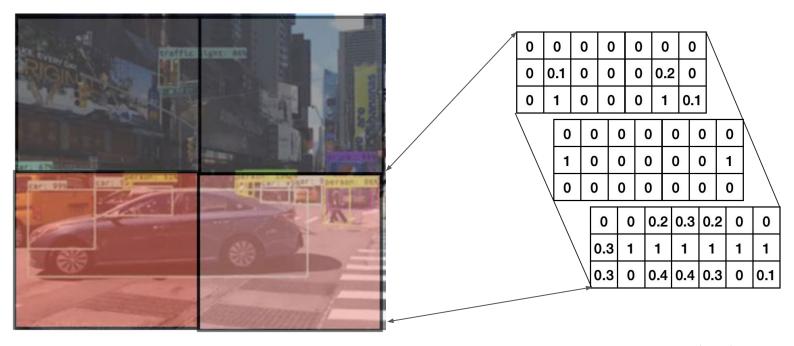


image Filter (cars)

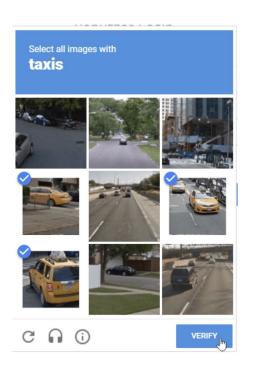




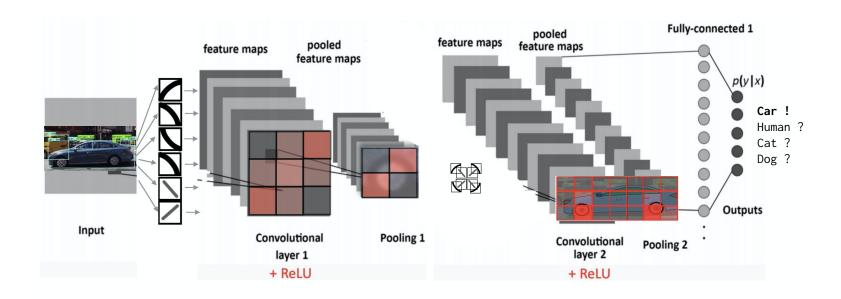
Feature map Filter (cars)





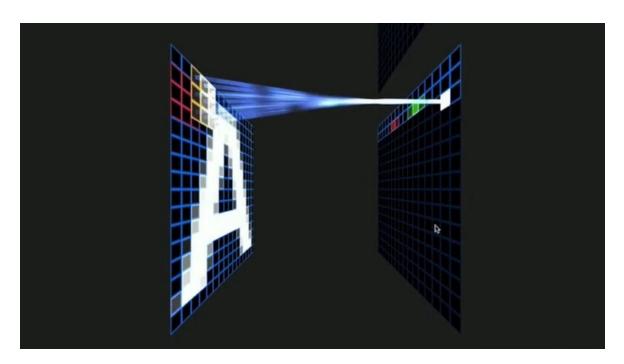


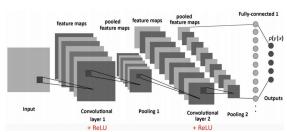






## Convolutional Neural Networks and how computers see images CLASSIFYING A CHARACTER







#### Deep Learning in the Built Environment

Generative models (GAN'S)

Generative Adversarial Networks (GAN)
Pix2pix

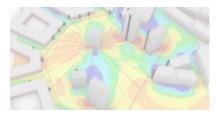
Generates new images based on an input image



Reinforcement learning (RL)

Deep-Q-learning

Trains a decision making and strategy developing agent



Convolutional Neural Networks (CNN)

Mask R-CNN model

Finds and labels objects in images



Generative Adversarial Networks (GAN)

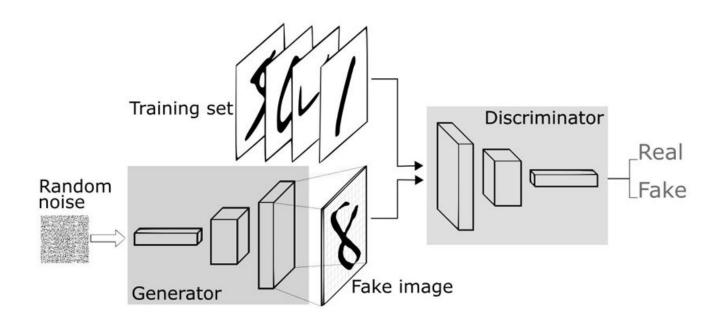
#### Style Transfer

Changes the look of images based on a reference image



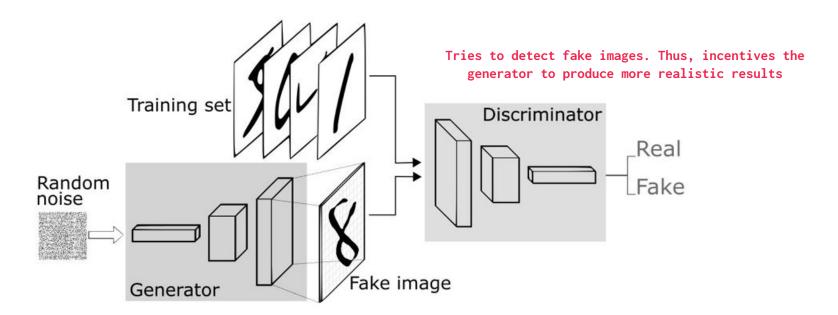


## Deep Learning in the Built Environment Generative models (GAN'S)





## Deep Learning in the Built Environment Generative models (GAN'S)



Tries to fool the discriminator into believing its generated image is true



#### Deep Learning in the Built Environment

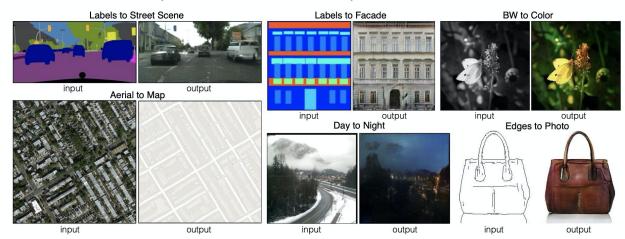
Image to image translation (pix2pix,, 2017)

#### **Image-to-Image Translation with Conditional Adversarial Networks**

Phillip Isola Jun-Yan Zhu Tinghui Zhou Alexei A. Efros

Berkeley AI Research (BAIR) Laboratory, UC Berkeley

{isola, junyanz, tinghuiz, efros}@eecs.berkeley.edu





#### Deep Learning in the Built Environment

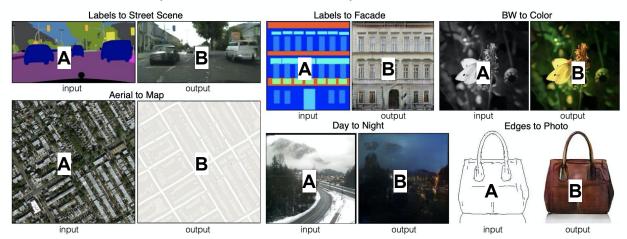
Image to image translation (pix2pix,, 2017)

#### **Image-to-Image Translation with Conditional Adversarial Networks**

Phillip Isola Jun-Yan Zhu Tinghui Zhou Alexei A. Efros

#### Berkeley AI Research (BAIR) Laboratory, UC Berkeley

{isola, junyanz, tinghuiz, efros}@eecs.berkeley.edu



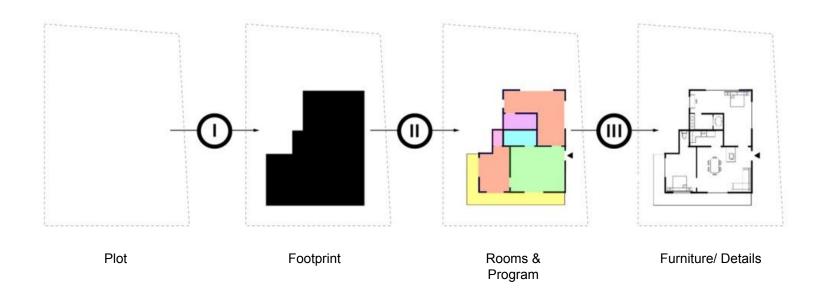
# Image to image translation Generating maps







# Image to image translation Generating floor plans





# Image to image translation Generating Urban Morphologies





## Image to image translation Generating Urban Morphologies

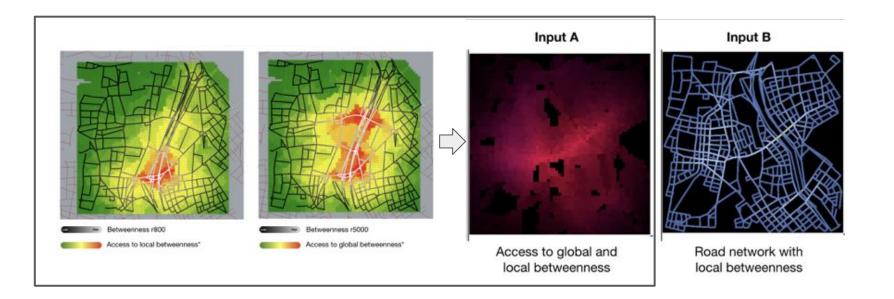




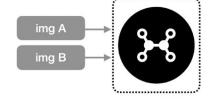
Image to Image
Translation with RHINO
GRASSHOPPER



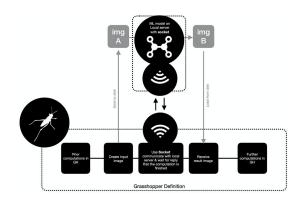
Local deployment with grasshopper



Create Training Data with Grasshopper



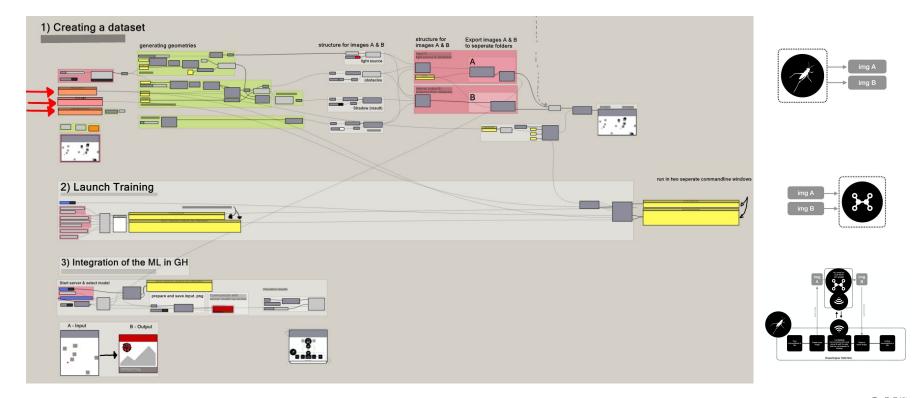
Train Model



Integrate with Grasshopper



#### Local deployment with grasshopper





Example 1: non-physical shadow prediction (or shadow removal)

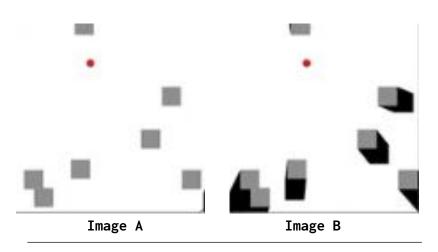


Image pairs for training
 A → B

Goal: Predict the shadows of building based on a light source and obstacles



**Example 2: Plots2Blocks** 



Goal: Train pix2pix to generate building footprints based on a plot shape. It should be able to distinct between different typologies

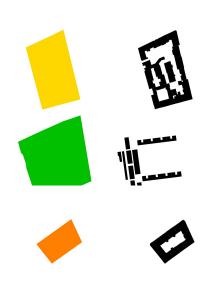


Image A Plots

Image B Building Blocks



#### Demo

