facebook Artificial Intelligence

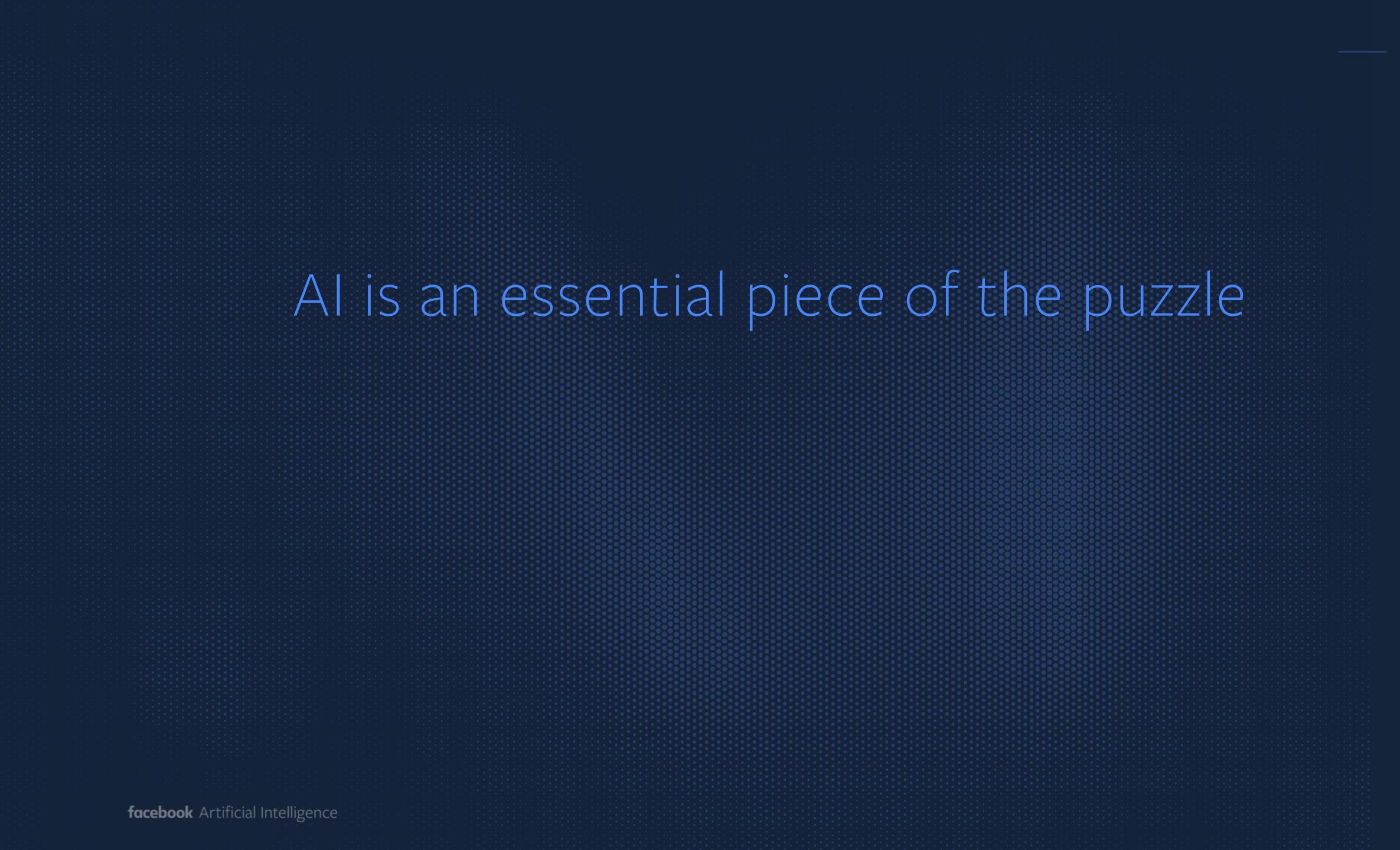
# Computer Vision @ Scale

Manohar Paluri **Director, Facebook Al** 

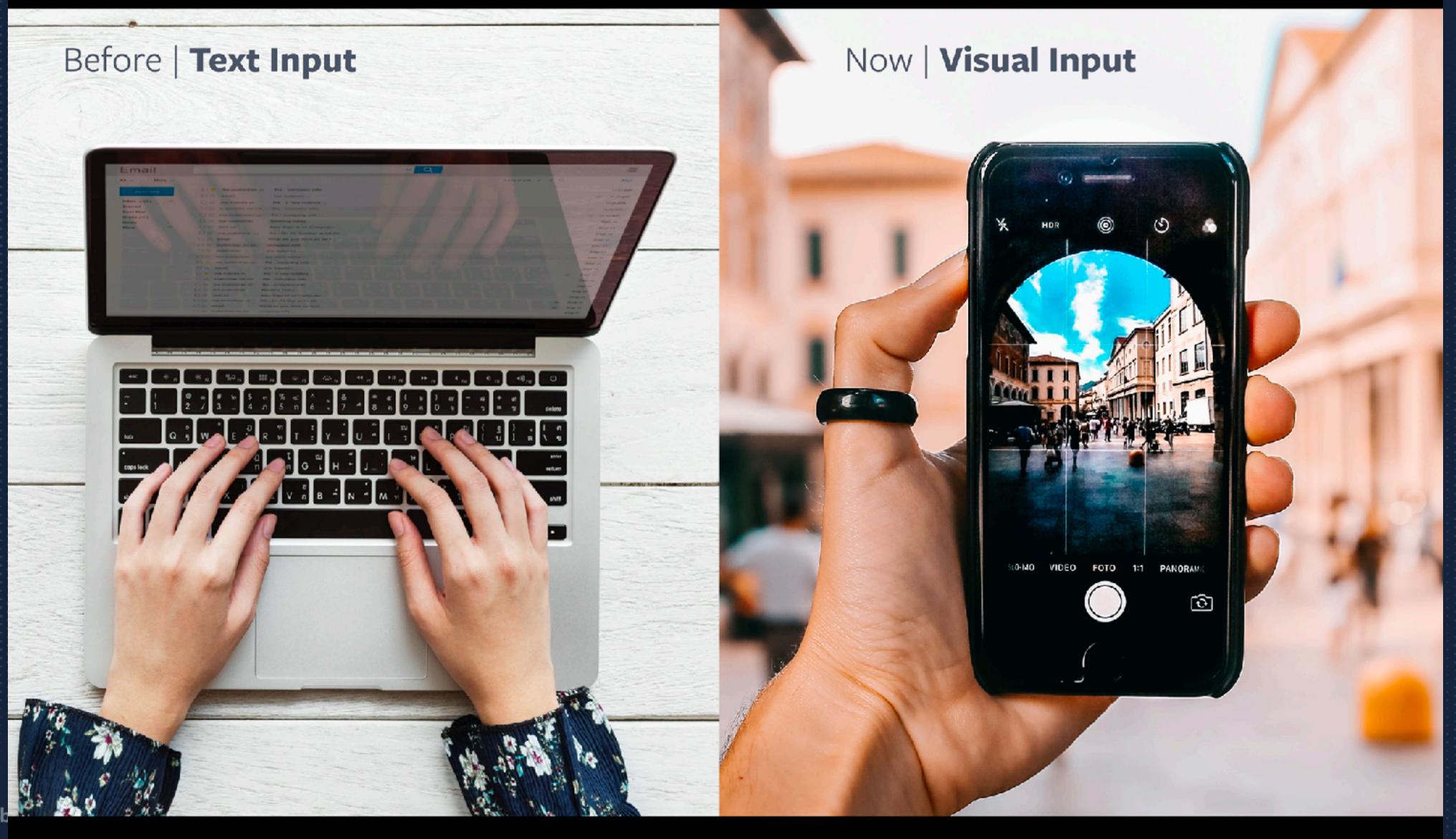


Connecting People to bring them closer together





### And helping machines understand the visual world is an important component!



facel

### What will you learn today?

How do you design a image and video recognition system for billion scale?

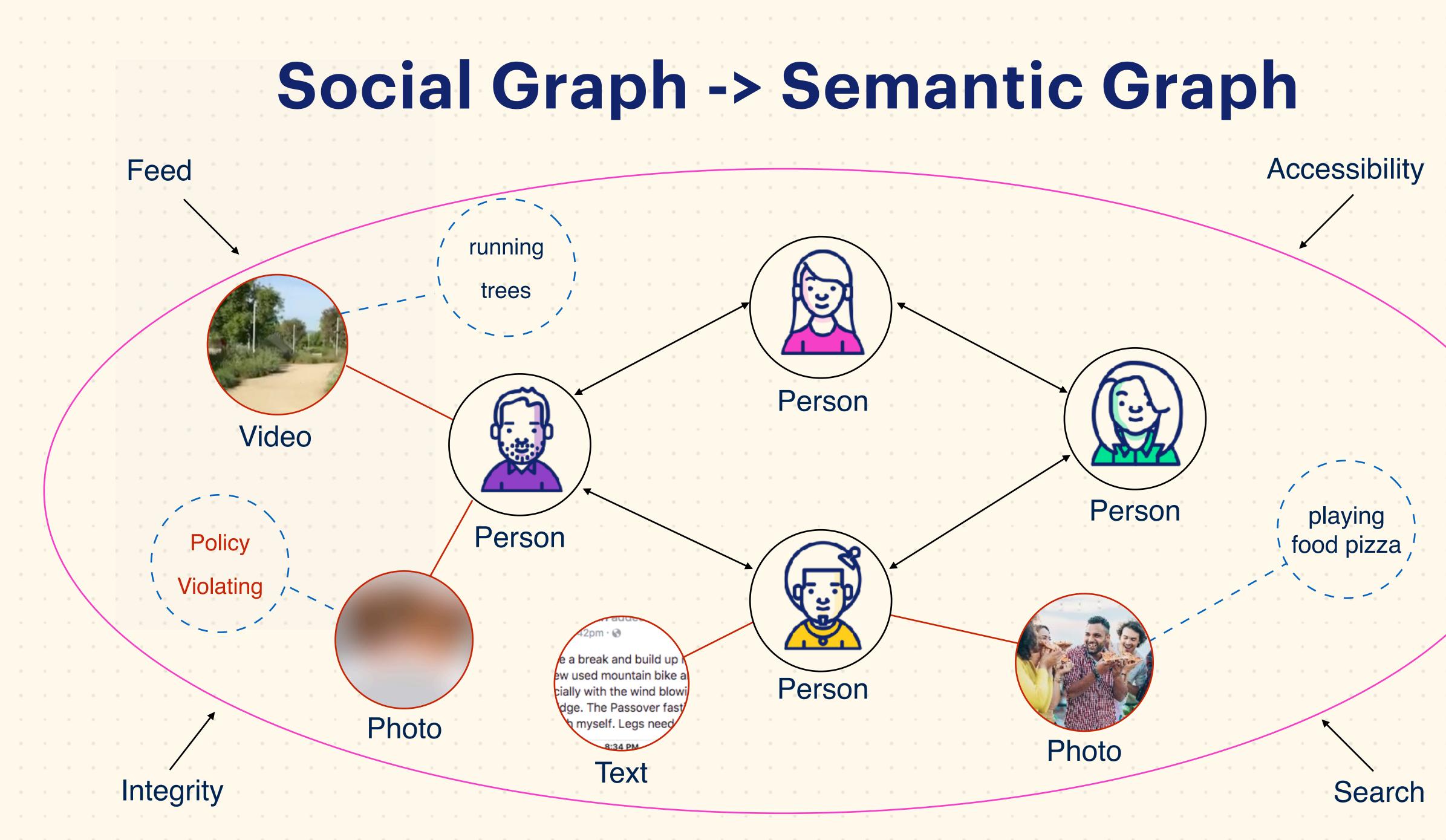
Can you remove the requirement of annotation to learn best representations?

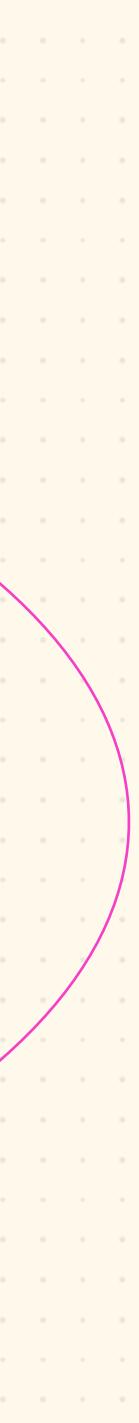
Can we understand video faster than understanding individual frames? How does pushing state of the art in CV make a meaningful difference to

everyone in the world?

facebook Artificial Intelligence







**Vision Models In Production** Multiple vision tasks need to be done Cannot afford one separate model for each task Explosion in computations cost and resources

TASK (T1)

### TRAINING

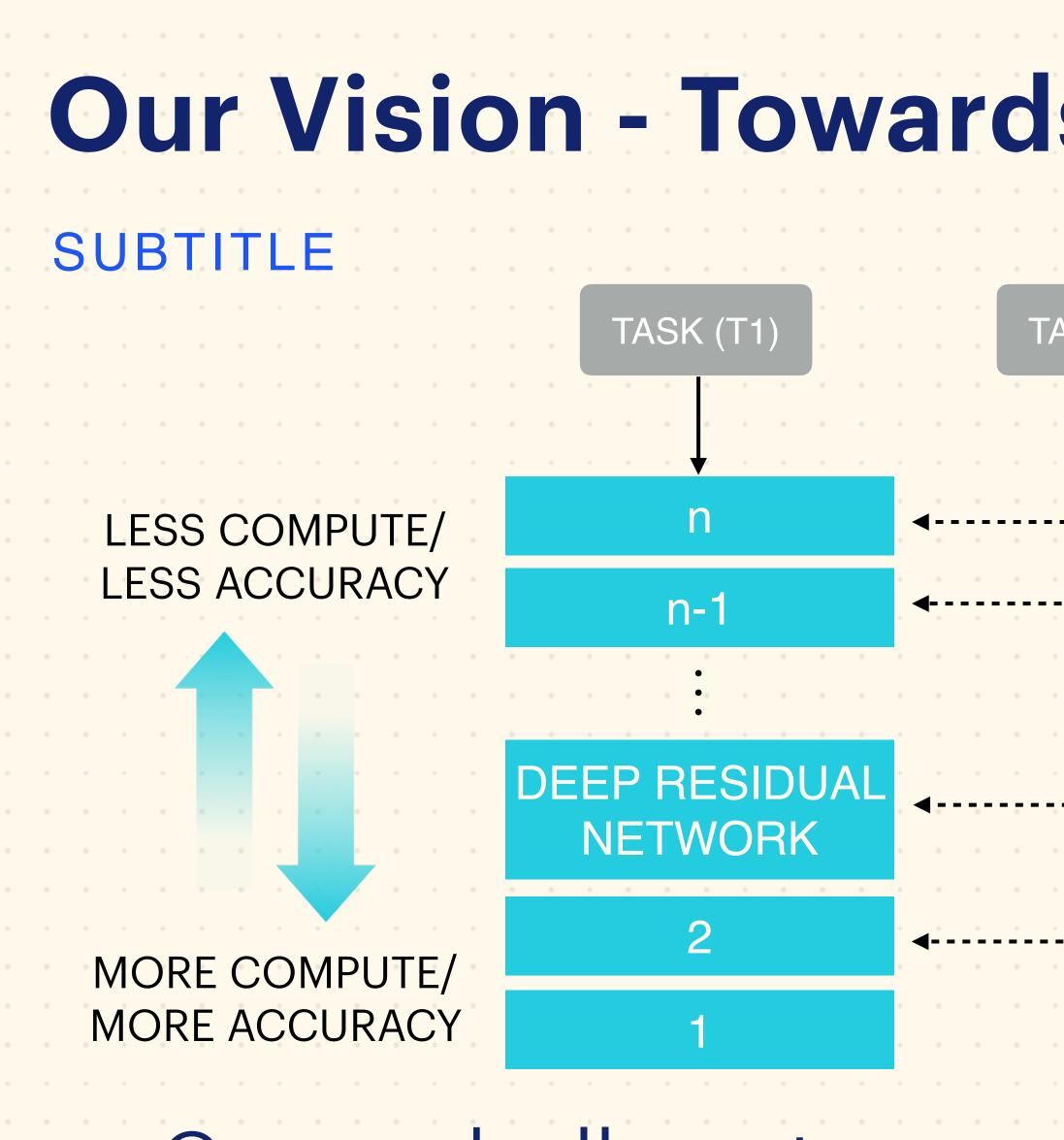
# NETWORK

# NETWORK

TASK





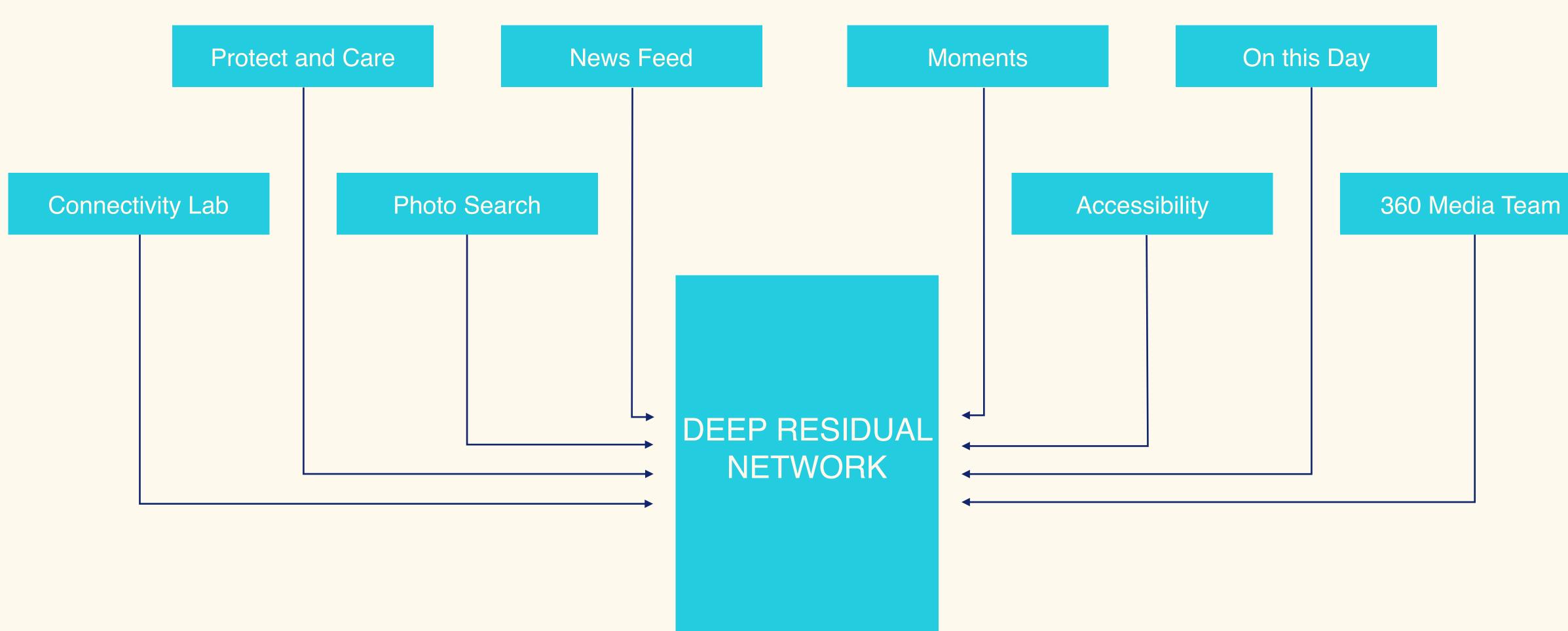


# **Our Vision - Towards Universal Vision Model**

TASK (T2)	TASK (T3)	TASK (T4)	 TASK (TM)
:			

### Our work allows to move the tasks towards upper layers





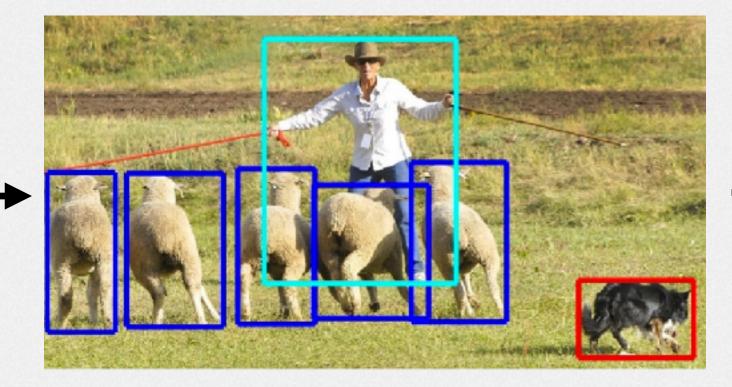


### **Branches**



# **Progress in Image Understanding**



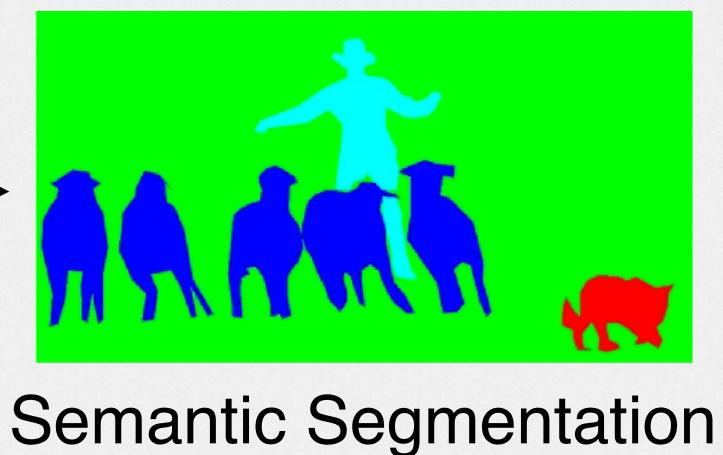


### Classification

### Detection

Relationships Fine grained Aesthetics







### Instance Segmentation

#### Attributes





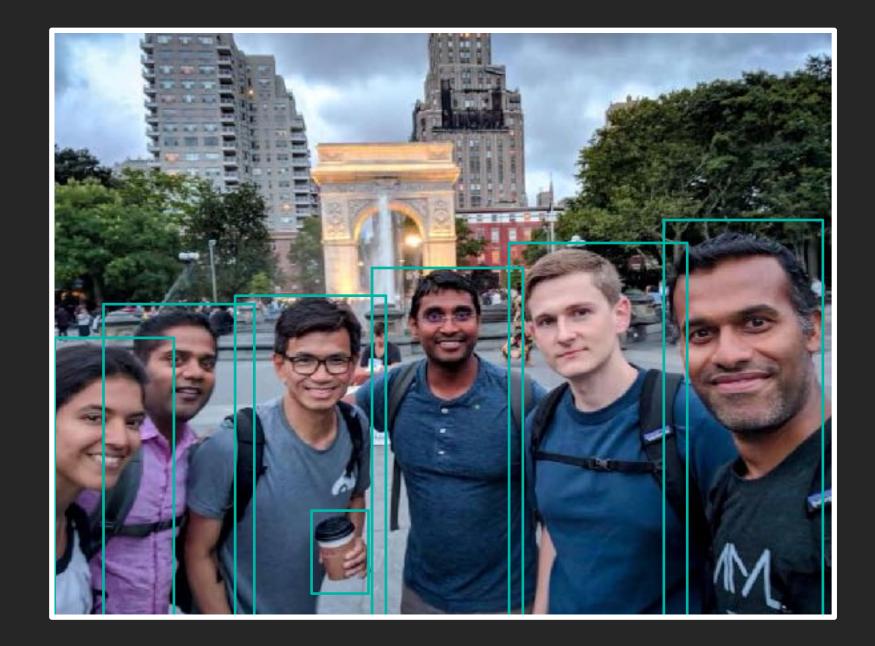
#### ALEXNET





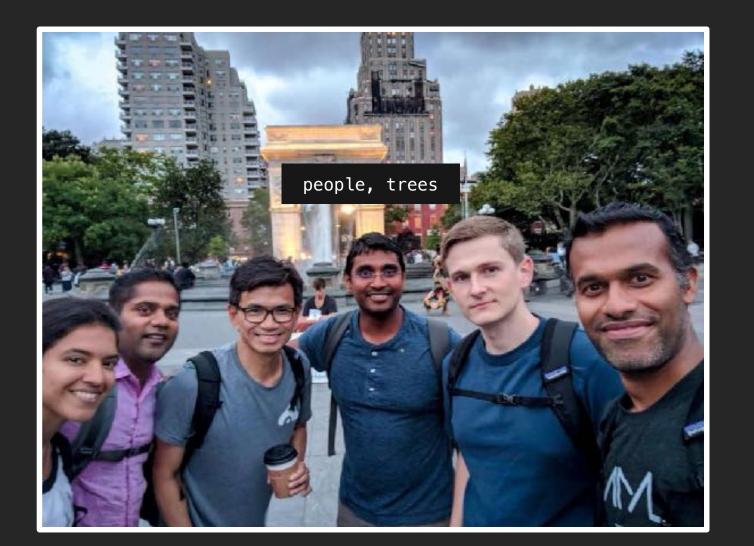
#### ALEXNET

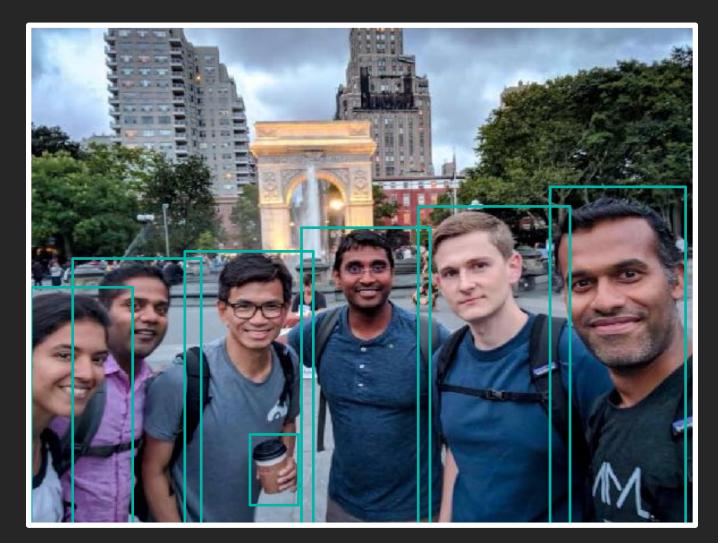




#### FASTER R-CNN

2015

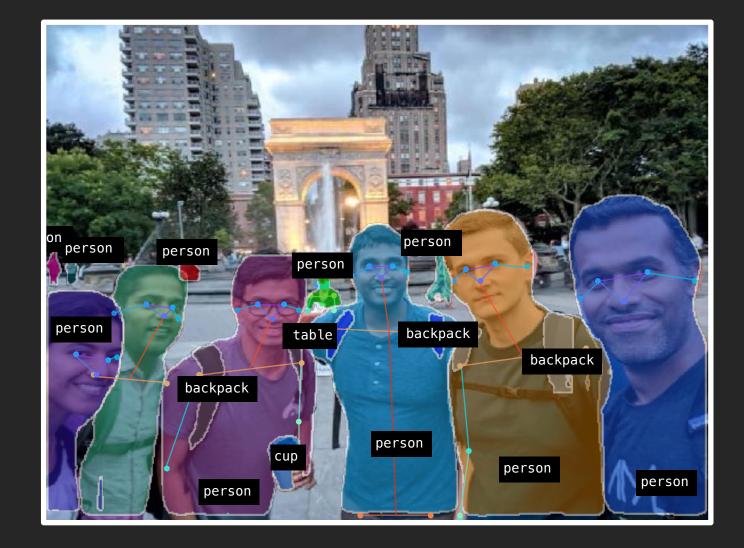




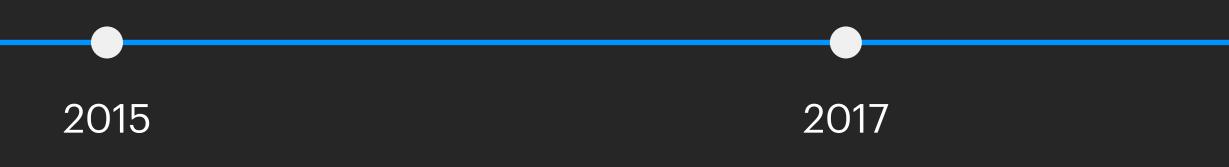
ALEXNET

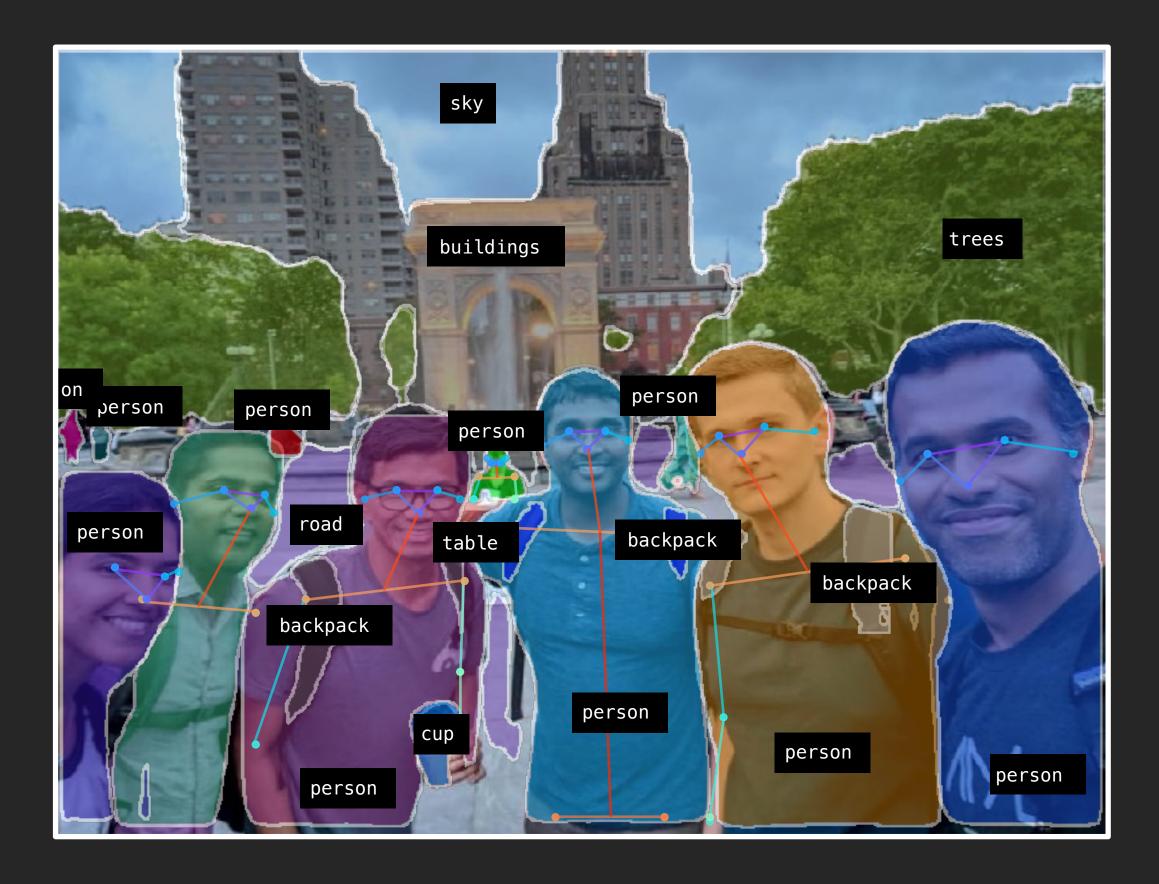
FASTER R-CNN

2012

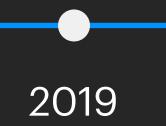


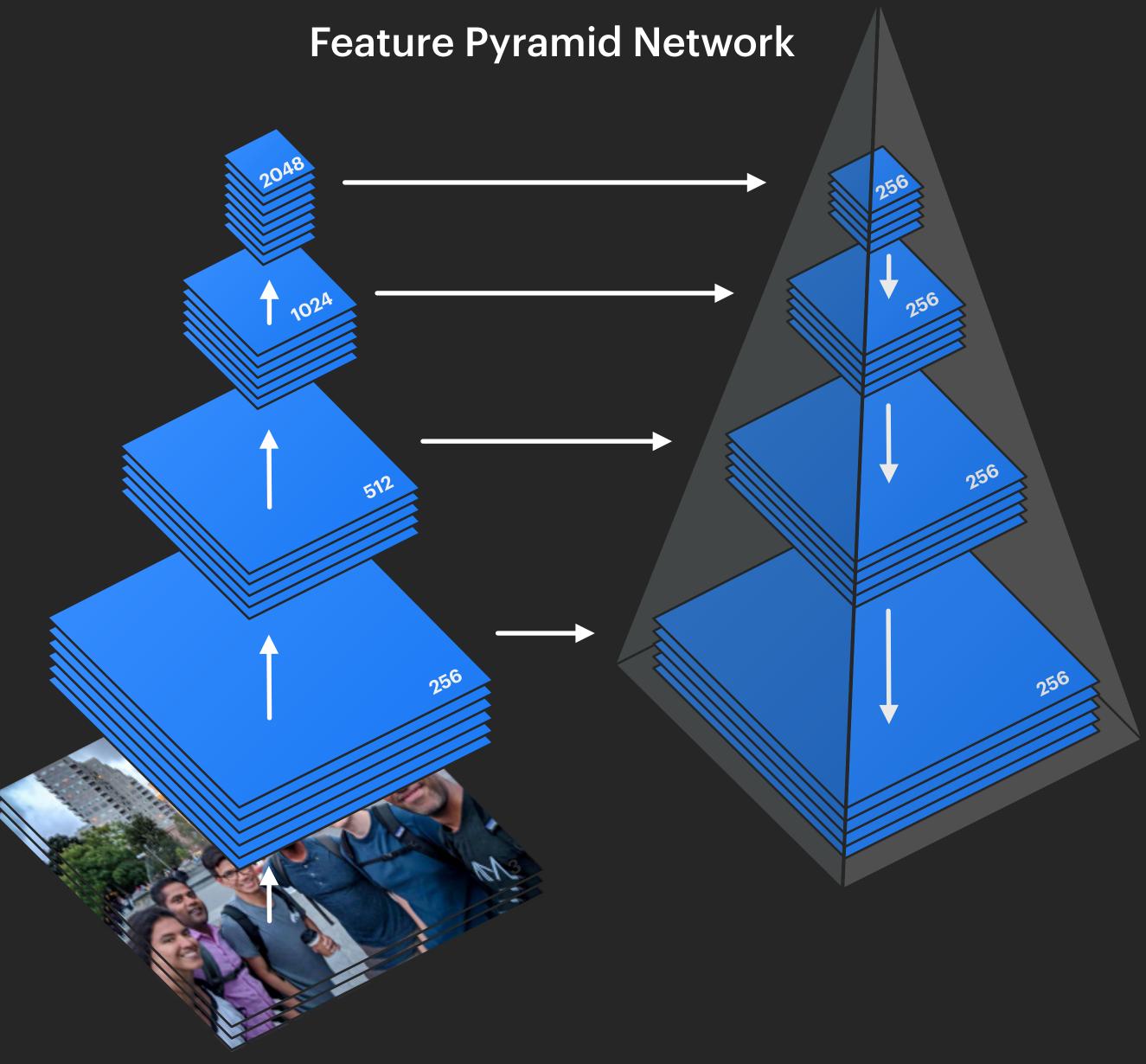
#### MASK R-CNN

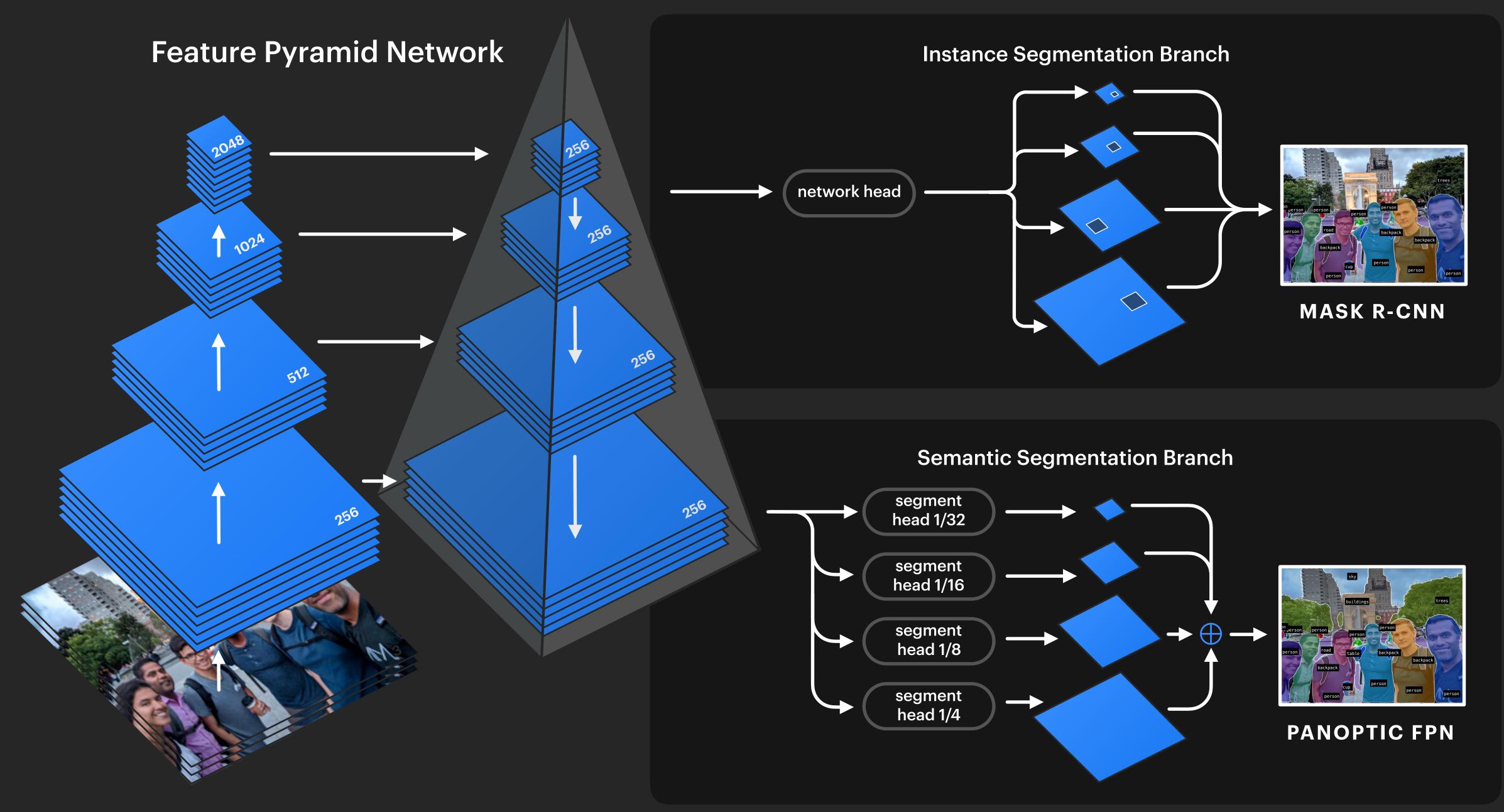




#### PANOPTIC FPN







combonhoto\_14h

Image & Video classification with thousands of concepts

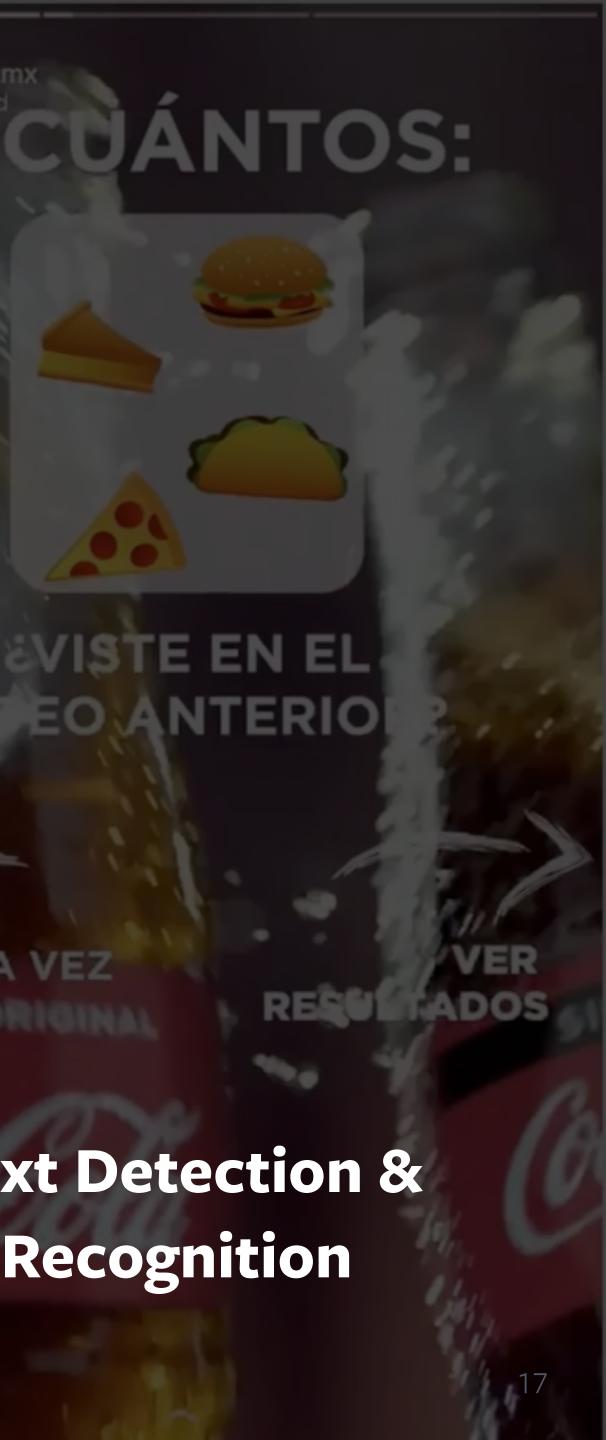
 $\times$ 

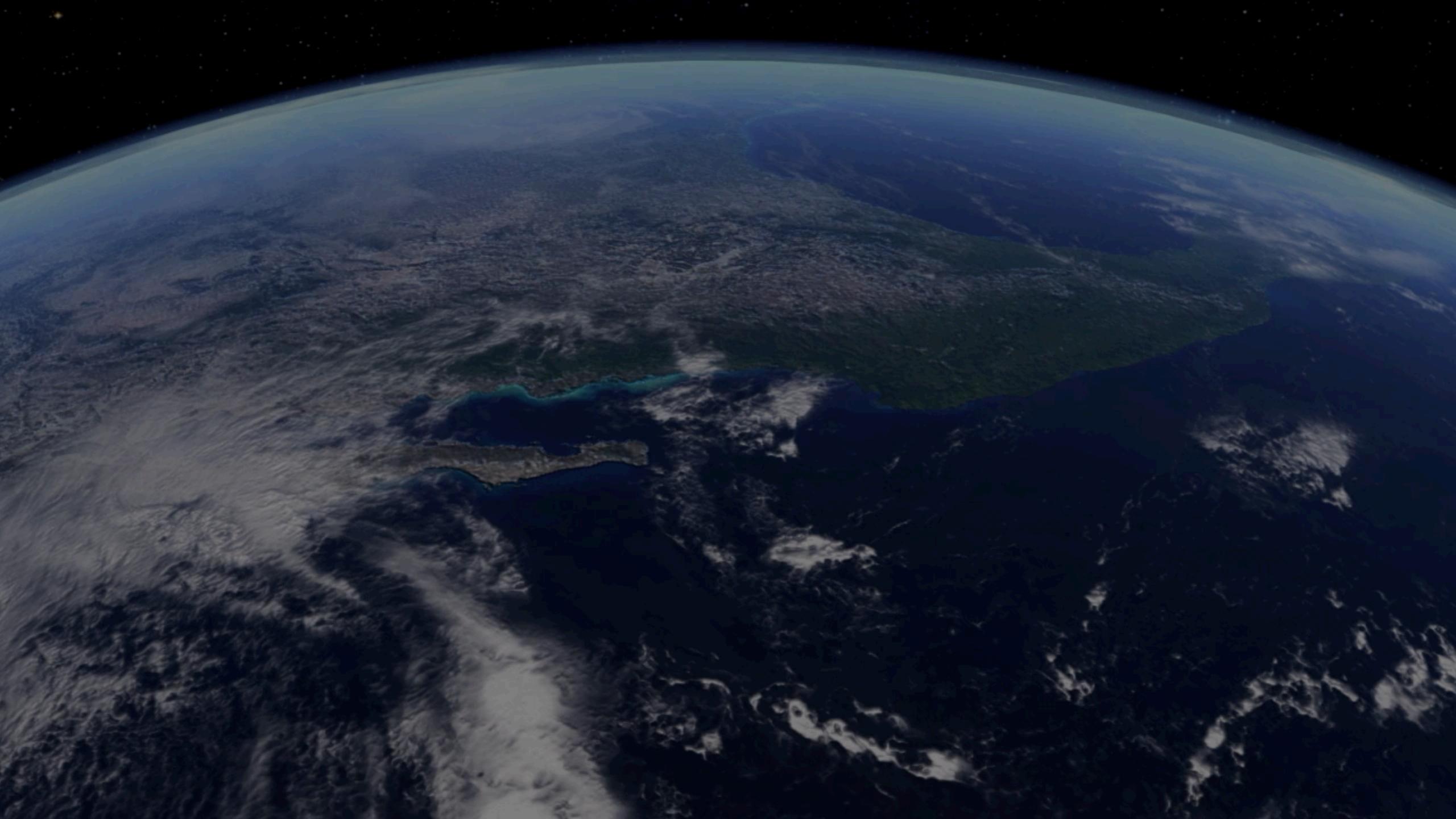
Face & People of **Interest recognition** 

### E EN EL EO ANTERIO

VER **OTRA VEZ** RES

> **Text Detection &** Recognition

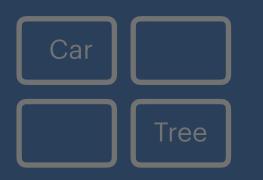








#### Weakly-Supervised



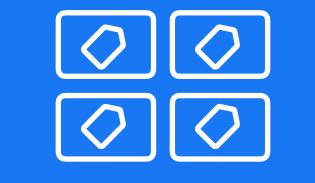
#### Semi-Supervised



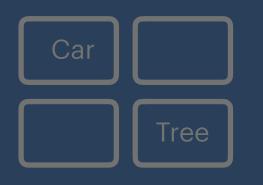




**Fully-Supervised** 



#### Weakly-Supervised



#### Semi-Supervised



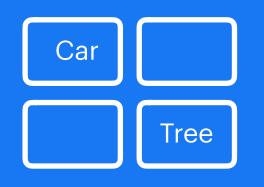




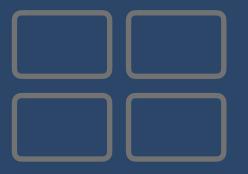
**Fully-Supervised** 



Weakly-Supervised



#### **Semi-Supervised**



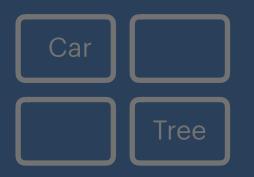




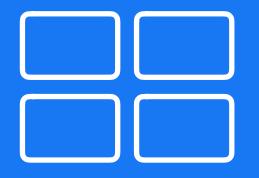
**Fully-Supervised** 



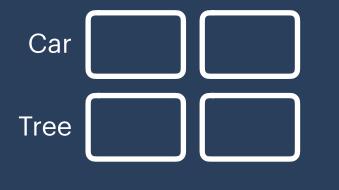
#### Weakly-Supervised



#### Semi-Supervised





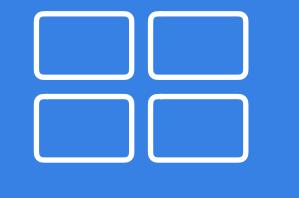


**Fully-Supervised** 





#### Semi-Supervised





# Weakly Supervised Learning @ Billion Scale Leverage large-scale, extremely noisy hashtags for weak-supervision

















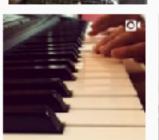


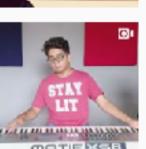
























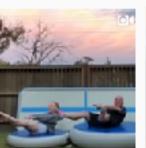




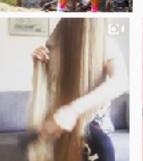






















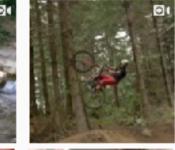






















# **Challenges of Training at Billion Scale LEVELS OF SUPERVISION**



#### Wfeely/s8pperisedd

**Un-supervised** 

???

#### CAT, DOG, #CODEN FLOOR

#### A CUTE CAT COUPLE

## **Challenges of Training at Billion Scale NOISY DATA**

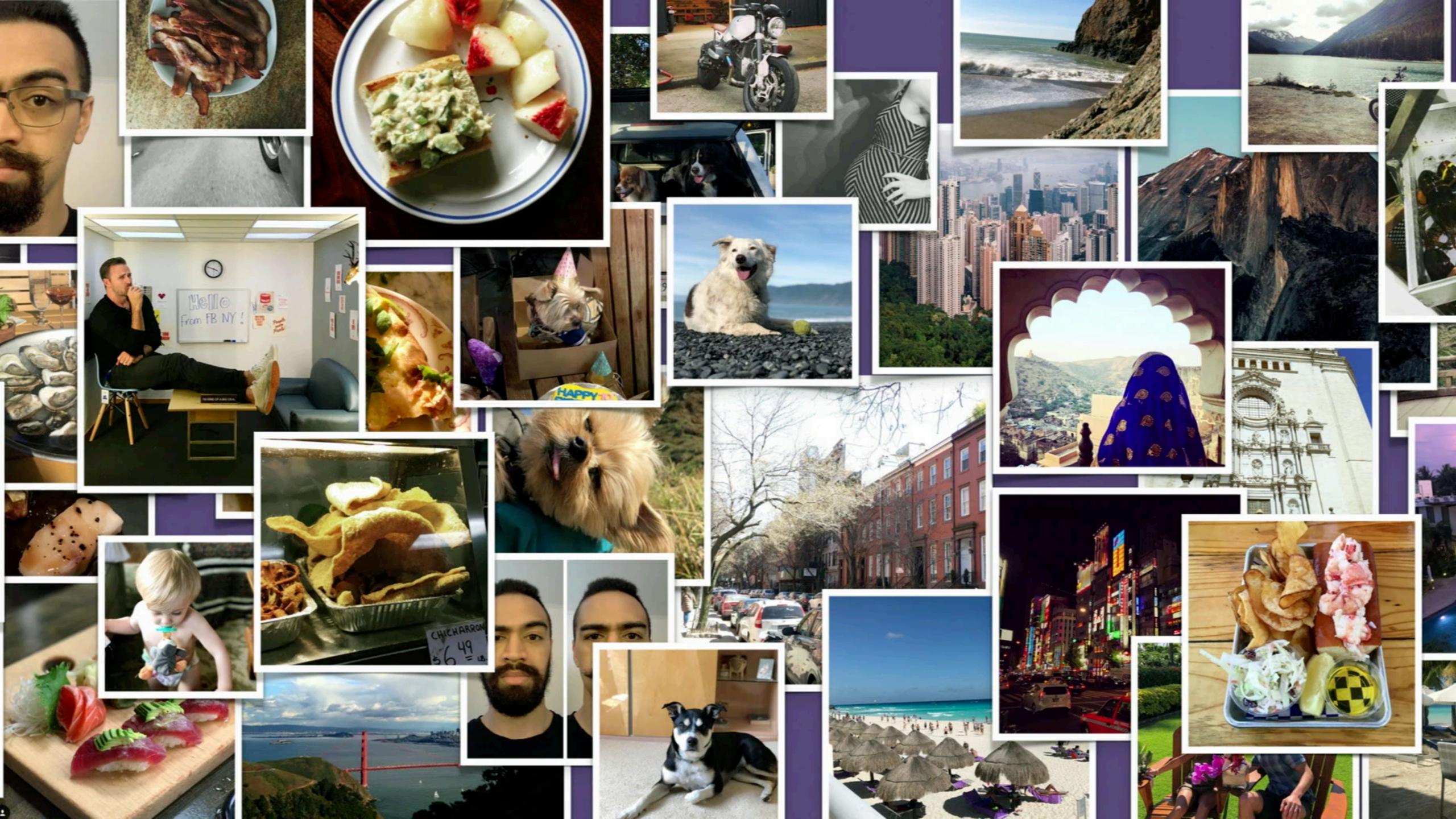




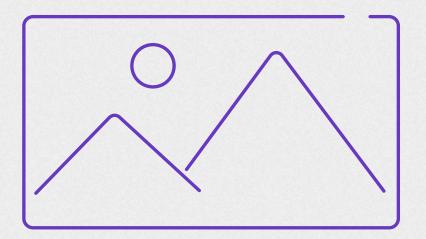


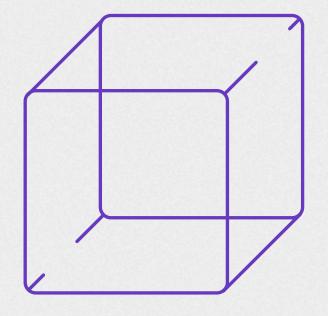
#### Non-Visual Labels → #LOVE #CAT #DOG #HUSKY ← **Incorrect Labels**

#### **Missing Labels**



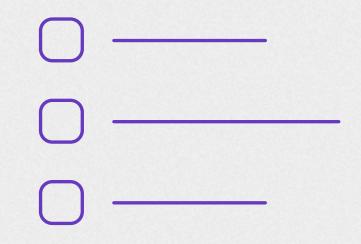
# Large Weakly Supervised Training





BILLIONS OF UNIQUE IMAGES

HUMUNGOUS MODELS



THOUSANDS OF LABELS



# ImageNet in one hour

- ImageNet 1K has
  - 1.28 Million sample
  - 1000 categories
  - ResNet50 architecture
  - P100 GPUs
  - Caffe2

#machines	#gpus	Training time (mins)	<b>Top-1 error</b>
1	8	1726.88	23.56
2	16	905.22	23.35
4	32	464.23	23.48
8	64	231.42	23.39
16	128	117.76	23.58
32	256	60.93	23.74
36	288	54	23.76
40	320	48.84	24.08
44	352	44.36	24.23

# **Billion Scale Training at FB**

### **IMAGENET-1K: STATE OF THE ART RESULTS**



**OUR 3.5B TRAINING RESNEXT101-32X32 MODEL** 



**PREVIOUS SOA** 

# 85.1%

# 83.1%

### Before



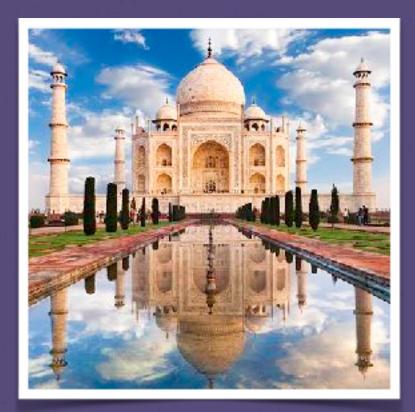




Food



Landmark

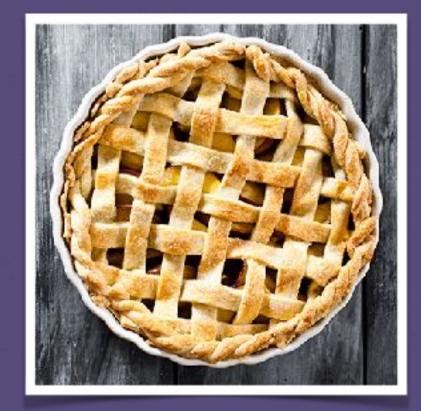


<u>;;;</u>

### After



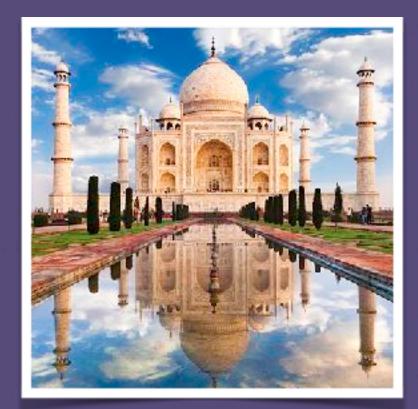
Cupcake



Apple pie



Statue of Liberty



#### Taj Mahal

#### WSL



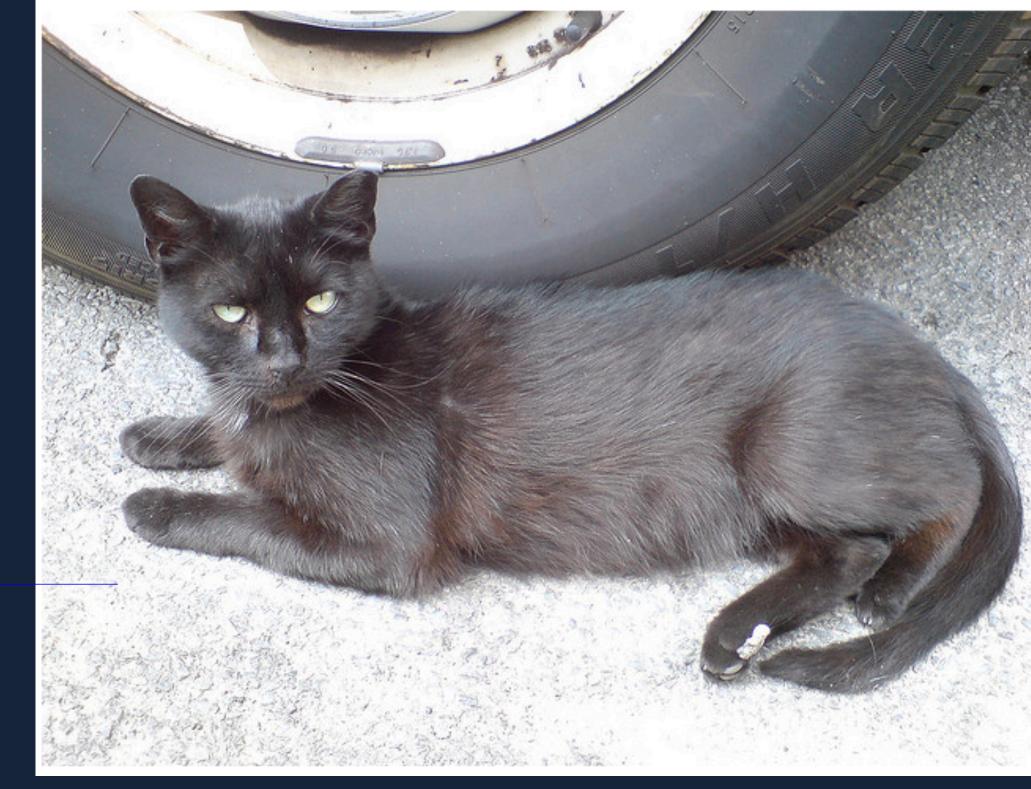
#### IMAGENET

A simple, minimalist kitchen with very low lighting.

#### WSL

#### A very modern bathroom with green glass tile work in the shower.

facebook Artificial Intelligence



Black cat next to toy mouse on carpet.

A cat sleeping next to a vehicle's tire on top of pavement.



# PyTorch Models Are Available

https://pytorch.org/hul Images\_resnext/

import torch
model = torch.hub.load('facebookresearch/WSL-Images', 'resnext101\_32x8d\_wsl')
# or
# model = torch.hub.load('facebookresearch/WSL-Images', 'resnext101\_32x32d\_wsl')
# or
# model = torch.hub.load('facebookresearch/WSL-Images', 'resnext101\_32x32d\_wsl')
# or
#model = torch.hub.load('facebookresearch/WSL-Images', 'resnext101\_32x48d\_wsl')
model.eval()

# https://pytorch.org/hub/facebookresearch\_WSL-

# How about Videos?





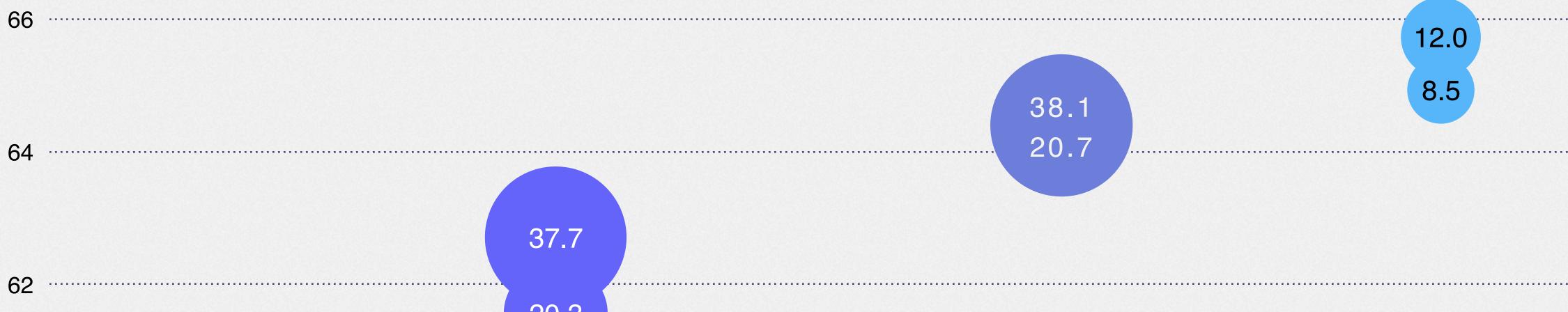
# ENRICH OUR USER'S EXPERIENCE

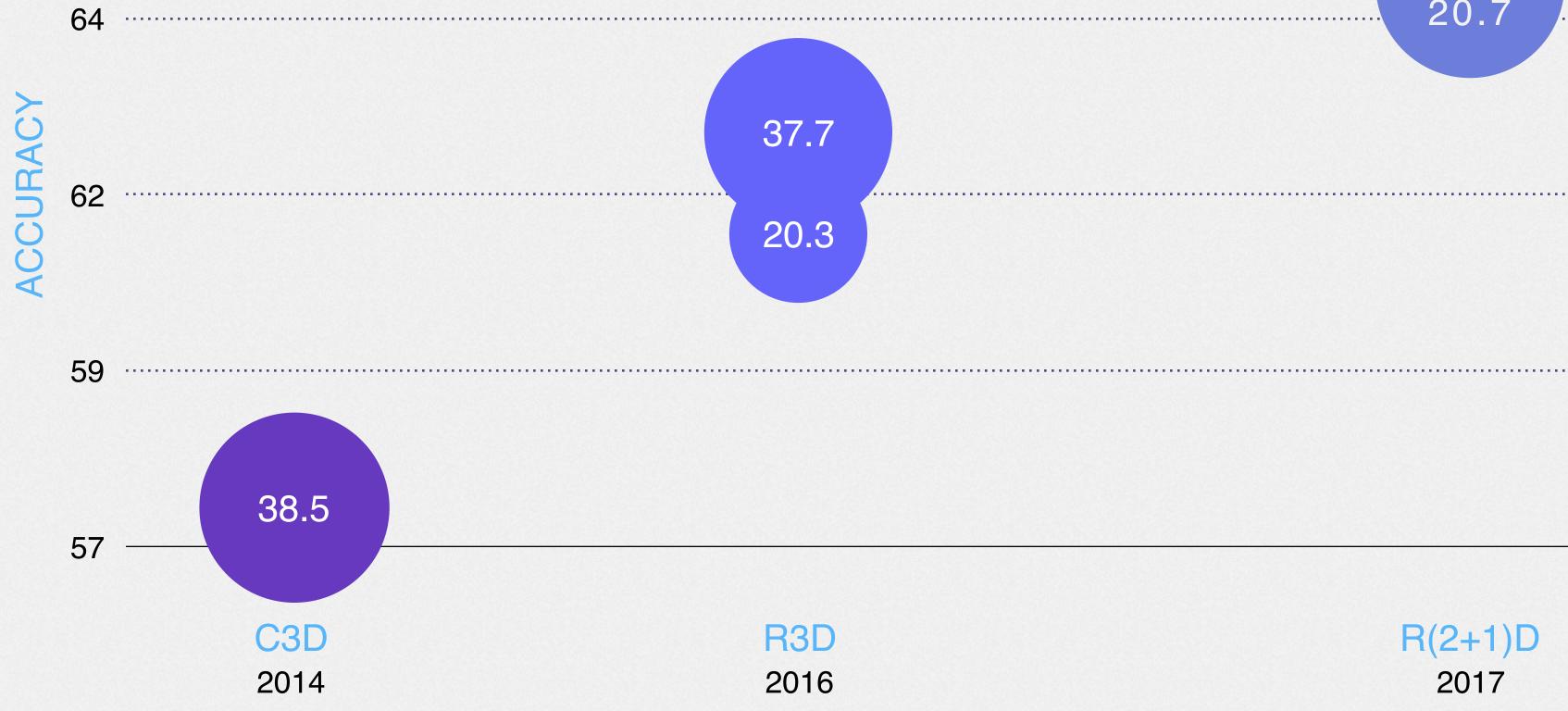
# **Did We Miss a Great Moment?**





### **Spatiotemporal Visual Modeling** SPACE AND TIME HAVE DIFFERENT STATISTICS





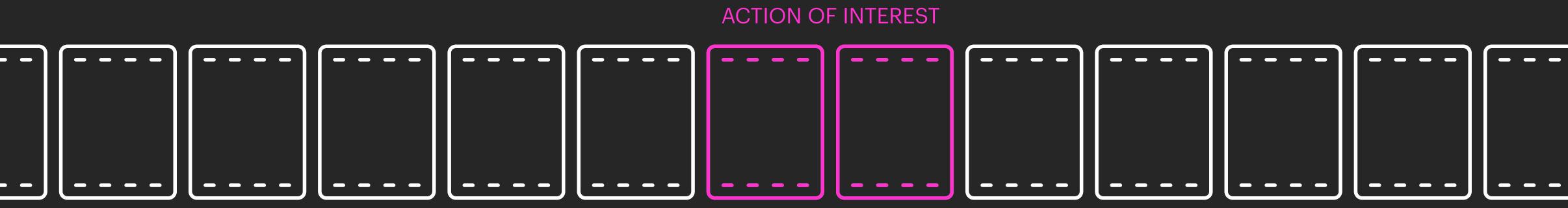


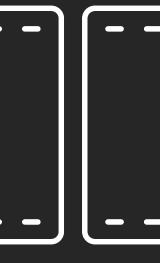




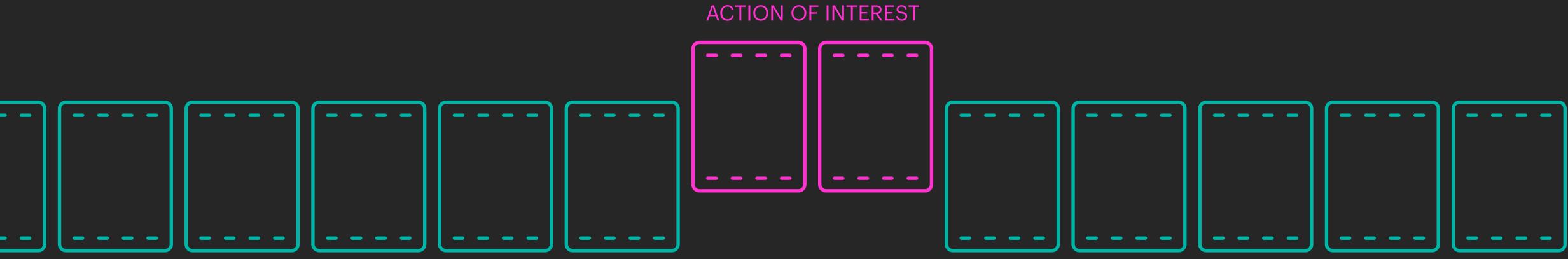
### 











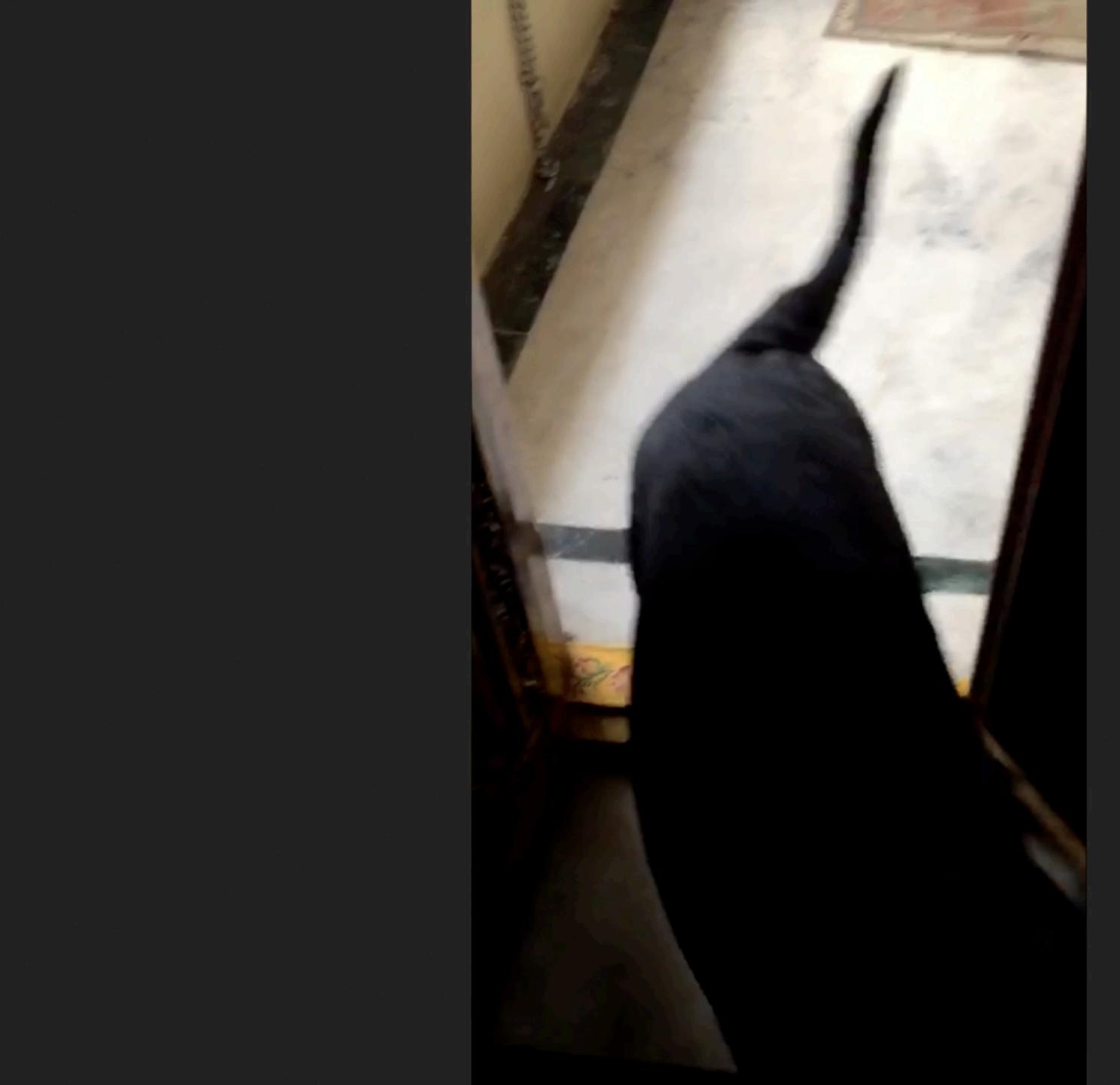


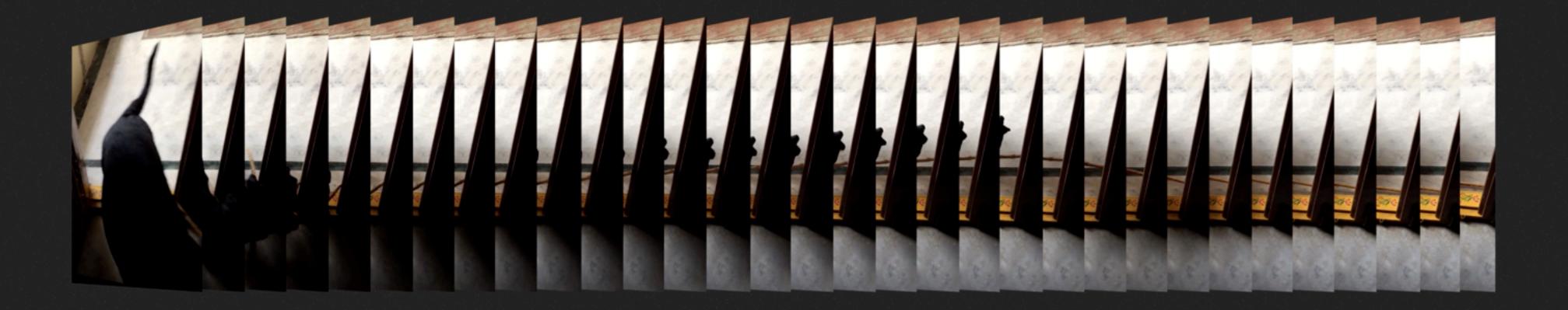












dog 0.99	door 0.8	wag 0.5	walk 0.8
stick 0.7	pickup 0.7	drop 0.8	tail 0.7



### Sampling Salient Clips



dog 0.99	door 0.8	wag 0.5	walk 0.8
stick 0.7	pickup 0.7	drop 0.8	tail 0.7

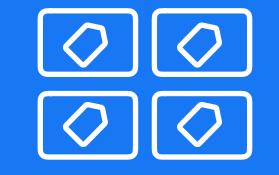
**Spatiotemporal CNN** 

### Levels of Supervision



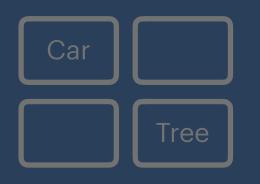
### **Fully-Supervised**

~ Millions



#### Weakly-Supervised

~ Billions



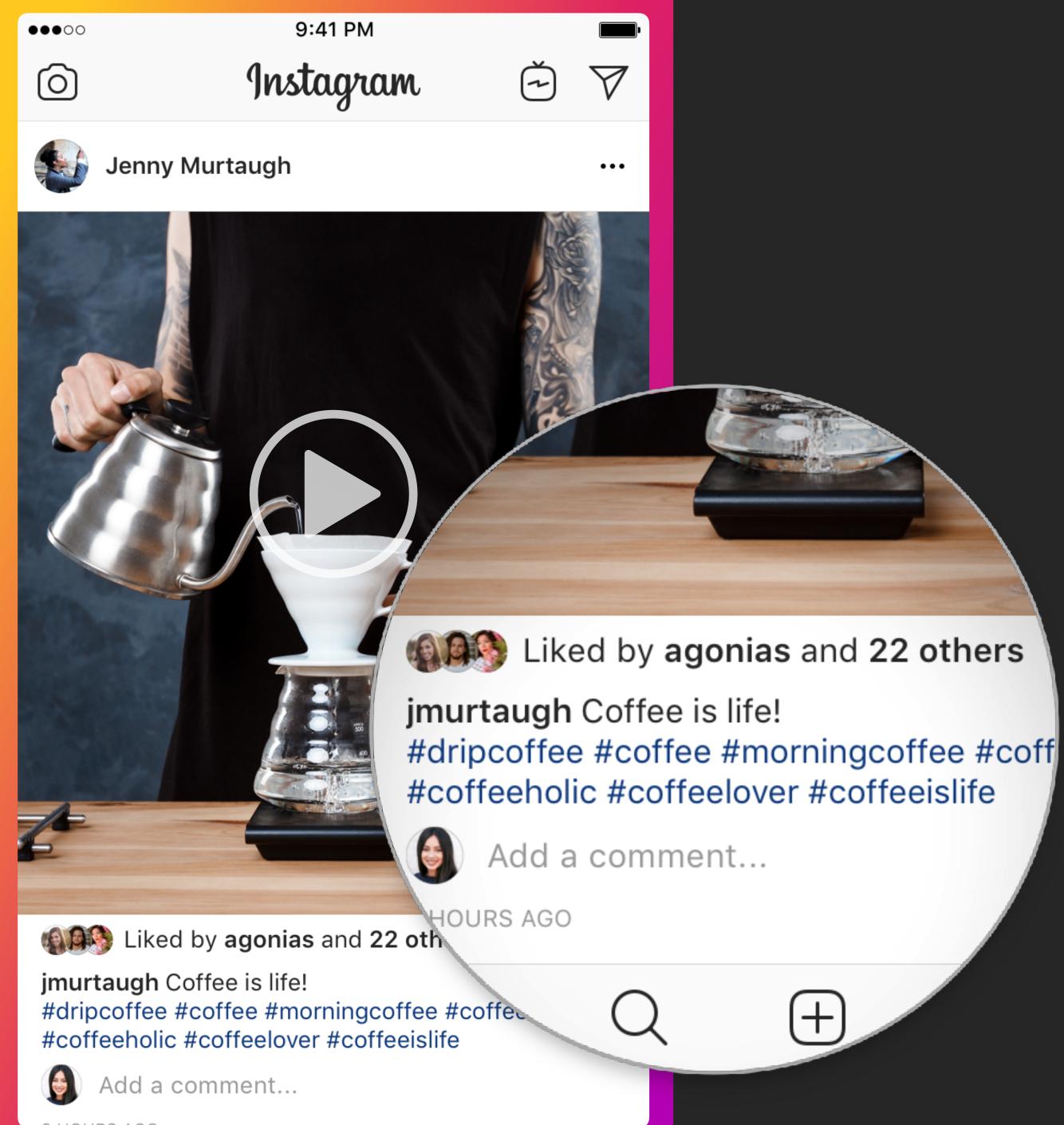
#### Semi-Supervised

~ Trillions



#### Self-Supervised

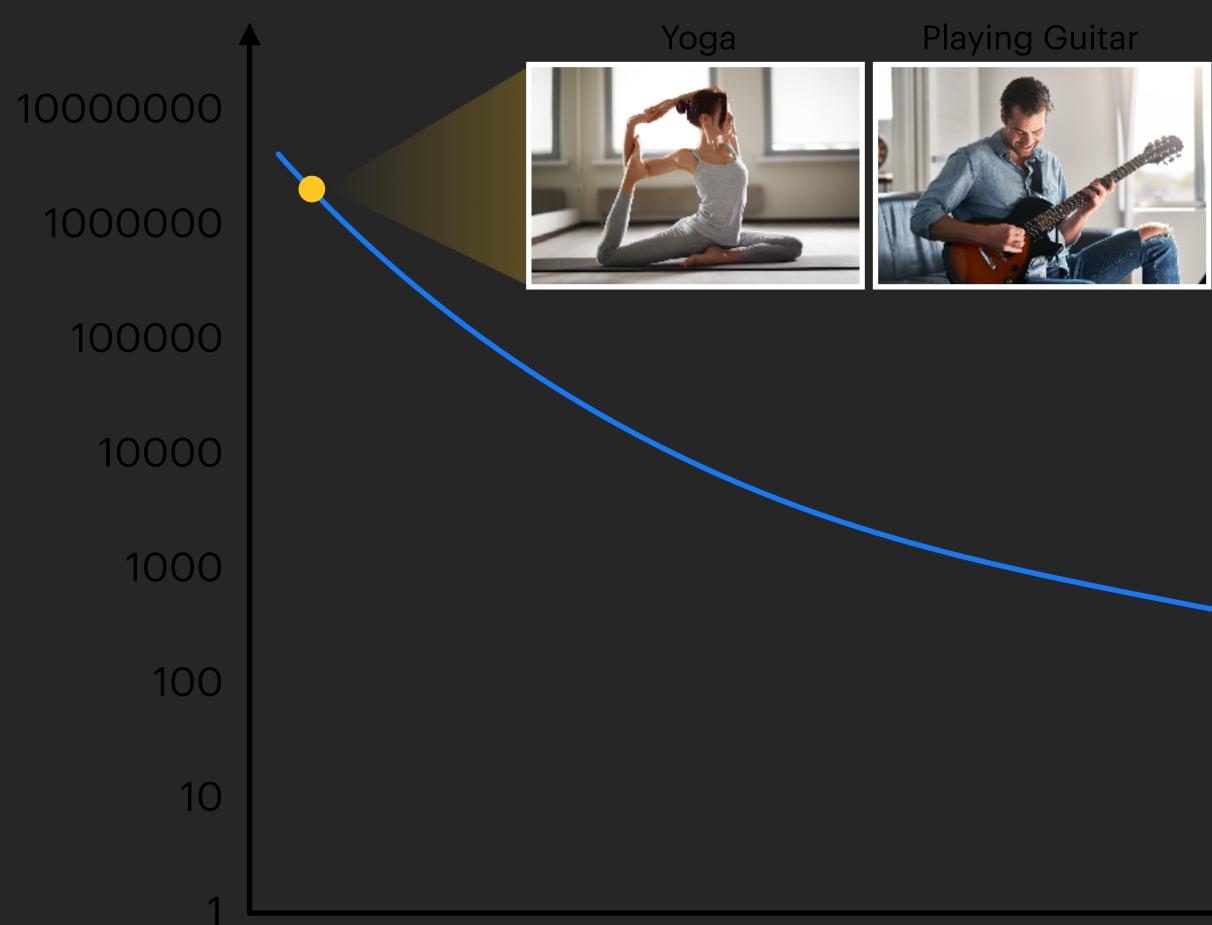




# Leveraging Rich Metadata

### HASHTAGS

### **Challenges With Training at Scale SKEWED (LONG-TAIL) DISTRIBUTION**



#### **MORE GENERIC**

#### Sign Language Interpreting



#### **LESS GENERIC**







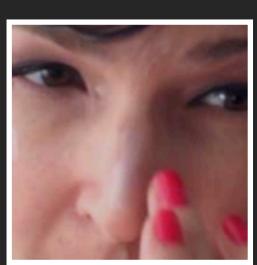
### PUBLIC VIDEOS

# 6NoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNoteNote

YouTube-8M Dataset







**APPLYING CREAM** 



**ARRANGING FLOWERS** 

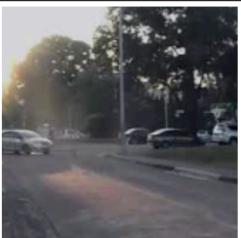


AUCTIONING



FLIPPING PANCAKE

SPEAKING



JOGGING



MAKING TEA



MOWING

**KINETICS: 300K VIDEOS, 400 ACTIONS** 





**BIKING THROUGH SNOW** 



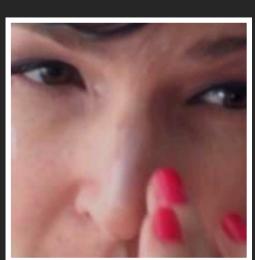
SCRAMBLING EGGS

#### Metric: Top-1 Accuracy

### **PREVIOUS SOA**



SPEAKING



APPLYING CREAM



**ARRANGING FLOWERS** 

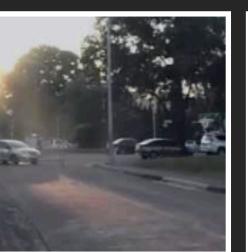


AUCTIONING



**FLIPPING PANCAKE** 

JOGGING



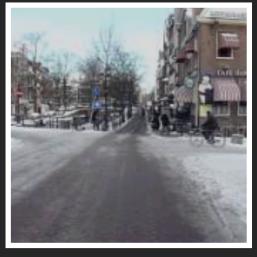


**MAKING TEA** 

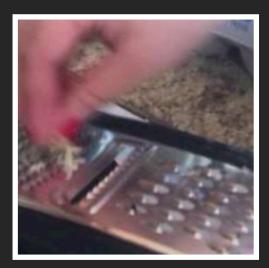
MOWING







**BIKING THROUGH SNOW** 



SCRAMBLING EGGS

### Metric: Top-1 Accuracy



### **PREVIOUS SOA**

# +5.1%

### **OUR 65M TRAINING**





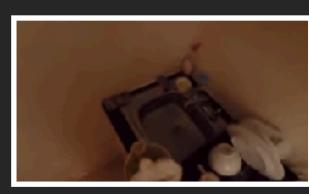




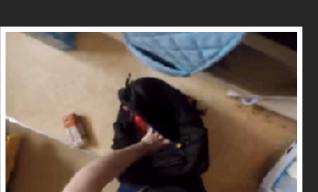




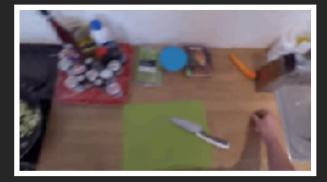














### **EPIC-KITCHENS: 28K VIDEOS, 2337 ACTIONS**

EPIC-Kitchens Action Recognition Challenge









#### Metric: Top-1 Accuracy

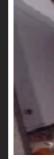
# 

**PREVIOUS SOA** 











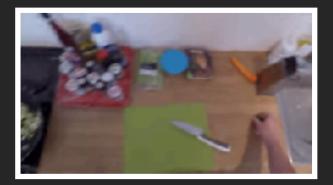














### **EPIC-KITCHENS: 28K VIDEOS, 2337 ACTIONS**









# Metric: Top-1 Accuracy 21.0%

### **PREVIOUS SOA**

# +4.6% 25.6%

### **OUR 65M TRAINING**



### References for the video understanding efforts

 SCSampler: Sampling Salient Clips from Video for Efficient Action Recognition <u>https://arxiv.org/abs/1904.04289</u>

Video Classification with Channel-Separated Convolutional Networks - <u>https://arxiv.org/abs/1904.02811</u>

 Large-scale weakly-supervised pre-training for video action recognition – <u>https://arxiv.org/abs/1905.00561</u>

facebook Artificial Intelligence

### Pushing State of the Art helps the world in significant ways

facebook Artificial Intelligence



### Levels of Supervision



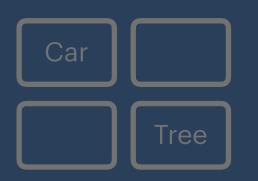
#### **Fully-Supervised**

~ Millions



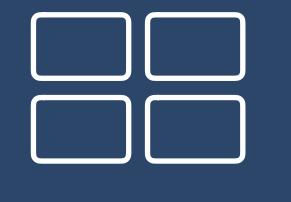
#### Weakly-Supervised

~ Billions



#### Semi-Supervised

~ Trillions



#### Self-Supervised



### NeurIPS 2018 - Al for Social Good workshop

### **Crowd From Satellite Imagery to Disaster Insights** Jigar Doshi<sup>1</sup>, Saikat Basu<sup>2</sup>, Guan Pang<sup>2</sup> CrowdAl<sup>1</sup>, Facebook<sup>2</sup>

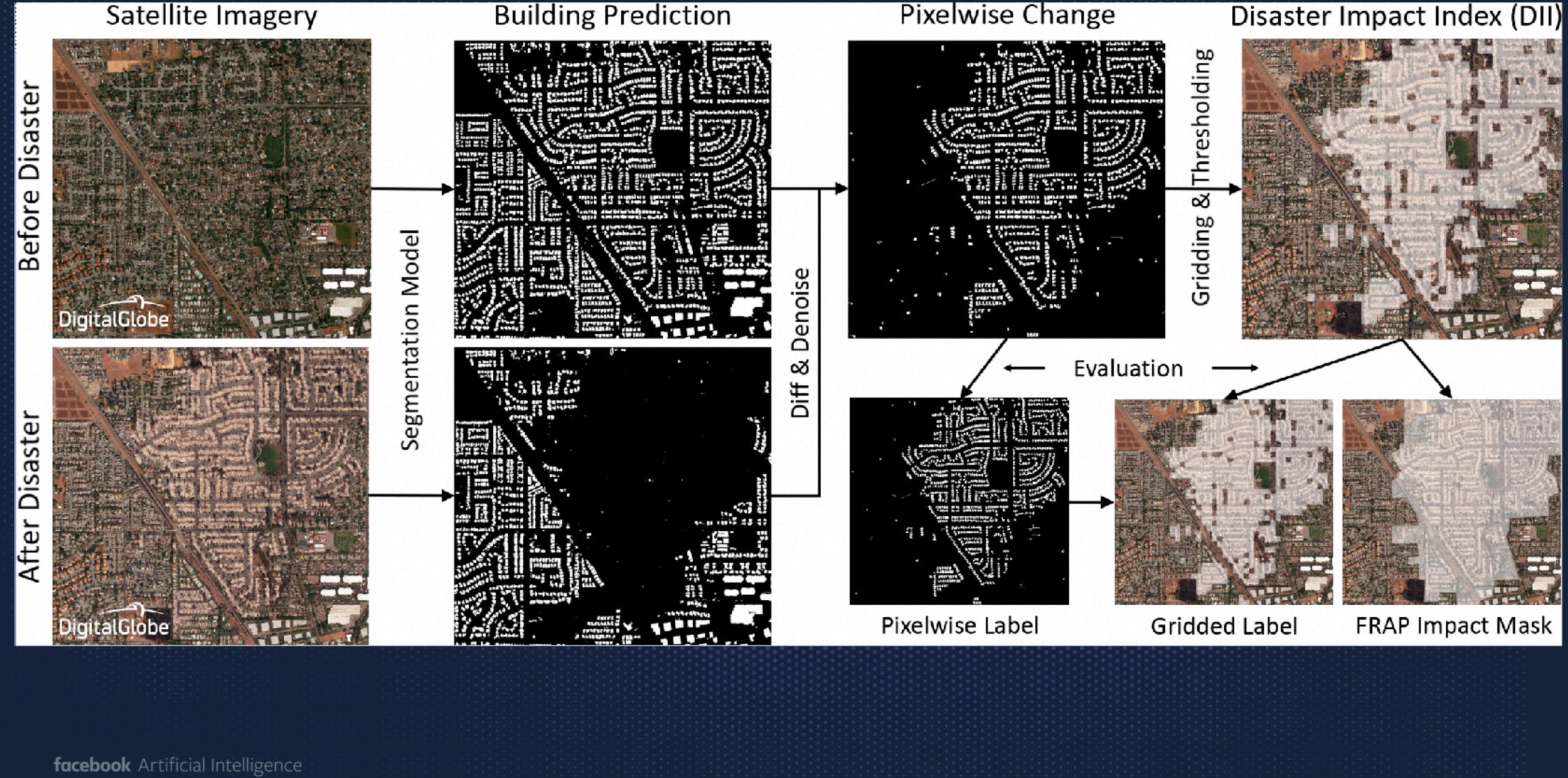
### What's the Research?

- A framework for using convolutional neural networks (CNNs) on satellite imagery to identify the areas most severely affected by a disaster. This new method potentially produces **more accurate** information in **far less time** than current manual methods.
- The goal of this work is to allow rescue workers to quickly identify where aid is needed most, without relying on manually annotated, disaster-specific data sets.



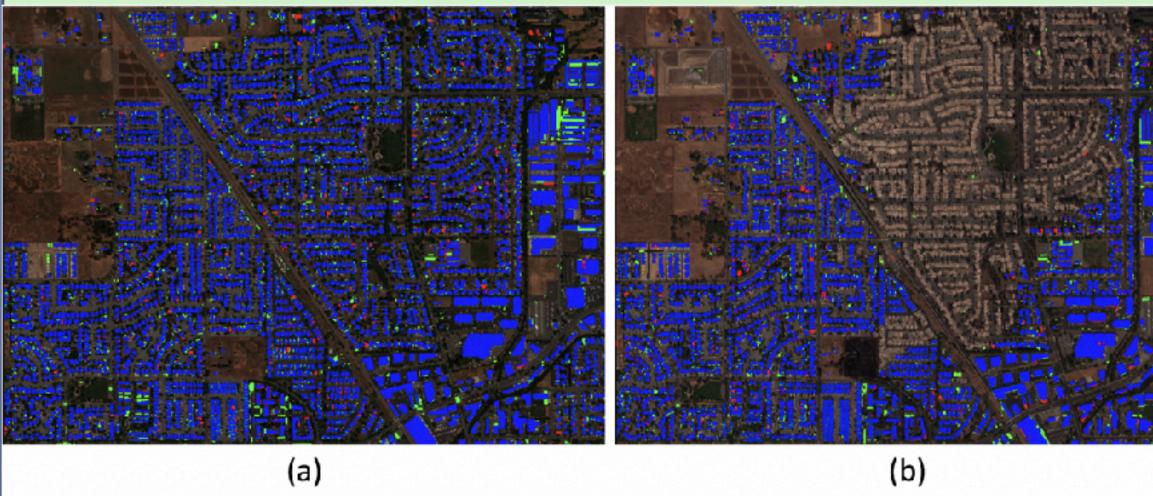
 $\begin{aligned} & Disaster Impact Index (DII) \\ DIII = \Delta Pred = \frac{\eta_{Pred_{before}} = 1 \& Pred_{after} = 0_{grid}}{\frac{1}{N_{grid}} \sum_{i=1}^{N_{grid}} \eta_{Pred_{before}} = 1_{grid_i}} \\ & \eta_{Pred_{before}} = 1 \& Pred_{after} = 0_{grid} \rightarrow \text{Pixels missing the feature post disaster}} \\ & \frac{1}{N_{grid}} \sum_{i=1}^{N_{grid}} \eta_{Pred_{before}} = 1_{grid_i}} \rightarrow \text{num of feature pixels predicted pre-disaster}} \\ & N_{grid} \rightarrow \text{total number of grids in this case } 256 \times 256 \end{aligned}$ 

### How it works!



### Helping in real world scenarios

### Santa Rosa Fire - Buildings

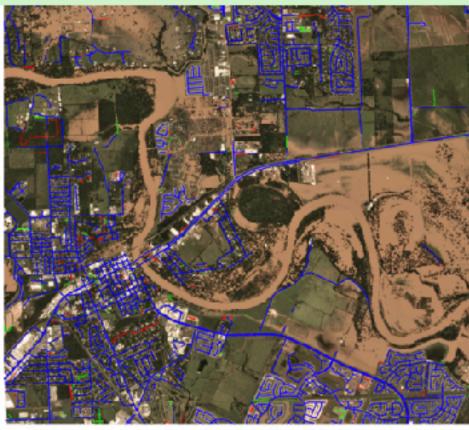




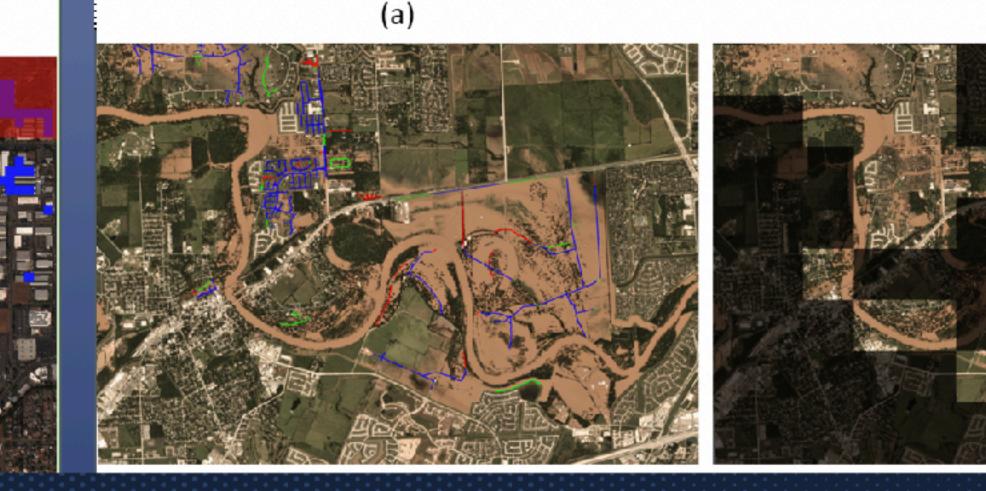
facebook Artificial Intelligence

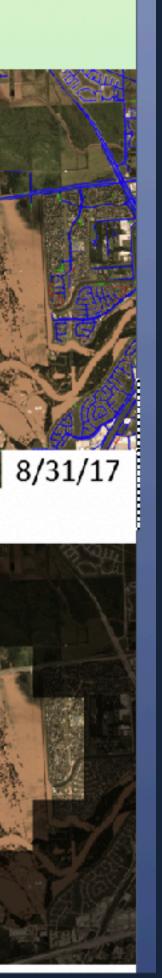
### **Hurricane Harvey Flooding - Roads**





(b)





### 1st CVPR Workshop on COMPUTER VISION FOR GLOBAL CHALLENGES 16/17 June 2019 Long Beach, CA

1st CVPR Workshop on COMPUTER VISION FOR GLOBAL CHALLENGES

**Computer Vision** for Global Challenges @cv4gc

Do you have an idea for a computer vision task that would impact the lives of many? Have you identified the limitations of a vision technique because of the geographical bias of the data you are using it on? Is there an application of computer vision that would be helpful to your community? Are you looking for potential vision expert partners or feedback on your idea?

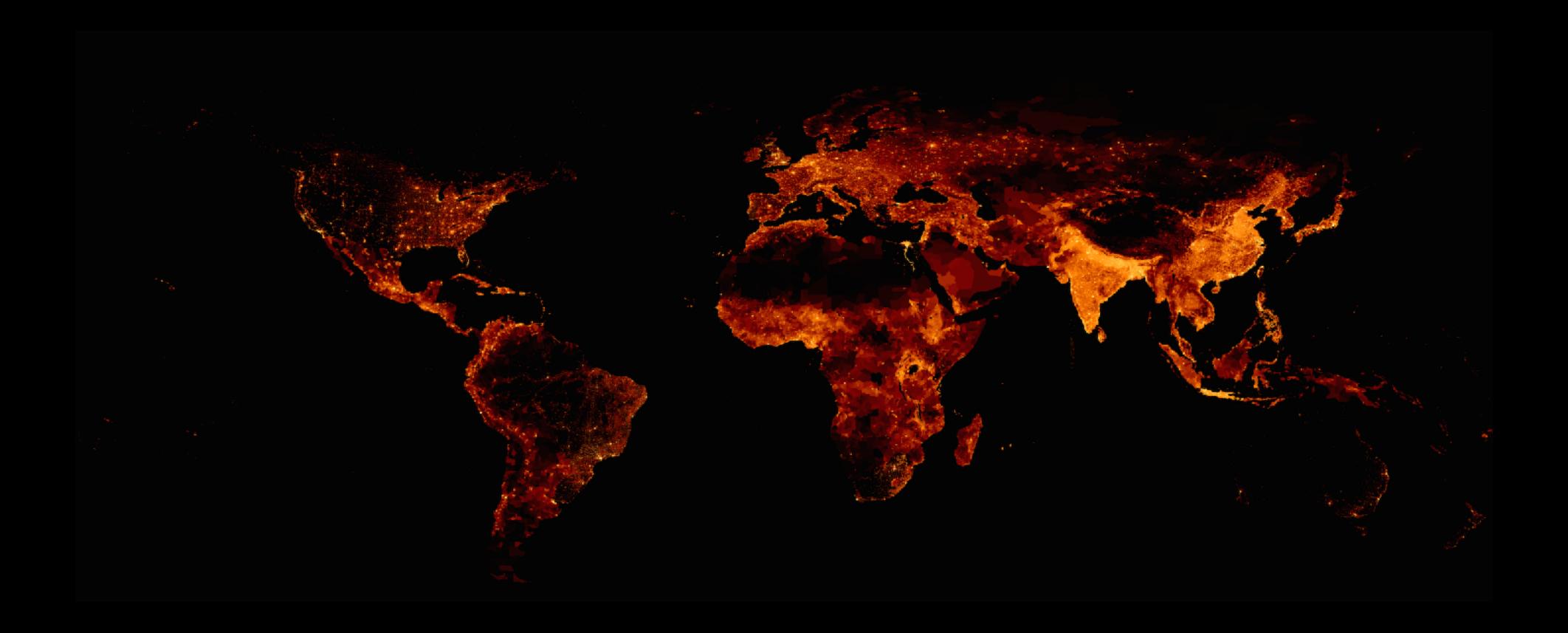
Apply for the Call of Challenges, and come and experience the premier computer vision conference, and participate in an active discussion with the top vision researchers!

facebook Artificial Intelligence





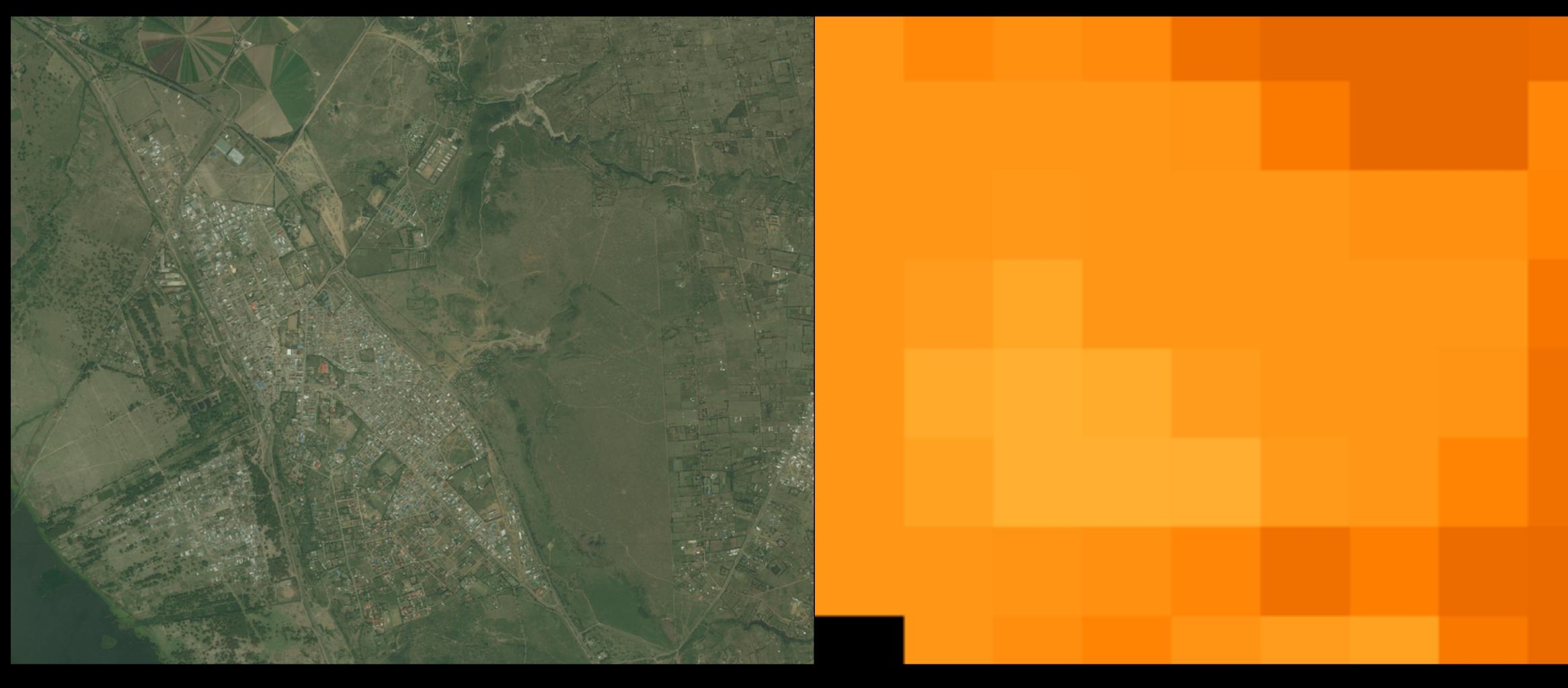
### Population Density Estimation



# Naivasha in Kenya

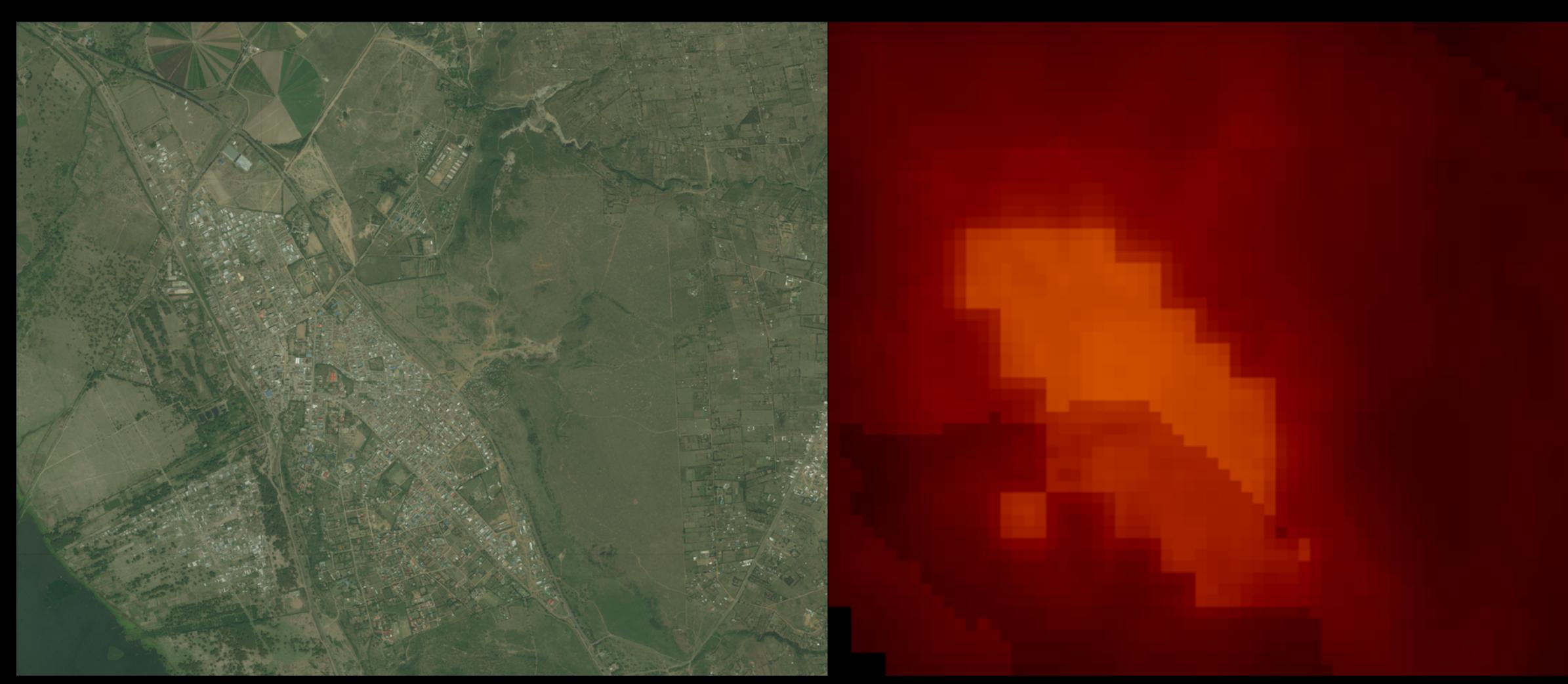


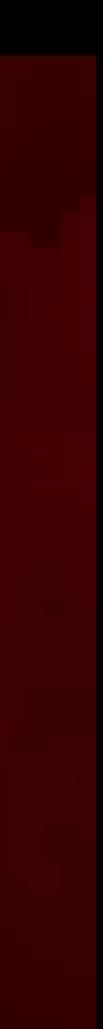
### **GPWv4 from CIESIN at Columbia University**



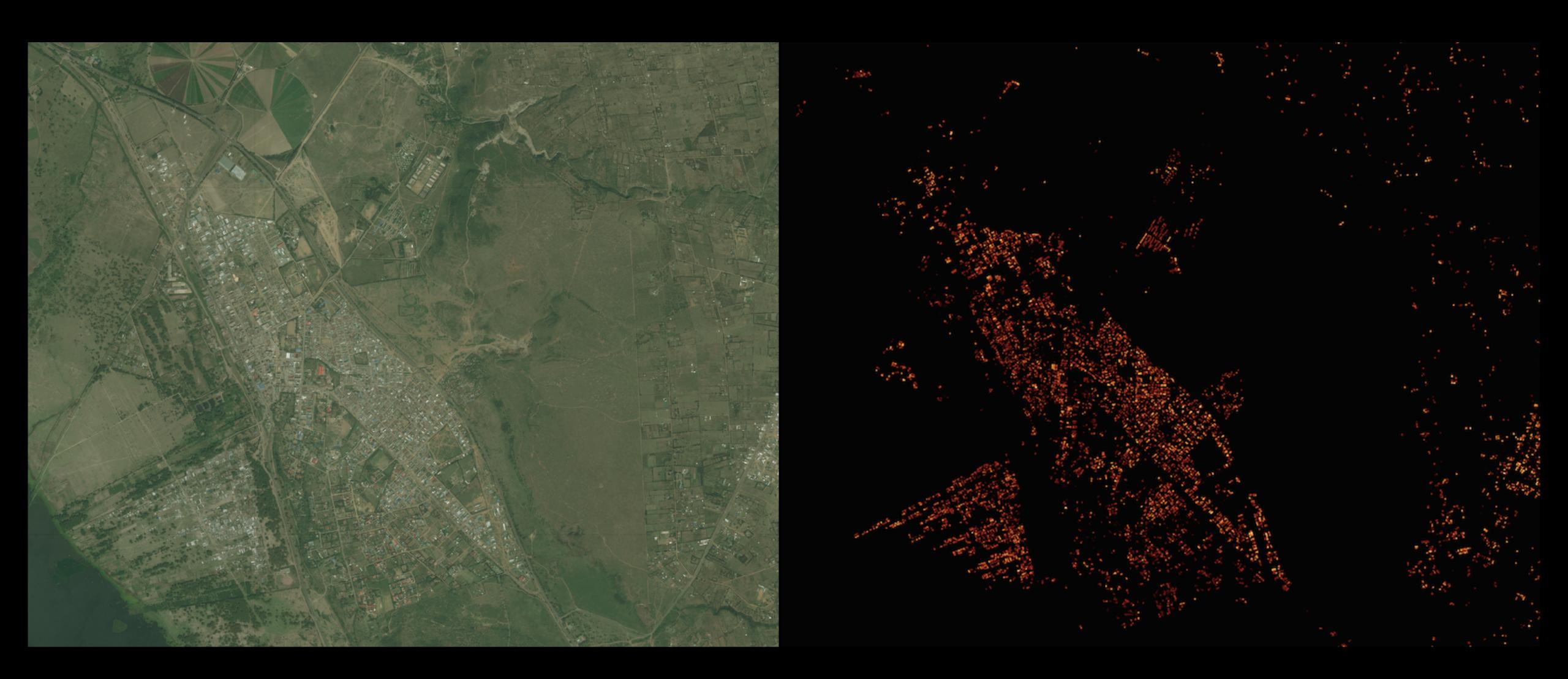


# WordPop





## Facebook



### What will you learn today?

How do you design a image and video recognition system for billion scale?

Can you remove the requirement of annotation to learn best representations?

Can we understand video faster than understanding individual frames? How does pushing state of the art in CV make a meaningful difference to

everyone in the world?

facebook Artificial Intelligence



