SPARK+AI
SUMMIT EUROPE

Deep Reality Simulation For Automated Poacher Detection

Mark Hamilton, Microsoft
Anand Raman, Microsoft

#SAISDD2

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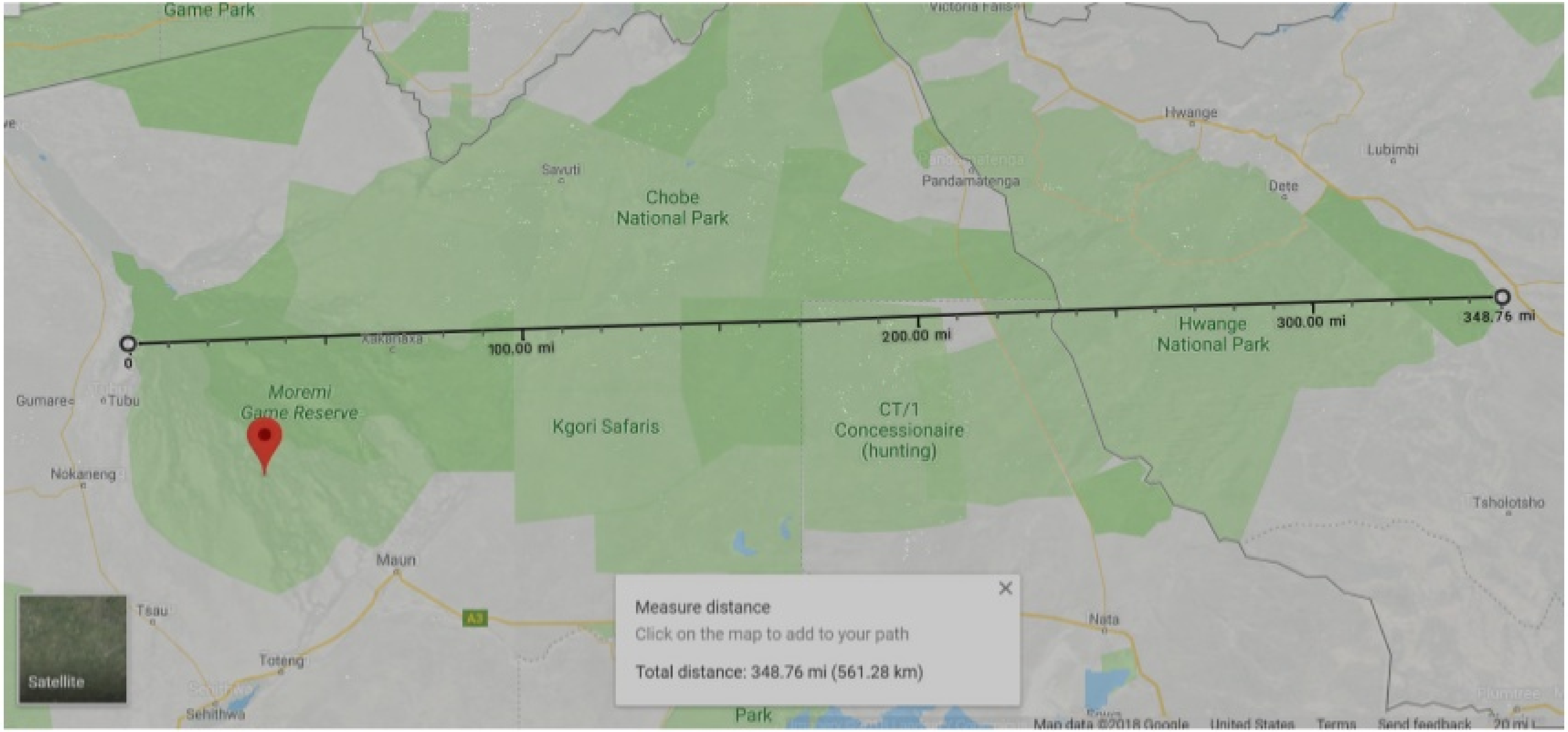
AFRICA

Nearly 90 Elephants Found Dead Near Botswana Sanctuary, Killed By Poachers

September 3, 2018 · 5:57 PM ET

EMILY SULLIVAN

Okavango Delta Wildlife Sanctuary



The Economics of Poaching

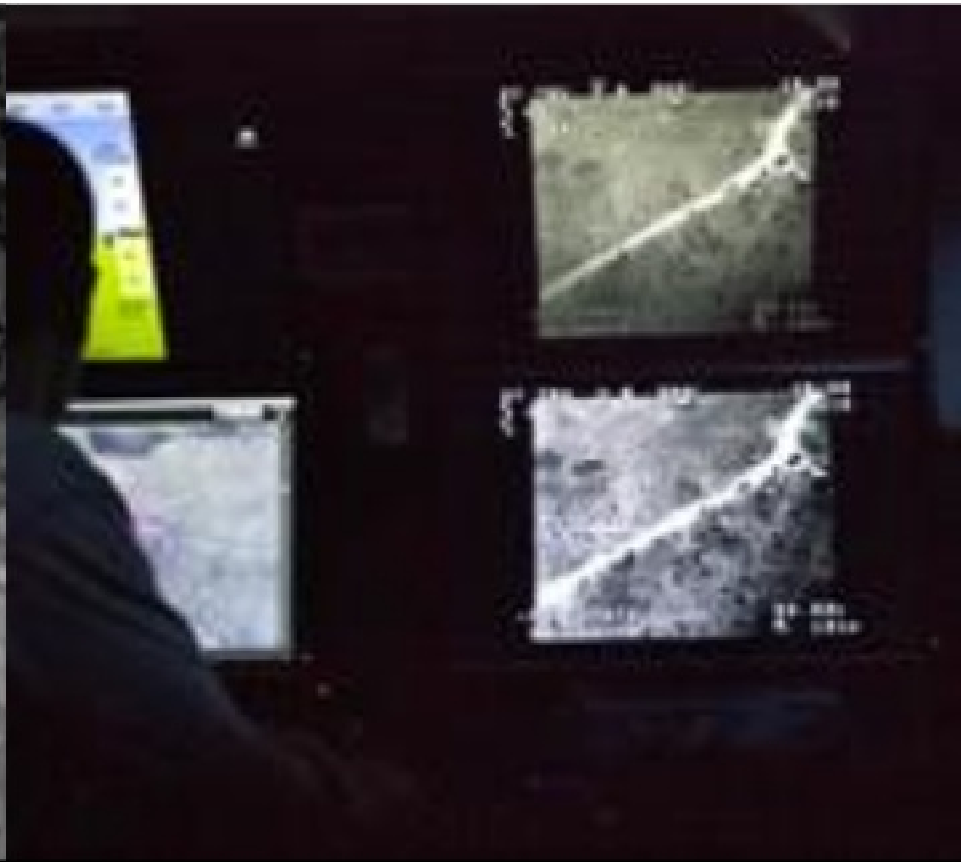
Average Elephant Tusk Wight:
20-40 lbs

Average Per Capita Income Across Sub-Saharn Africa (2008):
$762

Years of Average Income from one Poached Elephant:
52 – 104 years

Air Shepherd

The Lindbergh Foundation



Previous System: EyeSpy

SPOT Poachers in Action: Augmenting Conservation Drones with Automatic Detection in Near Real Time

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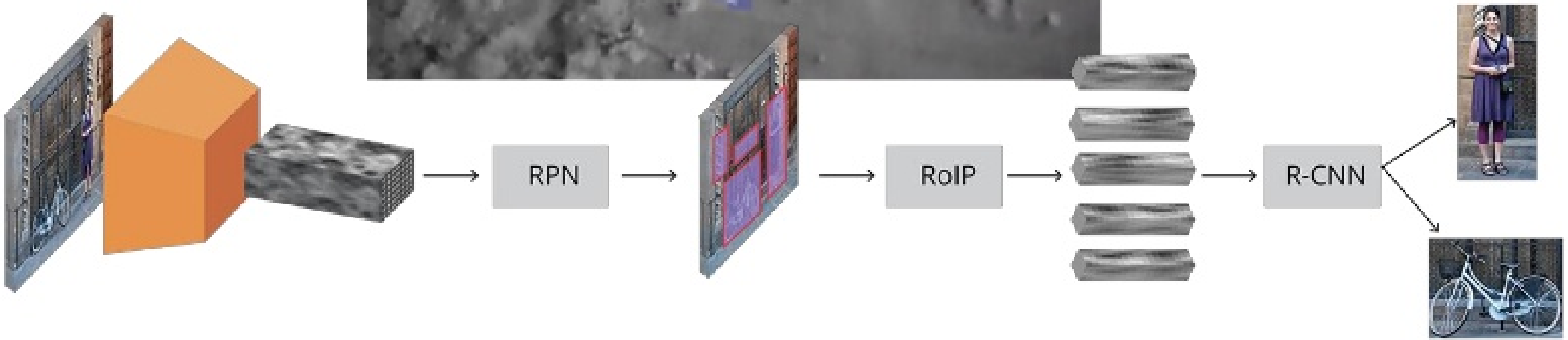
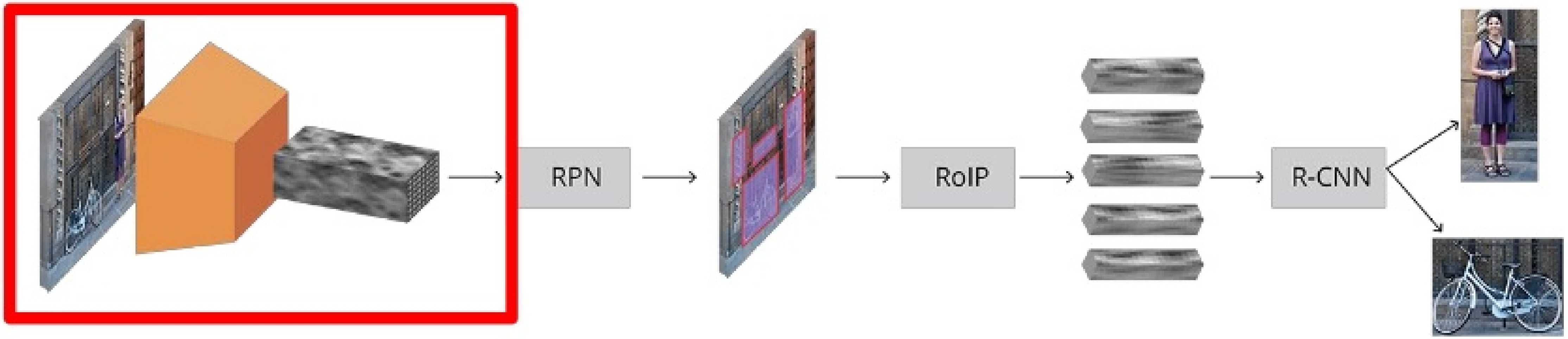


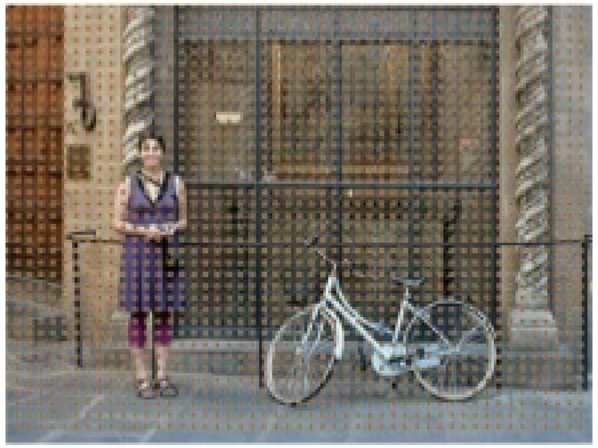
Faster R-CNN: Convolutional Featurization

Step 1

- A Convolutional network "featurizes" the image while maintaining its spatial structure

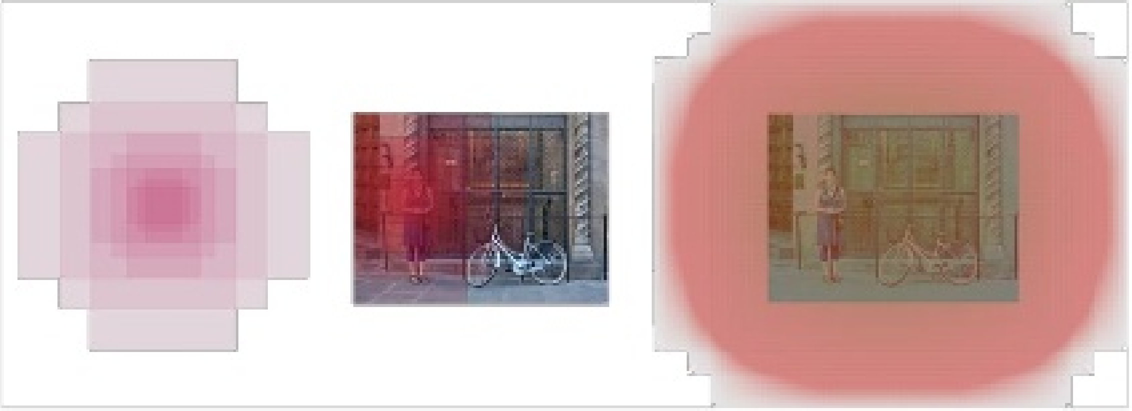


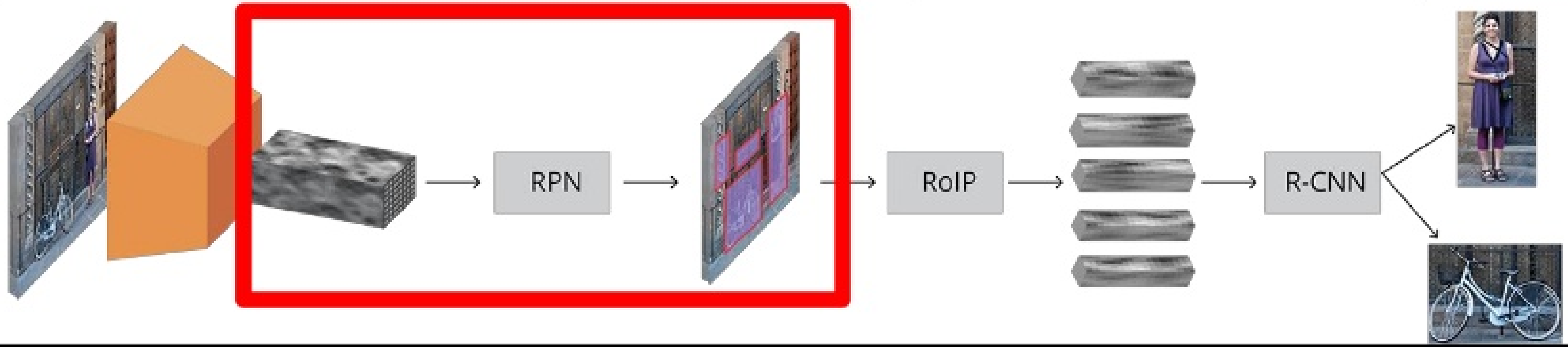
Faster R-CNN: Region Proposal Network



Step 2

- A “Region Proposal network” generates the probability that each “Anchor” has an object
- The RPN also predicts how to “adjust” the anchors to make them fit the object

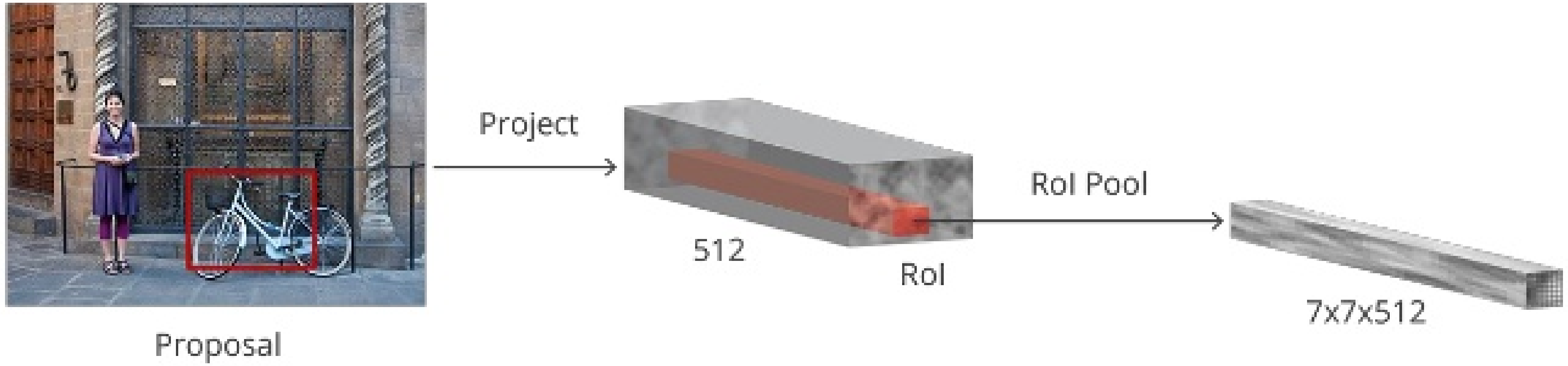


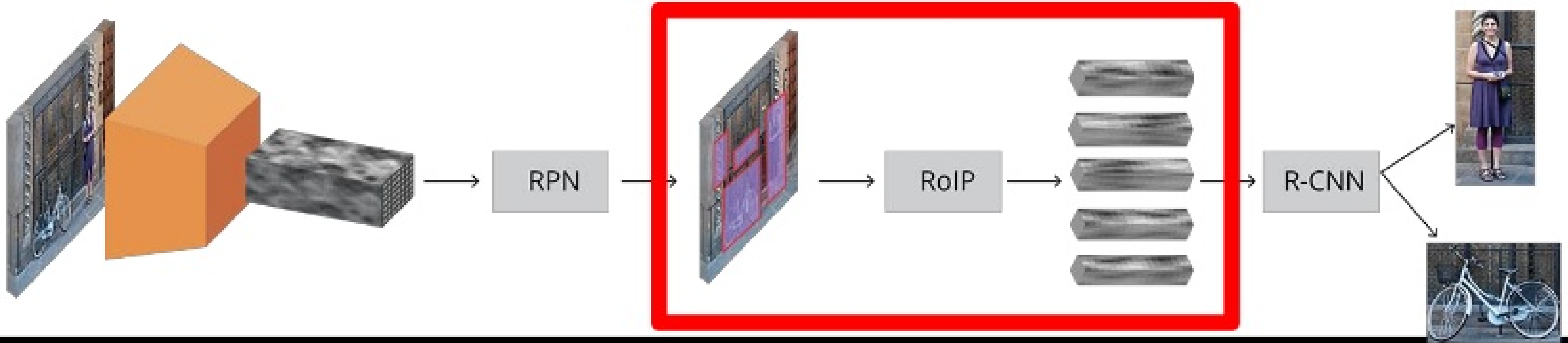


Faster R-CNN: Region of Interest Pooling

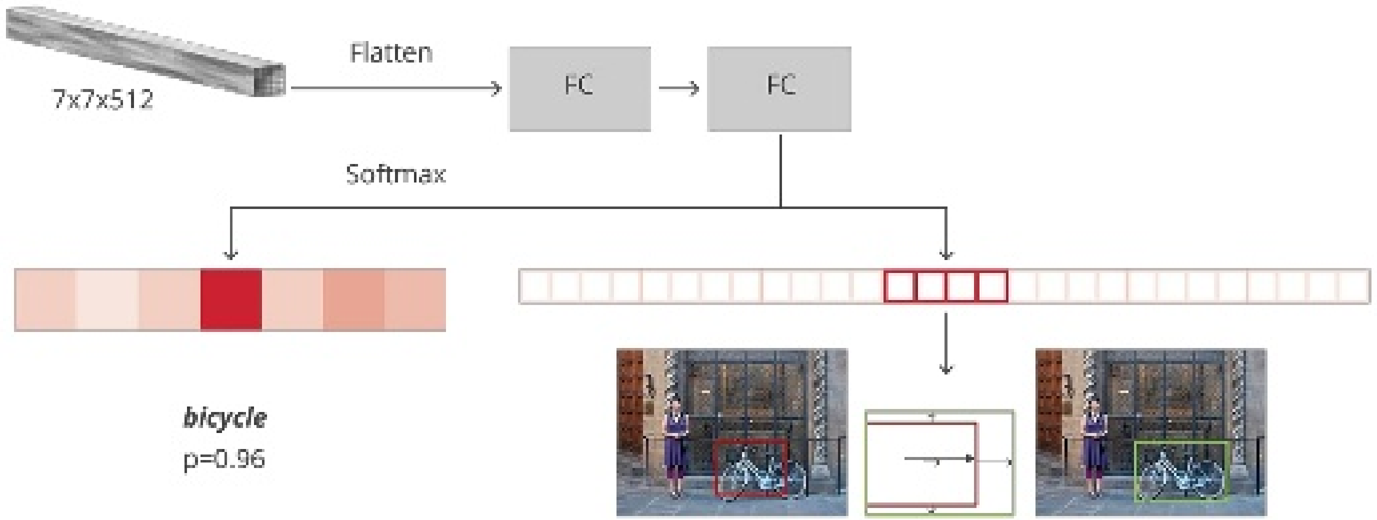
Step 3

- A "Region of Interest Pooling" stage condenses the convolutional features into a fixed size



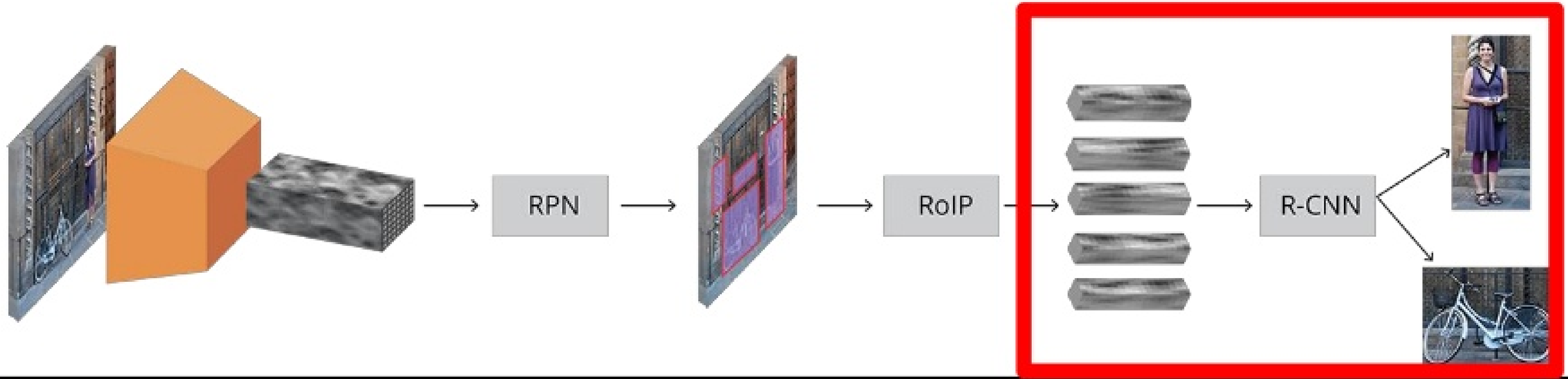


Faster R-CNN: Region Based CNN

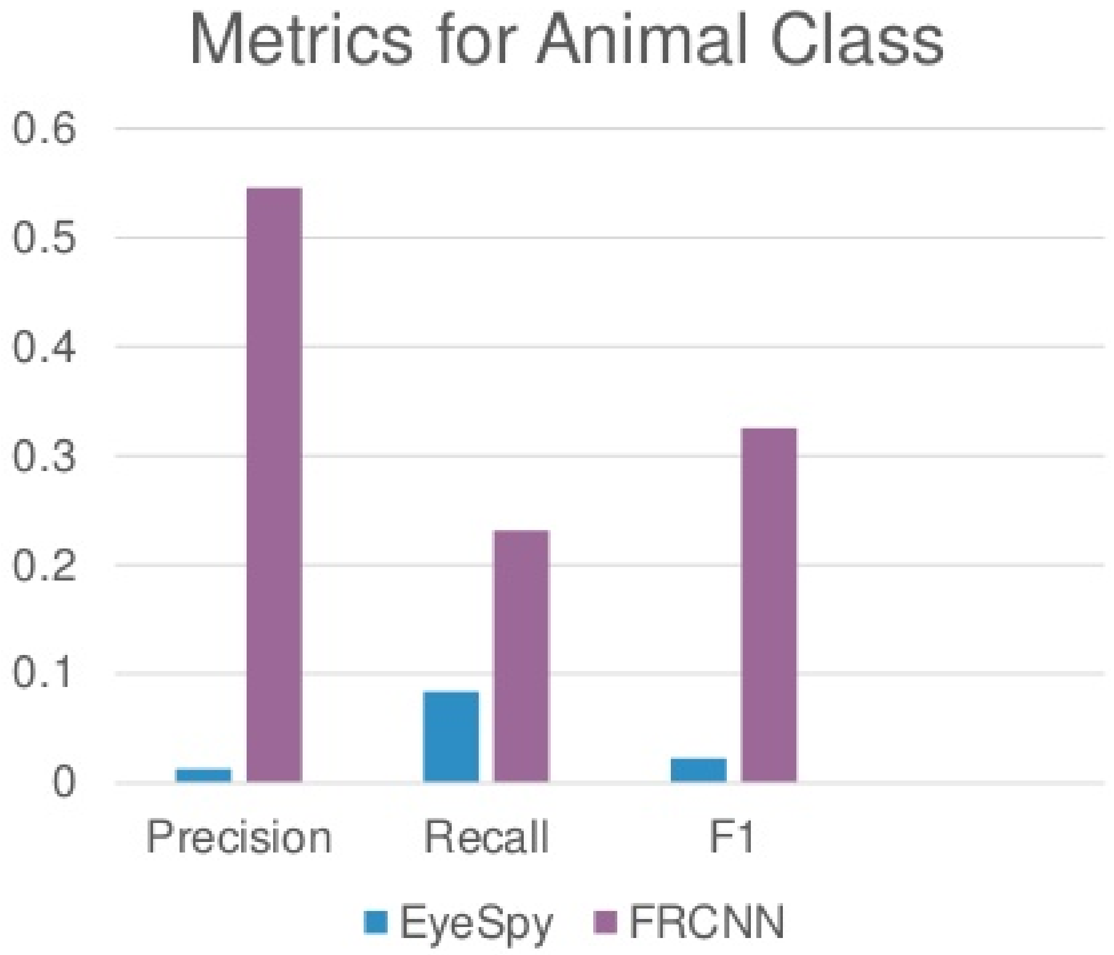


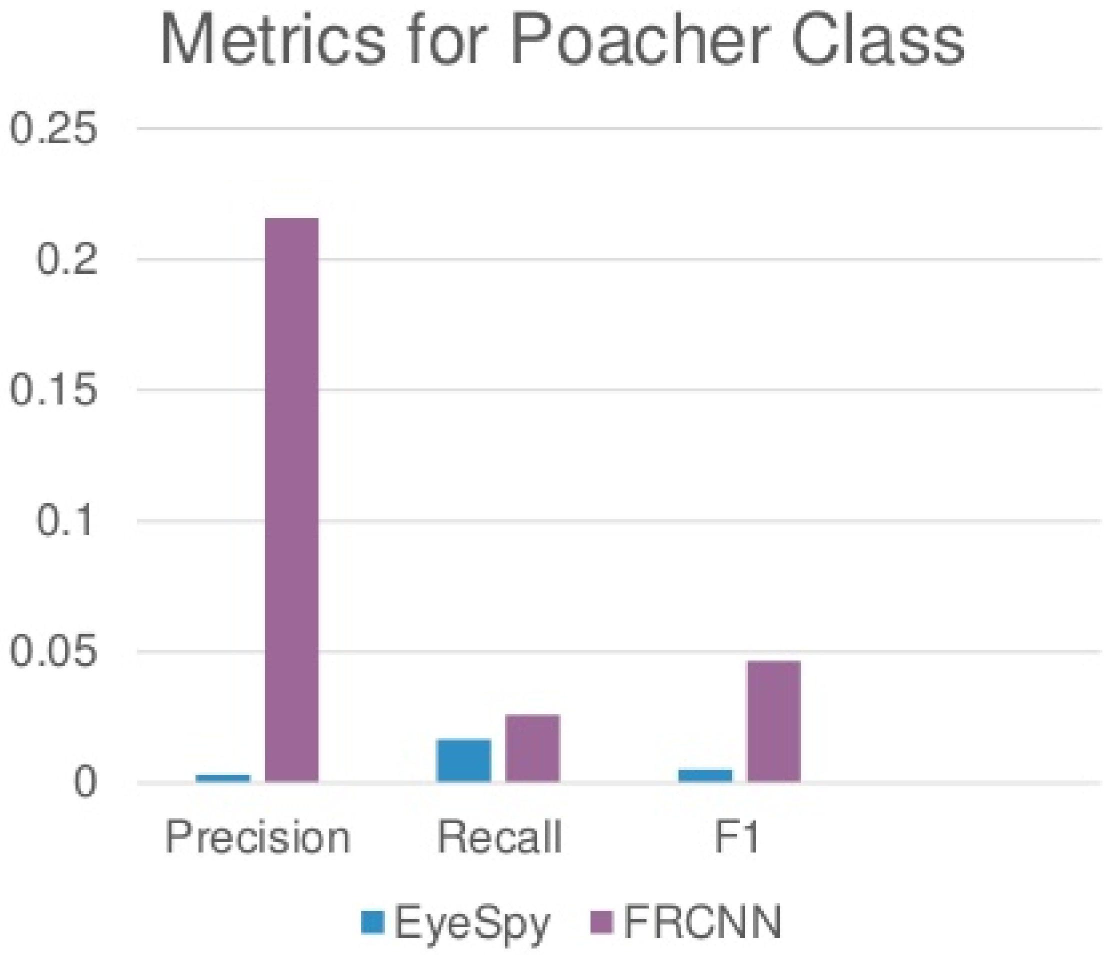
Step 4

- A convolutional network emits the class of the object and the bounding box “adjustments”



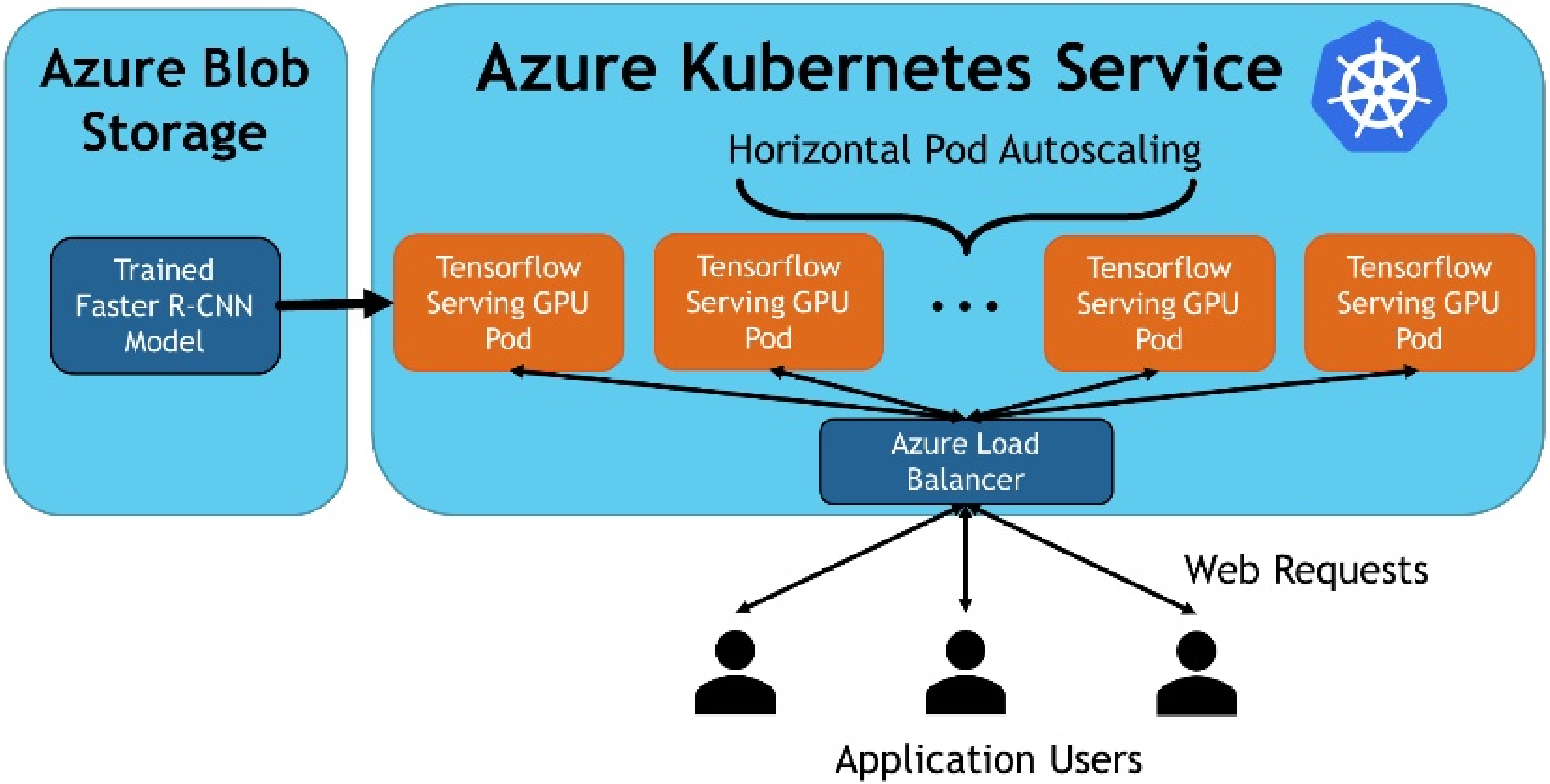
Results





"*AirSim-W: A Simulation Environment for Wildlife Conservation with UAVs*" – E. Bondi et al

Deployment of SPOT

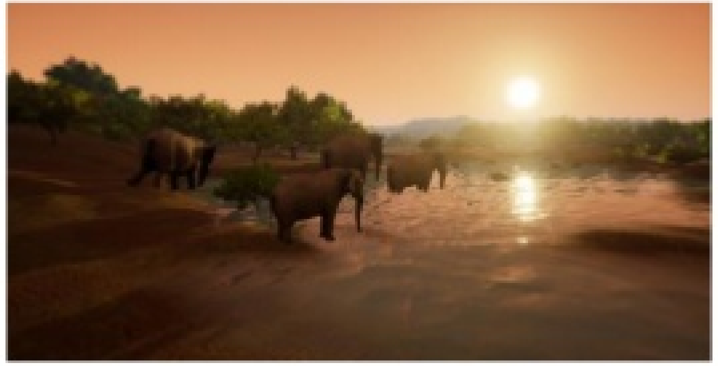


Sidestepping Labeling Woes with AirSim

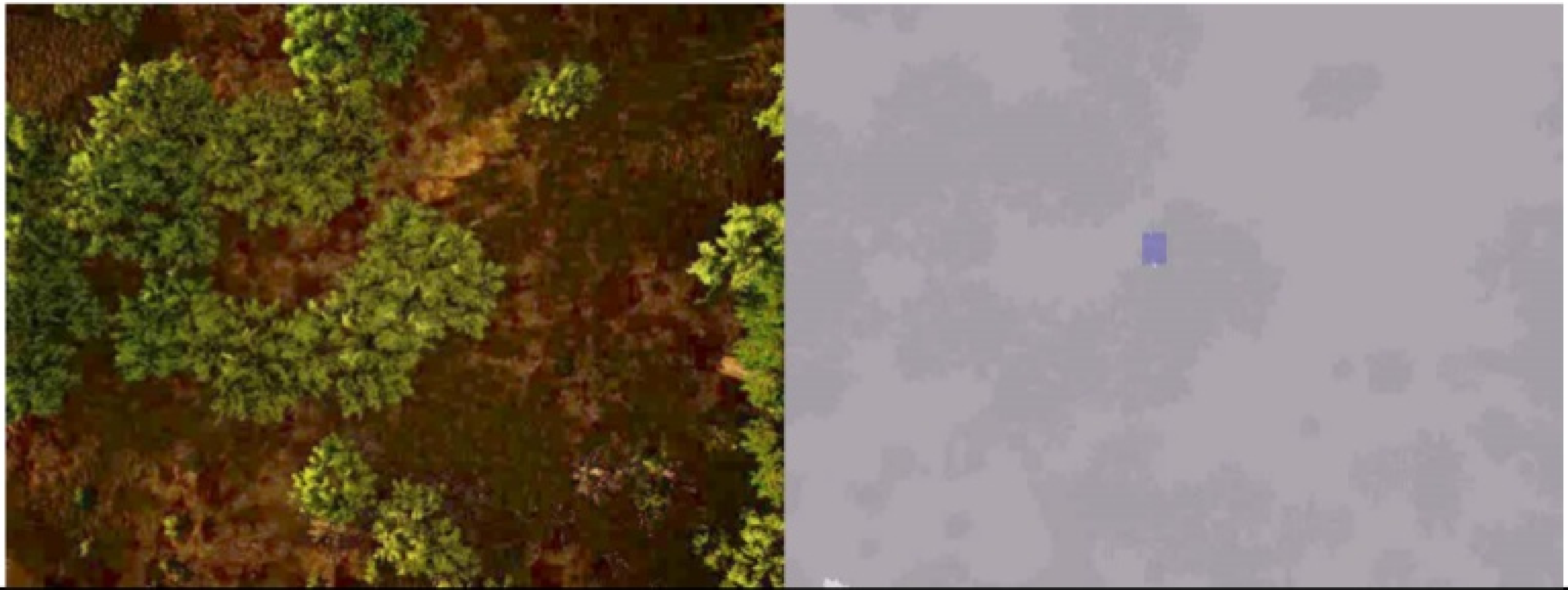
- 70 videos (~180,000 individual bounding boxes, 39,380 frames) labeled with VIOLA took **6 months**
- Goal: Bypass the need for human labelling

Shah, S., Dey, D., Lovett, C., & Kapoor, A. (2017). AirSim: High-fidelity visual and physical simulation for autonomous vehicles. In *Field and Service Robotics* (pp. 621-635). Springer, Cham.

AirSim-W: Africa Environment







"*AirSim-W: A Simulation Environment for Wildlife Conservation with UAVs*" – E. Bondi et al

Results

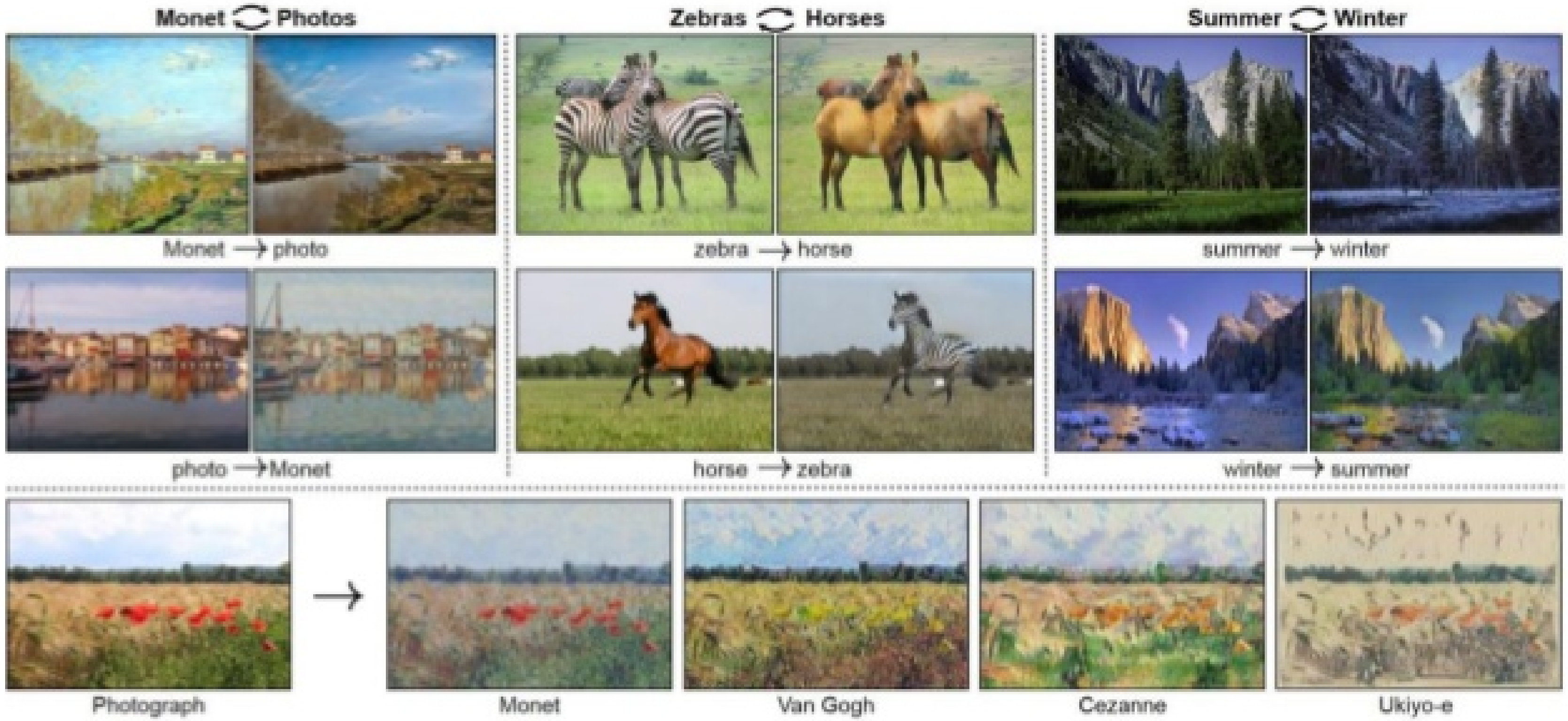
	Precision			
	EyeSpy	Only Real	Only Sim.	Sim. + Real
Animals	0.0128	**0.5463**	0.0202	0.5352
Poachers	0.0031	0.2160	0.0051	**0.3329**

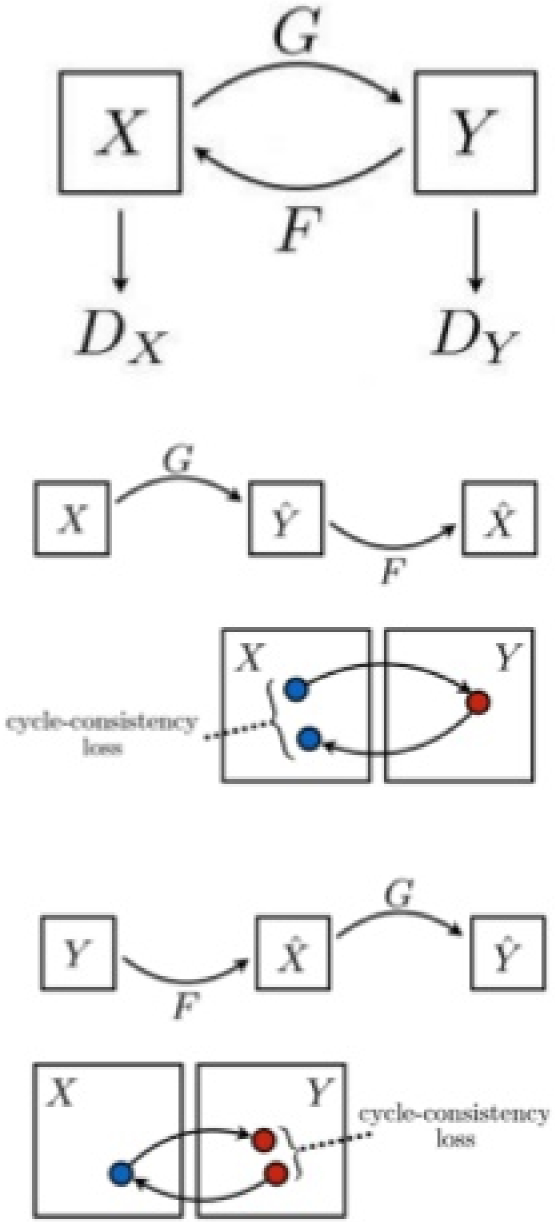
Recall			
EyeSpy	Only Real	Only Sim.	Sim. + Real
0.0839	0.2316	0.1458	**0.3207**
0.0167	0.0261	0.0038	**0.0485**

F1			
EyeSpy	Only Real	Only Sim.	Sim. + Real
0.0222	0.3253	0.0355	**0.4011**
0.0052	0.0466	0.0044	**0.0847**

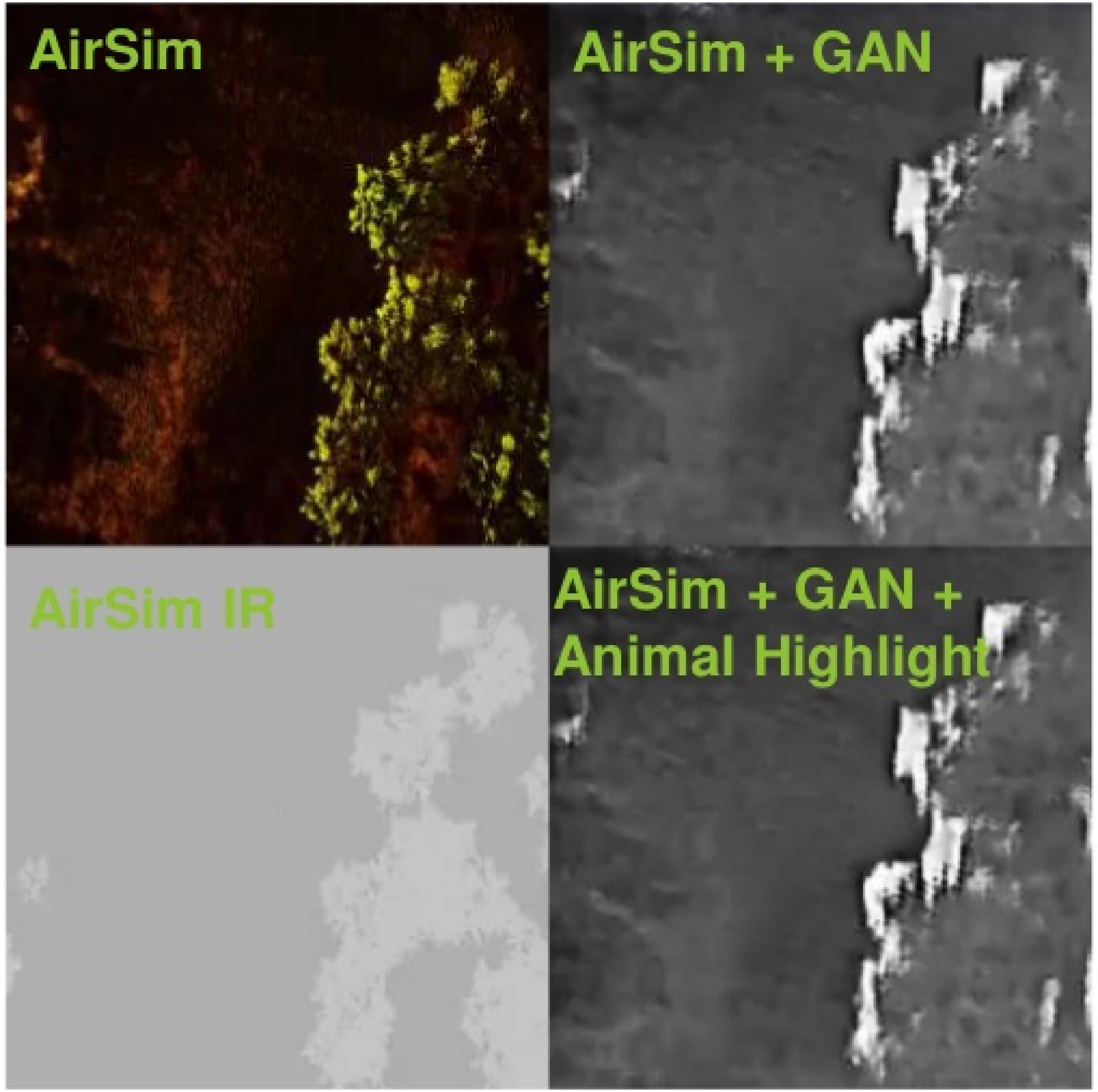
"*AirSim-W: A Simulation Environment for Wildlife Conservation with UAVs*" – E. Bondi et al

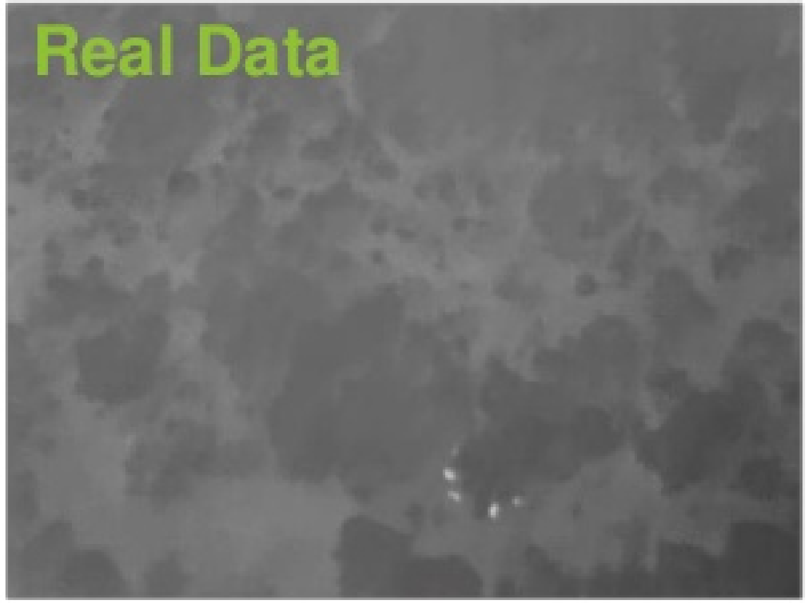
Deep Domain Adaptation

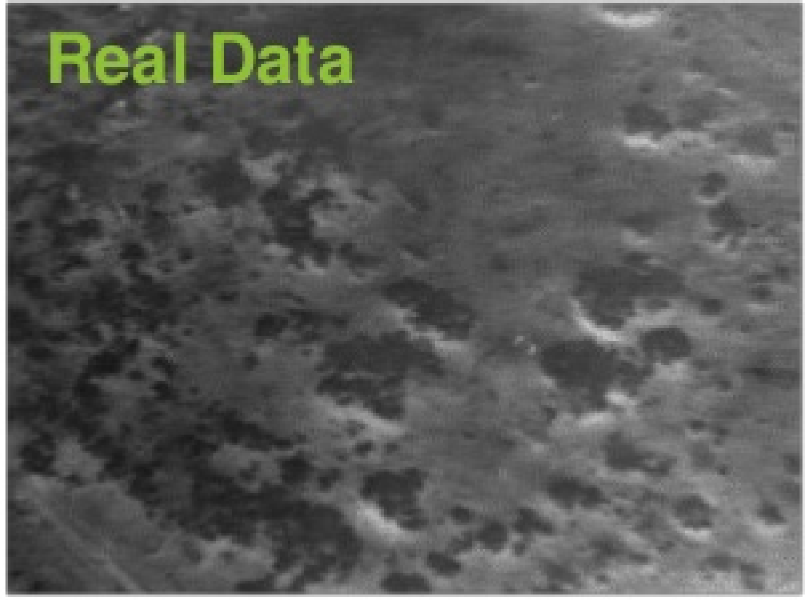




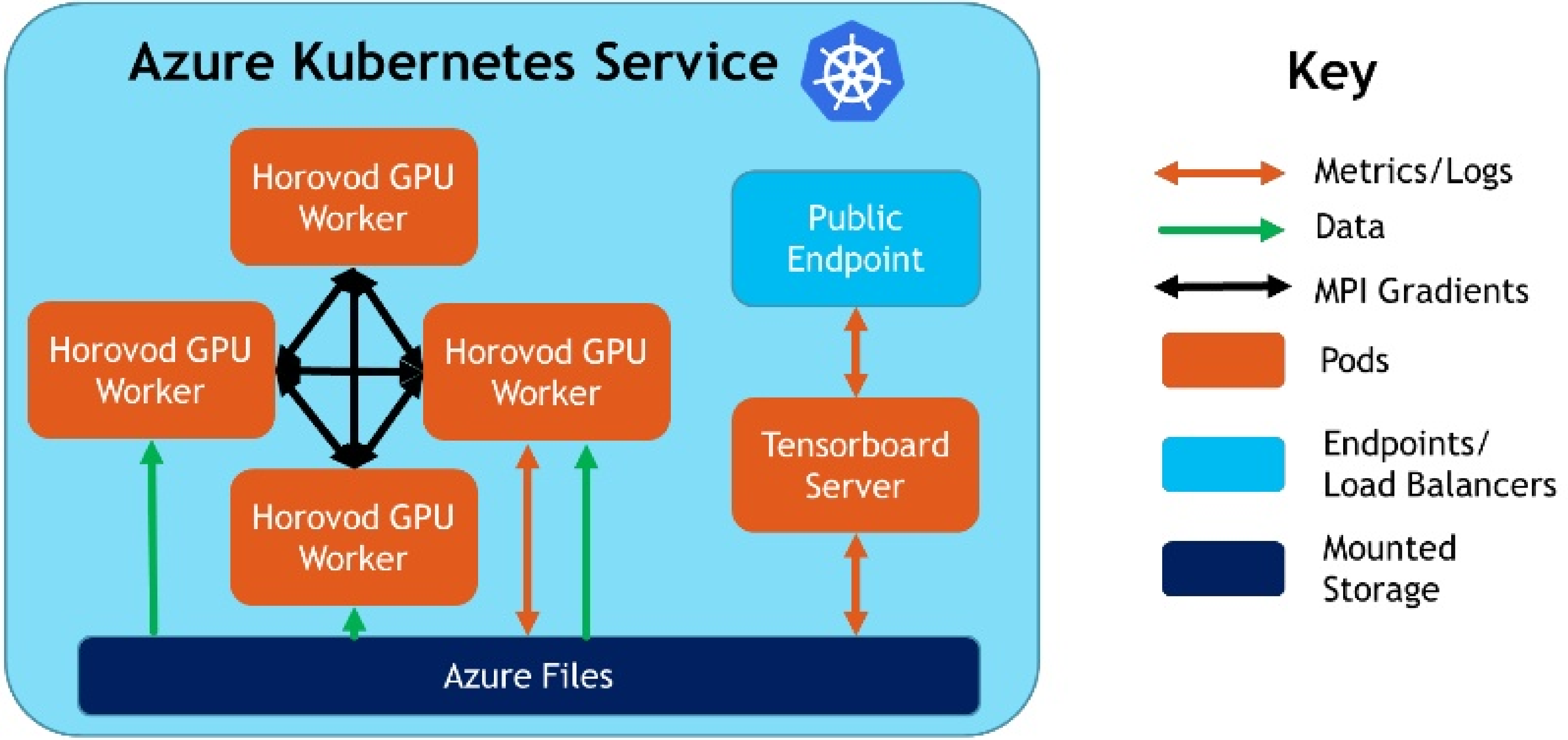
"*Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*" Jun-Yan Zhu*, Taesung Park*, Phillip Isola, Alexei A. Efros
Berkeley AI Research Lab, UC Berkeley


AirSim
AirSim + GAN
AirSim IR
AirSim + GAN +
Animal Highlight


Real Data


Real Data

Distributed Training Architecture



Easy Deployment with HELM

- Helm acts as a “package manager” for Kubernetes
- Easily deploy and share recipes for complex architectures
  - Uses parameters for easy CLI configuration
- Works on any Kubernetes Cluster (AKS, ACI, On-Prem)
- Open Source “Helm Chart” Coming Soon!

```
charts/horovod$ helm install ./horovod -n cycle-gan
```

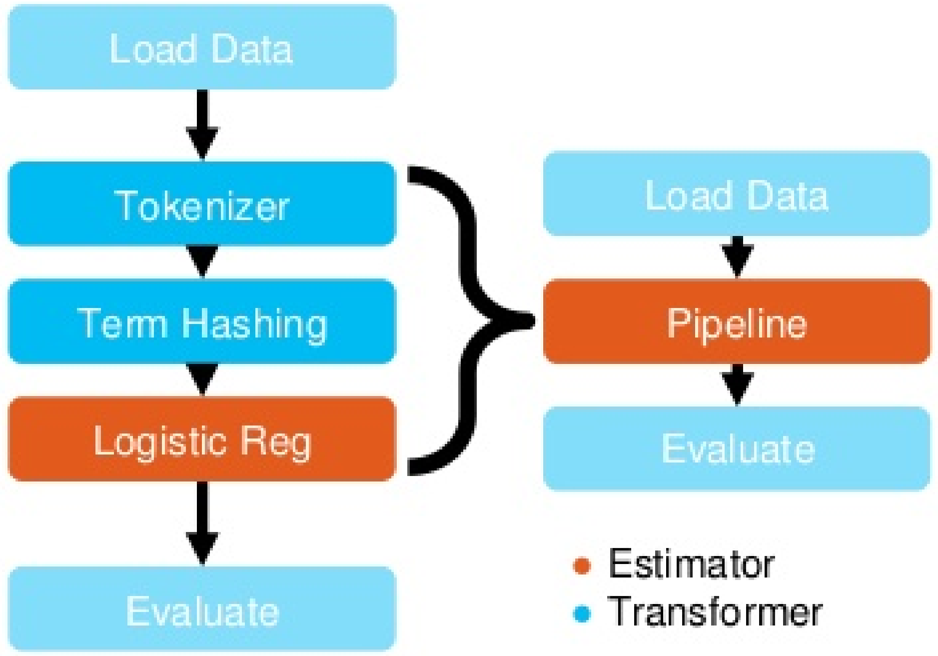
Challenges

- No unified procedures for storing data
- Serving and training architectures fundamentally different
  - Inconsistent APIS
  - Inconsistent architectures (different base pods)
- No single point of entry to run entire workflow

Apache Spark ML

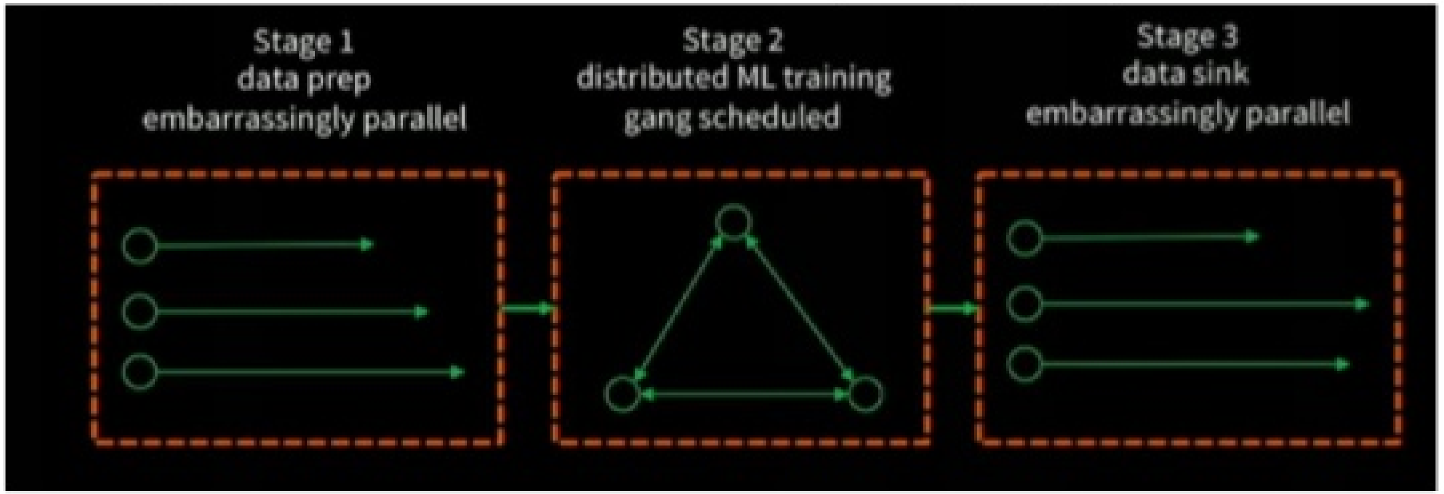
```
data = spark.read.csv("hdfs://...")
train, test = data.randomSplit([.5,.5])
model = LogisticRegression().fit(train)
predictions = model.transform(test)
```

- High level library for distributed machine learning
- More general than SciKit-Learn
- All models have a uniform interface
  - Can compose models into complex pipelines
  - Can save, load, and transport models



Horovod on Spark

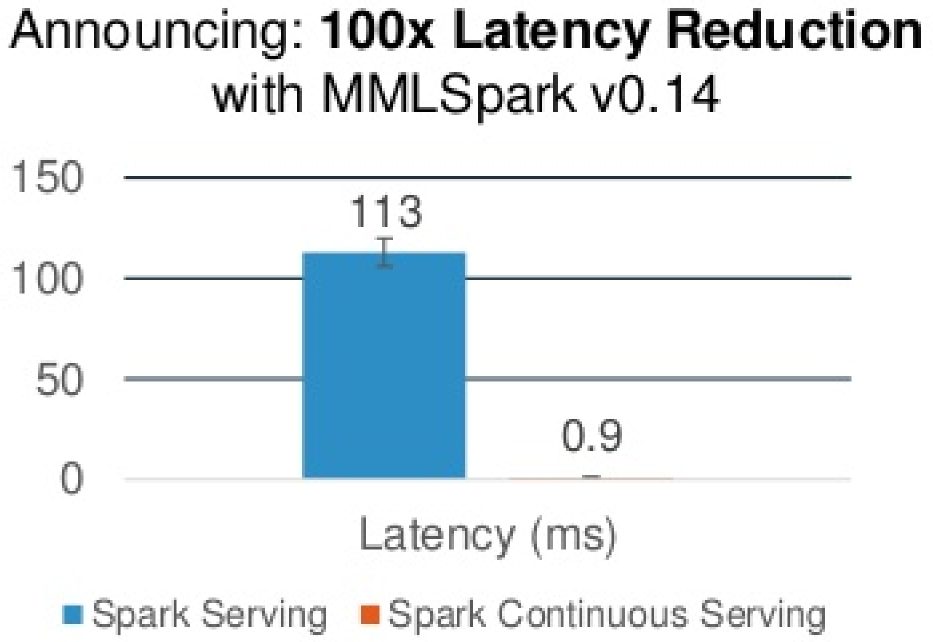
- High level SparkML API for launching distributed deep learning jobs on the spark cluster
- Built on Project Hydrogen: Gang Scheduled Job
- Enables integration with data prep pipeline on Spark



Apache Spark Serving

Lightning Fast Web Services on ***Any*** Spark Cluster

- Sub-millisecond latencies
- Fully Distributed
- Spins up in seconds
- Same API as Batch and Streaming
- Scala, Python, R and Java
- Fully Open Source



www.aka.ms/spark

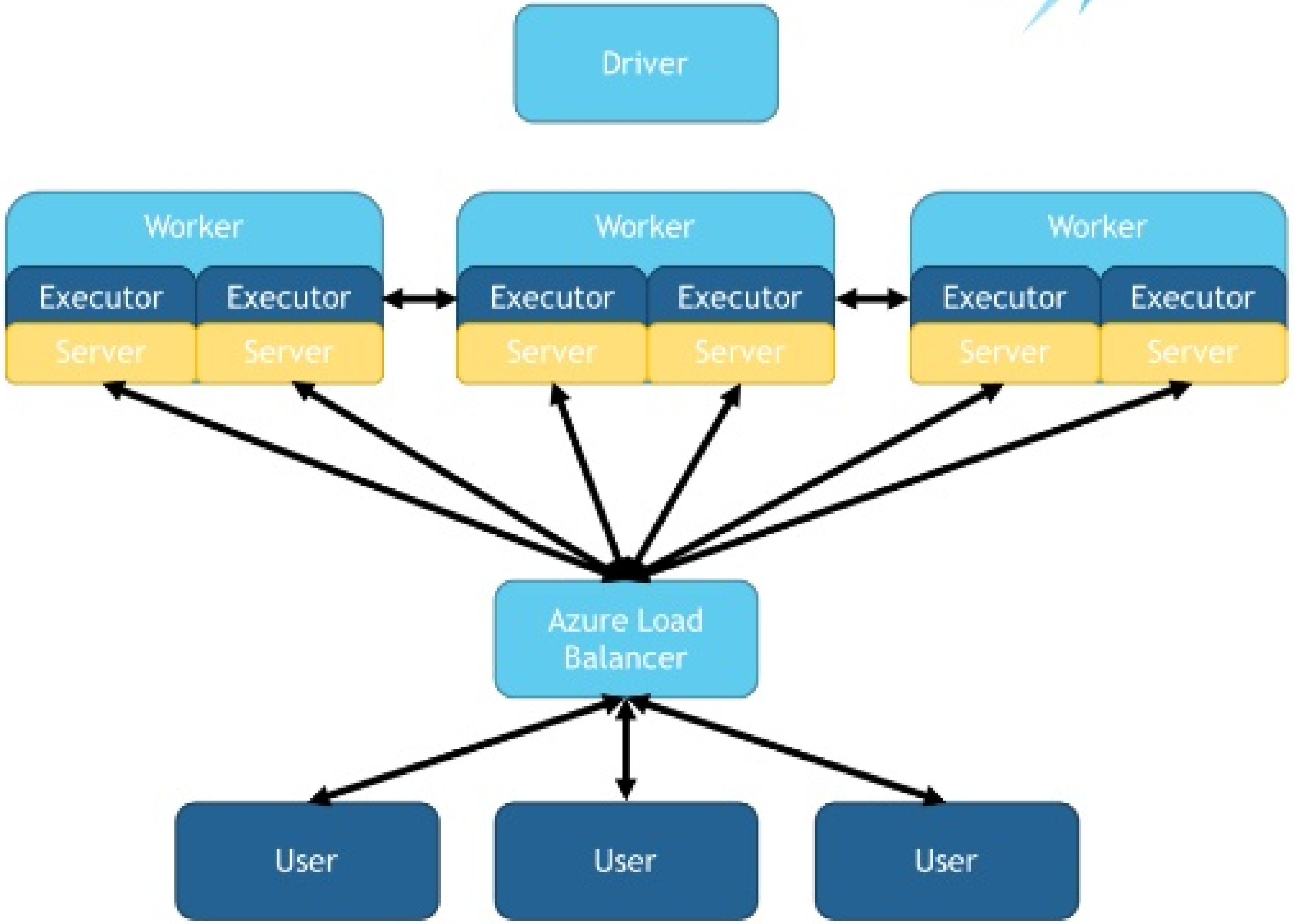
JIRA: SPARK-25350

The Spark Serving API

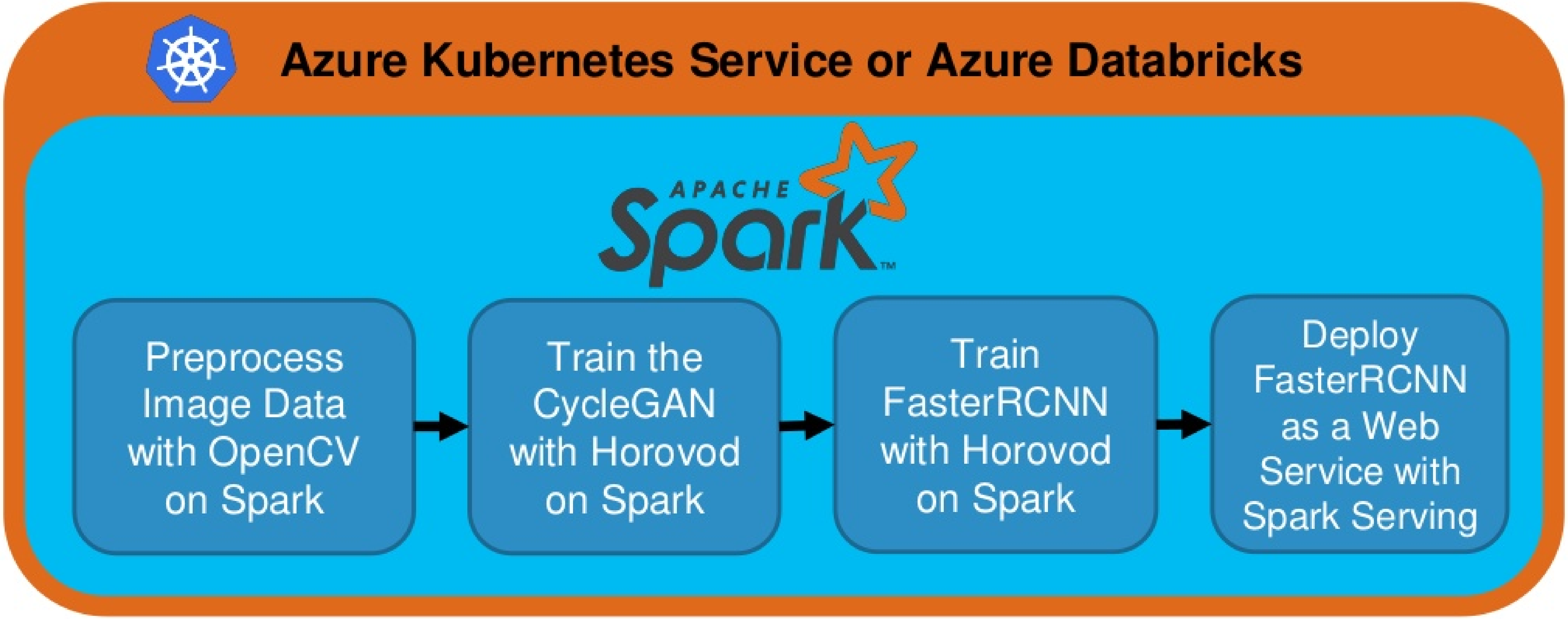
```
# Create a new "Serving" Dataframe
serving_df = (spark.readStream.server()
  .address("0.0.0.0", 8889, "danger_detector").load()
  .parseRequest(BinaryType())
  .withColumnRenamed("bytes", "image"))

# Manipulate your dataframe using ANY Spark/SparkML operations
replies = fitModel.transform(serving_df).makeReply("probability")

# Write your serving dataframe to the api to reply
server = (replies.writeStream.server()
  .replyTo("danger_detector")
  .queryName("my_service")
  .start())
```

Spark Serving Architecture

- 3 main modes:
  - server: 1 service on the head node
  - distributedServer: 1 service per executor
  - continuousServer: 1 service per partition
- Built on top of Spark Streaming
- Each worker keeps a running service, and a routing table
- Use HTTP on Spark objects to represent requests and responses in Spark SQL



Ideal Architecture



In Conclusion

- Big Releases in MMLSpark v0.14:
  - Sub-Millisecond latency distributed web services
  - 2 more large announcements in our next Session!
    - Semi-Supervised Object Detection Using the Azure Cognitive Services on Spark: **Oct 3, 14:00**
- We aim to give all work back to the community!
- Easy to Get Started on Databricks:
  - 16 Jupiter notebook guide

MMLSpark v0.14

www.aka.ms/spark

Contributions Welcome!
github.com/Azure/mmlspark

Thanks to

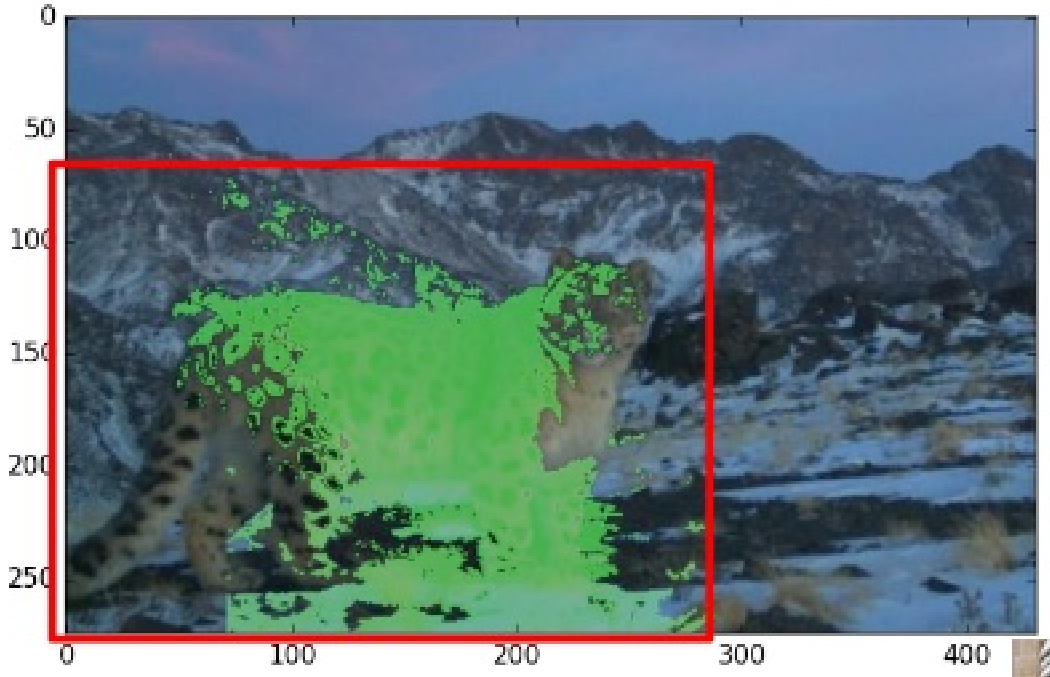
- You all!
- MMLSpark Team: Sudarshan Raghunathan, Ilya Matiach, Eli Barzilay, Tong Wen, Ben Brodsky
- Microsoft AI Development Acceleration Program: Abhiram Eswaran, Ari Green, Courtney Cochrane, Janhavi Suresh Mahajan, Karthik Rajendran, Minsoo Thigpen, Casey Hong, Soundar Srinivasan
- University of Southern California: Elizabeth Bondi, Millind Timbe
- Microsoft: Joseph Sirosh, Lucas Joppa, WeeHyong Tok

MMLSpark Website: aka.ms/spark

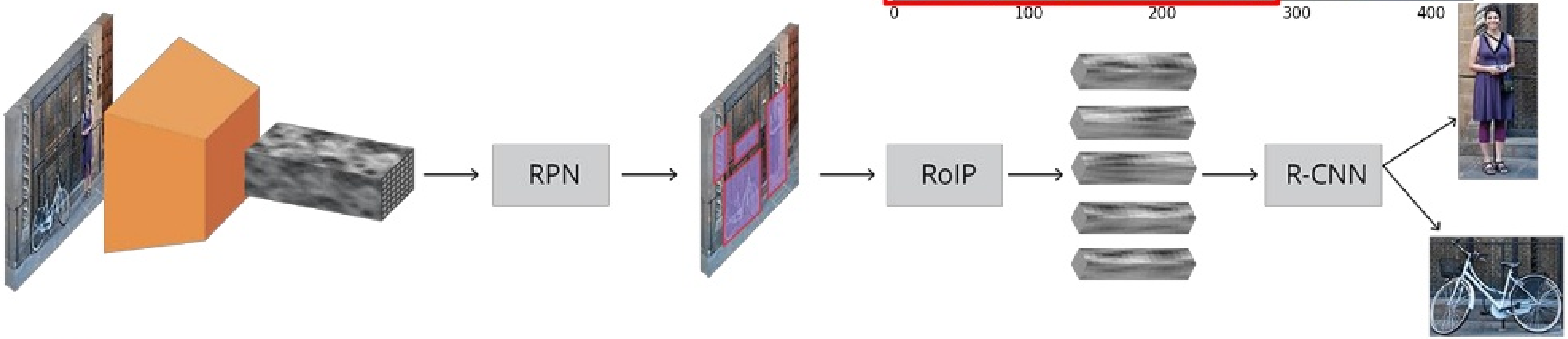
Get in touch: marhamil@microsoft.com

Using LIME to generate bounding boxes

Transferring LIME's Knowledge to FasterRCNN

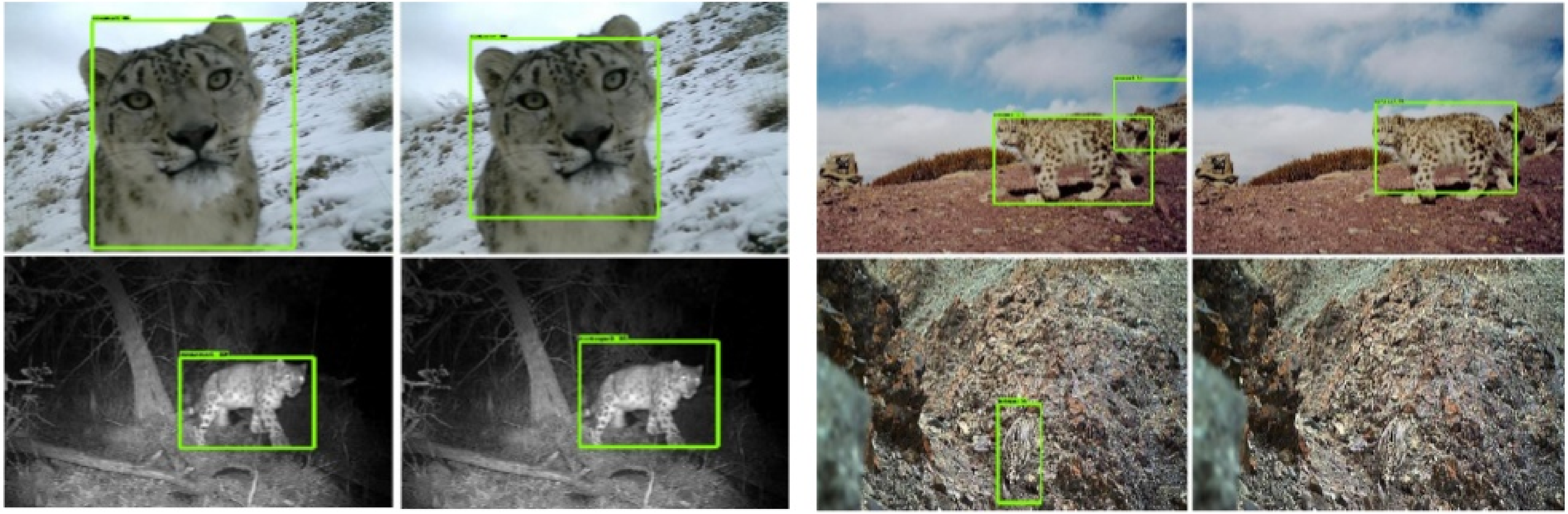


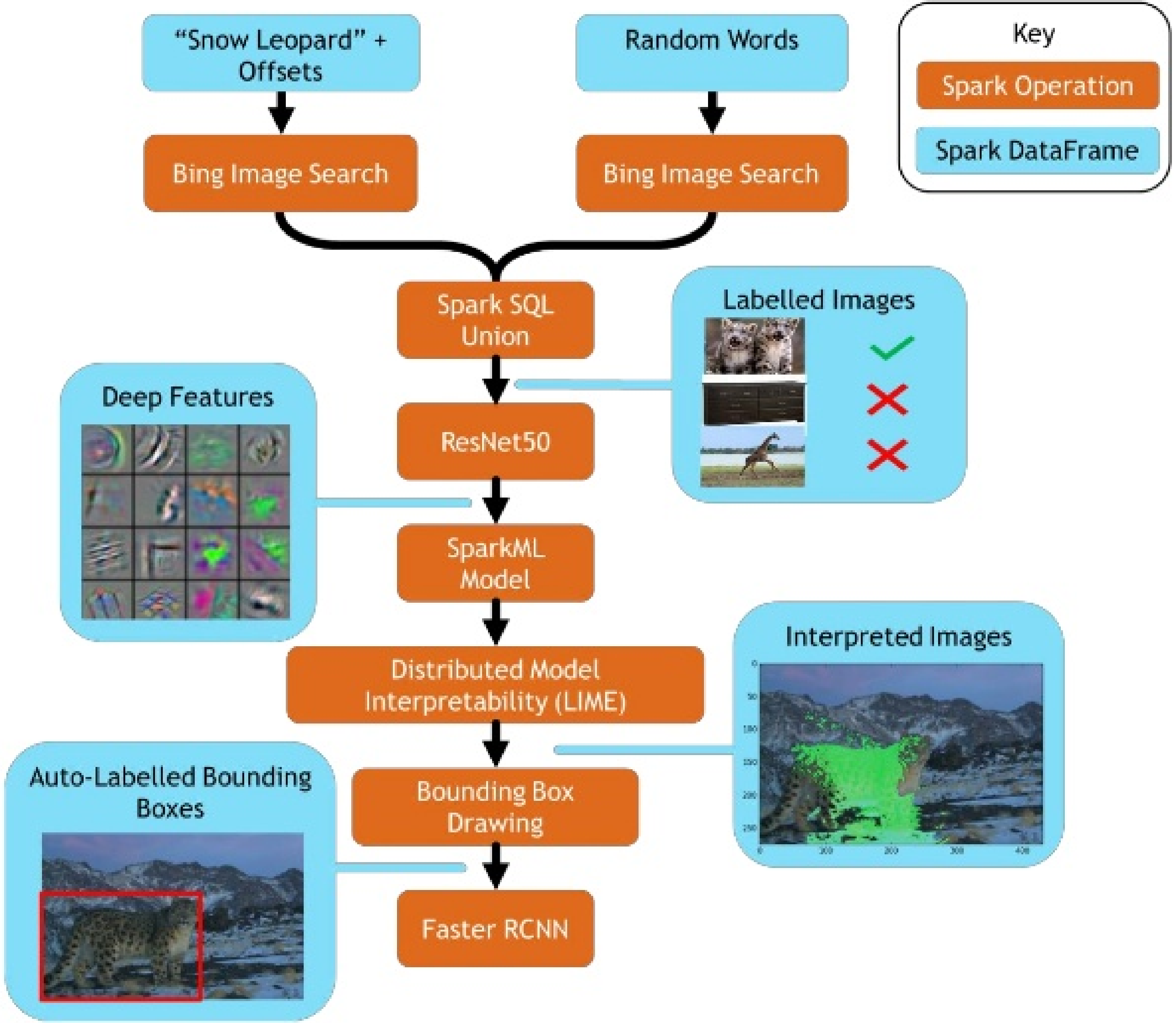
$$mask = union(superpixels \mid top\ 70\%\ of\ weights)$$
$$x1, y1 = \min(mask_x), \min(mask_y)$$
$$x2, y2 = \max(mask_x), \max(mask_y)$$



Results

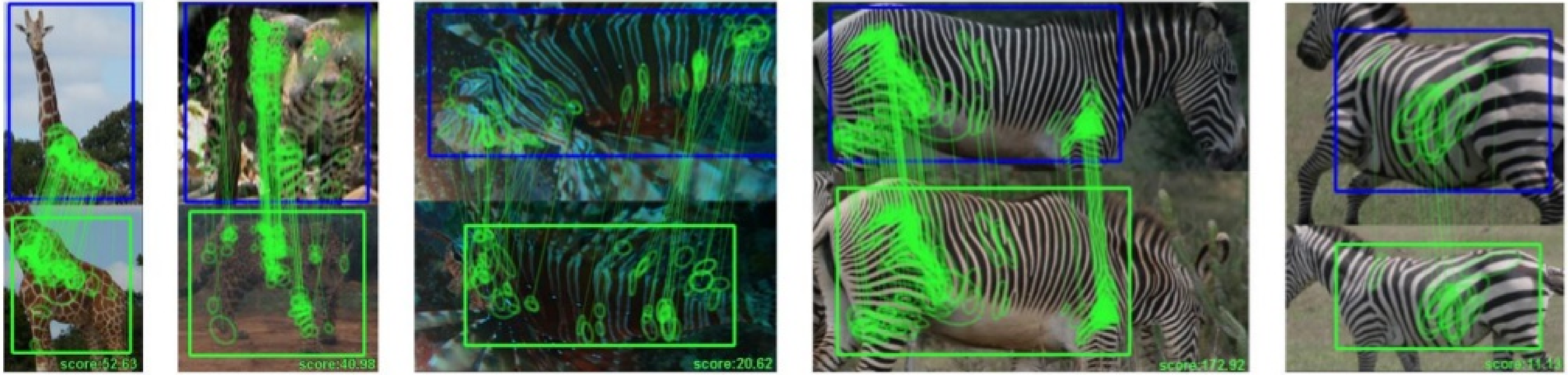
Human Labels	Unsupervised FRCNN Outputs	Human Labels	Unsupervised FRCNN Outputs





"Snow Leopard" + Offsets
Random Words
Key
Spark Operation
Spark DataFrame
Bing Image Search
Bing Image Search
Spark SQL Union
Labelled Images
Deep Features
ResNet50
SparkML Model
Interpreted Images
Distributed Model Interpretability (LIME)
Auto-Labelled Bounding Boxes
Bounding Box Drawing
Faster RCNN

Next Steps: Hotspotter



Source: HotSpotter - Patterned Species Instance Recognition

In Conclusion

- Big Releases in v0.14:
  - **Cognitive Services on Spark**
  - **Sub-Millisecond latency distributed web services**
  - **Distributed Model Interpretability**
- Easy batch, streaming apps, PowerBI dashboards, or RESTful web services
- We aim to give all work back to the community!
- Easy to Get Started on Databricks:
  - 16 Jupiter notebook guide

MMLSpark v0.14

www.aka.ms/spark

Contributions Welcome!
github.com/Azure/mmlspark

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- The Snow Leopard Trust: Rhetick Sengupta, Koustubh Sharma, Jeff Brown, Michael Despines
- Microsoft: Joseph Sirosh, Lucas Joppa, WeeHyong Tok

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