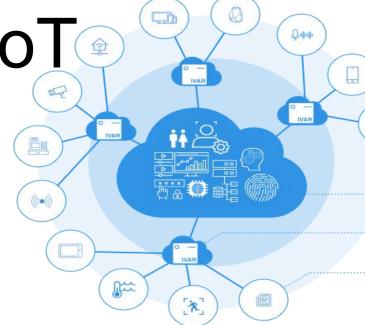
Real-Time Data processing and Al for Distributed IoT

Group 15

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Why it's so hard to do real time Al processing at the end device?

Problem definition

- Resource Limited IoT devices
- Latency and network congestion
- Inefficient use of cloud resources
- When data is offloaded to the cloud, it causes some privacy issues



What are current solutions?

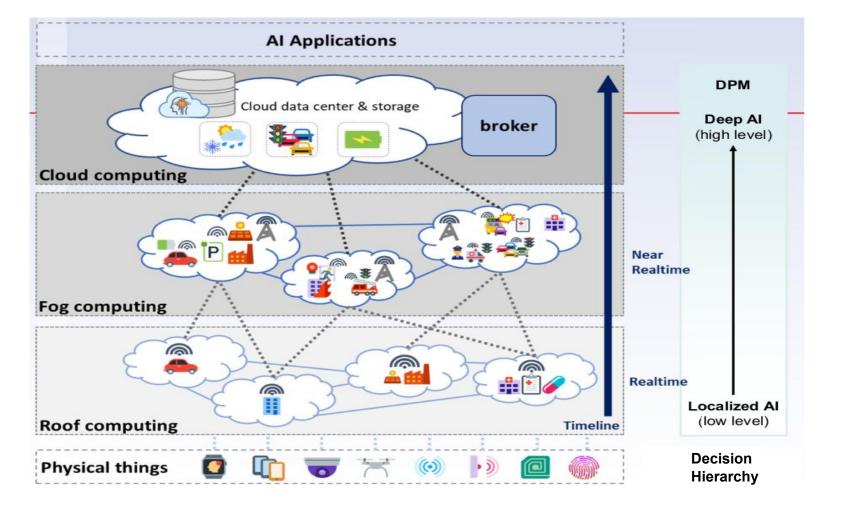


Related work

Related work	Proposed work			
Use Fog computing for real time process	Use ROOF and Fog for real time process			
Map reduce to distribute computation	Map reduce based approach focus on limited resource devices			
Top down approach to train model in cloud and deploy to edge	Train the model at the edge and IoT devices			
Train the global model at the edge or cloud(Federated Learning)	Peer to Peer /Cluster (Static /Dynamic)/Master slave architecture			
Use policy technology to deploy model trained in top to deploy in bottom edge devices	Use bottom up approach, having defined threshold limits and priorities to decide when to offload.			

Proposed methodology:

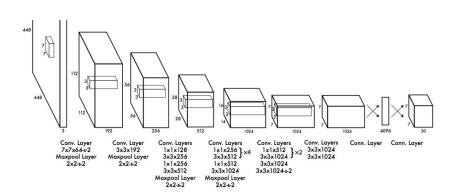
- Instead of developing deep AI in cloud center, novel localized AI algorithms to be implemented in low level edge using ROOF and Fog computing.
- Policy technology-As decisions are need to made in real time. There should be a
 policies to when to offload data to cloud as data communication is costly.
- Federated Learning to fine tune the learning parameters
- Distribute Computation using MapReduce based approach

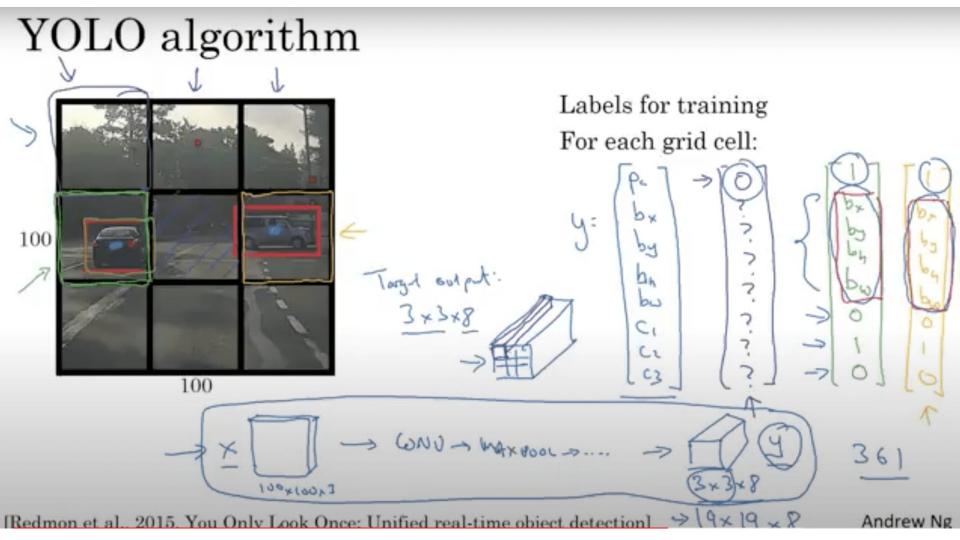


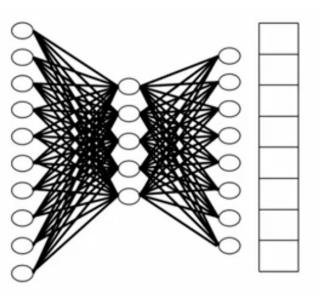
So our plan is to run a object detection algorithms on IoT devices in real time

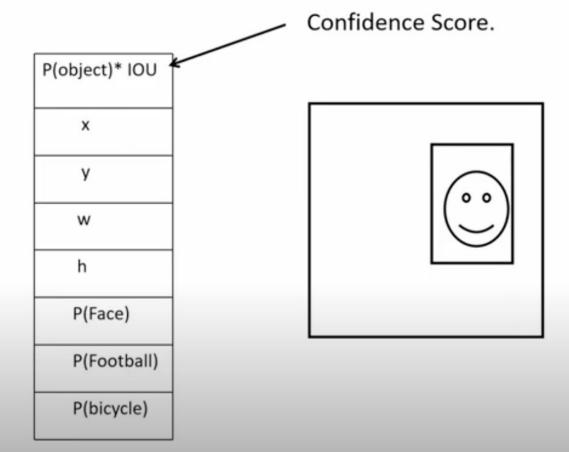
Why Yolo?

- Fast
- High accuracy









Our changes to Yolo

MapReduce based approach

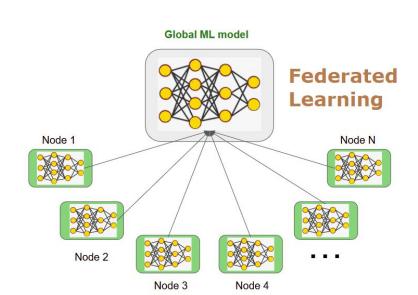
Distribute computation over multiple nodes

Bottom up approach

- Less network delays
- Computation in closer proximity to the user

Federated learning

- Data privacy
- Learn a shared model for prediction



Evaluation

Optimized YOLO CNN Performance Results in different environment

Environment	Execution time (ms)
Google Colab cloud CPU	3060.6624
Google Colab cloud GPU	93.4970
Single Raspberry Pi	65531
Three Raspberry Pi	32744

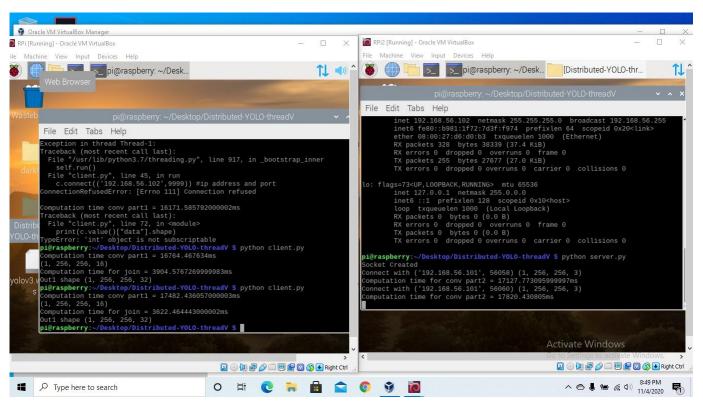
Compare and Analysis

$$\frac{CPU\ Execution\ time\ (s)}{GPU\ Execution\ time(s)} = \frac{3.0606}{0.0934} = _{32.76} \tag{1}$$

Resource Availability in Colab Cloud – GP
$$U(RAM)$$
 = $\frac{12 \text{ GB}}{512 \text{ MB}}$ = $\frac{12 \text{ GB}}{512 \text{$

$$\frac{P \, arallel \, implementation \, Execution \, time(ms)}{Single \, Raspberry \, P \, i \, Execution \, time \, (ms)} = \frac{32744}{65531} = _{0.499}$$

DEMO



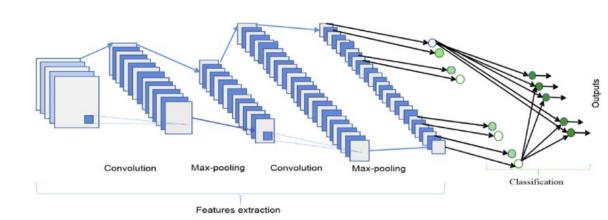
Conclusion and future direction

Recap

- Real time decision using FL ,map reduce base techniques with limited resource
- Computation distribution

Next steps

- Apply federated learning
- Offloading techniques
- Improve CNN



Project Plan

Title	T/M	Start	End	0
Start of Semester 7	► M +	06/07/2020	06/07/2020	170
Research	■ T •	13/07/2020	07/08/2020	20 days
Research	■ T •	05/10/2020	23/10/2020	15 days
Implement CNN	■T •	05/10/2020	19/10/2020	11 days
Distribute CNN	■ T •	11/10/2020	23/10/2020	10 days
Start of Semester 8	► M -	09/11/2020	09/11/2020	-
Improve CNN and accuracy	■ T •	09/11/2020	30/01/2021	60 days
Apply Federated Learning	■T •	09/11/2020	15/02/2021	71 days
Apply offloading techniques	■ T •	09/11/2020	15/02/2021	71 days
Finalize Project	● T ▼	01/02/2021	26/03/2021	40 days
End	► M -	26/03/2021	26/03/2021	-

Our Proposed Work

Milestones

7 semester

ML model for limited resources IoT devices

8 semester

- Designing a federated learning algorithm.
- Designing offloading based on the threshold
- Designing the Policy framework based on the priorities



Our Accomplishments

- CNN for YOLO
- Approach to distribute computation



THANK YOU

<u>8</u>4