Frugal Following: Power Thrifty Object Detection and Tracking for Mobile Augmented Reality

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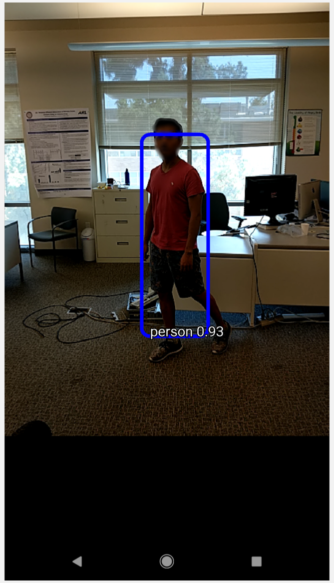
ACM SenSys, November 10-13, 2019, Columbia University, New York, USA

Augmented Reality (AR)

- AR devices are forecast to be a $100 billion market by 2021

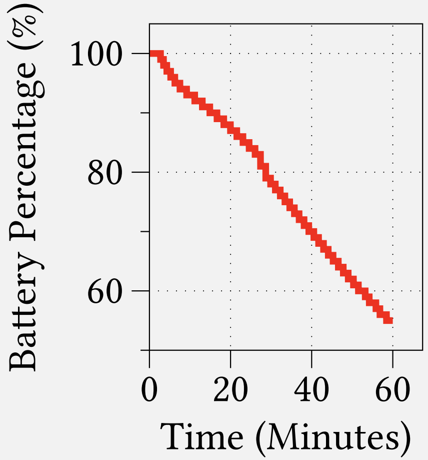
- AR is a killer app, with diverse applications
  - Pokemon Go, Google Translate, etc.

- In AR, virtual objects are overlaid onto real world objects to provide information



Motivation

Example of Object Detection-based AR



Energy drain from continuous DNN executions

- Object detection is an important task in the AR pipeline
  - Estimate object locations and their classes to overlay virtual holograms
- Deep Neural Networks (DNNs) yield highly-precise object detection but are energy-heavy on mobile devices

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Design Goals

- **Precise classification** of real-world objects (e.g., cat vs dog)
- **Real-time, accurate tracking** of multiple, potentially moving objects → seamless user experience
- **Effective with other energy-saving techniques** such as mobile CPU throttling, mobile GPU, compressed DNNs
- Cope with **dynamic camera sensor inputs** due to handheld/wearable AR devices

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Problem Statement

How can AR apps achieve good object detection and tracking performance and yet consume low energy?

- Key Idea
  - Interleave heavyweight DNNs with lightweight methods (object tracking and change detectors)
- Challenges
  - How to design trackers and change detectors that are lightweight yet effective?
  - How often to trigger lightweight methods?
  - How to cope with automatic CPU throttling?

Contributions

- Develop **MARLIN** framework to mediate between DNNs and lightweight methods
- Design a lightweight change detector to determine when to trigger DNNs
- Evaluate on Android smartphones with standard datasets and live experiments
  - *Dataset*: up to **73.3% energy savings**, losing at most 7.36% accuracy for most cases
  - *Live*: up to **81% energy savings** with negligible accuracy loss
- Compatible with a developer's chosen DNN
  - E.g., Tiny YOLO, MobileNets, MobileNets w/ GPU, quantized (compressed) MobileNets
  - Up to **45.1% energy savings,** *beyond* what GPU or quantization already saves

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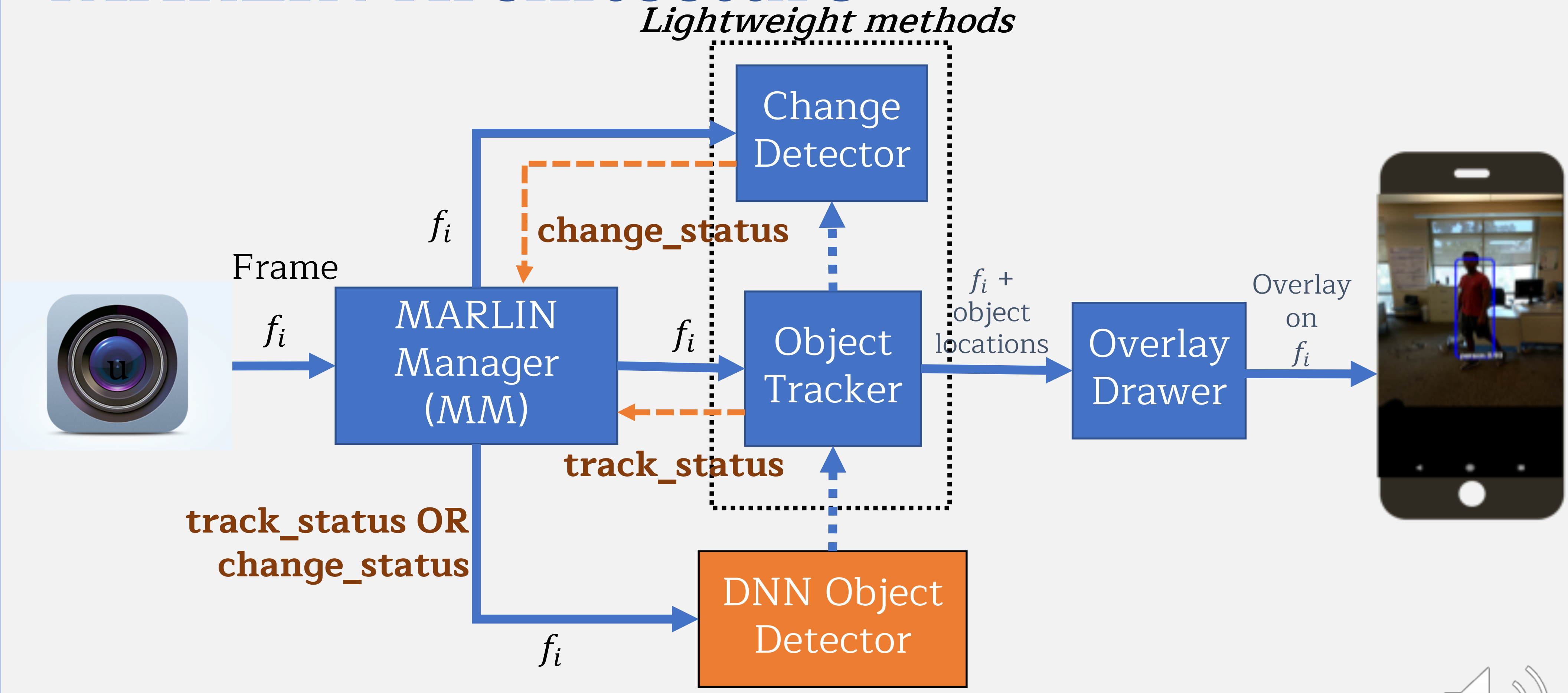
Design of MARLIN Framework

- MARLIN Architecture
- MARLIN Manager
- Real-time Object Tracker
- Lightweight Change Detector
- DNN Object Detector

MARLIN Architecture



MARLIN is thrifty in triggering DNNs and only does so on a need-to basis.

Real-time Object Tracker

- What tracking algorithm to use?
  - ORB image features + Lucas-Kanade optical flow
  - Real-time (update in < 10ms) and low power (0.2-0.3 W)

- How to know if the tracker failed?
  - Use normalized cross correlation (NCC) to estimate tracking accuracy
    - Because we do not know the ground truth object locations *a priori*
    - NCC measures object feature similarity between two frames

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Lightweight Change Detector

- **Requirements:** real-time, low-power, low false positive rates, ignore existing objects
- **Existing methods:** Background subtraction is susceptible to camera motion → frequent DNN triggers → high energy consumption
- **Our method:** Random forest with image features (color histogram)
  - Fast (~ 4ms), low-power (< 0.1 W), accurate compared to other lightweight ML techniques
  - Color existing objects with a "white box" to avoid triggering changes on them

ML techniques	Precision (%)	Recall (%)
Random Forest with color histogram (MARLIN)	88.0	81.7
SVM using HOG features	64.9	61.4

change_status=true

change_status=false

To avoid triggering on existing objects, they are "whited out".

DNN Object Detector

- DNNs provide high classification and detection accuracy
  - extract image features automatically
  - pass through convolutional layers
  - output class labels + object locations
- We use off-the-shelf DNNs
- They can be plugged into MARLIN to save energy

Trained and tested DNNs	Abbreviation
YOLO	-
Tiny YOLO	TYL
MobileNets	MNet
GPU-assisted MobileNets	MNet-GPU
Quantized MobileNets	MNet-Q

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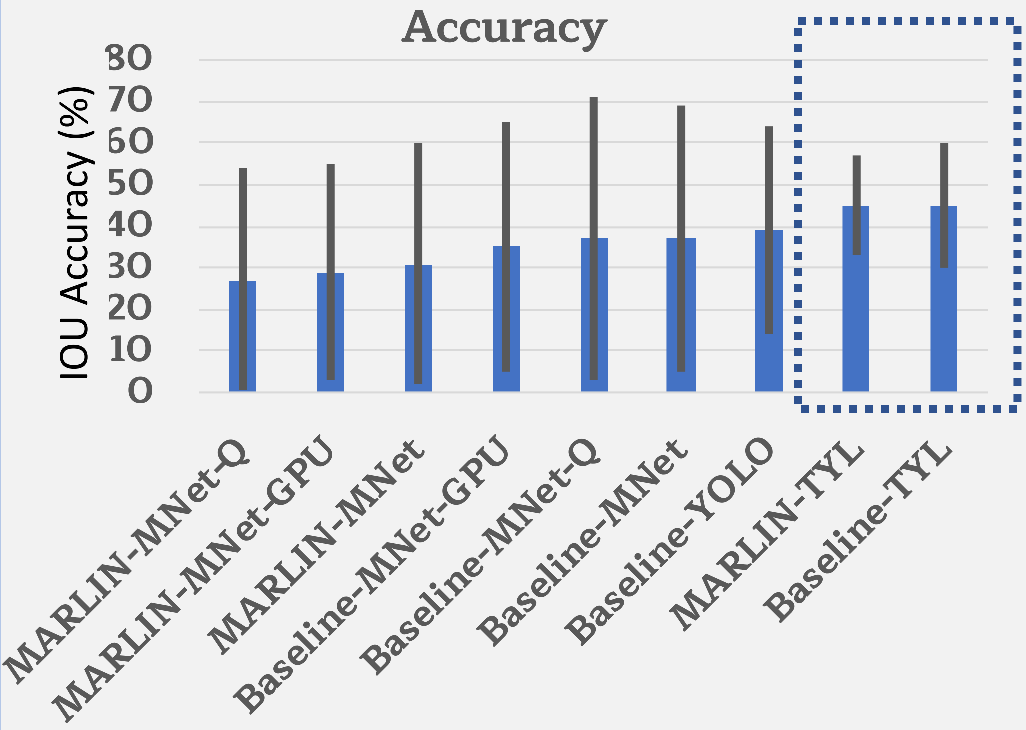
MARLIN Evaluations

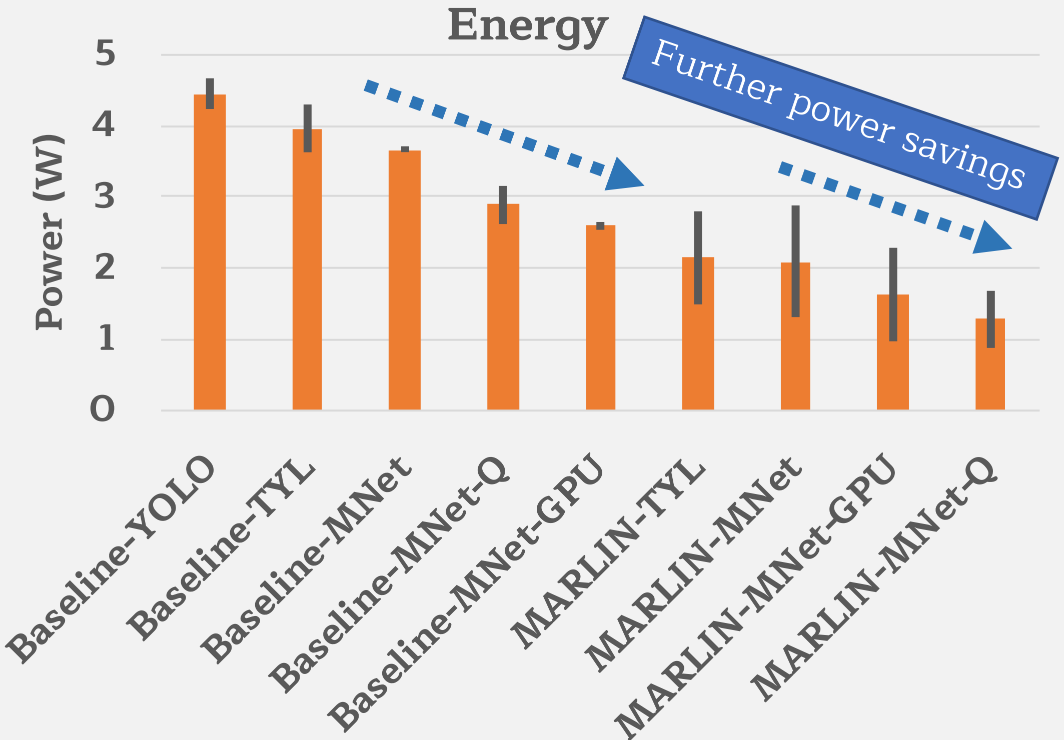
- Offline evaluations
  - Comparing multiple DNN baseline approaches
  - Comparing with the best baseline
  - Case study: zoomed-in video
  - Impact of mobile CPU throttling
- Online (live) evaluations

Experimental Setup

- **Devices**: Google Pixel 2 running Android 8.0 and LG G6 running Android 7.0 (for automatic CPU throttling)
- **Datasets**
  - ImageNet-Video for offline experiments
  - VOC-2007, VOC-2012, and Penn-Fudan Pedestrian to train DNN for live experiments
- **Training/validation/test**
  - 350 videos for offline training and validation
  - 15-80 other videos for online testing
- **Baseline**
  - Continuous executions of DNN (DNN triggered immediately after previous one)

How much energy does MARLIN save?

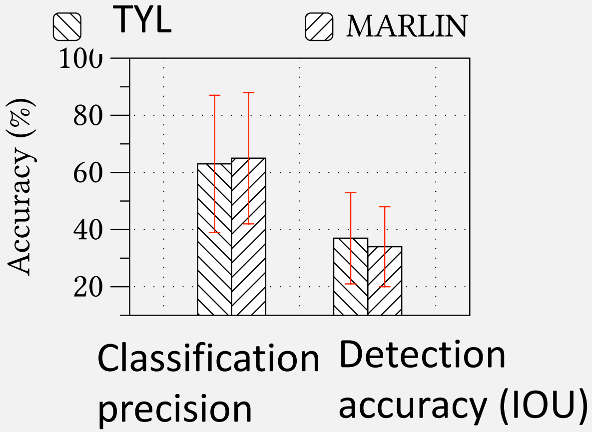


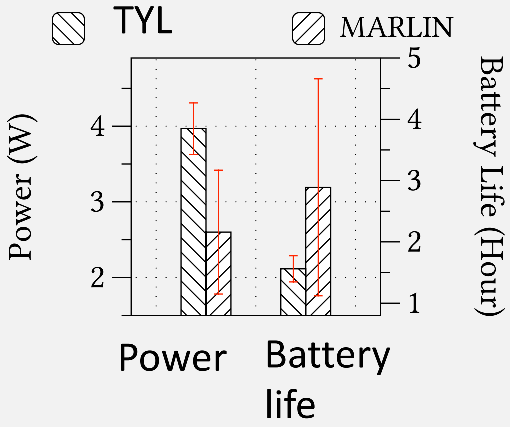


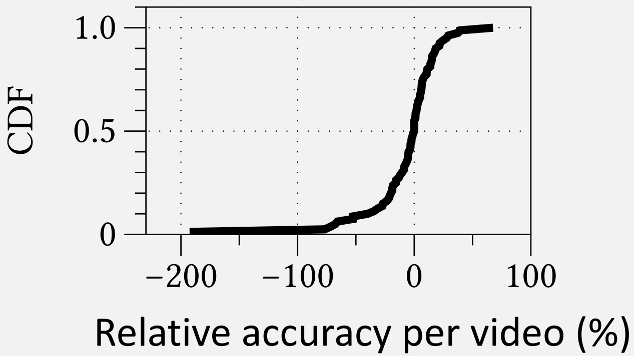
MARLIN saves power consumption by **45.1%**, compared to baseline quantized DNN or GPU-assisted DNN, while suffering **8.3%** accuracy loss

- In terms of accuracy, Tiny YOLO (TYL) is the best baseline to compare with MARLIN.

Comparing with the best baseline (Tiny YOLO)



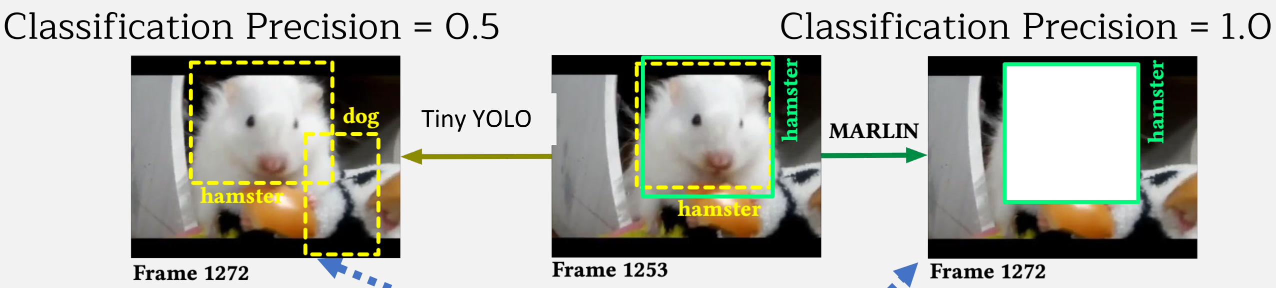


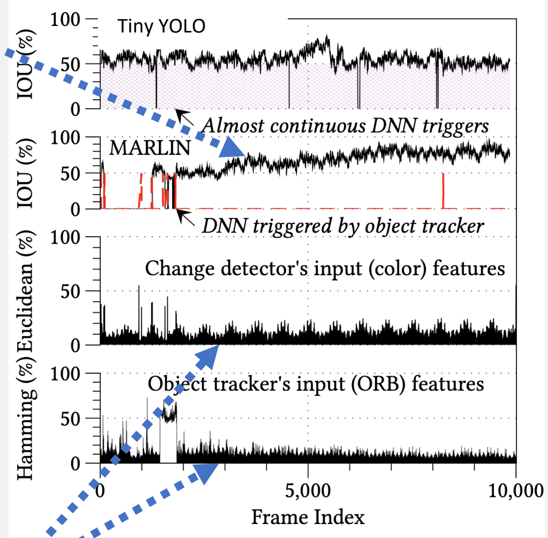


- MARLIN extends battery life by **1.85×,** with a small accuracy loss
- In terms of relative accuracy per video $\frac{Accuracy_{TYL} - Accuracy_{MARLIN}}{Accuracy_{TYL}}$ for **46.3%** of the videos, MARLIN can even improve accuracy!

Surprisingly, accuracy increases sometimes… why?

A case study of a zoom-in video





- Baseline Tiny-YOLO sometimes yields false results due to frequently executing DNNs and tracking bad features
- MARLIN tracks good, stable image features found by the object tracker and change detector
- For this video, MARLIN has 55% ACP accuracy gain, and saves **2.5 W** of power and extends battery life by **3.5 hours**!

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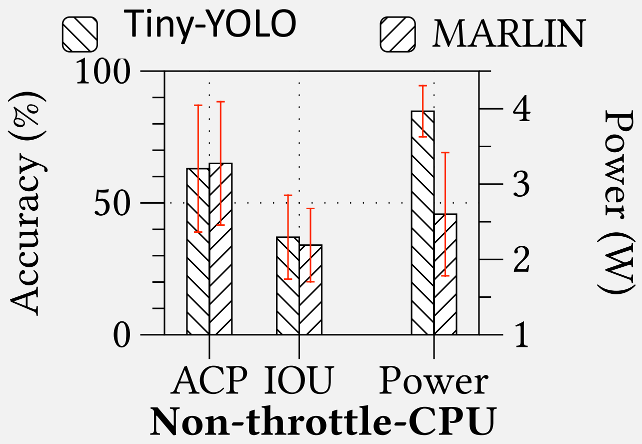
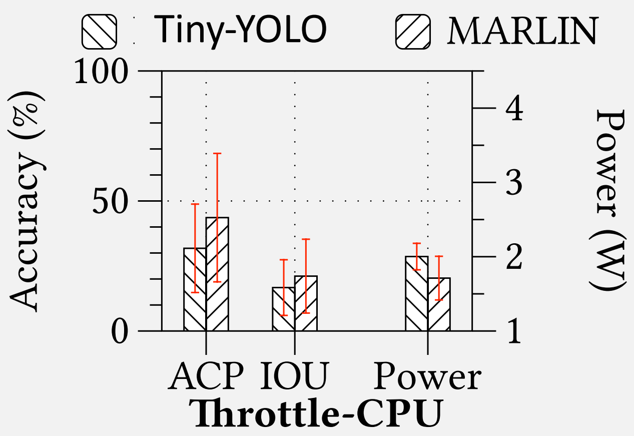
* ACP = Average Classification Precision

Automatic CPU throttling can save energy – Does MARLIN still help?





- Default throttled CPU → tracking latency increased → tracking accuracy reduced
- MARLIN reduces DNN executions → fewer throttling instances → improved tracking accuracy and reduce power consumption

* ACP = Average Classification Precision
IOU = Intersection Over Union

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Live experiments

Sets	Methods	IOU (%)	Power (W)
Live 1	Tiny-YOLO	61	1.724
	MARLIN	61	0.319
Live 2	Tiny-YOLO	56	1.710
	MARLIN	51	0.880

- AR user holds two Google Pixel 2 phones
  - One device runs Tiny YOLO, the other MARLIN
  - Ttrack 2-3 people in the field-of-view

- MARLIN achieves similar tracking accuracy to Tiny-YOLO , while using only ~**20%** (Live 1) and ~**50%** (Live 2)* of the power

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*In Live 2, there are more subjects with more movements than Live 1

Conclusions

- **Energy consumption** is a major concern for AR
  - Battery percentage drops 45% after 60 minutes

- We design MARLIN as power-thrifty framework for object detection and tracking for AR that is **compatible with multiple DNNs**

- MARLIN intelligently alternates between DNNs and lightweight methods to achieve high accuracy while **saving ~45% energy**

- **Future work** includes using inertial odometry to further save energy

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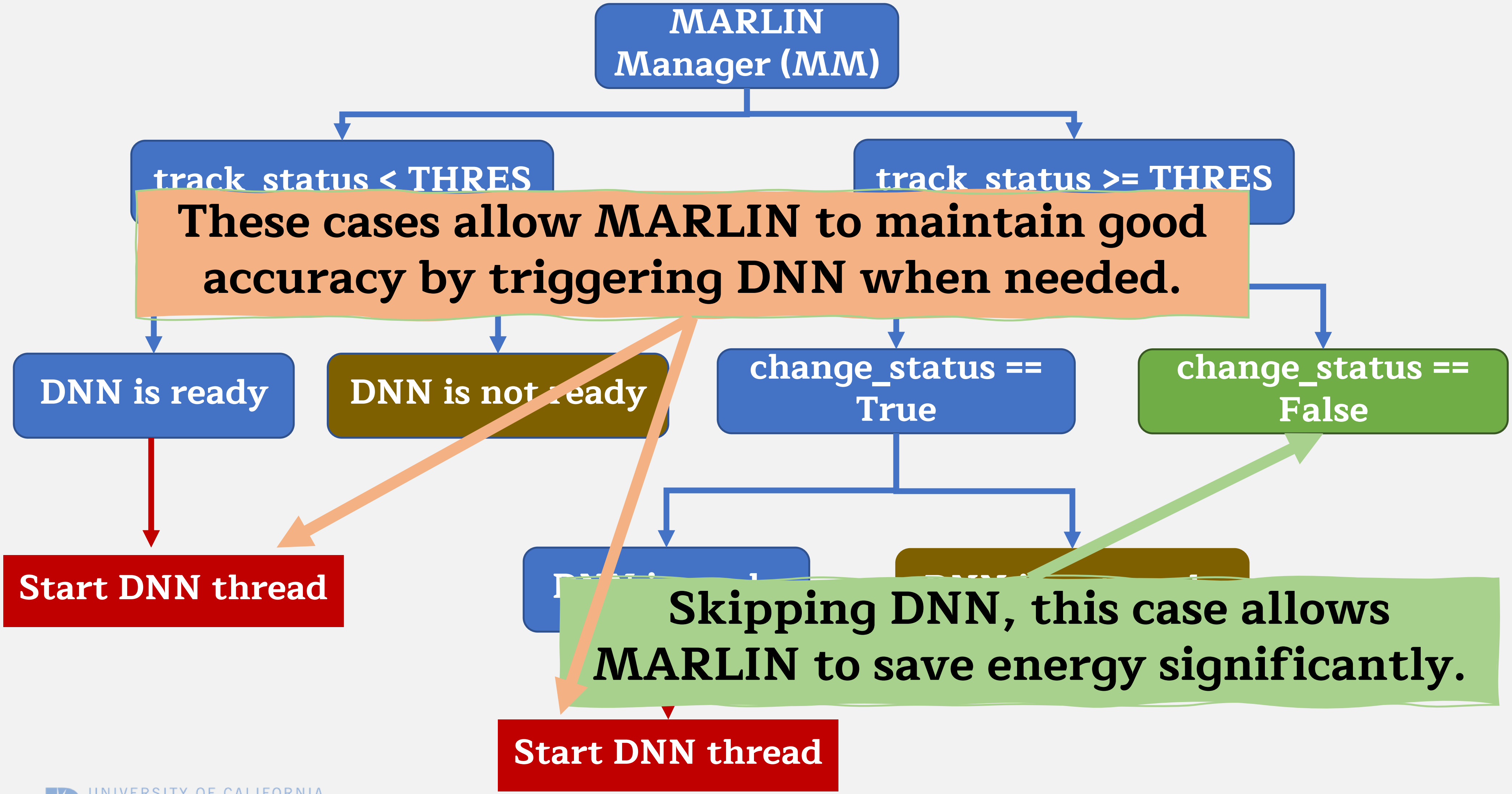
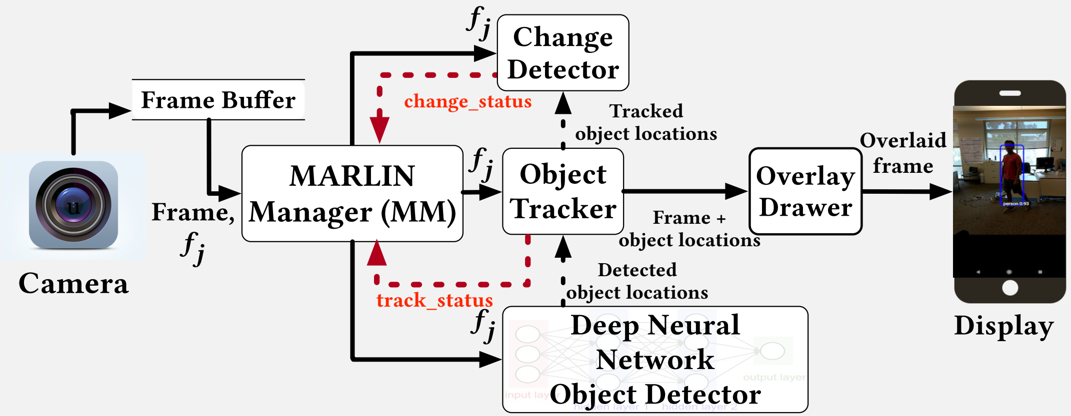
Thank you.

Backup Slides


MARLIN Manager (MM)
track_status < THRES
track_status >= THRES
These cases allow MARLIN to maintain good accuracy by triggering DNN when needed.
DNN is ready
DNN is not ready
change_status == True
change_status == False
Start DNN thread
Skipping DNN, this case allows MARLIN to save energy significantly.
Start DNN thread

MARLIN Architecture



- MARLIN Manager (MM) receives frame from camera and feed it to object tracker and/or change detector, which provide feedback to MM to decide whether or not to feed the frame to DNN (energy-heavy but may recover the system from low accuracy)

- MM first looks at track_status (how much a tracked object change in appearance compared to that in a previous frame)
  - If track_status < threshold, check DR flag and send this frame to DNN
  - Otherwise, send this frame to change detector and if there is a significant change (e.g. likely to have objects of interest in the scene) outside of the tracked object, check DR and send this frame to DNN

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Real-time Object Tracker

- ORB feature extraction can be done in near-real-time
- Object tracking by optical flow (of ORB features)
  - Extraction + tracking can be done < 10ms with 0.2-0.3 W, so this is practical for a 30-fps 640x480 camera
- Calculate normalized cross correlation (NCC) of a tracked object from a previous to the current frame
  - NCC is a good estimation of tracking quality (NCC is low when there is an occlusion or object deformation)
  - Ex. NCC from frame 1 to 2 = 0.92, and NCC from 2 to 3 = 0.69
  - Send this information as track_status to *MM*


Frame 1


Frame 2


Frame 3

Lightweight Change Detector

- A supervised learning agent that takes a vector of floating-point numbers (compressed from an image frame) and returns a binary decision as change_status back to *MM*
- Input vector represents color features in the frame after the areas of the tracked objects have been removed (whited out)
- Train the agent to learn color features of foreground (tiger or elephant etc.) and background (sky or grass etc.)
- It uses random forest (the best among different *ML* techniques tested), consisting of 50 decision trees
- It works very fast (~ 4ms per frame) and is very low-powered (< 0.1 W)

change_status=true

change_status=false

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