

面向移动与边缘设备的人工智能系统

AITime分享 徐梦炜

2020年8月21日





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- **本科 – 计算机系，北京大学**
- **联合培养博士 – 普渡大学**
 - 指导老师：Prof. Felix Lin
- **访问学生 – 系统组，微软亚洲研究院**
 - Mentor: 刘云新 研究员

- **研究方向: 移动与边缘计算**
 - 移动与边缘设备上的人工智能系统
 - 主页：<https://xumengwei.github.io/>



2015年9月 – 2020年6月

2011年9月 – 2015年6月



2018年11月 – 2019年11月



2015年3月 – 2016年3月



- The increasing attention on **AI systems**



Ion Stoica
Berkeley



Michael I.J.
Berkeley



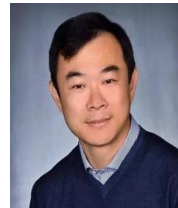
Jeff Dean
Google



Fei-Fei Li
Stanford



Yann Lecun
Facebook



Eric Xing
CMU

The 1st SysML
conference in 2018

A Berkeley View of Systems Challenges for AI

Ion Stoica, Dawn Song, Raluca Ada Popa, David Patterson, Michael W. Mahoney, Randy Katz, Anthony D. Joseph, Michael Jordan, Joseph M. Hellerstein, Joseph Gonzalez, Ken Goldberg, Ali Ghodsi, David Culler, Pieter Abbeel*

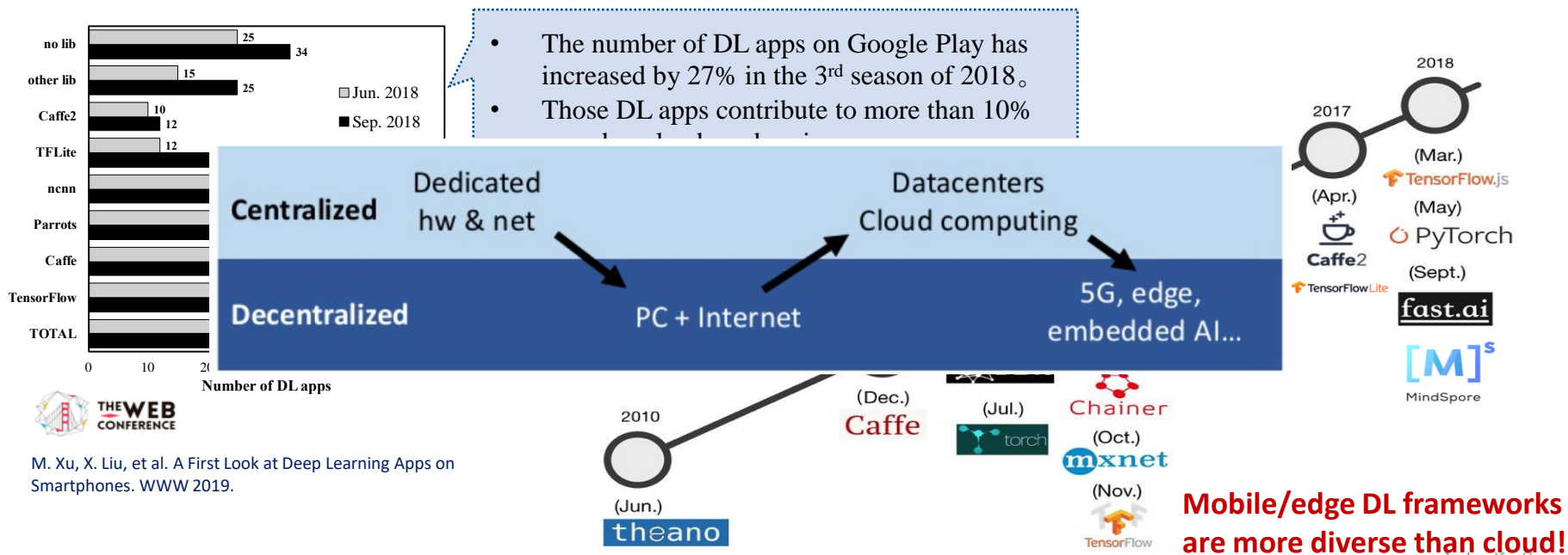
The opportunities and
challenges in the new AI
era for systems



Background



- The increasing attention on (**mobile and edge**) AI systems



Mobile/edge DL frameworks are more diverse than cloud!

- **Supporting DL on smartphones**

- CNN Cache to reduce inference time/energy (MobiCom 2018)
- On-device training for input personalization (UbiComp 2018)
- The first empirical study on smartphone DL apps (WWW 2019)
- Adaptive Local Offloading for On-Wearable DL (TMC 2019)



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- **More efficient federated learning**

- Heterogeneity-aware, automatic architecture search (arxiv)



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- **Camera-centric Video Analytics**

- Enabling video query on autonomous cameras (MobiSys'20)
- Approximate video query on zero-streaming cameras (arxiv)



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Video Analytics is a Killer App



- Busy cross roads
- Retailing store
- Sports stadium
- Parking lots
- ...



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Urban, residential areas

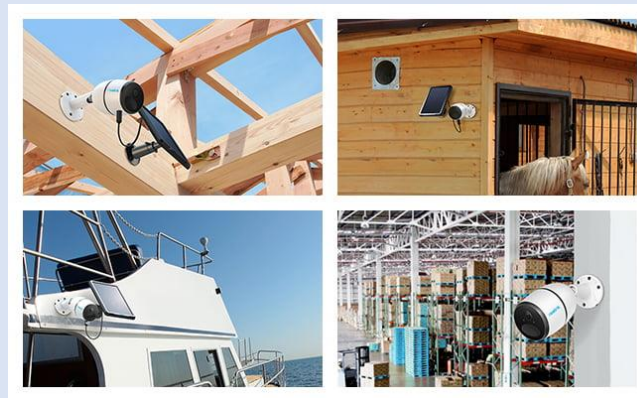
- ✓ Wired electricity
- ✓ Good internet



Video Analytics is a Killer App



- Busy cross roads
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- Construction sites
- Cattle farms
- Highways
- Wildlifes
- ...

Urban, residential areas

Rural, off-grid areas

- **Energy-independent** and **Compute-independent**



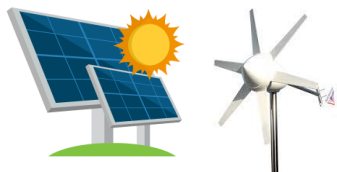
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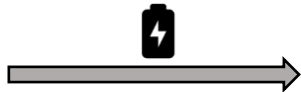
Commodity SoCs, RPI-like, chargeable battery



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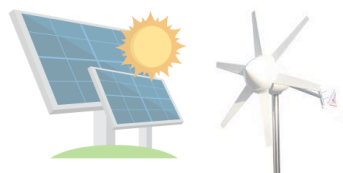
Small-sized
energy harvester
e.g., "10Wh today"



Commodity SoCs, RPI-
like, chargeable battery

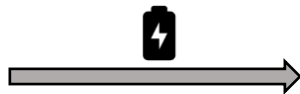


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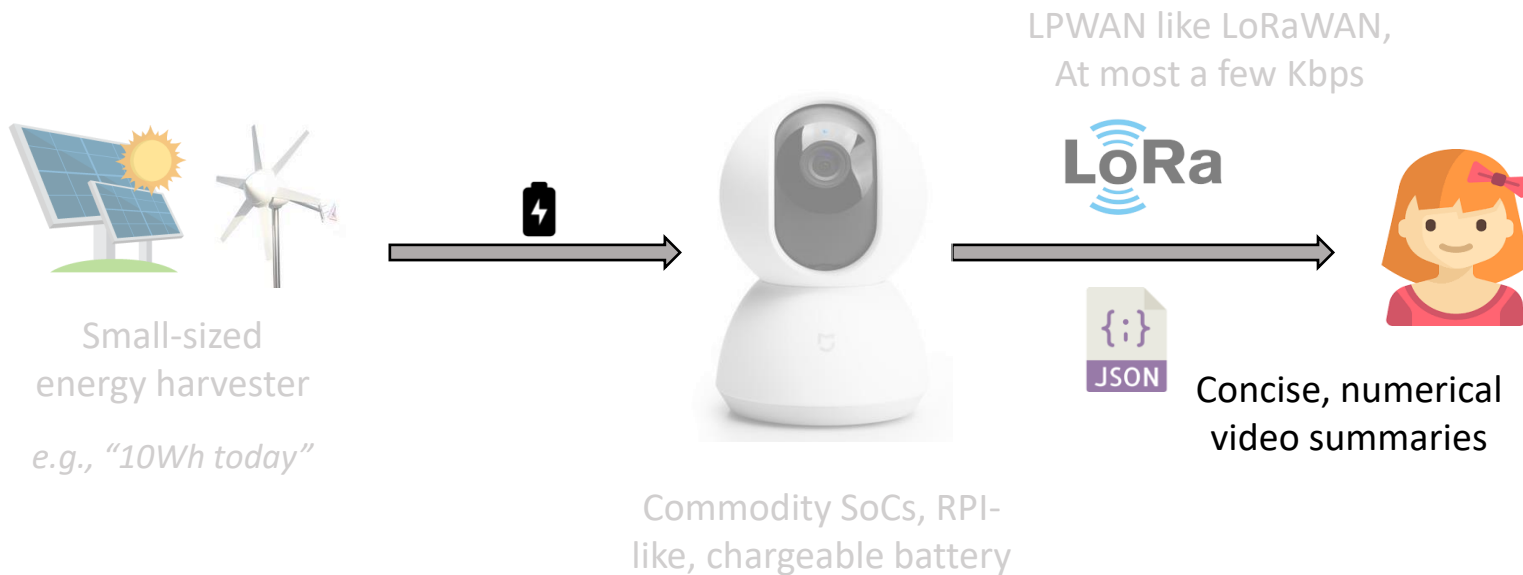


LPWAN like LoRaWAN,
At most a few Kbps

LoRa



- **Energy-independent** and **Compute-independent**



- Target video query: **object counting**



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Query: (car, 30 mins)

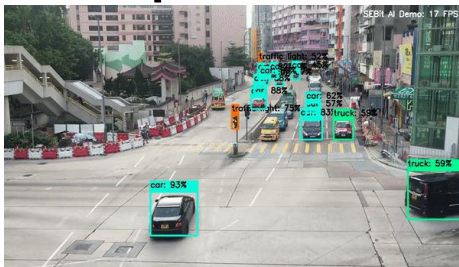


- Target video query: **object counting**

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Install

Sample & capture

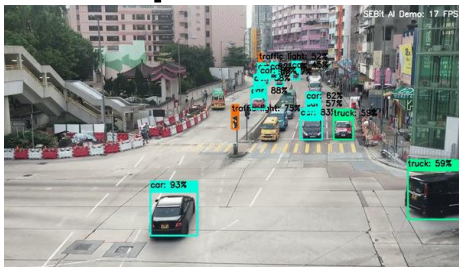


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Sample & capture



7:00AM-7:30AM [500 ± 100] Cars

7:30AM-8:00AM [700 ± 140] Cars

8:00AM-8:30AM [800 ± 180] Cars

8:30AM-9:00AM [400 ± 100] Cars

9:30AM-10:00AM [200 ± 80] Cars

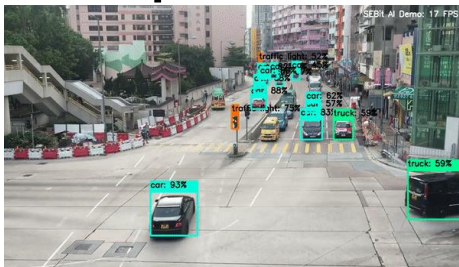


- Target video query: **object counting** with confidence interval (CI)

Query: (car, 30 mins)

Install

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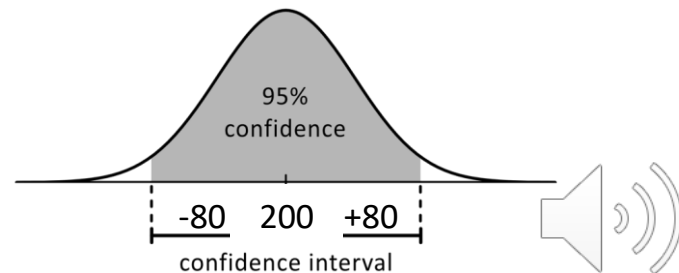
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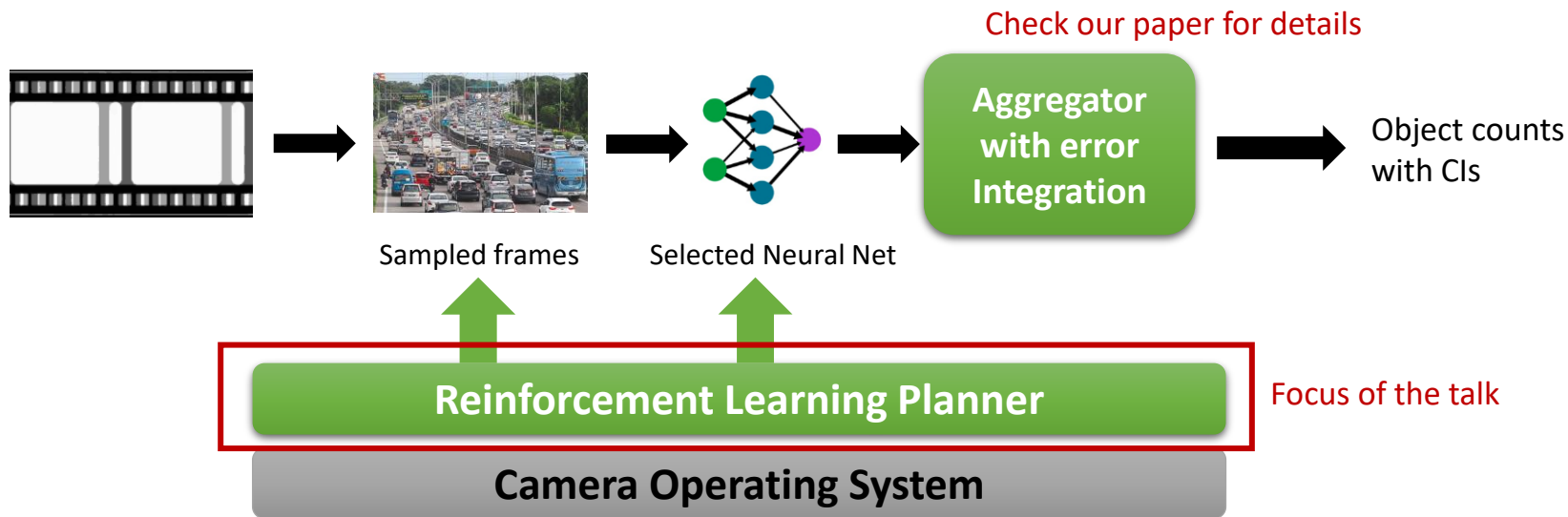
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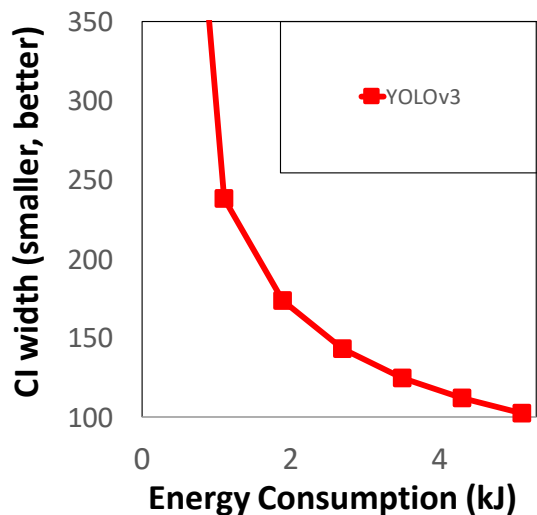


- Target video query: **object counting** with confidence interval (CI)
- The central problem: **planning constrained energy for counting**
 - Energy model: a budget that cannot be exceeded in a horizon (e.g., 24 hrs)
 - Trade-offs: frame sampling and NN selection
 - Target: smallest mean CI widths across all (30-min) windows in a horizon





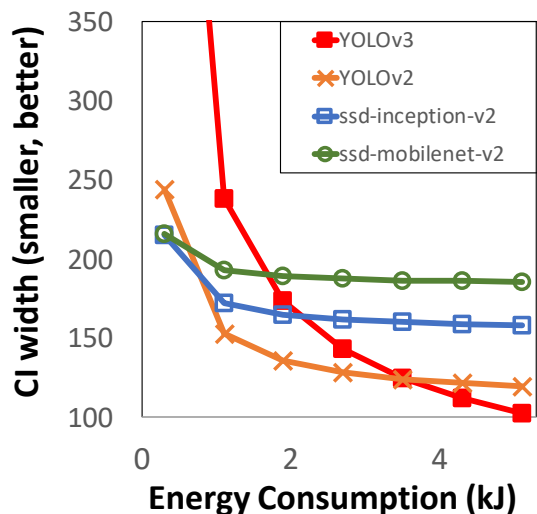
- What's the best count action for a window?
 - A *count action*: determining (1) an NN and (2) # of frames to process



$$\text{Energy Consumption} = E(\text{NN}) * \text{frame_num}$$



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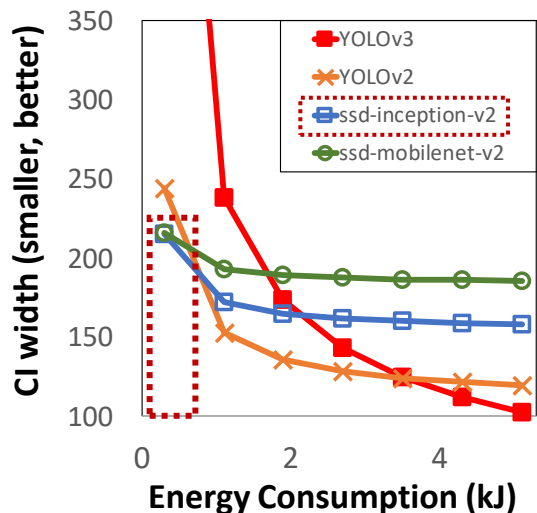


$$\text{Energy Consumption} = E(\text{NN}) * \text{frame_num}$$

NN Counters	Input	mAP	Energy
YOLOv3 (Golden, GT) [85]	608x608	33.0	1.00
YOLOv2 [84]	416x416	21.6	0.22
faster rcnn inception-v2 [86]	300x300	28.0	0.40
ssd inception-v2 [68]	300x300	24.0	0.08
ssd mobilenet-v2 [88]	300x300	22.0	0.05
ssdlite mobilenet-v2 [88]	300x300	22.0	0.04



- What's the best count action for a window? **No silver bullet.**
 - A *count action*: determining (1) an NN and (2) # of frames to process

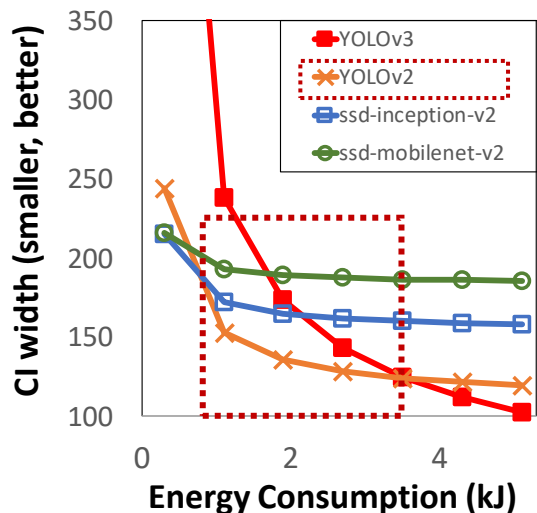


When energy is low: cheaper NNs win

- Bottlenecked by sampling error (**frame quantity**)



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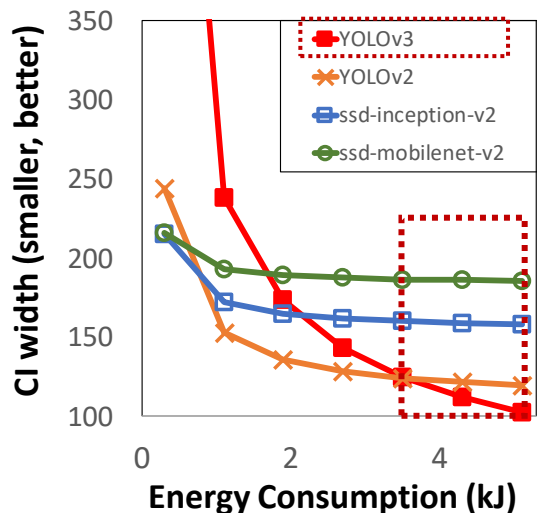
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When energy is low: more accurate NNs win

- Bottlenecked by NN error (**frame quality**)



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When energy is low: cheaper NNs win

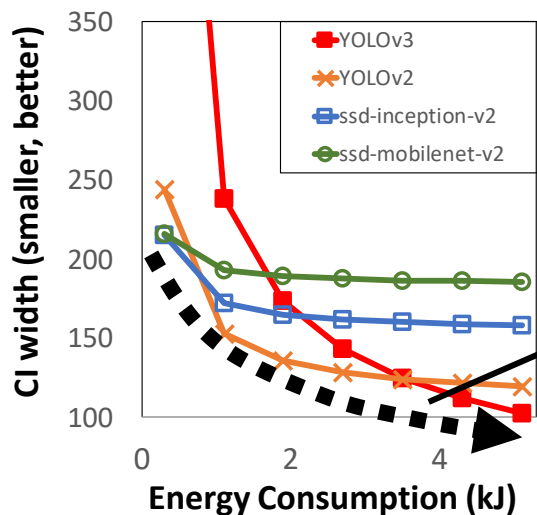
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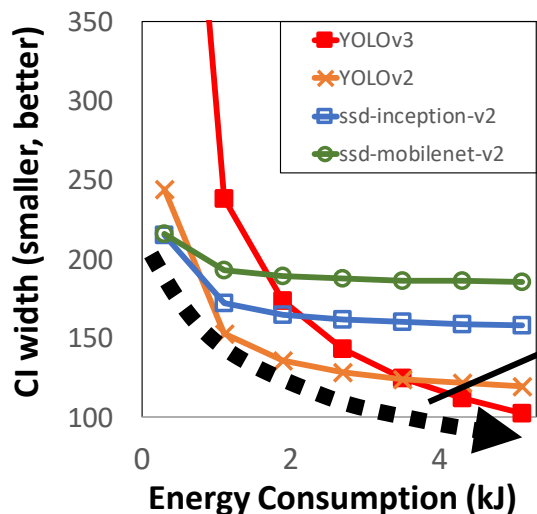


When energy is low: cheaper NNs win
When energy is low: more accurate NNs win

Energy/CI front: the combination of all “optimal” count actions with varied energy



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When energy is low: cheaper NNs win
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Energy/CI front: the combination of all “optimal” count actions with varied energy

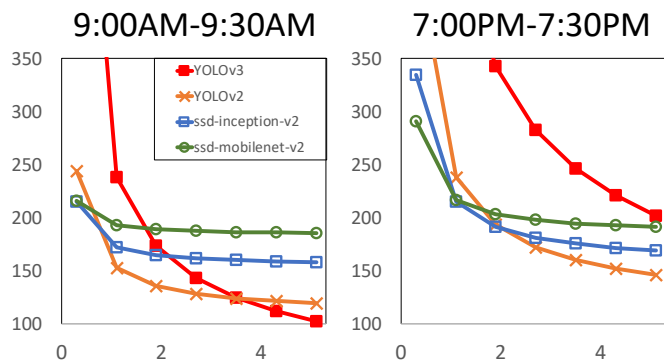
- How to construct? Error integration
- Depends on the video characteristics



Elf tech #1: per-window energy/CI fronts



- What's the best count action for a window? **No silver bullet.**
 - A *count action*: determining (1) an NN and (2) # of frames to process



Different windows have different energy/CI fronts

When energy is low: cheaper NNs win
When energy is low: more accurate NNs win

Energy/CI front: the combination of all “optimal” count actions with varied energy

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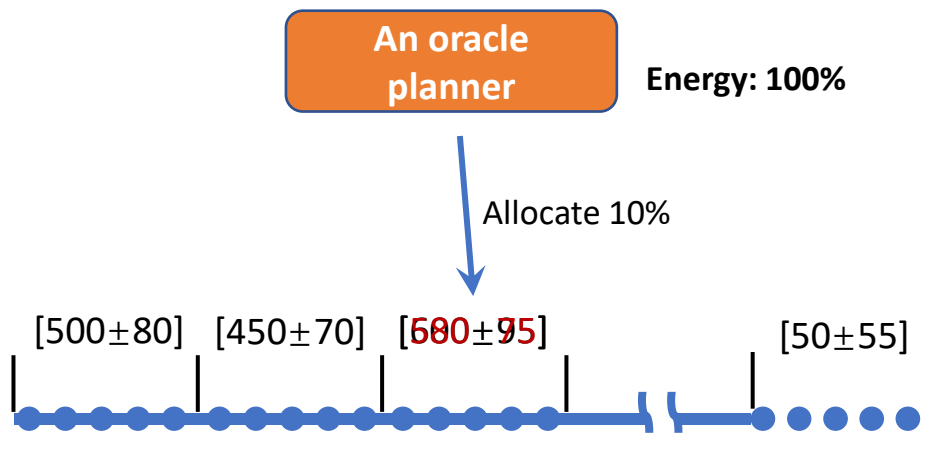




- An Oracle Planner: best performance but unrealistic
 - knows all energy/CI fronts



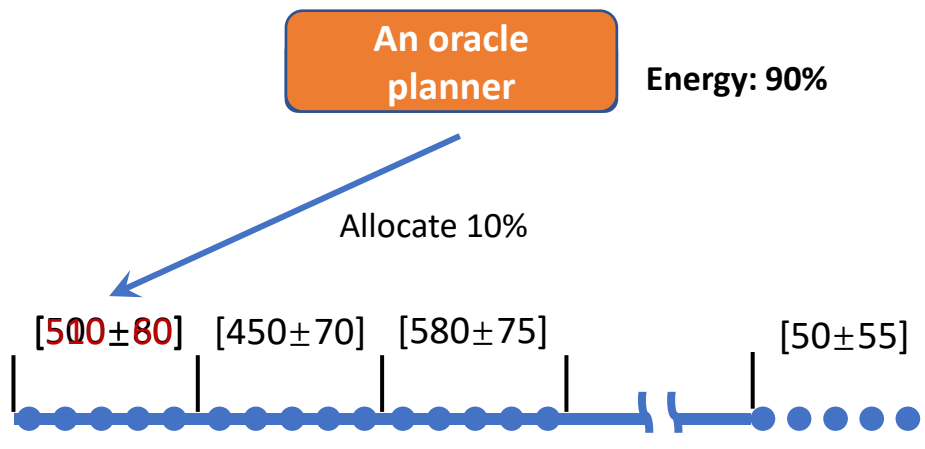
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A greedy approach: giving energy to the window with the most benefit (i.e., CI width reduction).



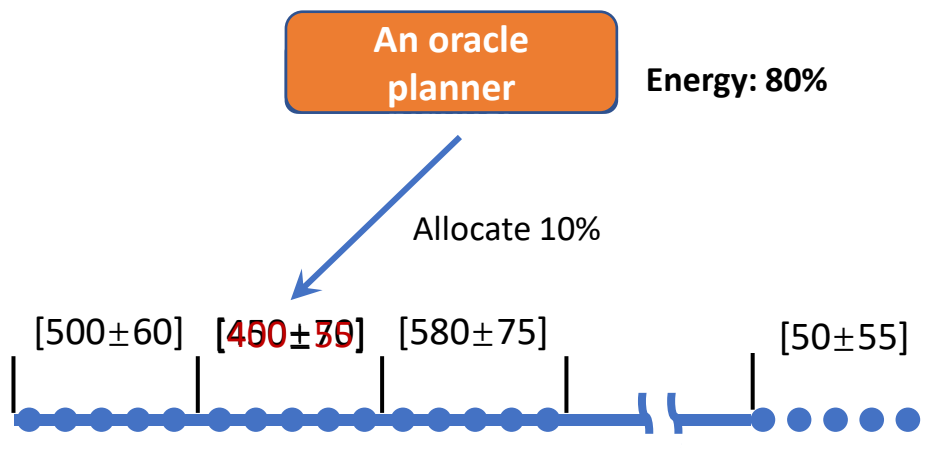
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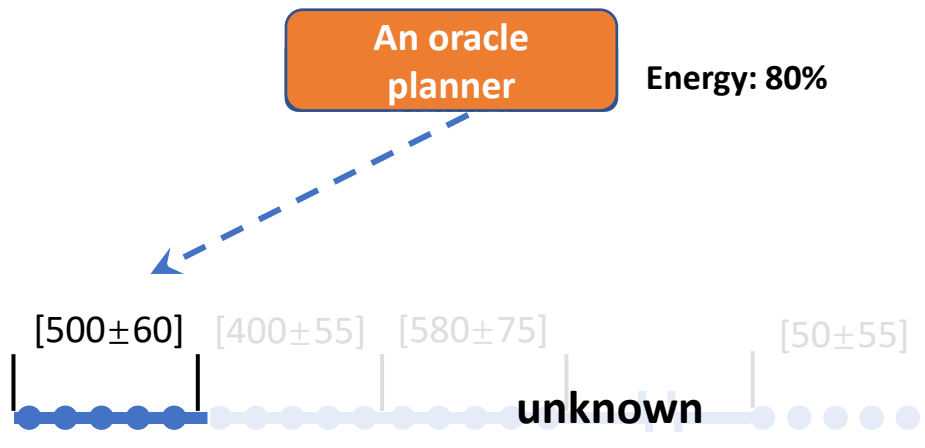
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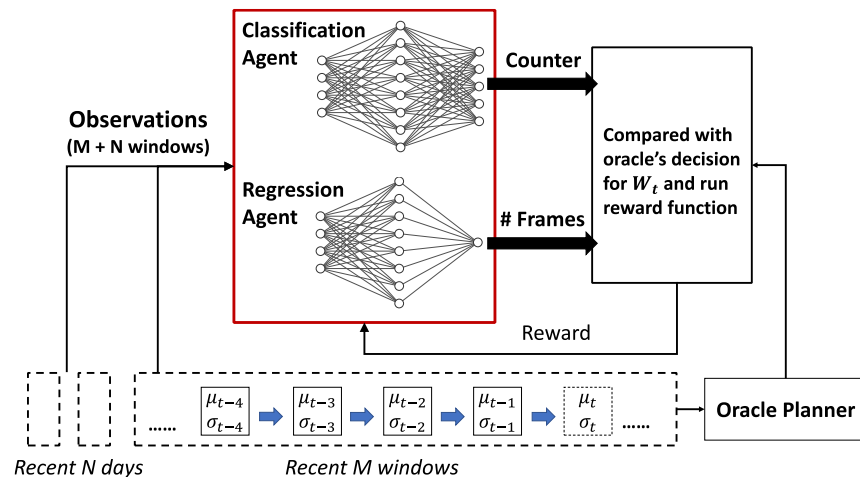
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Elf tech #2: across-window joint planning



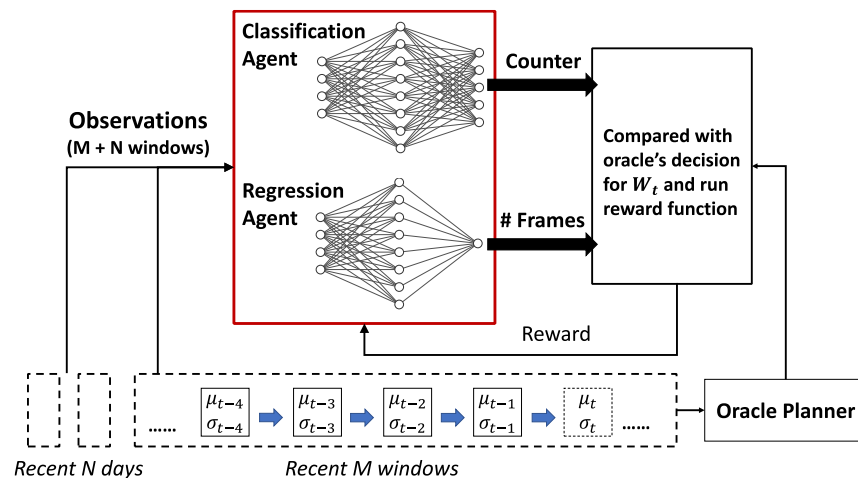
- An Oracle Planner: best performance but unrealistic
 - knows all energy/CI fronts
 - planned offline
- A learning-based planner: imitating the oracle planner
 - basis: reinforcement learning
 - rationale: daily and temporal patterns



Elf tech #2: across-window joint planning



- An Oracle Planner: best performance but unrealistic
 - knows all energy/CI fronts
 - planned offline
- A learning-based planner: imitating the oracle planner
 - basis: reinforcement learning
 - rationale: daily and temporal patterns
 - offline training -> online prediction
 - Two agents: NN selection and # of frames
 - Observations: knowledge of past windows
 - Penalty: deviation from oracle's decision





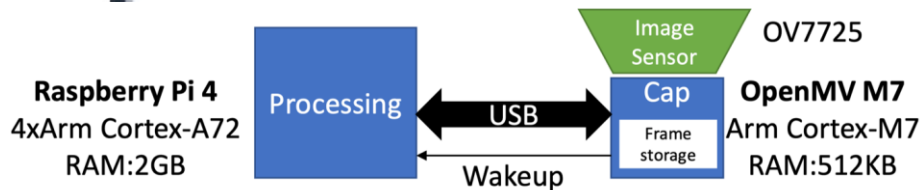
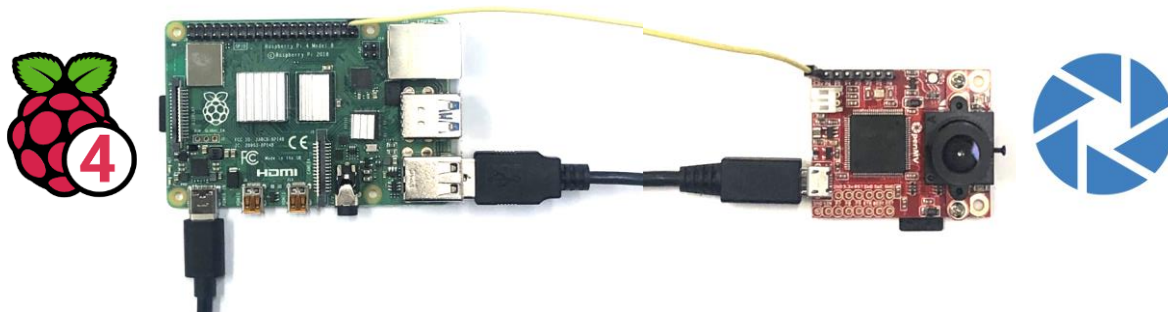
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- A learning-based planner: imitating the oracle planner
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 - offline training -> online prediction
 - Enforce energy budget: make reservation for future windows
 - 30 frames to be statistically meaningful



Elf Implementation



- Capture & processing decoupled for higher energy efficiency
 - Processing batched at the end of each window



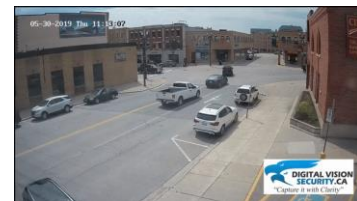
Elf Evaluation



- Over 1,000-hr videos
 - Public, 2-week long each stream
- Baselines
 1. *GoldenNN*: most accurate NN
 2. *UniNN*: one fixed best NN
 3. *Oracle*: offline planned
- Small solar panel
 - 10Wh~30Wh per day



Auburn, AL



Unknown



Hampton, NY



Jackson, WY



Taipei

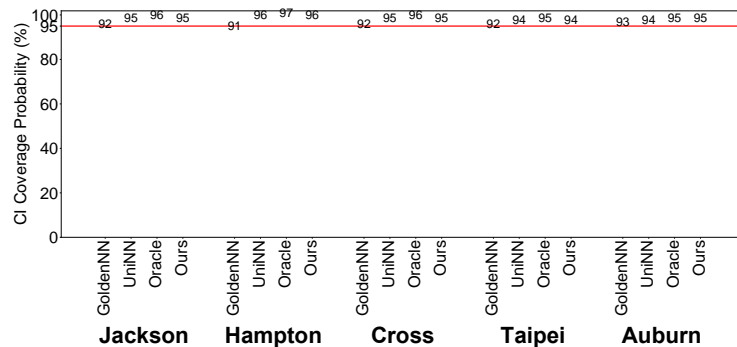
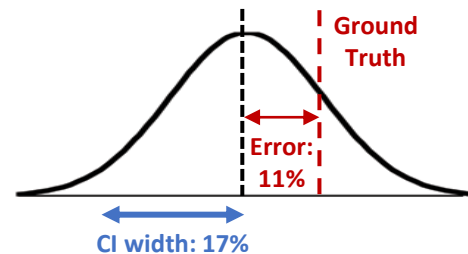


Taipei

Elf Evaluation



- Average: 11% error, valid and 17%-width CI
 - 95% confidence level

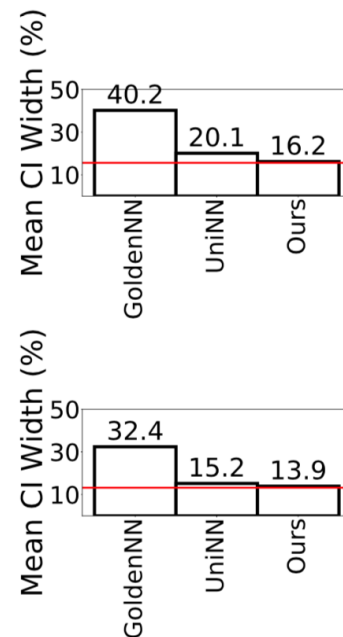


Cis cover ground truth
with 95% probability
(specified)



- Average: 11% error, valid and 17%-width CI
- Significant improvements over baselines in CI widths
 - 66.6%, 59.8%, and 56.2% smaller over *GoldenNN* (up to 3.4x)
 - 41.1%, 16.6%, and 9.7% smaller over *UniNN*

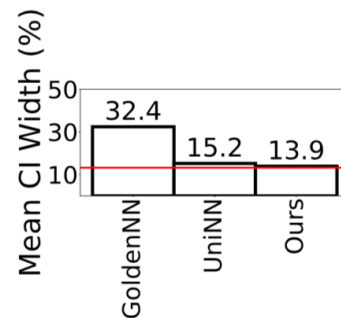
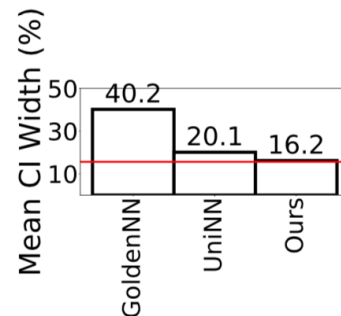
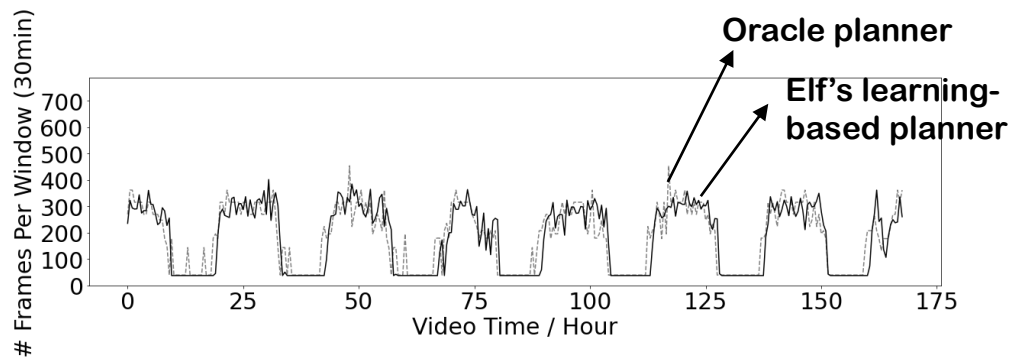
10Wh per day 20Wh per day 30Wh per day



Elf Evaluation

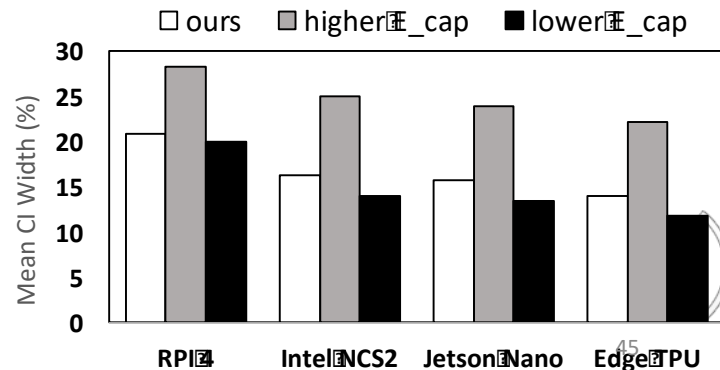


- Average: 11% error, valid and 17%-width CI
- Significant improvements over baselines in CI widths
- Very close to *Oracle*
 - < 5% wider CI
 - Well imitating the oracle planner



(a) Jackson

- Average: 11% error, valid and 17%-width CI
- Significant improvements over baselines in CI widths
- Very close to *Oracle*
- What if we have AI accelerators?
 - CIs are reduced noticeably (by 22.1%–33.1%)
 - Still cannot process every frame (short of energy)



- Autonomous camera: expanding the geo-frontier of video analytics
 - Energy-independent and compute-independent
- **Elf**: the first runtime for autonomous camera
 - Target query: object counting
 - Key idea: count planning per- and across-windows
- Prototyped on heterogeneous hardware
- Evaluated on over 1,000-hr videos
 - 11% error, 17% CI width

