Distributed Perception and Learning Between Robots and the Cloud

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Robot sensory data + compute models are becoming increasingly complex.

Fleets of *networked* robots

Growing volumes of rich video and LIDAR sensory streams

Increasingly compute-intensive models
How Can **Network Connectivity** Help Robots?

1. Better Inference Results (Real-time)
2. Better, *specialized* models (Offline)

**Challenge:** Conserve System Resources
Key Challenges of Cloud Robotics

1. Distributed Inference
2. Distributed learning

- Network Latency
- Annotation, Storage, Cloud Computing

Challenge: Limit Communication

~4 TB per car/day [Intel]
1. **Distributed Inference: The Robot-Cloud Offloading Problem**

Can robots *learn* when to query the cloud for higher accuracy but minimal communication cost?
Can robots *intelligently sample* minimal training examples for continual learning in the cloud?
Outline

1. Motivation:
   A. The Robot-Cloud Accuracy Gap (of Deep Neural Nets)
   B. Network Costs of Streaming Sensory Data
2. Distributed Inference: The Robot-Cloud Offloading Problem
3. Distributed Learning: The Robot Sensory Sampling Problem
4. Future Directions in Networked Control
The Robot – Cloud Accuracy Gap

By what margin does the cloud improve perception accuracy?
Advances in Embedded AI

Running MobileNet SSD v1 on Edge TPU

Objects: 19
Inference time: 14.09 ms (70.96 fps)

Running MobileNet SSD v1 on CPU

Objects: 18
Inference time: 386.89 ms (2.58 fps)

Edge Tensor Processing Unit (TPU)
(March 2019, $75)

Quad-Core ARM CPU
Accuracy of Robot and Cloud DNNs

<table>
<thead>
<tr>
<th>Platform</th>
<th>Cost</th>
<th>Accuracy (mAP)</th>
<th>Inf. Time (ms)</th>
<th>DNN</th>
<th>Size (MB)</th>
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<td>183</td>
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Cloud DNNs localize far-off objects

MobileNet 2 (Fast, power-efficient)

Faster R-CNN (slow, accurate)

MN2 takes 9 more seconds than Faster R-CNN to localize the far-off tractor. Ample time to query the cloud.
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Hidden Costs of Network Congestion

Can we experimentally quantify the systems cost of streaming video and LIDAR?
Network Costs of Cloud Communication

1. Congested Wireless Links

Chinchali *et. al.* “Neural Networks Meet Physical Networks” (ACM HotNets ’18)
Our Network Congestion Experiments

“ROS Ate My Network Bandwidth!”
(Robot Operating System [ROS] User Forums)

~70 Mbps
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1. **Distributed Inference: The Robot-Cloud Offloading Problem**

Can robots learn to best interleave on-board and cloud computation?

![Diagram showing a network with robots connected to a neural net, indicating succinct feedback and minimal data.](image)
Cloud Offloading: A Dynamic Decision-Making Problem

Query the cloud for better accuracy?
Latency vs. Accuracy vs. Power ...

Sensory Input

Robot Model

Offload Logic

Offload

Local Compute

Cloud Model

Congested, Stochastic
Robot-Cloud Offloading: Sequential Model Selection

*State:* sensory input, remaining query budget, age of past prediction, ...

*Action:* which model to choose?
- use past prediction: cheap, potentially stale prediction
- use robot model: more expensive, potentially low accuracy
- query cloud model: most expensive, highest accuracy, limited budget

*Reward:* balance **prediction accuracy** with **cost of querying model**

Key Constraint: Limited Queries to the Cloud

Video Frames Over Time
Robot-Cloud Offloading: A Learning Problem

Video Frames Over Time

Use Robot Model

Use Past Prediction

Use Cloud

State: Hard to model dynamics of Network and Video Evolution $\rightarrow$ Model-Free RL

Action: which model to choose?

- use past prediction: cheap, potentially stale prediction
- use robot model: more expensive, potentially low accuracy
- query cloud model: most expensive, highest accuracy, limited budget

Constraint: Limited Queries to the Cloud

Reward: balance prediction accuracy with cost of querying model
A Learning-Based Approach to Cloud Offloading

[Diagram showing a drone connected to a neural network with succinct feedback and minimal data]
Reinforcement Learning (RL)

Goal: Maximize the total reward $\sum_t r_t$

Agent $\rightarrow$ Environment
- Reward $r^t$
- Action $a^t$
- Measure state $s^t$

Exploration vs. Exploitation Tradeoff
- **Exploit**: On-board Robot Model
- **Explore**: Utility of Cloud by *learning*

Hard to Model Dynamics
- What will a robot see next?
- Wireless network evolution
Robot

State $s^t$

$\pi_{\text{offload}}$

$\alpha^t = 2$

$x^t$

$\gamma^t_{\text{robot}}$

$\alpha^t = \{0, 1\}$

Past Predictions

Limited Network

$\alpha^t = 3$

Cloud

Cloud Model

Predict

$y^t_{\text{cloud}}$

Offload

Reward
The Robot Offloading MDP

\[ \mathcal{M}_{\text{offload}} = (\mathcal{S}_{\text{offload}}, \mathcal{A}_{\text{offload}}, \mathcal{R}_{\text{offload}}, \mathcal{P}_{\text{offload}}, T) \]

\[ \hat{y}^t_{\text{robot}}, \text{conf}^t_{\text{robot}} = f_{\text{robot}}(x^t) \]
\[ \hat{y}^t_{\text{cloud}}, \text{conf}^t_{\text{cloud}} = f_{\text{cloud}}(x^t) \]

Modular robot and cloud models

Widely Applicable Beyond Neural Nets

Only assume predictions + confidences
The Robot Offloading MDP: Action Space

\[
\alpha_{\text{offload}}^t = \begin{cases} 
0, & \text{use past robot prediction } \hat{y}^t = f_{\text{robot}}(x_{\tau_{\text{robot}}}^t) \\
1, & \text{use past cloud prediction } \hat{y}^t = f_{\text{cloud}}(x_{\tau_{\text{cloud}}}^t) \\
2, & \text{use current robot prediction } \hat{y}^t = f_{\text{robot}}(x^t) \\
3, & \text{use current cloud prediction } \hat{y}^t = f_{\text{cloud}}(x^t) 
\end{cases}
\]

Past predictions, local model, or cloud

4 succinct actions: easy to run on hardware

No network? Use local model (safety)
The Robot Offloading MDP: State Space

\[ s^t_{\text{offload}} = \left[ \phi(x^t), f_{\text{robot}}(x^{T_{\text{robot}}}), f_{\text{cloud}}(x^{T_{\text{cloud}}}), \Delta t_{\text{robot}}, \Delta t_{\text{cloud}}, \Delta N_{\text{budget}}, T - t \right] \]

1. Has the visual input *changed* much?
2. What do stored, past predictions say?
3. How *old* are past predictions?
4. What *cloud budget + time* remain?
The Robot Offloading MDP: Reward

\[ R^t_{\text{offload}}(s^t, a^t) = -\alpha_{\text{accuracy}} - \beta_{\text{cost}} \text{cost}(a^t) \]

\[ \mathcal{L}(y^t, \hat{y}^t) - \text{model error} \]

\[ \text{latency, compute} \]

Balance accuracy and systems cost

Rigorously define costs from experiments

<table>
<thead>
<tr>
<th>DNN</th>
<th>Accuracy (mAP)</th>
<th>Size</th>
<th>Inf. Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>MobileNet v1</td>
<td>18</td>
<td>18 MB</td>
<td>26 ms</td>
</tr>
<tr>
<td>MobileNet v2</td>
<td>22</td>
<td>67 MB</td>
<td>31 ms</td>
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<tr>
<td>Mask R-CNN</td>
<td>45.2</td>
<td>1.6 GB</td>
<td>325 ms</td>
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</tbody>
</table>
1. **Distributed Inference**: The Robot-Cloud Offloading Problem

Hardware Experiments

- **Succinct Feedback**
- **Minimal Data**

- Neural Net
Query Cloud

Robot Model

FaceNet

SVM Classifier

Embed

\( x_t \)

Face A

Coherence Time

\( t = 0 \)

\( t = T \)
Deep RL beats benchmark offloading policies

Reward: Balance **Accuracy** and **Model Cost**

**RL**: 2.3x Benchmark Reward

*Interleave* On-Robot and Server Compute

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![Graph showing accuracy and cost comparison](image)

- **Oracle**
- **Heuristic**
- **All-Robot**
- **All-Cloud**

**Cloud, ID-0**: 70.52%

**Cloud, ID-4**: 34.5%

**Robot, ID-0**: 85.70%
Hardware Experiments on Live Video + Embedded Compute Platform

Compact RL Offloader!

Chinchali et. al. “Network Offloading Policies for Cloud Robotics: A Learning—Based Approach” (RSS 2019, Finalist for Best Student Paper)
2. **Distributed Learning: The Robot Sensory Sampling Problem**

Can robots sample task-relevant training examples from large sensory streams?
Can we make actionable insights from growing robotic sensory data?

Learning Rare Events Can Improve Decision-Making Models
Robotic Fleets: Distributed, passive collectors of training data
Intelligent Sampling reduces systems bottlenecks
Outline

1. Motivation
2. Distributed Inference: The Robot-Cloud Offloading Problem
3. Distributed Learning: The Robot Sensory Sampling Problem
   A. Benefits of Cloud Re-training
   B. Systems Costs of Acquiring Training Images
   C. Sampling Approach
   D. Results
4. Future Directions in Networked Control
2. **Distributed Learning: The Robot Sensory Sampling Problem**

A. Why specialize vision models in the cloud?

- **Succinct Feedback**
- **Minimal Data**

![Diagram showing drone connected to neural network and database]
Rationale 1: Specialization corrects errors

Default Vision Model
Pre-trained on COCO dataset

Our Re-trained Model
Using minimal images
Model specialization can correct key errors

Default Vision Model
Pre-trained on COCO dataset

Our Re-trained Model
Using minimal images
Rationale 2: The real world is *constantly changing*

3 months of *my dashcam* footage

Can robots update HD maps with roadblocks, potholes?
2. Distributed Learning: The Robot Sensory Sampling Problem

B. What is the cost of distributed learning?
Why sample?: Reduce **systems costs**

~13 GB of video clips (small)  
340k images to select from

**Automatically Sample**

Google Cloud Labeling Service:  
$49 for 1000 bounding boxes  
$850 for 1000 masks

**Our experiments:** We labeled 1000 boxes in 1.4 hours (~200 images)

Worse for even 1% of autonomous car data

Our Sampler: $400 for 8k detailed annotations
2. Distributed Learning: The Robot Sensory Sampling Problem

C. But how do I automatically sample?: Technical Approach
Insight 1: Minimal Images are Needed

**Static Targets:** Law of Diminishing Returns

**Dynamic Targets:** Continual Learning Needed

Robots update HD maps to reflect real-world changes
Insight 2: **Efficiently** filter images of interest during inference

Transfer Learning: Adapt pre-trained CNN to new classes

Insight: Use CNN confidence scores/embeddings to filter targets (red) from noise (blue)

Embeddings/scores come “for free” during inference
Insight 3: **Delegate** compute-intensive tasks to the cloud

Use **cloud feedback** to adjust confidence thresholds from growing dataset.
Annotate

Cache

Stored

Dataset

Robot

Limited Network

Cloud

Vision Model

Sampler

“Interesting” Image?

Sample Cache

Update Model

Re-train Model

Stored Dataset

Annotate Cache

Upload
2. The Robot Sensory Sampling Problem

D. Distributed Learning Results

Distributed Learning Results

Minimal Data

Succinct Feedback

Neural Net

Minimal Data

Succinct Feedback
Continual Learning on Road-Scene Domains

Sample only 18-34% of all possible images, reduces systems costs
Adapting Vision Models with Minimal Images

Default Vision Model
Pre-trained on COCO dataset

Our Re-trained Model
Using minimal images

Domain-Specific
Future Directions

Task-Driven Representations for Control

Succinct Feedback

Minimal Data

Neural Net
Future Technology Trends

Edge TPU USB
(March 2019, $75)

Nvidia Jetson TX2
(March 2017, $450)

5G Wireless

Cloud AI:
- Constantly updated maps / databases
- Human annotation
- Model re-training
- Multi-robot view

Edge AI: Faster, Cheaper, and Smaller

Hardware gap may be transient, but the utility of the cloud and distributed learning will persist
Future 1. **Task-Driven** Representations for Perception

More concise representations than raw images

Co-design sensory representation with inference/control task
Early Results: **Task-Driven** Representations

**Co-design** representation with final task

Encoder: \( q(z^t | x^t; \theta_e) \)

Decoder: \( p(x^t | z^t; \theta_d) \)

Pre-trained Model: \( y^t = f(x^t; \theta_p) \)

Reduce information by 8x for same classification accuracy (MNIST)
Future 2. (Semi) Federated Learning for Robots

Why not specialize models (re-train) on the robot ("edge")?
Most training data resides on robot, extrapolate from few human labels

*Robot-specific* model + data

Ideally, no private data
Network operators have a wealth of data, some private. Can agents trade concise representations for cooperative control?

Limit the scope and volume of data traded across boundary.

Re-think the separation principle for “data-driven” control.
Robot Network Cloud

Sensory Input

(1) Offloader
(2) Sampler
(3) Task-Encoder
(5) Private Training

Network

New Models + Feedback

Inference + Learning

Cloud

Multi-Device Coordination

(4) Traffic Scheduling

Task-Driven Representation

Thanks! Questions:
csandeep@stanford.edu
IoT Traffic Scheduling (AAAI 2018)

Melbourne Central Business District, Rolling Average = 1 min

Network State

IoT Scheduler

IoT rate

Diverse city-wide cell patterns
Extra Slides
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<tr>
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<th>Acc. (mAP)</th>
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<tr>
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Motivating Technology Trends

1. **Rich Sensory Data:**
   High-bitrate + volume

2. **Compute-intensive Models:**
   Perception + Control, some deep nets

3. **Better wireless networks:**
   Low-latency access to compute (even cell towers!)
   *But* more mobile traffic!

4. **Robot – Cloud Computing Gap:**
   Edge AI: Fast, low-power, less-accurate*
   Cloud AI: Slow, more-accurate* but “global” view
RL beats benchmark offloading policies

> 2.6x reward of benchmarks

RL: 70% of oracle reward

All-Robot: today’s de-facto
RL intelligently, but **sparingly** queries cloud
Cloud Offloading as a Decision Problem

Contending goals:
- Maximize Accuracy
- Minimize latency
- Limited Network Share

Optimal Control

Robot Correct

Limited Cloud Queries

Wasted Queries

Robot Confidence

t

Limited Cloud Queries

Wasted Queries

Cloud Queries
Continual Learning on FaceNet Domains

![Graph showing test accuracy over rounds for Face A and Face B. The graph compares different methods: Oracle, HarvestNet, Non-adaptive, and Random.](image)
**Labeling Team**: How do we proceed when there is no good visibility (highlighted in the image)
- Few cases the edges of the car are not visible
- Few cases the lidar is not clearly visible.
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(1) New Image

(2) Vision Model $i$ - Predictions, Embeddings

(3) Target Images, Thresholds $i$

(4) Sampler - Store?

(5) Sample Cache $i$

(6) Annotate Cache - Upload

(7) Re-train Model

(8) Adapt Thresholds, Target Images

Cloud

Limited Network

Robot

New Targets, Thresholds $i+1$
Growing Volumes of Robotic Sensory Data

• Learning Rare Events Can Improve Decision-Making Models

• Robotic Fleets: Distributed, passive collectors of training data

• Intelligent Sampling reduces systems bottlenecks
Limited Network Robot Vision Model

Sample Cache

Sampler

“Interesting” Image?

Sample Cache

Cloud

Update Model

Stored Dataset

Re-train Model

Annotate Cache

Upload

Dataset

W

Upload